

Data-Driven Neural Predictors-Based Robust MPC for Power Converters

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Abstract—This article proposes a novel data-driven neural predictors-based robust finite control-set model predictive control (FCS-MPC) methodology for power converters, which aims to enhance the robustness of the control system and the flexibility of multiple control objectives. To be specific, the data-driven predictors-based neural network solution, which has a good potential to estimate the unknown nonlinear system dynamics by deploying real-time and historical data, is incorporated into the proposed design with a cost function derived intuitively from Lyapunov's control theory. The key feature of this work is that the undesired effects of the uncertainties and the complex multiobjective optimization procedure can be explicitly dealt with, without involving accurate modeling information and weighting factor combinations, while guaranteeing adaptability to unknown nonlinear system dynamics, model variations, and environment changes. Finally, the stability analysis is given, and the effectiveness of the proposed FCS-MPC methodology is verified analytically and confirmed by comprehensive results that prove the theoretical investigations for active front-end modular multilevel converter.

Index Terms—Active front-end modular multilevel converter, Lyapunov-based cost function, predictor-based neural network, robust finite control-set model predictive control.

I. INTRODUCTION

A. Motivation

Finite control-set model predictive control (FCS-MPC), due to its inherent merits, such as fast and accurate response, finite number of optimizations, and inclusion of system constraints has been widely applied to control the power converters [1], [2]. Particularly, the FCS-MPC utilizes an explicit model of the converter to predict its future plant behavior for all feasible switching state configurations and select the optimal input signals based on a user-predefined design criteria that defines the optimal performance of the system. By virtue of this property, the power converter is directly driven by employing the desired control commands without the intervention of a pulse-width modulation (PWM) block. However, from a practical standpoint, uncertainties, such as unknown physical parameters, unmodeled dynamics, and environmental disturbances exist in the control process of the described method. In this sense, the presence of uncertainties fundamentally challenges robustness performance in the controlled system, and thus ultimately leads to performance degradation or even causes instability. Furthermore, this method also suffers from lack of flexibility to effectively balance multiple control objectives [3]–[5].

B. Related Work

Aiming to alleviate the aforementioned scarcities, various control schemes have been explored in detail by numerous researchers [6]–[8]. The authors in [6] proposed an improved Lyapunov-based FCS-MPC approach to effectively balance multiple control objectives for a multilevel inverter. In the proposed scheme, the cost function formula in the conventional FCS-MPC is reconstructed by employing the Lyapunov control theory point of view. Meanwhile, a solution that can to some extent balance multiple control objectives is explored in [7], where a sliding-mode control design-based cost function formula is introduced into the FCS-MPC, which can be regarded as an extension of [6]. Alternatively, the authors in [8] proposed a cascade-free fuzzy FCS-MPC strategy with low switching frequency (SF) for multilevel converters, which a new cost function is formulated by taking into account the multiconstrained objectives and the various operating condition. Despite the significant research progress, the aforementioned control methods still undergo similar limitation as robustness

Manuscript received November 15, 2021; revised January 17, 2022; accepted April 24, 2022. Date of publication April 28, 2022; date of current version June 24, 2022. This work was supported in part by the National Natural Science Foundation of China under Grants 51807177, 51827810, and 51979020, 52071044, by China Postdoctoral Science Foundation under Grant 2020M681855, by the National Key Research and Development Program of China under Grant 2019YFB1504603, and in part by Natural Science Foundation of Zhejiang Province under Grants LY21E070004 and LY22E070003. The work of Jose Rodríguez was supported by ANID through projects under Grants FB0008, ACT192013, and 1210208. Recommended for publication by Associate Editor D. Dujic. (Corresponding author: Lin Qiu.)

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Color versions of one or more figures in this article are available at <https://doi.org/10.1109/TPEL.2022.3171100>.

Digital Object Identifier 10.1109/TPEL.2022.3171100

issue against parametric uncertainty, which is still an ongoing research.

As an attempt to address this issue, the authors in [9] proposed a sensorless predictive direct power control for the active front-end converters (AFEs). In this proposed approach, the value of the grid-side inductance is identified online by deploying a model reference adaptive system (MRAS) parameter estimation technique. Meanwhile, an analytic scheme to examine the influence of model parametric uncertainties on the prediction error of FCS-MPC is presented in [10]. Alternatively, a solution that can to some extent improve the robustness is reported in [11], where authors presented an extended-state-observer (ESO) based second-order sliding-mode control for AFEs. Recently, various modified model-free predictive control approaches have also been investigated to realize the enhancement of robust control performance, such as model-free sequential predictive control [12], predictor-based neural network predictive control [13], reinforcement learning-based optimal control [14], deep reinforcement learning-based PWM control [15], event-triggered neural predictor-based FCS-MPC [16], and neural predictor-based dynamic surface predictive control [17]. To the best of the authors' knowledge, there are a great amount of advanced control techniques with respect to the model parameter sensitiveness, the investigation on incorporating a data-driven predictors-based neural network solution with Lyapunov control theory into FCS-MPC framework for power converters has not been reported. This consideration constitutes the main motivation of this article.

C. Contribution

Motivated by the defects of the state-of-the-art FCS-MPC strategies discussed in previous section, aiming at enhancing the robustness of the control system and the flexibility of multiple control objectives, this article goes one step further and focuses on an alternative solution to this long-standing research issue with the use of an artificial intelligence technique for power converters. First of all, a data-driven predictors-based neural network solution, endowed with the merits of data-driven technique and neural predictor design, is first presented to estimate the unknown nonlinear system dynamics and total uncertainties based on real-time and historical data, without the accurate modeling information of the system. Second, an improved cost function formula, which is based on Lyapunov control theory framework, is developed from system stability point of view. In view of it, the data-driven predictors-based neural network solution along with the suggested cost function is introduced into the proposed FCS-MPC methodology. As such, the robustness performance of the whole control system can be enhanced significantly in the presence of parametric uncertainties, and the desired control performance can be achieved by the proposed predictive controller. Alternatively, the stability analysis is provided, and it shows that the control system is input-to-state stable (ISS) and the estimated errors are uniformly ultimately bounded (UUB). Finally, the effectiveness of the proposed FCS-MPC methodology is verified analytically and confirmed by comprehensive

results that prove the theoretical investigations for AFE modular multilevel converter (AFE-MMC).

To sufficiently clear the main contribution of this article, we contribute three salient features to the relevant literature.

- 1) A data-driven technique is integrated into the neural predictor design. In that sense, the proposed data-driven predictors-based neural network solution can deploy and learn from historical data, while guaranteeing adaptability to unknown nonlinear system dynamics, model variations, and environment changes.
- 2) The proposal has a good potential to cope effectively with the undesired effects of the uncertainties and the complex multiobjective optimization control problem. As such, the robustness performance of the whole control system can be enhanced significantly in the presence of parametric uncertainties, and the circulating currents in three-phase AFE-MMC can be suppressed effectively.
- 3) To illustrate the feasibility and effectiveness of our innovative proposal, the benefits of the suggested FCS-MPC methodology are experimentally tested and confirmed on a laboratory prototype of the three-phase AFE-MMC, and the results found are promising and motivate further research in this field. Alternatively, it is noteworthy that the proposed solution can be extended easily to other power converter control systems.

D. Outline of the Article

The article is organized as follows. First, the main idea in relation with the conventional FCS-MPC technique for AFE-MMC is described in Section II. Next, the basis of the proposed enhanced Lyapunov-based FCS-MPC using data-driven predictors-based neural network solution for AFE-MMC is detailed, and the stability analysis is given in Section III. The application of the proposed predictive controller to three-phase AFE-MMC control system is conducted in Section IV along with the analysis of the obtained results, while conclusions are outlined in Section V.

