FCS-MPC Based Dual-module ANN Controller for Three-level Converter

Kun Wang[1], Xinliang Yang[1], Shuiqi Chen[2] and Ki-Bum Park[1]
[1] Cho Chun Shik Graduate School of Mobility, KAIST, Korea
[2] Electrical and Computer Engineering department, UCLA, USA

***Abstract*--Finite-control-set model predictive control (FCS-MPC) shows great control performance and adaptability for different converter topologies and operating modes. However. The computation burden increases significantly for long prediction step and multi-level topology. Artificial neuron network (ANN) is developed to imitate FCS-MPC controller for similar control effect with lower computation burden. However, the imitation accuracy is not good enough for single ANN. To achieve acceptable control effect using a simple ANN, we propose an FCS-MPC-based dual-module ANN controller. We first off-line train the ANN to imitating the FCS-MPC. Then we designed a dual-module structure which combines ANN and FCS-MPC to increase the imitation accuracy. The simulation result shows that the accuracy of our design increases to 99.87% while the computation burden is reduced by 58.8% compared with FCS-MPC. It can achieve similarly control performance and significantly reduce computation burden.**

***Index Terms*—ANN, Computation burden, FCS-MPC, THD.**

I. Introduction

Finite control set model predictive control (FCS-MPC) is an effective method for controlling power converters, offering a flexible and intuitive approach that can manage multivariable problems and incorporate system constraints [1]. It is treated as an alternative promising candidate for controlling modular multi-level converters (MMC) which shows great advantages of high power level, low harmonics, and easy expansion. [2][24].

However. with the increase of the number of output levels and prediction period, FCS-MPC's computational burden increases rapidly, put a cell on the MMC's performance. In this regard, people have carried out many research to reduce them computation burden [8] [9] [10]. Reference [11] filters the switch state for next time step by considering some neighboring switching combinations of current state. Reference [12] groups submodules in MMC and use adjacent voltage level evaluation to reduce the computation burden. These methods are all based on traditional MPC, and use different methods to pre-select candidate states to reduce the computational burden. However, when the topology of MMC is more complex and the number of candidate states cannot be effectively reduced, the computational burden of such methods is very heavy. Therefore, machine learning (ML) based methods that do not rely on traversing candidate states are proposed [13].

ML have been widely used in power electronics due to their excellent nonlinearity and data processing capabilities [14] [23]. Artificial neuron network (ANN), which is also known as multi-layer perceptron (MLP), has been developed for many years since its invention in 1958 due to their simple structure and easy deployment. Some researchers have developed ANN to imitate FCS-MPC [15][16]. ANN has been adapted in voltage tracking for three-phase converter [17] and weighting factor design for FCS-MPC [21]. In [18], a similar performance is achieved by ANN compared with model predictive control in a two-level topology with a reduced computation burden. The performance of the ANN is affected by the network structure [14].

In this paper, we first introduce a new evaluation method for the ANN. Then we propose a dual-module controller structure based on ANN and FCS-MPC, which use ANN to shrink the state space for FCS-MPC. According to the simulation, our design achieves qualified control effect and low computation burden at the same time. The computation burden is reduced up to 58.8% compared to conventional FCS-MPC and the imitation accuracy is increased to 99.87%. Our design also provides sufficient flexibility for the controller. By introducing artificially controlled parameters, the Pareto boundary of the controller's performance is given, and it can cope with the scenario where the control frequency and control effect are traded off. Although these methods exhibit excellent efficiency in terms of computational burden, their imitation accuracy, or control effect, can't fully match that of FCS-MPC. [23]

The arrangement of this paper is as follows: In the second section, we introduce the components of the whole system, including the topology of the three-level converter, the design of the MPC, the design of the ANN, and the definition of the TOP-n accuracy. In the section III, we propose a dual-module controller structure, and design the working mode and working standard for it. Then we test our design in MATLAB SIMULINK and present the simulation results in Section IV, and then we analyze and discuss the simulation results. Finally, we give the conclusion of this paper and the follow-up work plan in Section V.

II. Model Explanation

In this section, we illustrate the details of our model including circuit topology, FCS-MPC design, ANN model and TOP-n accuracy.

A. Converter topology

The three-level neutral-point clamped (NPC) converter is used as the topology of this paper which is shown in Fig. 1, and the specific parameters are given in TABEL I. Three phase AC grid is connected to the converter with via a filter.

