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Machine Learning Emulation of Model Predictive Control for Modular Multilevel Converters

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***Abstract*—This paper proposes a machine learning (ML) based emulation of model predictive control (MPC) for modular multilevel converters (MMCs). In particular, the artificial neural network model, trained offline by the data collected from the traditional fast MPC method, is used to control the MMCs with high accuracy. With this offline training, the majority of computational burden is transferred from online to offline. Therefore, the proposed ML MPC can replace the role of the traditional MPC. The experimental results show that the proposed ML based MPC has the same performance as the conventional MPC but a significantly computationally efficient structure. The finding from the letter provides ground for many other applications for ML based emulation of complex controllers in power electronic systems.**

***Index Terms* — Modular multilevel converter, machine learning, model predictive control, computational burden.**

I. INTRODUCTION

WITH the large-scale development of renewable power transmission, Modular Multilevel Converter (MMC) is the most dominant topology in voltage source - high voltage direct current (VSC-HVDC) application. Because of the modular nature of MMC, MMC has good expandability and redundancy fault tolerance. And the MMC output current harmonics are very small, making it possible to use a small (or even no) filter [1]. However, the complicated structure of series-connected submodules needs to be controlled properly.

Traditional proportional-integral (PI) /proportional resonance (PR) based controllers rely heavily on the careful design of individual controller parameters (output current controller and circulating current controller), and the bandwidths of controllers need to be carefully designed

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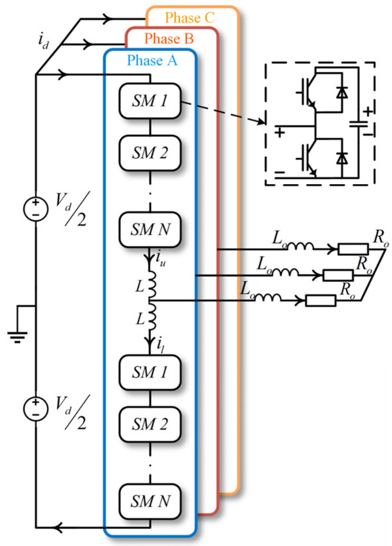

Fig. 1. Three-phase MMC circuit diagram.

according to the actual situations. Model predictive control is a mathematical model-based multi-input-multi-output (MIMO) control algorithm, which was proved to have a good dynamic response even under significant parameter variations [2]. Paper [3] first proposed the MPC controller in the MMC system, from the results, the output currents and the circulating current are well controlled by the MPC controller. However, since each bridge arm of the MMC has many sub-modules, the MPC imposes a high computational cost in order to balance the capacitive voltages of these sub-modules, which is a major disadvantage of the MPC MMC. Many papers proposed computational efficient methods for MPC based MMC [5]–[7]. However, those solutions cannot change the MPC's key trait: The model predict controller evaluates all possible switching signals at each control cycle and selects the best set of control signals to minimize the cost function. This online exhaustive approach can lead to a heavy controller computational cost.

In this letter, a machine learning emulation of the model predictive control is proposed to significantly reduce the computational cost but while maintaining excellent dynamic response. ML technology is widely applied in power electronics applications, for example, a short-term memory recurrent neural network based power fluctuations identification method is proposed to maintain the power system frequency in [10]. In [9], an artificial neural network (ANN)

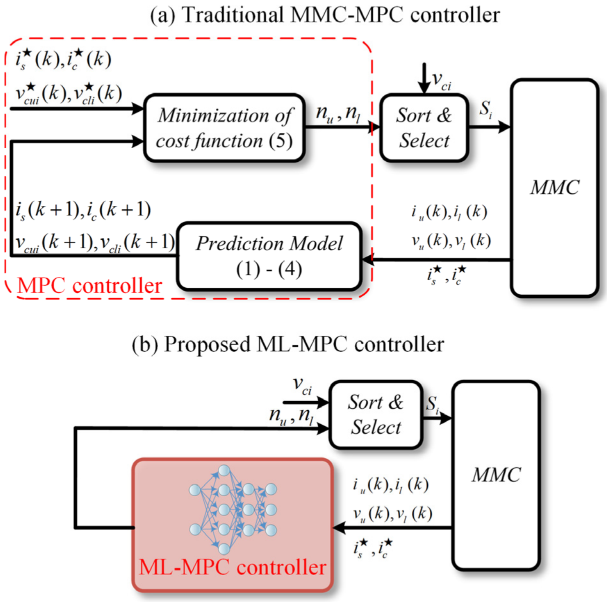

Fig. 2. (a). Traditional MPC for MMCs; (b) The proposed ML based controller for MMCs.

based power electronics design method by including the reliability is proposed to achieve a better comprehensive performance of power electronics systems.