II. FCS-MPC OF AFE-MMC

Fig. 1 depicts a main circuit topology of the three-phase AFE-MMC, which is connected to the main AC power supply via three grid-side filter inductors L_g and resistors R_g . In this topology, it is recognized that an important role is played as an interface between grid and electronic equipments from the industry perspective, making it an ideal candidate as a case study [18], [19]. Next section describes the model of the AFE-MMC topology.

The upper and lower arm voltage of phase- x ($x = a, b, c$) with respect to the dc-link mid-point can be expressed as

$$\begin{cases} \frac{U_{dc}}{2} = v_{gux} + L_{arm} \frac{di_{ux}}{dt} + i_{ux} R_{arm} - i_{gx} R_g - L_g \frac{di_{gx}}{dt} \\ \quad + e_{gx} \\ -\frac{U_{dc}}{2} = -v_{glx} - L_{arm} \frac{di_{lx}}{dt} - i_{lx} R_{arm} - i_{gx} R_g - L_g \frac{di_{gx}}{dt} \\ \quad + e_{gx} \end{cases} \quad (1)$$

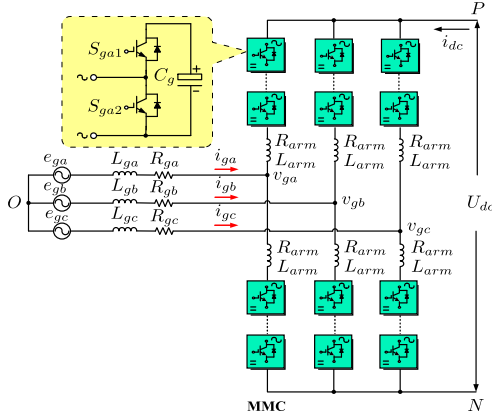


Fig. 1. Circuit topology of the three-phase AFE-MMC.

where U_{dc} denotes dc-link voltage, R_{arm} and L_{arm} denote the arm filter resistance and inductance, respectively. e_{gx} denotes the input voltage of phase- x , and i_{gx} denotes the input current of phase- x . i_{ux} and i_{lx} denote the upper and lower arm currents, respectively. v_{gux} and v_{glx} denote the upper and lower arm voltages, respectively.

Without loss of generality, the dynamic models of the grid-side current and the circulating current can be described as

$$\begin{cases} \frac{di_{gx}}{dt} = \frac{1}{L_z}(e_{gx} - v_{gx}) - \frac{R_z}{L_z}i_{gx} \\ \frac{di_{cirx}}{dt} = \frac{1}{2L_{arm}}(U_{dc} - v_{gux} - v_{glx}) - \frac{R_{arm}}{L_{arm}}i_{cirx} \end{cases} \quad (2)$$

where $R_z = R_g + 0.5R_{arm}$, and $L_z = L_g + 0.5L_{arm}$. $v_{gx} = \frac{v_{glx} - v_{gux}}{2}$. i_{cirx} denotes the circulating current of phase- x .

The system dynamics model, particularized for discretized employing the forward Euler approximation, can be calculated by regarding the present sample (k) and future sample ($k+1$) as demonstrated below

$$\begin{cases} i_g(k+1) = (1 - \frac{R_z T_s}{L_z})i_g(k) + \frac{T_s}{L_z}[e_g(k) - v_g(k)] \\ i_{cir}(k+1) = (1 - \frac{R_{arm} T_s}{L_{arm}})i_{cir}(k) \\ \quad + \frac{T_s}{2L_{arm}}(U_{dc}(k) - v_{gu}(k) - v_{gl}(k)) \end{cases} \quad (3)$$

where T_s denotes the sampling period.

Next, based on the instantaneous power theory [20], the predicted grid-side active and reactive powers can be described by the following form:

$$\begin{cases} P_g(k+1) = 1.5 \operatorname{Re} \{e_g(k+1)\bar{i}_g(k+1)\} \\ Q_g(k+1) = 1.5 \operatorname{Im} \{e_g(k+1)\bar{i}_g(k+1)\} \end{cases} \quad (4)$$

where “ $-$ ” denotes the complex conjugate of the future input current vector, and $e_g(k+1)$ is the predicted grid-side voltage.

Then, a cost function that contains the errors of all these control variables is constructed as an optimization criteria to evaluate system performance. It yields

$$\begin{aligned} f_g = & \lambda_{gp}(P_g^* - P_g(k+1))^2 + \lambda_{gq}(Q_g^* - Q_g(k+1))^2 \\ & + \lambda_{gc} \sum_{x=a,b,c} (i_{cirx}^* - i_{cirx}(k+1))^2 \end{aligned} \quad (5)$$

where P_g^* and Q_g^* denote the grid-side active/reactive power references, respectively. i_{cirx}^* denotes the circulating current reference of phase- x . After the cost function is formulated,

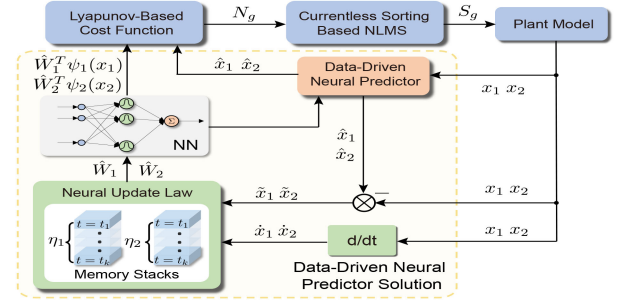


Fig. 2. Schematic representation of the proposed FCS-MPC based on data-driven neural predictor solution for AFE-MMC.

the weighting factors λ_{gp} , λ_{gq} , and λ_{gc} need to be tuned appropriately to obtain the optimal balance between the different control objectives. Meanwhile, the weighting factors employed with the current equations have also crucial influences on the quality of the controlled variables. It is thus worthwhile to investigate this effect so as to obtain the satisfactory system control performance. However, this process is still a challenge due to the lack of the systematic design methodology [21], [22]. In this sense, a heuristic tuning procedure to determine weighting factors for conventional FCS-MPC scheme is usually deployed.

Another important aspect in the FCS-MPC technique is model parameter sensitiveness due to the fact that the FCS-MPC algorithm requires the knowledge of the evolution of the system variables [23]. Alternatively, the circulating currents flowing through the AFE-MMC legs should also be controlled at a certain value. As a consequence, it can be noticed that, in order to obtain the desired control performance, parametric uncertainties and circulating current must be properly addressed in the whole FCS-MPC design process. To this end, it is necessary to exploit a fundamentally different control strategy subject to robustness characteristics so as to boost the performance of the controller, as described in the following section that provides the overall framework of the proposed solution.

III. PROPOSED FCS-MPC SOLUTION

In this section, a novel data-driven neural predictors-based robust FCS-MPC methodology for AFE-MMC is proposed. Meanwhile, an improved cost function formula, which is based on a Lyapunov control theory framework, is designed. The proposal yields a simple and intuitive implementation, which has a good potential to estimate the unknown nonlinear system dynamics and total uncertainties based on real time and historical data and to cope effectively with the complex multiobjective optimization control problem in regulated AFE-MMC. In what follows, this formulation allows overcoming conventional issues known for FCS-MPC scheme, such as parametric uncertainties, external disturbances, and weighting factors. To illustrate our approach clearly, the schematic representation of the proposed solution for AFE-MMC is shown in Fig. 2.

A. Data-Driven Predictor-Based Neural Network Design

In this section, a data-driven technique is integrated into the neural predictor design. More specifically, the proposed data-driven predictors-based neural network solution can deploy and

learn from historical data, while guaranteeing adaptability to different system model variations and environment changes, as it will be elaborated as follows.