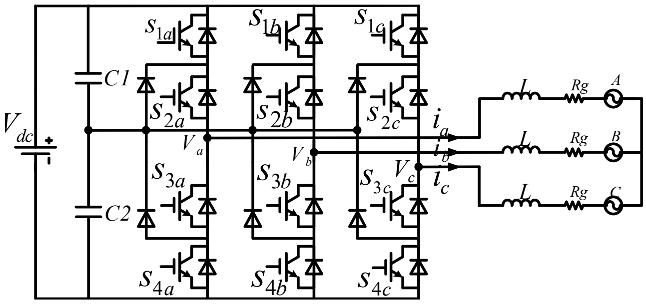

Fig. 1 Topology of 3-level NPC

TABEL I
System parameters of 3-level NPC

Parameter	Value
V_{dc}	800 V
C_1	3.1 mF
C_2	3.1 mF
R_g	0.1 Ω
L_g	6 mH
T_s	10 μs
f_{res}	50 Hz
E_{phase}	220 V

B. FCS-MPC model

The conventional FCS-MPC control is built on the cost function. In this paper, control objectives include output current tracking and DC-link voltage balancing. The cost function is as follows in the $\alpha - \beta$ axis [22][22]:

$$g = \omega_1 (i_\alpha^* - i_\alpha^P)^2 + \omega_2 \left(i_\beta^* - i_\beta^P\right)^2 + \lambda_{DC} |V_{C1}^P - V_{C2}^P| \quad (1)$$

g stands for the cost for FCS-MPC. i is the current and V is the voltage. Variables with the superscript P represent the corresponding predicted value for the next time step while that with superscript $*$ represent the reference value. ω_1, ω_2 and λ_{DC} are the weight coefficient to adjust the proportion of each component in the cost function. In this paper, ω_1 and ω_2 are 1 while λ_{DC} is 0.1. The prediction value is calculated as follows for the topology in this paper:

$$i^P(k+1) = \left(1 - R_g \frac{T_s}{L_g}\right) i(k) + \frac{T_s}{L_g}\left(v(k) - e(k)\right) \quad (2)$$

$$v_o^P(k+1) = v_o(k) - \frac{T_s}{C}(i_{abc})^T |v_{abc}| \quad (3)$$

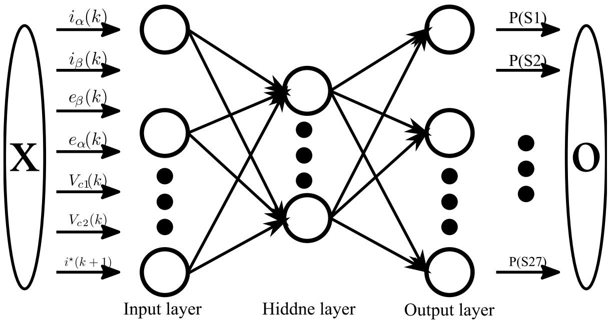

Fig. 2 ANN imitating FCS-MPC

In each control cycle, controller will traverse the state space and select the state with the smallest cost as the control output for next time step. For the three-level topology in this paper, the number of possible states is 27, which means the size of state space is 27.

C. ANN model

ANN consist of fully connected layers. It can handle different problems including classification. Take the control problem as a classification problem, ANN can achieve similar control effect of FCS-MPC [20][22]. The structure of ANN is shown in Fig. 2. In order to show the superiority of our design, ANN's structure is extremely simple, which has one input layer with 7 neurons, one hidden layer with 5 neurons and one output layer with 27 neurons.

The input layer normalizes all inputs based on these data to avoid impressions of controller effects for magnitudes of different input variables.

The size of hidden layer has a strong effect on the network's performance. Within a suitable range, the classification ability of a neural network is positively correlated with its size. After get the sum of product from input layer, each neuron will perform activation and generate the layer output. The activation function is the key point for no-linear ability.

The output layer will apply softmax function to give the probability for each switch state.

D. TOP-n accuracy

More than the portion of correct classification, the indicators for evaluating model performance include TOP-n accuracy. It is defined as follows: TOP-n accuracy refers to whether n categories with the highest probability include the correct results [19] for classification problem[19]. This TOP-n accuracy somehow relax the evaluation of the neural network, as a component of introduction of subsequent processing, which brings different possibilities to the training goal of a neural network.

When n is 1, the TOP-n accuracy is degraded to the classification accuracy. When n is as large as the categories number, the TOP-n accuracy is 100%.