The machine learning models can be trained by data get non-parameter models to represent the real-world input-input relationships [8], [9]. The ANN is a subset of machine learning technology which is applied in this letter. The machine learning network can be trained offline and then the trained network can be applied in the offline simulation or implemented in a real-time microprocessor system such as DSP and dSPACE controller. And also, this letter shows the computational cost of the proposed method is significantly lower than the MPC controller and also perfectly emulates the MPC controller.

II. MPC FOR MMCs

To train the ML MPC controller, the traditional MPC need to be established first to collect the input/output data.

A. The model predictive control for MMCs

Fig. 2(a) presents the MPC based MMC system, and the controller structure comparison between MPC and the proposed ML based controller is also shown. The implementation of the MPC in MMC is described step by step. The comprehensive introduction of the MPC MMC implementation is in [7].

1) The MMC sensors measure the variables: upper/lower arm currents, upper/lower arm voltages, output current, and internal circulating current;
2) The MPC algorithms predict the all the possible output variable values in next sampling interval for all the possible switching signals;
3) The MPC algorithms create the MPC cost function regarding the output/circulating current.
4) The MPC algorithms selected the optimized switching signal which can track the control references, i.e. achieve the lowest cost function;
5) The optimized switching signals are used to control the MMC.

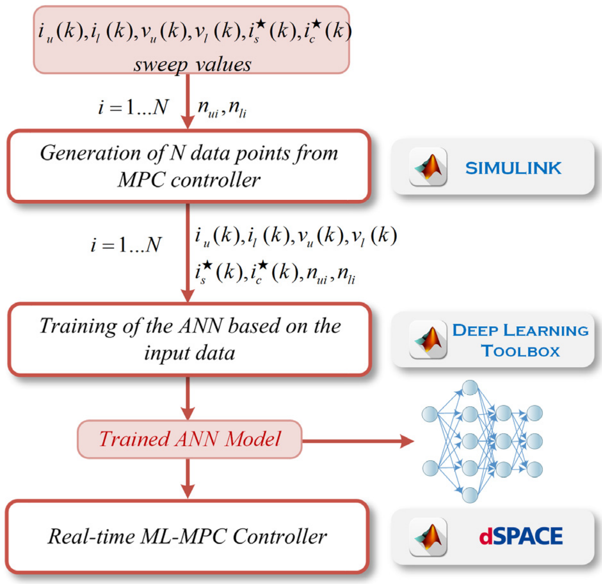

Fig. 3. The training and implementation procedures of ML MPC

The discrete-domain dynamics of output variables are [8]:

$$i_s(k+1) = \mathrm{A}[(n_l(k)\cdot v_{cl}(k+1) - n_u(k)\cdot v_{cu}(k+1))/N] + \mathrm{B}i_s(k)$$
$$\mathrm{A} = 2T_s/(L_{arm}+2L_s), \mathrm{B} = 1-2T_sR_s/(L_{arm}+2L_s) \quad (1)$$

$$i_c(k+1) = \mathrm{C}[V_d - (n_l(k)\cdot v_{cl}(k+1) + n_u(k)\cdot v_{cu}(k+1))/N] + i_c(k)$$
$$\mathrm{C} = T_s/(2L_s) \quad (2)$$

$$v_{cu}(k+1) = \frac{n_u(k)\cdot T_s}{C_{SM}} i_u(k) + v_{cu}(k) \quad (3)$$

$$v_{cl}(k+1) = \frac{n_l(k)\cdot T_s}{C_{SM}} i_l(k) + v_{cl}(k) \quad (4)$$

where v_{cu}, v_{cl} / i_u, i_l are upper/lower arm voltages/currents respectively, n_u, n_l are upper/lower submodule inserted numbers, respectively, T_s is digital sampling interval, L_{arm} is arm inductance, L_s, R_s are load inductance and resistance, respectively, V_d is DC voltage, C_{SM} is the capacitance of the submodule capacitor, $x(k+1)$, $x(k)$ are the values of the variables at sampling moment k+1 and k.