The corresponding grid-side power state-space model of AFE-MMC can be described via [24]

$$\frac{d\mathbf{x}_1}{dt} = a_1 \mathbf{e}_1 \mathbf{v}_1 - c_1 \mathbf{x}_1 + \mathbf{m} \quad (6)$$

where $a_1 = \frac{1.5}{L_z}$, $c_1 = \frac{R_z}{L_z}$, $\mathbf{e}_1 = \begin{bmatrix} -e_{g\alpha} & -e_{g\beta} \\ -e_{g\beta} & e_{g\alpha} \end{bmatrix}$, $\mathbf{m} = \begin{bmatrix} \frac{1.5(e_{g\alpha}^2 + e_{g\beta}^2)}{L_z} - \omega_g Q_g \\ \omega_g P_g \end{bmatrix}$, $\mathbf{x}_1 = \begin{bmatrix} P_g \\ Q_g \end{bmatrix}$, and $\mathbf{v}_1 = \begin{bmatrix} v_{g\alpha} \\ v_{g\beta} \end{bmatrix}$.

Meanwhile, in our work, the presentable output voltage-level N_{gx} is taken into account as finite control set (FCS), and then, it can be expressed as [25], [26]:

$$\mathbf{v}_g(k) = \frac{1}{N} U_{dc} N_{gx} \quad (7)$$

where

$$N_{gx} = \left[-\frac{N}{2}, -\frac{N-2}{2}, \dots, 0, \dots, \frac{N-2}{2}, \frac{N}{2} \right]$$

and where N denotes the submodule (SM) number per arm.

Next, according on (6), the ultralocal mathematical model of AFE-MMC yields [23]

$$\frac{d\mathbf{x}_1}{dt} = \mathbf{f}_1(\mathbf{x}_1) + \mathbf{b}_1 \mathbf{v}_1 \quad (8)$$

where $\mathbf{f}_1(\mathbf{x}_1) = \mathbf{m} - c_1 \mathbf{x}_1$ and $\mathbf{b}_1 = a_1 \mathbf{e}_1$.

The unknown function $\mathbf{f}_1(\mathbf{x}_1)$ can be estimated by a neural network as follows [27], [28]:

$$\mathbf{f}_1(\mathbf{x}_1) = \mathbf{W}_1^T \psi_1(\mathbf{x}_1) + \epsilon_1 \quad (9)$$

where $\psi_1(\cdot)$ is a known activation function, $\mathbf{W}_1$ is the output weight matrix, and ϵ_1 is the approximation error satisfying $\|\epsilon_1\| \leq \epsilon_1^*$ with ϵ_1^* being a positive constant. The ideal neural network weight $\mathbf{W}_1$ is bounded by a known positive constant, i.e., $\|\mathbf{W}_1\|_F \leq W_1^*$ with W_1^* is a positive constant, where “F” denotes the Frobenius norm.

To design an update law for $\hat{\mathbf{W}}_1$, consider a state predictor as

$$\dot{\hat{\mathbf{x}}}_1 = \hat{\mathbf{W}}_1^T \psi_1(\mathbf{x}_1) + \mathbf{b}_1 \mathbf{v}_1 - k_1 \tilde{\mathbf{x}}_1 \quad (10)$$

where $\tilde{\mathbf{x}}_1 = \hat{\mathbf{x}}_1 - \mathbf{x}_1$, and $\hat{\mathbf{x}}_1$ denotes the observed value. $k_1 \in \mathbb{R}_+$ is a positive constant. $\mathbb{R}_+$ is the set of positive real numbers expressed as $y \in \mathbb{R}_+ = \{y \in \mathbb{R} | y > 0\}$.

Based on the stored data, data-driven neural update law for $\hat{\mathbf{W}}_1$ can be expressed as [29]

$$\dot{\hat{\mathbf{W}}}_1 = -\Gamma_1 [\psi_1(\mathbf{x}_1) \tilde{\mathbf{x}}_1^T + k_{w1} \Phi_1] \quad (11)$$

where

$$\Phi_1 = \sum_{k=1}^{\eta_1} \psi_1^k(\mathbf{x}_1) \left(\sigma_1 \hat{\mathbf{W}}_1^T \psi_1^k(\mathbf{x}_1) - \dot{\hat{\mathbf{x}}}_1^T \right)^T \quad (12)$$

and where η_1 denotes the length of the memory stack satisfying $\eta_1 \in \mathbb{Z}_+$. $\mathbb{Z}_+$ is the set of positive integer numbers expressed as $y \in \mathbb{Z}_+ = \{y \in \mathbb{Z} | y > 0\}$. $\sigma_1 \in \mathbb{R}_+$ is a positive constant. $\Gamma_1 \in \mathbb{R}_+$ and $k_{w1} \in \mathbb{R}_+$ are positive constants, respectively.

Based on the previously discussed, for clarity, the discrete-time model of (9)–(11) with respect to the approximate Euler

formula can be given by

$$\begin{cases} \hat{\mathbf{x}}_1(k+1) = \hat{\mathbf{x}}_1(k) + T_s [\hat{\mathbf{W}}_1^T(k) \psi_1(\mathbf{x}_1(k)) + \mathbf{b}_1(k) \mathbf{v}_1(k) - k_1 \tilde{\mathbf{x}}_1(k)] \\ \hat{\mathbf{W}}_1(k+1) = (1 - \Gamma_1 T_s k_{w1}) \hat{\mathbf{W}}_1(k) - \Gamma_1 T_s \psi_1(\mathbf{x}_1(k)) \tilde{\mathbf{x}}_1^T(k) \\ \hat{\mathbf{f}}_1(k+1) = \hat{\mathbf{W}}_1^T(k+1) \psi_1(\mathbf{x}_1(k+1)). \end{cases} \quad (13)$$

Following a similar analysis, based on (2), the corresponding circulating current state-space model of AFE-MMC can be expressed as

$$\frac{d\mathbf{x}_2}{dt} = b_2 \mathbf{v}_2 - c_2 \mathbf{x}_2 \quad (14)$$

where $\mathbf{v}_2 = \begin{bmatrix} U_{dc} - v_{gua} - v_{gla} \\ U_{dc} - v_{gub} - v_{glb} \\ U_{dc} - v_{guc} - v_{glc} \end{bmatrix}$, $\mathbf{x}_2 = \mathbf{i}_{cir} = \begin{bmatrix} i_{cira} \\ i_{cirb} \\ i_{circ} \end{bmatrix}$, $b_2 = \frac{1}{2L_{arm}}$, and $c_2 = \frac{R_{arm}}{L_{arm}}$.

Next, according on (14), the ultralocal mathematical model of AFE-MMC has the following form:

$$\frac{d\mathbf{x}_2}{dt} = \mathbf{f}_2(\mathbf{x}_2) + b_2 \mathbf{v}_2 \quad (15)$$

where $\mathbf{f}_2(\mathbf{x}_2) = -c_2 \mathbf{x}_2$.

Then, the unknown function $\mathbf{f}_2(\mathbf{x}_2)$ can be estimated by a neural network as follows:

$$\mathbf{f}_2(\mathbf{x}_2) = \mathbf{W}_2^T \psi_2(\mathbf{x}_2) + \epsilon_2 \quad (16)$$

where $\psi_2(\cdot)$ is a known activation function, $\mathbf{W}_2$ is the output weight matrix, and ϵ_2 is the approximation error satisfying $\|\epsilon_2\| \leq \epsilon_2^*$ with ϵ_2^* being a positive constant. The ideal neural network weight $\mathbf{W}_2$ is bounded by a known positive constant, i.e., $\|\mathbf{W}_2\|_F \leq W_2^*$ with W_2^* is a positive constant.

To design an update law for $\hat{\mathbf{W}}_2$, consider a state predictor as

$$\dot{\hat{\mathbf{x}}}_2 = \hat{\mathbf{W}}_2^T \psi_2(\mathbf{x}_2) + b_2 \mathbf{v}_2 - k_2 \tilde{\mathbf{x}}_2 \quad (17)$$

where $\tilde{\mathbf{x}}_2 = \hat{\mathbf{x}}_2 - \mathbf{x}_2$, and $\hat{\mathbf{x}}_2$ denotes the observed value and $k_2 \in \mathbb{R}_+$ is a positive constant.

