Three-level 변환기에 대한 ANN 보조 계산 효율적인 FCS-MPC

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Computational efficient FCS-MPC assisted by ANN for Three-level Converter

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ABSTRACT

Finite-control-set model predictive control (FCS-MPC) is currently a widely used control method in power electronic converters. However, it is difficult for MPC to control the topology like modular multilevel converter (MMC). The main reason is that the increase of possible switching states increases the computation burden of FCS-MPC, making it difficult to traverse all switching states in one control cycle. To solve this problem, this paper designs an FCS-MPC based artificial neural network (ANN) controller to reduce the computation burden, and proposes a dual-module structure to increase the imitation accuracy of ANN. The simulation result shows that the imitation accuracy of our design is significantly increased up to 99.87%. The computation burden is reduced over 50% compared with FCS-MPC.

1. Introduction

Finite control set model predictive control (FCS-MPC) is a powerful technique used to regulate power converters. This approach provides a versatile and straightforward method to handle complex control problems while considering system limitations [1]. FCS-MPC has emerged as a promising option for controlling modular multi-level converters (MMC), showcasing notable benefits such as increased power capacity, reduced harmonic distortions, and simplified scalability [2].

However, as the number of output levels and prediction periods increases, the computational burden of Finite Control Set Model Predictive Control (FCS-MPC) imposes limitations on the performance of Modular Multi-Level Converters (MMC). Researchers have conducted extensive research to alleviate this computational burden [8][9][10]. Some approaches, such as filtering the switch state based on neighboring switching combinations [11] and grouping submodules while considering adjacent voltage level evaluation [12], have been proposed within the framework of traditional Model Predictive Control (MPC) to reduce the computational load. However, in cases where MMC topology is complex and the effective reduction of candidate states is challenging, these methods still impose significant computational burdens. Consequently, machine learning (ML)-based methods have been proposed [13], which do not rely on traversing candidate states. ML techniques, particularly Artificial Neural Networks (ANNs), have shown promise in power electronics due to their ability to handle nonlinearity and process data effectively [14] The structure of the ANN network plays a crucial role in determining its performance [14].

In this paper, we firstly present a novel assessment method for the ANN. Subsequently, we propose a dual-module controller structure that utilizes both the ANN and FCS-MPC. The ANN is employed to reduce the state space for FCS-MPC. Through simulations, our design achieves satisfactory control effectiveness while minimizing computational workload. Compared to conventional FCS-MPC, our design reduces computational burden by up to 58.8% and increases imitation accuracy to 99.87%.

2. MODEL EXPLANATION

2.1 Three-level NPC converter

The three-level neutral-point clamped (NPC) converter is used in this paper as is shown in Fig. 1 and Table. 1.

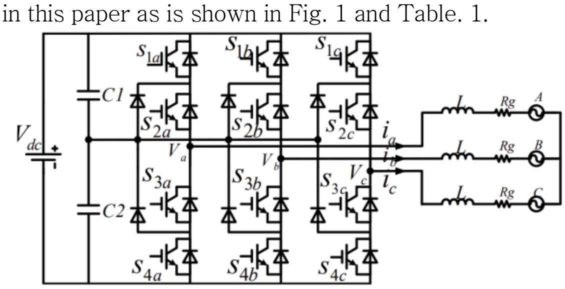

Fig.1 Topology of three-level NPC converter

Table 1 System parameters of three-level NPC converter

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

2.2 FCS-MPC design

The traditional FCS-MPC control relies on the cost function. This paper introduces control objectives that encompass output current tracking and DC-link voltage balancing. The cost function in the $\alpha-\beta$ axis is presented as follows:

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

In the context of this paper, g represents the cost function for FCS-MPC. i denotes the current, and V represents the voltage. Variables with the superscript P indicate the predicted values for the next time step, while those with the superscript $*$ represent the reference values. $\omega 1$, $\omega 2$, and λ_{DC} are weight coefficients used to adjust the proportion of each component in the cost function. For this particular paper, and $\omega 1$ and $\omega 2$ are set to 1, while λ_{DC} is set to 0.1. The prediction value for the topology discussed in this paper is calculated as follows:

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

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

During each control cycle, the controller explores the state space and chooses the state with the lowest cost as the control output for the next time step. In the case of the three-level topology discussed in this paper, there are 27 possible states, resulting in a state space size of 27.