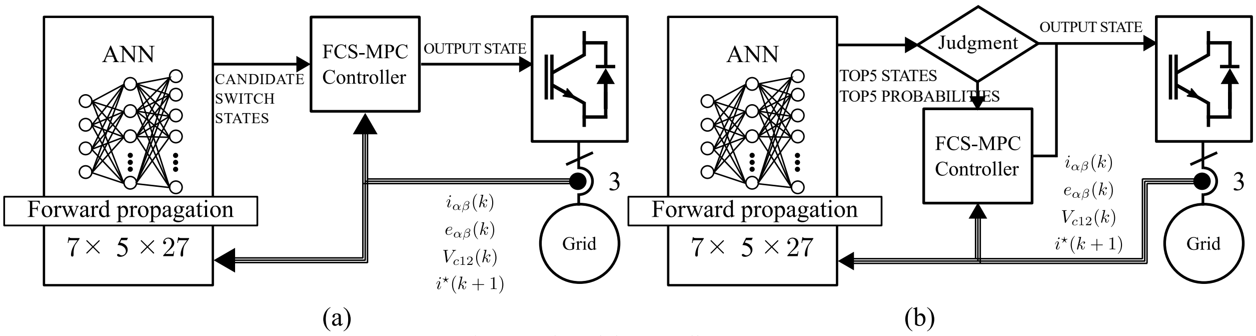

Fig. 3 Dual-module controller structure

III. Dual-module FCS-MPC

In this section, a detailed explanation of our dual-module structure is presented. Two modules are conventional FCS-MPC and ANN.

A. *Main idea*

The main steps of our design are as follows:

- Training:
  1. Use FCS-MPC to generate the training data and train ANN to imitating FCS-MPC.
  2. Find n which makes ANN's accuracy close to 100% according to TOP-n accuracy
- Operating:
  1. Use ANN as the main controller, record TOP-n states and final state.
  2. (optional) Make a judgment on whether additional computation is needed.
  3. (optional) If so, reselect the final state based on FCS-MPC among n states.
  4. Else, output the final state.

If no judgment is used, FCS-MPC will traverse TOP-n states and find the optimal one among them as the output. ANN is used to shrink the state space for FCS-MPC.

B. *Training of ANN*

The training data is generated by FCS-MPC. We load the input vector of FCS-MPC including phase current, phase voltage and DC link voltage. The selected switch state is recorded as the classification label. To improve the robustness of our model, we consider the step transient load in training data generation.

Based on initial weight and bias matrix (h), a forward propagation is applied to generate a switch state. We calculate the error (e) between generated state and ground truth. The derivative of error is calculated with chain rule and gradient descent. For a quick convergence of the network, we applied adaptive learning rate in the training.

$$\frac{\partial e}{\partial h} = \frac{\partial e}{\partial x} \times \frac{\partial x}{\partial h} \tag{4}$$

$$h = h - \lambda \frac{\partial e}{\partial h} \tag{5}$$

x is the intermediate variable in hidden layers.

C. *Probability difference judgment*

TOP-n states are sorted in descending order of probability. Manually set a threshold T. Calculate the probability gap P_{diff} of state with highest and lowest probability. If it is $T > P_{diff}$, no additional computation is needed and ANN's final state is directly output. Or FCS-MPC is utilized to reselect the state among TOP-n states.

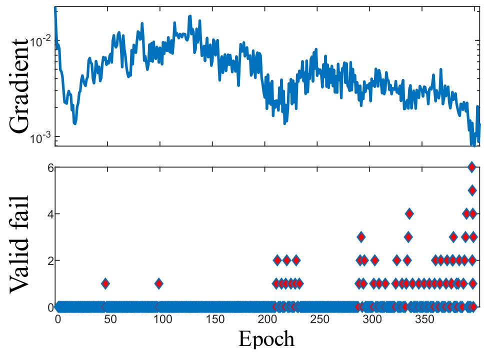

Fig. 4 Variation of training process parameters

D. *ANN-MPC structure explanation (FCS-MPC based)*

The ANN is used as the filter for FCS-MPC to reduce the state space size. As is shown in Fig. 3 (a), the control parameters are fed into both ANN and FCS-MPC. After the ANN generate the candidate states, FCS-MPC will traverse the reduced state space to generate the final output.

It introduces extra computation burden from FCS-MPC compared to single ANN, although the computation burden is still significantly reduced compared to conventional FCS-MPC.

E. *ANN-MPC structure explanation (ANN based)*

After the ANN gives the candidate states, probability difference judgment is applied. If the judgment is met, ANN's final state is directly used, otherwise FCS-MPC is called for reselect the output state as is shown in Fig. 3 (b).

IV. Simulation and Analysis

A. *Training procedure*

We split the control data of FCS-MPC, 70% as training set, 15% as validation set, and 15% as test set. The training is based on MATLAB Deep-learning Toolbox.