The data-driven neural update law based on the stored data for $\hat{\mathbf{W}}_2$ can be obtained as

$$\dot{\hat{\mathbf{W}}}_2 = -\Gamma_2 [\psi_2(\mathbf{x}_2) \tilde{\mathbf{x}}_2^T + k_{w2} \Phi_2] \quad (18)$$

where

$$\Phi_2 = \sum_{k=1}^{\eta_2} \psi_2^k(\mathbf{x}_2) \left(\sigma_2 \hat{\mathbf{W}}_2^T \psi_2^k(\mathbf{x}_2) - \dot{\hat{\mathbf{x}}}_2^T \right)^T \quad (19)$$

and where η_2 denotes the length of the memory stack satisfying $\eta_2 \in \mathbb{Z}_+$. $\sigma_2 \in \mathbb{R}_+$ is a positive constant. $\Gamma_2 \in \mathbb{R}_+$ and $k_{w2} \in \mathbb{R}_+$ are positive constants, respectively.

Then, by combining the above analyses, the discrete-time model of (16)–(18), particularized for discretized using the forward Euler approximation, can be represented by

$$\begin{cases} \hat{\mathbf{x}}_2(k+1) = \hat{\mathbf{x}}_2(k) + T_s [\hat{\mathbf{W}}_2^T(k) \psi_2(\mathbf{x}_2(k)) + b_2 \mathbf{v}_2(k) - k_2 \tilde{\mathbf{x}}_2(k)] \\ \hat{\mathbf{W}}_2(k+1) = (1 - \Gamma_2 T_s k_{w2}) \hat{\mathbf{W}}_2(k) - \Gamma_2 T_s \psi_2(\mathbf{x}_2(k)) \tilde{\mathbf{x}}_2^T(k) \\ \hat{\mathbf{f}}_2(k+1) = \hat{\mathbf{W}}_2^T(k+1) \psi_2(\mathbf{x}_2(k+1)). \end{cases} \quad (20)$$

Remark 1: It is worth emphasizing that the estimations of the unknown nonlinear system dynamics and total uncertainties can be achieved by the proposed data-driven neural update laws (11) and (18). In this sense, the proposed data-driven predictors-based

neural network solution can deploy and learn from historical data, while guaranteeing adaptability to unknown nonlinear system dynamics, model variations, and environment changes. Alternatively, if the memory stacks are full, one can select to forget the oldest set of data. As such, the data-driven neural update laws will continuously update based on the latest sets of data.

Remark 2: In our proposal, data-driven neural predictors by utilizing real-time and historical data are presented for estimating total uncertainties and unknown system dynamics. Based on the learned knowledge from neural predictors, data-driven neural update law is designed and no prior information on system model parameters is required. It can be seen that the neural weight is learned online based on the estimation errors $\tilde{x}_1$, $\tilde{x}_2$ and the historical information $\psi_1^k(\mathbf{x}_1)$, $\psi_2^k(\mathbf{x}_2)$, $\mathbf{x}_1^k$, $\mathbf{x}_2^k$ stored at the each t_k instant. During transients, the proportional terms $(\Gamma_1 \psi_1(\mathbf{x}_1) \tilde{x}_1^T)$ and $(\Gamma_2 \psi_2(\mathbf{x}_2) \tilde{x}_2^T)$ in (11) and (18) will play a predominant role to predict the system evolution. As a consequence, by using the proposed methodology, the estimated system state variables are able to converge to their corresponding references.

B. Stability Analysis

Assumption 1: The bounded regressor vectors $\psi_1(\mathbf{x}_1)$ and $\psi_2(\mathbf{x}_2)$ are exciting over a time sequence set $\{t_1, t_2, \dots, t_\Omega\}$ with $\Omega \in \mathbb{Z}_+$, if there exist $\gamma_1, \gamma_2 \in \mathbb{R}_+$ such that

$$\begin{cases} \sum_{k=1}^{\eta_1} \psi_1^k(\mathbf{x}_1)(\psi_1^k(\mathbf{x}_1))^T \geq \gamma_1 \mathbf{I}_n \\ \sum_{k=1}^{\eta_2} \psi_2^k(\mathbf{x}_2)(\psi_2^k(\mathbf{x}_2))^T \geq \gamma_2 \mathbf{I}_n \end{cases} \quad (21)$$

where $\mathbf{I}_n$ represents the identity matrix with n dimensions.

Define $\tilde{W}_1 = \hat{W}_1 - W_1$ and $\tilde{W}_2 = \hat{W}_2 - W_2$, and then, the error dynamic equations of $\tilde{x}_1$, $\tilde{x}_2$, $\tilde{W}_1$, and $\tilde{W}_2$ have the following form:

$$\begin{cases} \dot{\tilde{x}}_1 = \tilde{W}_1^T \psi_1(\mathbf{x}_1) - k_1 \tilde{x}_1 - \epsilon_1 \\ \dot{\tilde{x}}_2 = \tilde{W}_2^T \psi_2(\mathbf{x}_2) - k_2 \tilde{x}_2 - \epsilon_2 \\ \dot{\tilde{W}}_1 = -\Gamma_1 [\psi_1(\mathbf{x}_1) \tilde{x}_1^T + k_{w1} \Phi_1] \\ \dot{\tilde{W}}_2 = -\Gamma_2 [\psi_2(\mathbf{x}_2) \tilde{x}_2^T + k_{w2} \Phi_2] \end{cases} \quad (22)$$

Lemma 1: Under Assumption 1, the data-driven neural predictor solution (22) with the state beings $\tilde{x}_1$, $\tilde{x}_2$, $\tilde{W}_1$, and $\tilde{W}_2$ and the input beings W_1 , W_2 , ψ_1 , ψ_2 , ϵ_1 , and ϵ_2 is ISS.

Proof: First, a Lyapunov function is designed as

$$\begin{aligned} V = & \frac{1}{2} \tilde{x}_1^T \tilde{x}_1 + \frac{1}{2} \tilde{x}_2^T \tilde{x}_2 + \frac{1}{2} \Gamma_1^{-1} \text{tr}(\tilde{W}_1^T \tilde{W}_1) \\ & + \frac{1}{2} \Gamma_2^{-1} \text{tr}(\tilde{W}_2^T \tilde{W}_2). \end{aligned} \quad (23)$$

Then, the derivative of the Lyapunov function (23) can be written as

$$\begin{aligned} \dot{V} = & \tilde{x}_1^T \dot{\tilde{x}}_1 + \tilde{x}_2^T \dot{\tilde{x}}_2 + \Gamma_1^{-1} \text{tr}(\tilde{W}_1^T \dot{\tilde{W}}_1) + \Gamma_2^{-1} \text{tr}(\tilde{W}_2^T \dot{\tilde{W}}_2) \\ = & -k_1 \tilde{x}_1^T \tilde{x}_1 - \epsilon_1 \tilde{x}_1^T - k_2 \tilde{x}_2^T \tilde{x}_2 - \epsilon_2 \tilde{x}_2^T \\ & - k_{w1} \text{tr}(\tilde{W}_1^T \Phi_1) - k_{w2} \text{tr}(\tilde{W}_2^T \Phi_2). \end{aligned} \quad (24)$$