The cost function (CF) for the MMC control is:

$$g = w_1\cdot|i_s^\star(k) - i_s(k+1)| + w_2\cdot|i_c^\star(k) - i_c(k+1)| \quad (5)$$

where w_1 is the output current weighting factor w_2 is the circulating current weighing factor. $i_s^\star$ is the output current reference and $i_c^\star$ is the circulating current reference. In this letter, $w_1 = w_2 = 1$.

In the real-time experiment, the delay of the digital controller is compensated by the method which in introduced in [11]. This letter applied this delay compensation approach.

B. Deterministic input-output relationship of MPC

The deterministic relationship between input variables and output variables of MPC is the key feature that allows the ML

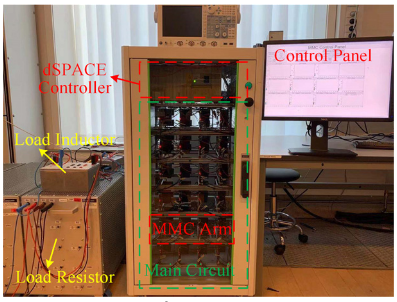

Fig. 4. The picture of the experimental prototype

based controller to accurately emulate the behavior of the MPC controller. This deterministic relationship is: all the possible output currents and circulating currents are predicted by the MPC controller by considering all possible switching configurations with a set of measured input variables. Then the best switching signal is selected to minimize the cost function. That is to say, the output variables (inserted number of MMC arm) will always be unchanged when the cost function and the measured input variables are unchanged. However, MPC has a heavy computational burden because the MPC controller has to search exhaustively for all the possible switching signals to find the suitable switching signal in every controller time interval. On the other hand, when this deterministic feature is represented by a more computationally light structure (i.e. neural network in our paper), an essentially the same control effect is achieved, but with a far lower online computational cost. In the next sections, a ML based controller is used to represent this deterministic feature of MPC.

II. Machine Learning Based Model Predictive Controller for MMCs

A. Machine learning based MPC for MMCs

Fig. 2 illustrates the comparison of the traditional MPC method and the proposed ML based MPC method. The only difference of these two methods is that ANN model replaces the MPC block. In next section, we will introduce the data collection steps for training the ANN model.

B. Data Acquisition and Model Training

The following describes how to get data from the MPC controller and use this data to train a machine learning model. The general steps are presented in Fig. 3.

1) *The Training Data Sampling:* To train the ML controller, the training data should be collected from the MPC controller first. The data collection algorithm will sample the variables within a certain range. The arm voltages v_{cu}, v_{cl} are sampled from a range [0,350], with a 10V step, then 36 values are sampled from upper/lower arm voltage. We use [0:10:350] to represent this sample operation. Similarly, upper/lower arm currents i_u, i_l, the output current reference $i_s^{\star}$, and the circulating current reference $i_c^{\star}$ are sampled as follows respectively: [-6:1:6], [-6:1:6], and [0:0.2:2]. It only takes 76 seconds to collect this data. In order to make sure the training performance is good, we recommend each input variable should be sampled at least 10 points for the whole variable range. What is more, it is important to consider the whole range of the input variable, otherwise the tracking performance is worse compared to traditional controller.

TABLE I
MMC PARAMETERS IN EXPERIMENT

	Experiment
Number of SMs per arm (N)	4
Rated DC voltage (V_d)	200 V
Nominal SM capacitance (C_{SM})	2000 µF
Nominal SM capacitor voltage (V_c)	50 V
Rated frequency (f)	50 Hz
Arm inductance (L_{arm})	10 mH
Sample frequency	10 kHz
Load inductance (L_s)	1.8mH
Load resistance (R_s)	10.8Ω