As is shown in Fig. 4, the number of validation accuracy increase as the gradient decreases. Training loss curve is shown in Fig. 5. The ANN performance doesn't further improve with more train turns which means at this point the performance cell of the neural network is achieved.

TABEL II Imitation accuracy for different operation modes

Operation mode / Judging principle	FCS-MPC	ANN	Our design (FCS-MPC based)	Our design (ANN based)		
Probability difference	/	/	/	T = 0.4	T = 0.6	T = 0.8
Imitation accuracy	100%	82.65%	99.87%	89.36%	97.6%	99.84 %
Call of FCS-MPC	/	/	/	11.67%	37.98%	64.69%
Computation burden	1215	275	500 (275+45*5)	500 (maximum)		

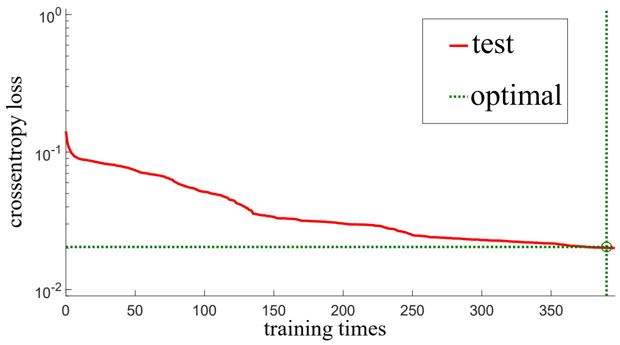

Fig. 5 Training loss curve

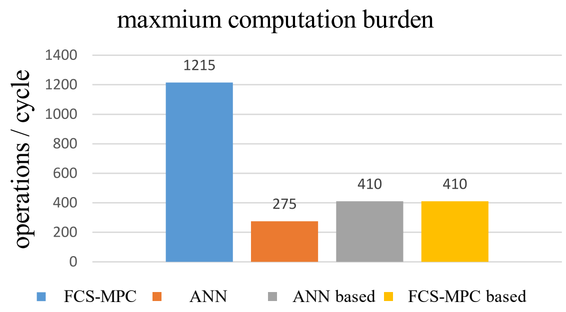

Fig. 6 Computation burden for different modes

The imitation accuracy of a single ANN converges to 82.65% after training 396 turns.

We conduct more experiments to explore the imitation accuracy as is shown in TABEL III.

TABEL III Accuracy VS layer size

Hidden layer size	Accuracy
5	82.6%
10	88%
15	88.8%

Here we notice that the accuracy is positive related to the size of size of network. Marginal growth decreases as size increases. The simulation accuracy converges predictably as the network size increases. This also indicates that additional methods are necessary to improve the performance of neural networks.

B. *Parameter selection*

We record the output of ANN based on TOP-1, TOP-3, and TOP-5 and check if the output of teacher network is included. We found that the shallow ANN almost perfectly reproduced the working mode of MPC when evaluating the model with TOP-5 accuracy as is shown in the TABEL IV. Therefore, we use the TOP-5 accuracy as the judgment criteria and use TOP-5 states as the candidate states for the rest of this paper.

TABEL IV TOP-n accuracy comparison

Parameter	Accuracy
TOP-1	82.65%
TOP-3	98.66%
TOP-5	99.87%

C. *Imitation accuracy of dual-module controller*

The accuracy of FCS-MPC is set to 100% as reference. For single ANN, the imitation accuracy is 82.65%. For MPC-based sequential operation, imitation accuracy is 99.87%. Other imitation accuracies are listed in TABEL II.

Obviously, the imitation accuracy of our design is much greater than that of single ANN. In our experiments, the accuracy improvement brought by a larger-scale ANN is very limited, and our design can easily improve the controller performance. The additional computational burden introduced will be discussed in the next section.

D. *Computation burden*

We count the number of operations performed in each cycle as a rough estimation of the computational burden. For the topology and cost function in this paper, 45 computations are needed to calculate the cost function for one switch state, 1215 computations are required in one control cycle for FCS-MPC. Single ANN only needs 275 computations to finish a control step. Histogram Fig. 6 makes a visual comparison of computation burden.

For FCS-MPC based mode, additional computation burden is introduced to increase the accuracy. The computation burden for this mode is 500 which is much lower than that of conventional FCS-MPC. For ANN based mode, the computation burden consists of two parts: ANN and FCS-MPC (optional). The maximum value is 500 which is also lower than that of conventional FCS-MPC. The computation burden for the whole task will increase with the increase of threshold T, originated from additional call of FCS-MPC.

E. *Call of FCS-MPC*

In addition to the evaluation of the accuracy, we also tested number of calling of FCS-MPC for error correction, and counted the number of calls of MPC. The result is shown in Fig. 7.