Next, by substituting (12) and (19) into (24), the derivative of the Lyapunov function (23) can be rewritten as

$$\dot{V} = \tilde{x}_1^T \dot{\tilde{x}}_1 + \tilde{x}_2^T \dot{\tilde{x}}_2 + \Gamma_1^{-1} \text{tr}(\tilde{W}_1^T \dot{\tilde{W}}_1) + \Gamma_2^{-1} \text{tr}(\tilde{W}_2^T \dot{\tilde{W}}_2)$$

$$\begin{aligned} = & -k_1 \tilde{x}_1^T \tilde{x}_1 - \epsilon_1 \tilde{x}_1^T - k_2 \tilde{x}_2^T \tilde{x}_2 - \epsilon_2 \tilde{x}_2^T \\ & - k_{w1} \tilde{W}_1^T \sum_{k=1}^{\eta_1} \psi_1^k(\mathbf{x}_1) (\sigma_1 \hat{W}_1^T \psi_1^k(\mathbf{x}_1) - \dot{\mathbf{x}}_1^k)^T \\ & - k_{w2} \tilde{W}_2^T \sum_{k=1}^{\eta_2} \psi_2^k(\mathbf{x}_2) (\sigma_2 \hat{W}_2^T \psi_2^k(\mathbf{x}_2) - \dot{\mathbf{x}}_2^k)^T \\ = & -k_1 \tilde{x}_1^T \tilde{x}_1 - \epsilon_1 \tilde{x}_1^T - k_2 \tilde{x}_2^T \tilde{x}_2 - \epsilon_2 \tilde{x}_2^T \\ & - k_{w1} \sigma_1 \sum_{k=1}^{\eta_1} \tilde{W}_1^T \psi_1^k(\mathbf{x}_1) (\psi_1^k(\mathbf{x}_1))^T \tilde{W}_1 \\ & - k_{w1} (\sigma_1 - 1) \sum_{k=1}^{\eta_1} \tilde{W}_1^T \psi_1^k(\mathbf{x}_1) (\psi_1^k(\mathbf{x}_1))^T W_1 \\ & + k_{w1} \sum_{k=1}^{\eta_1} \tilde{W}_1^T \psi_1^k(\mathbf{x}_1) (b_1 \mathbf{v}_1 + \epsilon_1) \\ & - k_{w2} \sigma_2 \sum_{k=1}^{\eta_2} \tilde{W}_2^T \psi_2^k(\mathbf{x}_2) (\psi_2^k(\mathbf{x}_2))^T \tilde{W}_2 \\ & - k_{w2} (\sigma_2 - 1) \sum_{k=1}^{\eta_2} \tilde{W}_2^T \psi_2^k(\mathbf{x}_2) (\psi_2^k(\mathbf{x}_2))^T W_2 \\ & + k_{w2} \sum_{k=1}^{\eta_2} \tilde{W}_2^T \psi_2^k(\mathbf{x}_2) (b_2 \mathbf{v}_2 + \epsilon_2) \\ = & -k_1 \tilde{x}_1^T \tilde{x}_1 - \epsilon_1 \tilde{x}_1^T - k_2 \tilde{x}_2^T \tilde{x}_2 - \epsilon_2 \tilde{x}_2^T \\ & - k_{w1} \sigma_1 \sum_{k=1}^{\eta_1} \tilde{W}_1^T \psi_1^k(\mathbf{x}_1) (\psi_1^k(\mathbf{x}_1))^T \tilde{W}_1 \\ & - k_{w2} \sigma_2 \sum_{k=1}^{\eta_2} \tilde{W}_2^T \psi_2^k(\mathbf{x}_2) (\psi_2^k(\mathbf{x}_2))^T \tilde{W}_2 \\ & - k_{w1} \sum_{k=1}^{\eta_1} \tilde{W}_1^T \psi_1^k(\mathbf{x}_1) \\ & \times \left((\sigma_1 - 1) (\psi_1^k(\mathbf{x}_1))^T W_1 - b_1 \mathbf{v}_1 - \epsilon_1 \right) \\ & - k_{w2} \sum_{k=1}^{\eta_2} \tilde{W}_2^T \psi_2^k(\mathbf{x}_2) \\ & \times \left((\sigma_2 - 1) (\psi_2^k(\mathbf{x}_2))^T W_2 - b_2 \mathbf{v}_2 - \epsilon_2 \right). \end{aligned} \quad (25)$$

Defining $E = [\tilde{x}_1, \tilde{x}_2, \|\tilde{W}_1\|_F, \|\tilde{W}_2\|_F]^T$ and employing Assumption 1, it yields

$$\dot{V} \leq -\lambda_{\min}(K) \|E\|^2 + \bar{k}_w (\|\xi_1\| + \|\xi_2\|) \|E\| \quad (26)$$

where $\xi_1 = (\sigma_1 - 1) \|\gamma_1\| \|W_1\|_F + \sum_{k=1}^{\eta_1} \|\psi_1(\mathbf{x}_1)\| (|b_1 \mathbf{v}_1| + 2|\epsilon_1|)$, $\xi_2 = (\sigma_2 - 1) \|\gamma_2\| \|W_2\|_F + \sum_{k=1}^{\eta_2} \|\psi_2(\mathbf{x}_2)\| (|b_2 \mathbf{v}_2| + 2|\epsilon_2|)$, $K = \text{diag}\{k_1, k_2, k_{w1} \sigma_1 \gamma_1, k_{w2} \sigma_2 \gamma_2\}$, $\bar{k}_w = \max\{1, k_{w1}, k_{w2}\}$, and where $\sigma_1 - 1 > 0$ and $\sigma_2 - 1 > 0$. Noting that $\|E\| \geq \frac{\bar{k}_w (\|\xi_1\| + \|\xi_2\|)}{\lambda_{\min}(K) \theta}$ renders $\dot{V} \leq -\lambda_{\min}(K) (1 - \theta) \|E\|^2$ where $\lambda_{\min}(\cdot)$ denotes the smallest eigenvalue of a square matrix. Alternatively, W_1 , W_2 , ψ_1 , ψ_2 , ϵ_1 , and ϵ_2 are bounded.

As a consequence, it is concluded that the data-driven neural predictor solution is ISS with $\theta \in (0, 1)$, and the estimated errors are UUB [30]. ■

C. Proposed Lyapunov-Based FCS-MPC Approach

In this section, a Lyapunov-based cost function derived intuitively along with a data-driven predictors-based neural network solution is presented to solve the multiobjective optimization control problem and to achieve a closer reference tracking control. Specifically, based on the learned knowledge from data-driven neural predictors, the estimations of total uncertainties and unknown nonlinear system dynamics are incorporated into the Lyapunov-based cost function. Furthermore, the proposed Lyapunov-based FCS-MPC controller replaces the cost function of the traditional FCS-MPC controller, and thus, the determination procedure of the fussy weighting factors can be avoided, and the flexibility of multiple control objectives can be achieved. Finally, the detailed mathematical derivation of the proposal will be elaborated in the following paragraphs based on the aforementioned ideas.