2) *ML Network Structure Selection:* Firstly, the ANN is selected because it is extremely simple. Although ANN is simple, it is still useful to deal with the problem that the data may consist of a completely different set of features, such as table data [13]. Secondly, we selected the hidden layer number of the network, the universal approximation theorem [14] states that an ANN with a single hidden layer, containing a finite number of neurons, can approximate any continuous function with mild assumptions on the activation function [15]. In this letter, one hidden layer structure is applied. The neuron number selection is based on a rule of thumb. To achieve a better training performance, a high neuron number is recommended to select within the range of the min/max neuron numbers

Minimum neuron number:

$$0.5(N_i + N_o) = 4 \quad (N_i = 6, N_o = 2) \tag{6}$$

Maximum neuron number:

$$2N_i = 12 \tag{7}$$

where N_i is the input unit number $N_i = 6$, N_{out} is the output unit number $N_{out} = 2$.

In this letter, we select the neuron number as 9.

3) *ML Model Training:* The data was used to train the proposed ML MPC network, i.e. a feedforward neural network, which represents the relationship between input variables and output variables. The trained ML model is used to calculate the upper and lower arm inserted number of MMC. With the changing of the insert numbers, the output variables can be controlled to track their references. The ANN contains three layers: input layer, hidden layer, and output layer. The hidden layer contains 9 neurons. The network training is implemented in MATLAB.

III. Experimental Results

The proposed ML MPC controller is verified in the lab prototype. A 24-submodule, three-phase MMC experimental platform is used to verify the proposed method. The digital

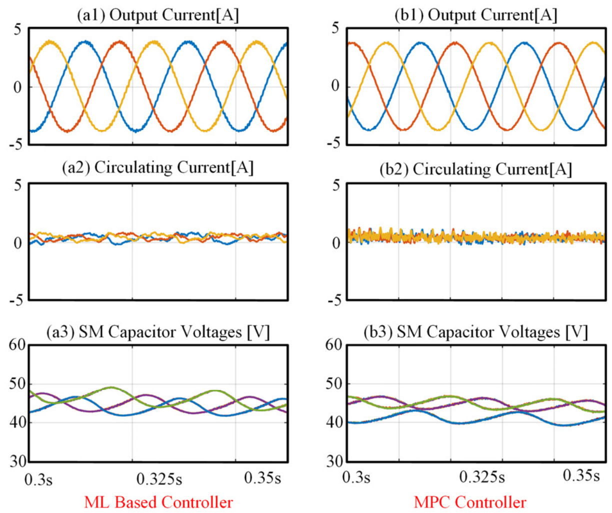

Fig. 5. The experimental results of ML MPC and traditional MPC

controller is based on the dSPACE real-time control platform, the controller model is DS1006. The parameter of the experimental platform is presented in Table. I. The prototype picture is presented in Fig. 4.

A. Steady State Performance

Fig. 5 presents the steady state performance of proposed ML MPC and the traditional MPC. From Fig. 5 (a1) and (b1), the output currents of the MMC are controlled to the references: AC currents with 4A amplitudes. The total harmonic distortion (THD) of the ML control output current is 0.023%. The THD of the MPC control output current is 0.021%. The circulating currents are suppressed by both control methods which are shown in Fig. 5 (a2) and (b2). The capacitor voltages are shown in Fig. 5 (a3) and (b3), the capacitors are sorted and balanced by the sort & select algorithm [12].

B. Dynamic Performance

Fig. 6 shows the dynamic performance when the reference

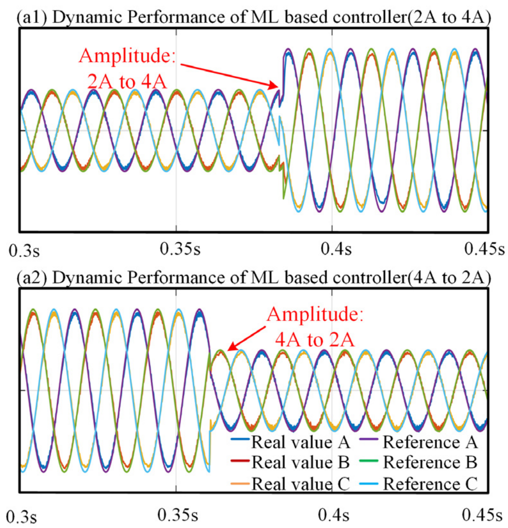

Fig. 6. Output Current dynamic.