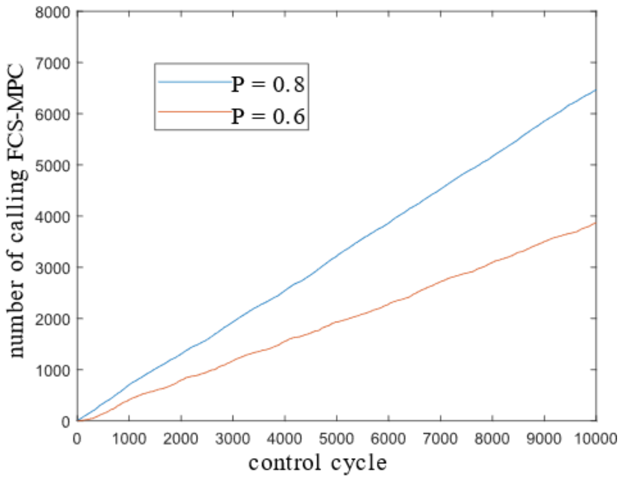

Fig. 7 Number of calls of FCS-MPC

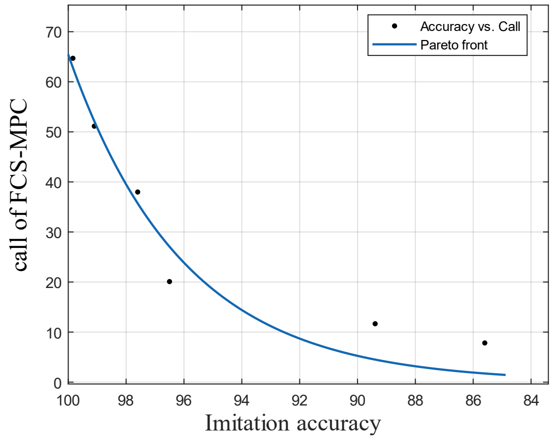

Fig. 8 Pareto front for accuracy VS number of calls

If we set a larger threshold T, it will be more difficult for the output of ANN to meet the judgment conditions, so FCS-MPC will be called more times, additional calculation burden will be introduced, and the accuracy rate will increase. When T is set to 1, our design degenerates into ANN and FCS-MPC operating in series, which is a totally useless design. If T is small, the number of FCS-MPC calls will be reduced, and additional calculation burden will be reduced accordingly, but the accuracy will decrease. When T is set to 0, our design degenerates to a single ANN control unit working.

This T brings great adaptability to our design. We use this parameter to bring the Pareto boundary to the control performance as is shown in Fig. 8. By changing T, different optimal solutions can be selected at this boundary. If extremely high imitation accuracy is required, a larger T can be selected. If it is sensitive to the computation burden, you can choose a smaller T.

F. Control effect and THD

To test the control performance of our design, we directly use dual-module controller to control the three-level converter. According to the simulation result in Fig. 9, our design achieves an acceptable control performance for the topology in this paper. The THD value is controlled below 4% and DC link voltage is totally balanced.

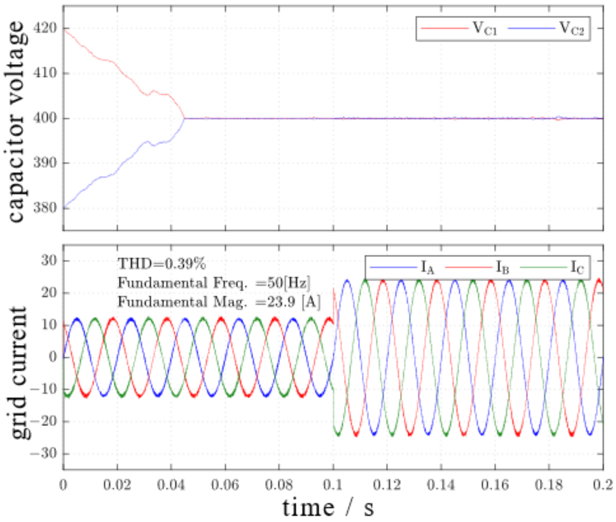

Fig. 9 Control performance of dual-module controller

V. Conclusion

In this paper, we designed a dual-module structure based on ANN and MPC. The working mode and control strategy is explained. Using the proposed structure, the imitation accuracy is increased up to 99% which is significantly higher than that of single ANN, while computational burden is reduced up to 58.8% compared with FCS-MPC. Our design shows acceptable control performance with very efficient computation. Experiment verification will be carried out in the future

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