First of all, the following error definitions can be obtained:

$$\begin{cases} e_P = \hat{P}_g - P_g^* \\ e_Q = \hat{Q}_g - Q_g^* \\ e_{Ca} = \hat{i}_{cira} - i_{cira}^* \\ e_{Cb} = \hat{i}_{cirb} - i_{cirb}^* \\ e_{Cc} = \hat{i}_{circ} - i_{circ}^* \end{cases} \quad (27)$$

Next, their errors derivative can be defined as

$$\begin{cases} \dot{e}_P = \dot{\hat{P}}_g - \dot{P}_g^* \\ \dot{e}_Q = \dot{\hat{Q}}_g - \dot{Q}_g^* \\ \dot{e}_{Ca} = \dot{\hat{i}}_{cira} - \dot{i}_{cira}^* \\ \dot{e}_{Cb} = \dot{\hat{i}}_{cirb} - \dot{i}_{cirb}^* \\ \dot{e}_{Cc} = \dot{\hat{i}}_{circ} - \dot{i}_{circ}^* \end{cases} \quad (28)$$

Based on the aforementioned equations, the following Lyapunov function is deployed:

$$V(x) = \frac{1}{2}e_P^2 + \frac{1}{2}e_Q^2 + \frac{1}{2}e_{Ca}^2 + \frac{1}{2}e_{Cb}^2 + \frac{1}{2}e_{Cc}^2. \quad (29)$$

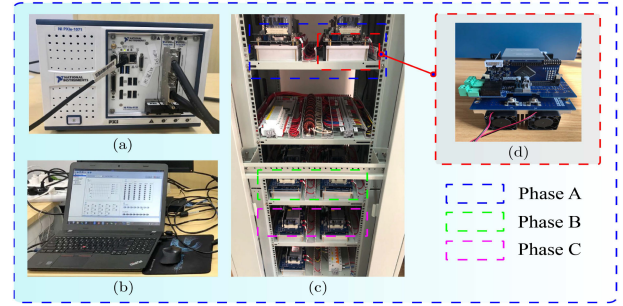


Fig. 3. Experimental platform of AFE-MMC system. (a) NI PXI testing platform for the AFE-MMC system. (b) PC. (c) Three-phase AFE-MMC system. (d) An SM overview.

Obviously, (29) is positive definite. The stability of controlled system presented by (6) and (14) is guaranteed based on Lyapunov control theory if we ensure that for all values of x

$$\dot{V}(x) < 0. \quad (30)$$

Taking the derivative of (29) yields (31) (at the bottom of the page). Based on the above detailed analysis, as for the cost function minimization procedure, it can be achieved through a Lyapunov-based cost function (32) (at the bottom of the page), which is deployed as an optimization criterion to effectively balance multiple control objectives. Next, it is noteworthy that the proposed Lyapunov-based FCS-MPC controller replaces the cost function of the traditional FCS-MPC controller. Thus, the control input can be evaluated and selected by the suggested controller, which corresponds to the minimum value of the derivative of the Lyapunov function (32). The minimum value of the cost function ensures that $\dot{V}_x(k+1)$ is negative, which implies that the stability of the controlled system is guaranteed [6], [31].

D. Parameter Design

In this section, the parameter selection guideline is described as follows. First, the sigmoid structure activation function used for the proposed methodology is chosen as $\psi_1(x_1) = \frac{1}{1+e^{-x_1}}$ and $\psi_2(x_2) = \frac{1}{1+e^{-x_2}}$. Second, the system stability can be mainly determined by the predictor gain k_1 and k_2 . If a faster error convergence is desired, then the parameters k_1 and k_2

$$\begin{aligned} \dot{V}(x) &= e_P \dot{e}_P + e_Q \dot{e}_Q + e_{Ca} \dot{e}_{Ca} + e_{Cb} \dot{e}_{Cb} + e_{Cc} \dot{e}_{Cc} \\ &= e_P (\dot{\hat{P}}_g - \dot{P}_g^*) + e_Q (\dot{\hat{Q}}_g - \dot{Q}_g^*) + e_{Ca} (\dot{\hat{i}}_{cira} - \dot{i}_{cira}^*) + e_{Cb} (\dot{\hat{i}}_{cirb} - \dot{i}_{cirb}^*) + e_{Cc} (\dot{\hat{i}}_{circ} - \dot{i}_{circ}^*) \\ &= (\dot{\hat{P}}_g - P_g^*) (\dot{\hat{P}}_g - \dot{P}_g^*) + (\dot{\hat{Q}}_g - Q_g^*) (\dot{\hat{Q}}_g - \dot{Q}_g^*) + (\dot{\hat{i}}_{cira} - i_{cira}^*) (\dot{\hat{i}}_{cira} - \dot{i}_{cira}^*) + (\dot{\hat{i}}_{cirb} - i_{cirb}^*) (\dot{\hat{i}}_{cirb} - \dot{i}_{cirb}^*) \\ &\quad + (\dot{\hat{i}}_{circ} - i_{circ}^*) (\dot{\hat{i}}_{circ} - \dot{i}_{circ}^*). \end{aligned} \quad (31)$$

$$\begin{aligned} \dot{V}_x(k+1) &= (\dot{\hat{P}}_g(k+1) - P_g^*(k+1)) (\dot{\hat{P}}_g(k+1) - \dot{P}_g^*(k+1)) + (\dot{\hat{Q}}_g(k+1) - Q_g^*(k+1)) (\dot{\hat{Q}}_g(k+1) - \dot{Q}_g^*(k+1)) \\ &\quad + (\dot{\hat{i}}_{cira}(k+1) - i_{cira}^*(k+1)) (\dot{\hat{i}}_{cira}(k+1) - \dot{i}_{cira}^*(k+1)) + (\dot{\hat{i}}_{cirb}(k+1) - i_{cirb}^*(k+1)) (\dot{\hat{i}}_{cirb}(k+1) - \dot{i}_{cirb}^*(k+1)) \\ &\quad + (\dot{\hat{i}}_{circ}(k+1) - i_{circ}^*(k+1)) (\dot{\hat{i}}_{circ}(k+1) - \dot{i}_{circ}^*(k+1)). \end{aligned} \quad (32)$$

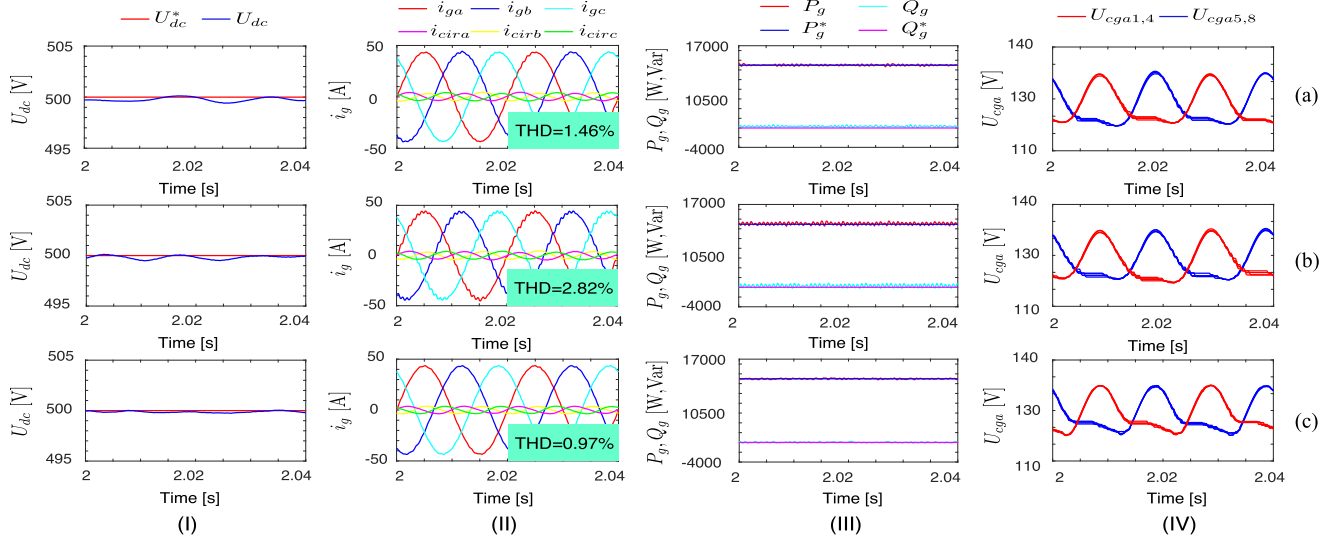


Fig. 4. Performance evaluation with three different control approaches in a steady state. (a) Conventional FCS-MPC method. (b) Deadbeat predictive control method. (c) Proposed FCS-MPC solution.

should be chosen large. This means that the control action may be oscillated. Besides, in order to avoid the parameter drift, the parameters k_{w1} and k_{w2} are adopted. Too large k_{w1} and k_{w2} will suppress the parameter adaptation speed. The adaptive gain Γ_1 and Γ_2 are selected at first to guarantee the system stability and then to improve the closed-loop tracking performance by a trial-and-error method. In this literature, the values of weighing factors λ_{gp} , λ_{gq} , and λ_{gc} used for conventional FCS-MPC method are selected as $\lambda_{gp} = 1$, $\lambda_{gq} = 1$, and $\lambda_{gc} = 0.05$, respectively. Furthermore, in the proposed methodology, the design parameters are also provided, and they are set as $k_1 = k_2 = 1 \times 10^4$, $k_{w1} = k_{w2} = 0.01$, $\sigma_1 = \sigma_2 = 2$, $\eta_1 = \eta_2 = 10$, and $\Gamma_1 = \Gamma_2 = 100$, respectively.