2.3 ANN design

The ANN in this study is composed of fully connected layers and can be applied to various problems, including classification. By considering the control problem as a classification problem, the ANN can achieve similar control effects as FCS-MPC. The structure of the ANN is illustrated in Figure 2. To highlight the superiority of our design, the ANN's structure is intentionally kept simple, consisting of one input layer with 7 neurons, one hidden layer with 5 neurons, and one output layer with 27 neurons.

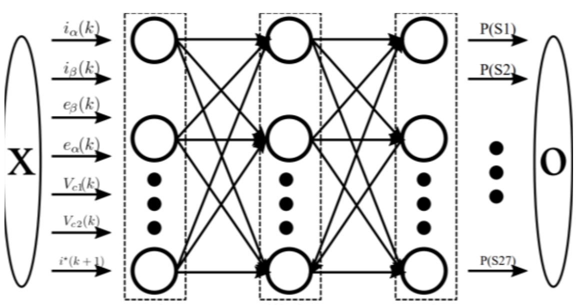

Fig.2 ANN structure

2.4 TOP-n accuracy

In addition to the correct classification rate, model performance evaluation indicators include the TOP-n accuracy. The TOP-n accuracy assesses whether the n categories with the highest probabilities include the correct results for a classification problem. This metric provides a more relaxed evaluation of the neural network's performance and introduces different possibilities for the training objective of the network.

When n is equal to 1, the TOP-n accuracy is equivalent to the classification accuracy. However, as n increases and approaches the total number of categories, the TOP-n accuracy reaches 100%. This means that when n is set to the number of categories, the model is considered to have correctly classified the samples.

3. DUAL-MODULE FCS-MPC

3.1 Main idea

The main steps this work are as follows:

Training:

1. use FCS-MPC to generate the training set and train ANN.
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. reselect final state based on FCS-MPC among n states.
3. generate the final state.

3.2 ANN-MPC explanation

The ANN is used as the filter for FCS-MPC to reduce the state space size. As is shown in Fig. 3, 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.

4. Simulation results

The accuracy of FCS-MPC is set to 100% as reference. For single ANN, the imitation accuracy is 82.65%. For dual-module FCS-MPC, imitation accuracy is 99.87%

4.1 Computation burden

The computational burden is estimated by counting the number of operations performed in each cycle. For the specific topology and cost function described in this paper, it takes 45 computations to calculate the cost function for one switch state in FCS-MPC. In one control cycle, FCS-MPC requires a total of 1,215 computations. On the other hand, a single ANN only requires 275 computations to complete a control step.

For dual-module FCS-MPC-based mode, additional computations are needed to enhance accuracy, resulting in a computational burden of 500, which is still much lower than that of conventional FCS-MPC. It's important to note that the overall computational burden for the entire task will increase because of the help from FCS-MPC.

4.2 Control effect and THD

We conducted simulations using the dual-module controller to control the three-level converter. Based on the results shown in Figure 3, our design demonstrates satisfactory control performance. The Total Harmonic Distortion (THD) value is successfully maintained below 4%, and the DC link voltage is fully balanced. These outcomes indicate that our design effectively achieves acceptable control performance for the considered system.

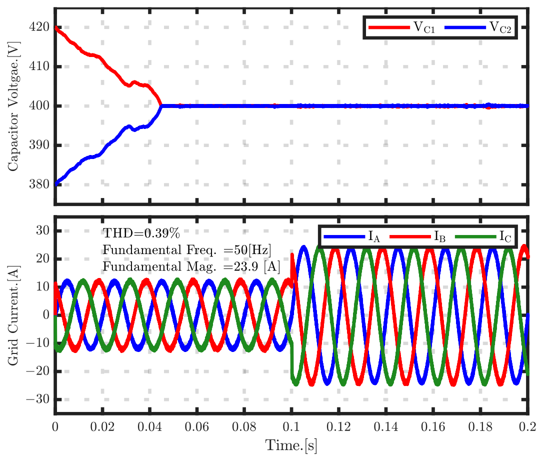

Fig.3 Control performance

5. Conclusion

We designed a cascade operated FCS-MPC assisted by ANN, which can show acceptable control performance with low computation burden.