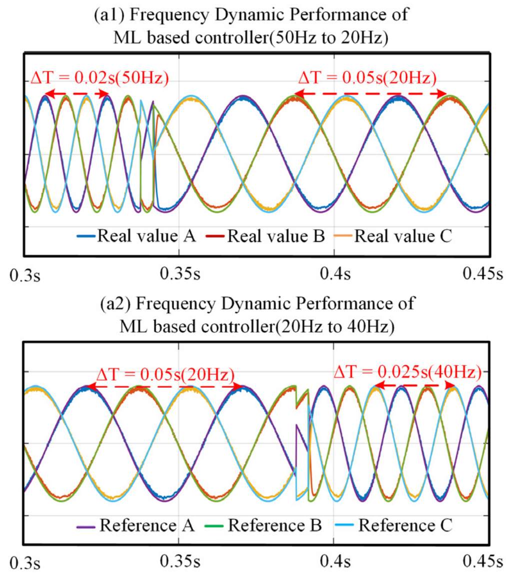

Fig. 7. Output Current frequency dynamic.

TABLE II
TRAINING PERFORMANCE

Number of Neurons	Training Time	MSE
4	2:15:56	0.302
6	2:52:58	0.199
9	3:26:54	0.177

TABLE III
COMPUTATIONAL BURDEN

	ML	Fast MPC	MPC
Mean Turnaround Time (μs)	1.123	1.615	9.790
Max Turnaround Time (μs)	1.252	1.788	9.690
Min Turnaround Time (μs)	1.070	1.561	9.947

amplitudes are suddenly increased and decreased. In Fig. 6 (a1), the output current references are suddenly stepped from 2A to 4A, the proposed ML controller can accurately follow the changed references in a short period of time. The output currents are suddenly decreased from 4A to 2A, which is shown in Fig. 6 (a2).

Fig. 7 shows the dynamic performance when the frequency of output current is changed. In Fig. 7 (a1), the frequency of output current is suddenly decreased from 50Hz to 20Hz. In Fig. 7 (a2), the frequency is increased from 20Hz to 40Hz. The results verify that the proposed controller can control the output current in different frequencies, which is an advantage comparing to traditional PI/PR controller because PI/PR controller need to set a specific working frequency or to extract the dq components from PLL [16], [17].

C. Performance with different neuron numbers.

The influence of the neuron numbers of the trained networks is introduced in this subsection. Table II shows the training performance of the trained networks with different neuron numbers. MSE is the mean squared error, a lower MSE means a better training performance. When the neuron number is 9, the

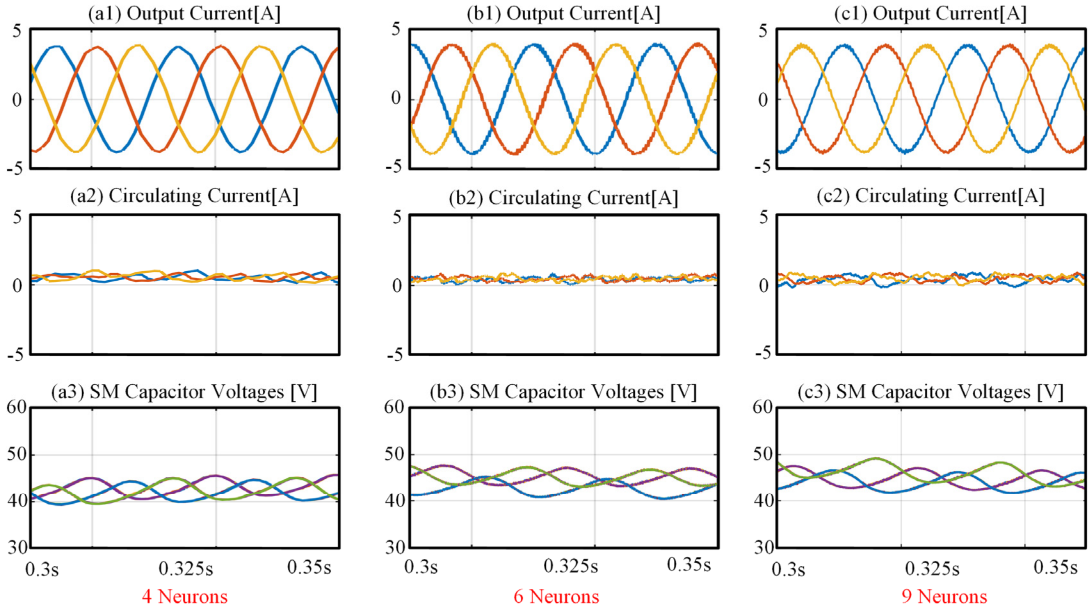

Fig. 8. Experimental Results of ML controller with different neuron numbers.

best performance is achieved (lowest MSE).