To sum up, in our work, the proposed solution is model-free in the sense that no accurate modeling information is required compared with the proposed methods in [6] and [31]. Meanwhile, by this proposal, the determination procedure of the fuzzy weighting factors can be avoided, and the flexibility of multiple control objectives can be achieved. Besides, to achieve the balancing control of SM capacitor voltages and low computational burden, in this article, we presented a new sensorless control approach for AFE-MMC. To be specific, a normalized least mean-square (NLMS)-based SM voltage online estimation technique along with a currentless sorting strategy in [32] is deployed, resulting in a simpler implementation and a lower associated costs. It is worth pointing out that, in practical applications, a large number of voltage and current sensors in system are required so as to provide signal measurements. In that sense, the sensors to install into the system are vulnerable, which may degrade the performance and even lead to the overall system instability. Hence, motivated by aforementioned limitation, it is crucial to develop an interesting alternative solution so as to enhance the system reliability by integrating normal and faulty measurement data for training, such investigation is beyond the scope of this article and further research will be done concerning that. Next section provides the simulation and experimental verification of the proposed FCS-MPC strategy.

TABLE I
SYSTEM AND CONTROL PARAMETERS

Parameter	Symbol	Simulation	Experiment
Grid resistance	R_g	0.01Ω	0.01Ω
Grid filter inductance	L_g	10mH	10mH
Arm resistance	R_{arm}	0.2Ω	0.2Ω
Arm filter inductance	L_{arm}	5mH	5.5mH
DC-link capacitor	C	$4400\mu F$	$2200\mu F$
SM capacitor	C_g	$4400\mu F$	$4400\mu F$
Load resistance	R_L	20Ω	15Ω
Phase voltage peak	e_g	200V	200V
Grid frequency	f	50Hz	50Hz
DC-link reference voltage	U_{dc}	400V/500V	400V/500V
Sampling/control period	T_s	100 μs	100 μs
Number of SMs per arm	N	4	2

IV. PERFORMANCE EVALUATION

For the implementation of this test, the real MMC prototype using Silicon Carbide Metal-Oxide-Semiconductor Field-Effect Transistors (SiC-MOSFETs) C3M0065100 K with the circuit parameters listed in Table I is controlled by deploying a NI PXI platform, as shown in Fig. 3. The software is implemented on StarSim Field-Programmable Gate Array (FPGA) Circuit Solver (MT FPGA 8000 Solver). In order to compensate the time delay of control command, the method proposed in [33] is adopted to serve this purpose. The overall design parameters of the system is given in Table I.

A. Simulation Result Analysis

Figs. 4(I)–6(I) indicate that good dc-link voltage tracking performance can be achieved by three different control algorithms in a steady state and transient state. Meanwhile, the grid-side currents and circulating currents are shown in Figs. 4(II)–6(II), where it can be seen that the proposed control solution provided good steady-state and transient-state performance. Besides, in order to illustrate the robustness under parameter mismatch

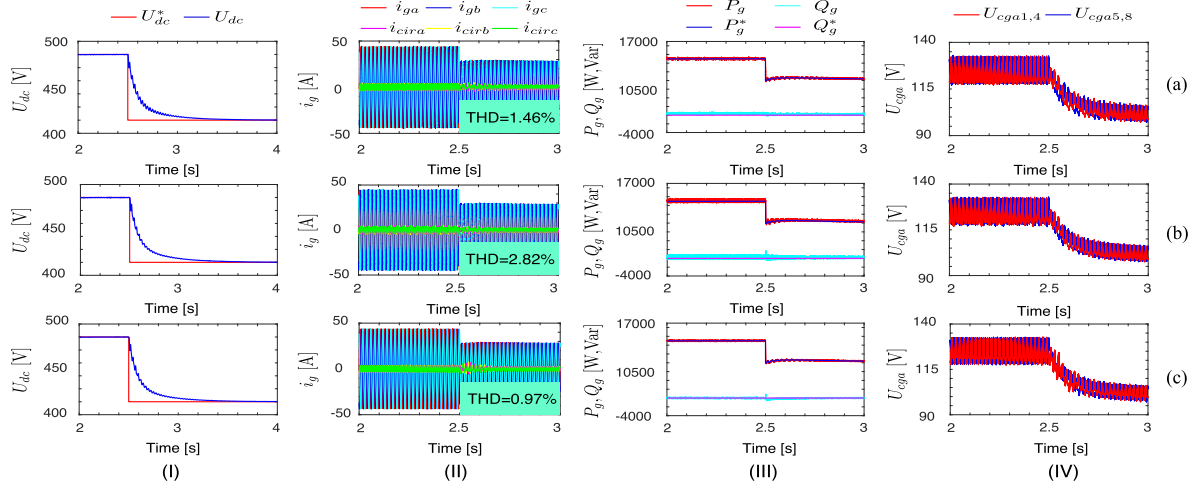


Fig. 5. Performance evaluation with three different control approaches in a transient state. (a) Conventional FCS-MPC method. (b) Deadbeat predictive control method. (c) Proposed FCS-MPC solution.

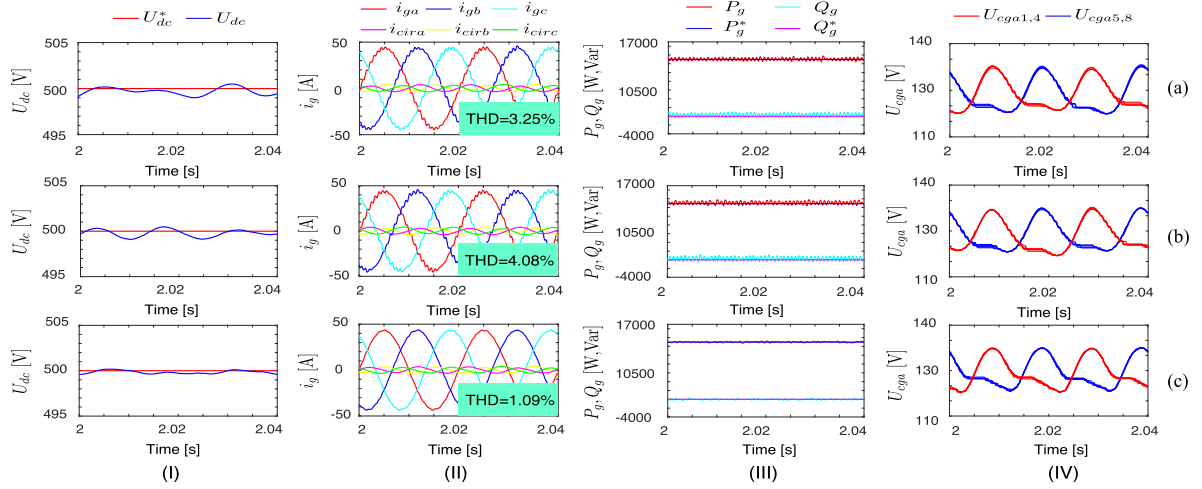


Fig. 6. Performance evaluation with three different control approaches under the parameter mismatch ($L_g = 8$ mH). (a) Conventional FCS-MPC method. (b) Deadbeat predictive control method. (c) Proposed FCS-MPC solution.