Reference

[1] J. Rodriguez et al., "State of the Art of Finite Control Set Model Predictive Control in Power Electronics," IEEE Transactions on Industrial Informatics, vol. 9, no. 2, pp. 1003-1016, May 2013.

[2] R. Vargas, P. Cortes, U. Ammann, J. Rodriguez, and J. Pontt, "Predictive control of a three phase neutral-point-clamped inverter," Trans. Power Electron., vol. , no. , pp. 2697–2705, 2007.

[3] A. Dekka, B. Wu, V. Yaramasu, R. L. Fuentes, and N. R. Zargari, "Model predictive control of high-power modular multilevel converters: An overview," IEEE Trans. Emerg. Sel. Top. Power Electron., vol. 7, no. 1, pp. 168–183, Mar. 2018.

[4] L. Hou, X. Li and M. Wang, "Grey-Fuzzy PI Optimal Control of MMC-HVDC System," 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2), 2020, pp. 3258-3262.

[5] S. Isik, M. Alharbi and S. Bhattacharya, "An Optimized Circulating Current Control Method Based on PR and PI Controller for MMC Applications," IEEE Trans. Ind. Applicat., vol. 57, no. 5, pp. 5074-5085, Sept.-Oct. 2021.

[6] W. Chen, W. Anna, Z. Tao and Z. Hualiang, "Adaptive Imitation Accuracy Call of FCS-MPC Integrated Coordinated Control Strategy Based on Sliding Mode Control for MMC-MTDC," 2021 IEEE 4th International Conference on Electronics Technology (ICET), 2021, pp. 892-897.

[7] P. Cortes, M. P. Kazmierkowski, R. M. Kennel, D. E. Quevedo, and J. Rodriguez, "Predictive control in power electronics and drives," Trans. Power Electron., vol. , no. 12, pp. 4312–4324, 2008.

[8] J. W. Moon, J. S. Gwon, J. W. Park, D. W. Kang, and J. M. Kim, "Model predictive control with a reduced number of considered states in a modular multilevel converter for DC system," Trans. Power Del., vol. 0, no. , pp. 608–617, Apr. 2015.

[9] B. Yang, F. Qu, Z. Zhang, and X. Tong, "Priority sorting approach for modular multilevel converter based on simplified model," Trans. Power Electron., vol. 6, no. 6, pp. 4819–4830, Jun. 2018.

[10] Z. Hong, P. Dai, X. Yuan, X. Liu, and F. Qu, "Design and experimental evaluation of fast model predictive control for modular multilevel converters," Trans. Power Electron., vol. 63, no. 6, pp. 3845–3856, Jun. 2016.

[11] X. Chen, J. Liu, S. Ouyang, S. Song, H. Wu and X. Hu, "A Increased-Levels Model Predictive Control Method for Modular Multilevel Converter With Reduced Computation Burden," 2018 IEEE Energy Conversion Congress and Exposition (ECCE), 2018, pp. 3976-3979

[12] J. Yin, J. I. Leon, M. A. Perez, A. Marquez, L. G. Franquelo and S. Vazquez, "FS-MPC Method for MMCs with Large Number of Submodules with Reduced Computational Cost," 2020 IEEE International Conference on Industrial Technology (ICIT), 2020, pp. 1083-1088.

[13] D. Wang et al., "Model Predictive Control Using Artificial Neural Network for Power Converters," IEEE Transactions on Industrial Electronics, vol. 69, no. 4, pp. 3689-3699, April 2022.

[14] S. Wang, T. Dragicevic, Y. Gao and R. Teodorescu, "Neural Network Based Model Predictive Controllers for Modular Multilevel Converters," IEEE Transactions on Energy Conversion, vol. 36, no. 2, pp. 1562-1571, June 2021.