Fig. 8 shows the experimental results of the trained networks with different neuron numbers. Those three networks all can achieve good performance, the experimental results show that this ML controller is not under a specific structure that a good control effect can be achieved

D. Performance with different data size

The size of the training data influences the control performance of the proposed controller. Fig. 9 shows the output current results and the tracking errors of the trained networks. The definition of the testing error is as below:

$$TrackingError = (1 - \frac{V_{ispp}}{V_{isrefpp}}) \times 100\% \tag{8}$$

where V_{ispp} is the peak to peak value of the output current, $V_{isrefpp}$ is the peak to peak value of the output current reference.

In Fig. 9, when the data size is low (4860 and 22500), the tracking errors are unacceptable (11.18% and 13.46% respectively). When the data size is increased to 249018, the tracking error is reduced to 2.61%. When the data size is further increased to 4889808, the tracking error is further reduced to 1.97%. Finally, when the data number is 31320432, the tracking error is below 1%. So in this letter, we recommend each input variable should be sampled at least 10 points for the whole variable range, and the recommended training error should below 1%.

E. Computational Burden

The computational burden can be estimated by the calculation number of the controllers [19]. The calculation number of traditional MPC in [18] is $C_8^4 = 70$ because the this MPC algorithm will select 4 out of 8 submodules to be inserted. All those insertion conditions need to be calculated and predicted by the MPC [4]. The calculation number of the fast MPC with experimental delay compensation algorithm in [7] is $4^2 = 16$ because it has 2 loops, each loop has 4 vectors to predict. And the calculation number of the proposed ML based controller is 9 because it has 9 neurons in the hidden layer [19]. Thus, the traditional MPC's calculation number is almost 8 times the ML based controller's calculation number, and the calculation number of MPC controller is 43.75% higher than the ML controller' s calculation number.

The computational cost of the proposed ML based controller is very small because the pre-trained ANN structure. Thus this method can be easily implemented in DSP or dSPACE controller. The computation cost of the MMC controllers can be measured by the dSPACE Profiler. Table III shows the computational burden in dSPACE platform of the proposed ML controller, the fast MPC method in [7], and the traditional MPC method in [18]. From Table III, the mean turnaround time of the traditional MPC is 9.790 μs which is almost 8 times the mean turnaround time of the proposed ML controller (1.123μs). And also, the mean turnaround time of the computational efficient MPC is 1.615μs which is still 49.2% higher than the proposed ML-based controller.

F. ML Based Method VS Lookup Table

Since the ANN is to emulate the deterministic relationship of MPC, lookup table is another opinion to represent this deterministic relationship. In this section, we discuss the advantages of ML based compare to lookup table method.

Once the network with suitable structure is trained, its evaluation is computationally light as it takes only around 1.1 μsec to generate the output signals. Interestingly, if the same amount of data as in the ANN training set is used to try and create a look-up table, the system runs out of memory. For instance, the data size we used as a training set is 31320432, and the system was not able compile such a huge amount data.

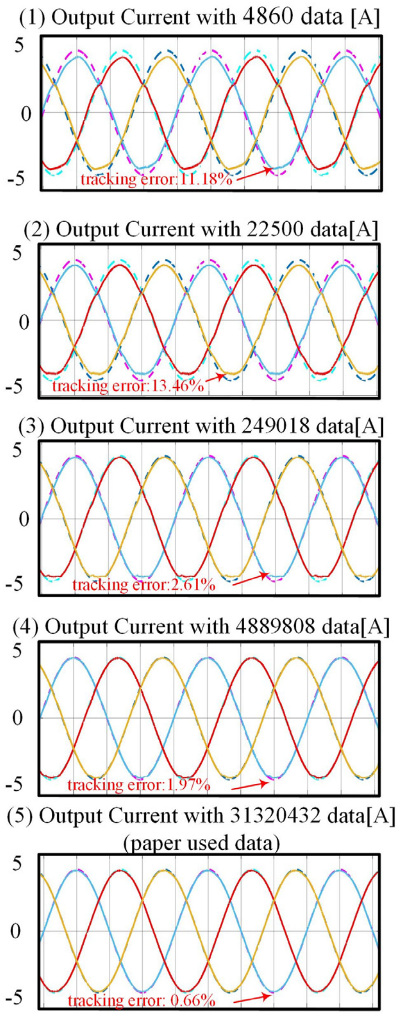

Fig. 9. Results of ML controller with different size of data

Therefore, it can be concluded that due to large data size, ML methods are suitable for use for fast real time applications as opposed to lookup tables.

G. Performance of Unseen Input data

The ML network is trained by the data with a given range. In this subsection, the performance of the unseen input data performance is discussed. In this letter, the training range of the output current reference is [-6A, 6A]. When the output current reference exceeds [-6A, 6A], this reference is unseen data. We tested 2 unseen output current references: 7A and 9A amplitudes of the output current. The results are shown in Fig. 10.

From Fig. 10, two unseen output current references results are shown. In Fig. 10(a), the output current reference amplitude is 7A, which is 1A above the training range [-6A, 6A]. Both the MPC and ML based controller can track the reference precisely. These results prove the ML network has the ability to work properly even under the unseen data, which is slightly beyond the training range.

However, when the unseen output reference is 9A, which is 50% above the training range, Fig. 10 (b) shows the ML based controller cannot track the reference precisely. To prevent this problem, we suggest the original range should be at least 30% higher than the rated condition.

IV. Conclusion

This paper proposes a machine learning based MPC controller for MMCs. The artificial neural network is offline trained by the data extracted from the traditional MPC algorithm. The experimental results show that this artificial neural network can control the MMCs with a good steady state and fast dynamic performance, but at the same time with a low computational burden. In future, this method can simulate more complex model predictive control algorithms

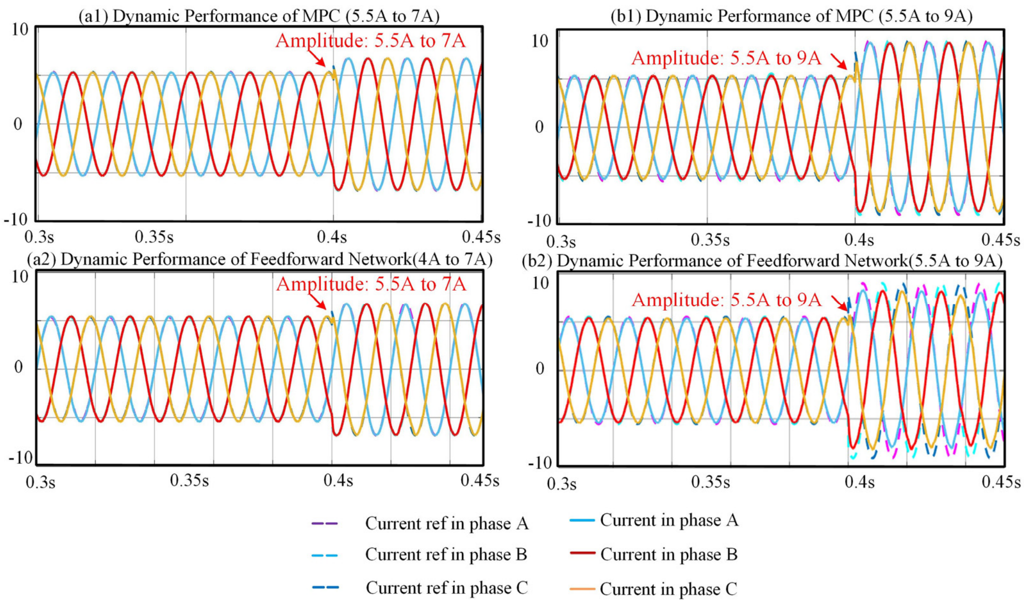

Fig. 10 The results when the output current references exceed the training range.

and reduce further the computational burden.

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