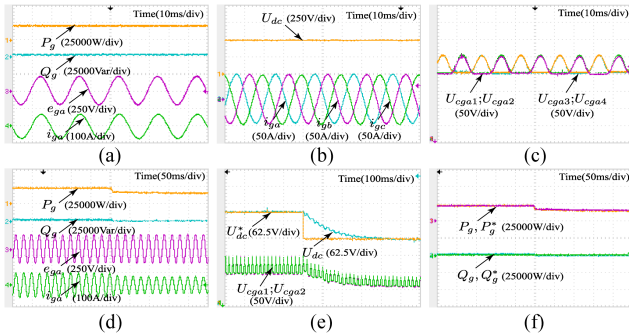


Fig. 7. Experimental results with the conventional FCS-MPC method. (a) Active and reactive powers; grid-side voltage and current. (b) DC-link voltage and grid-side currents. (c) Measured SM capacitor voltages. (d) Active and reactive powers; grid-side voltage and current. (e) DC-link voltage and measured SM capacitor voltages. (f) Active and reactive powers and references.

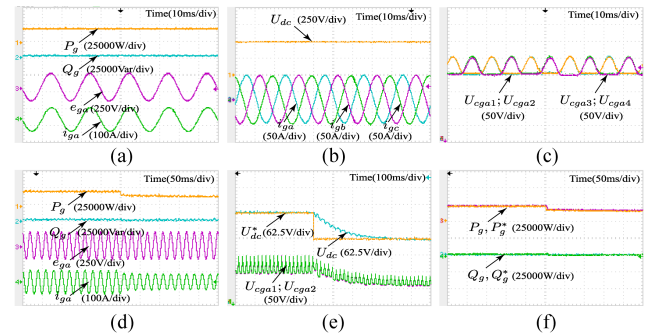


Fig. 8. Experimental results with the deadbeat predictive control method. (a) Active and reactive powers; grid-side voltage and current. (b) DC-link voltage and grid-side currents. (c) Measured SM capacitor voltages. (d) Active and reactive powers; grid-side voltage and current. (e) DC-link voltage and measured SM capacitor voltages. (f) Active and reactive powers and references.

($L_g = 8$ mH), we tried to evaluate a variation in the filter inductance with three different control solutions, as shown in

Fig. 6. It depicts the grid-side currents with a THD value of 3.25%, 4.08%, and 1.09% in filter inductance mismatch,

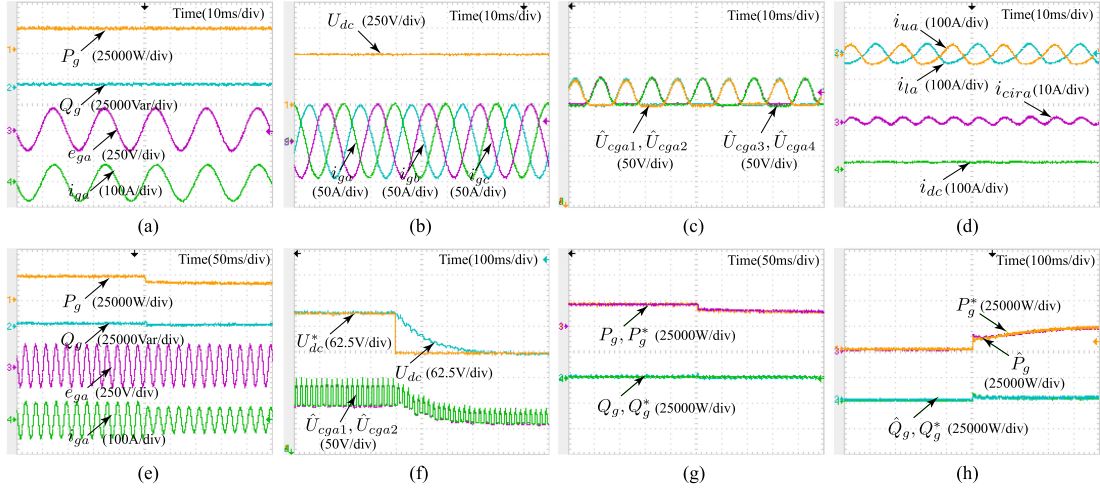


Fig. 9. Experimental results with the proposed FCS-MPC solution. (a) Active and reactive powers; grid-side voltage and current. (b) DC-link voltage and grid-side currents. (c) Estimated SM capacitor voltages. (d) Upper and lower arm currents; circulating current and rectifier DC current. (e) Active and reactive powers; grid-side voltage and current. (f) DC-link voltage and estimated SM capacitor voltages. (g) Active and reactive power references; estimated active and reactive powers. (h) Active and reactive power references; estimated active and reactive powers.

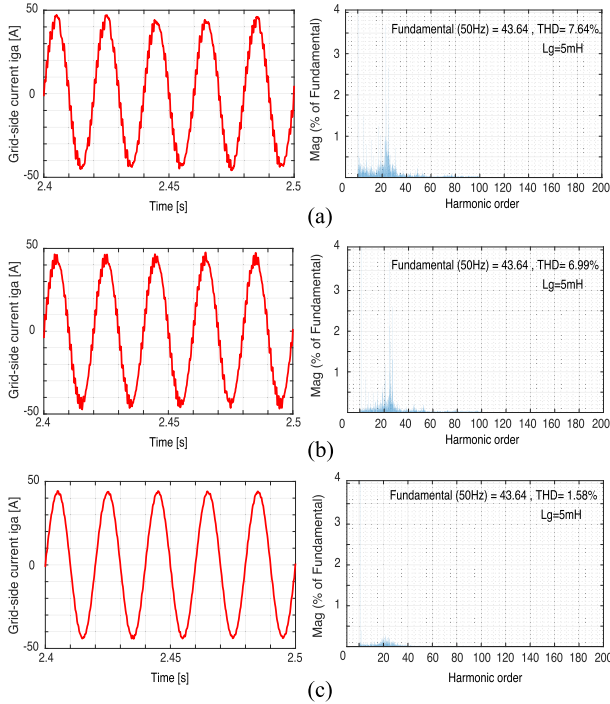


Fig. 10. Comparison of robustness performance with three different methods under the parameter mismatch ($L_g=5\text{mH}$). (a) Conventional FCS-MPC method. (b) Deadbeat predictive control. (c) Proposed FCS-MPC solution.

respectively. Next, the tracking control performance of the grid-side active and reactive powers can be presented for three different control approaches in steady state and transient state, as depicted in Figs. 4(III)–6(III). Furthermore, the transient response of of SMs capacitor voltage is presented in Figs. 4(IV)–6(IV), respectively. Finally, as expected, this modification allows an enhancement of the converter's control performance in comparison to the state-of-the-art FCS-MPC schemes under parameters mismatch for AFE-MMC.

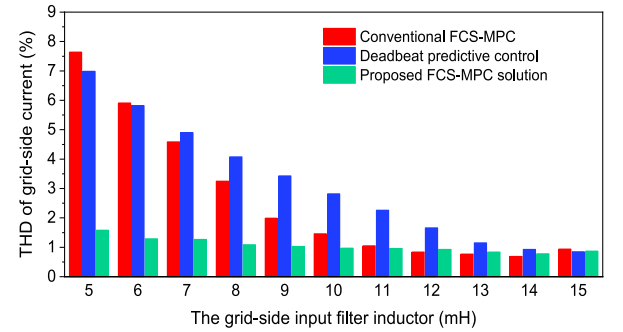


Fig. 11. Robustness of the proposed controller under grid-side filter inductance values mismatch ($N=4$).

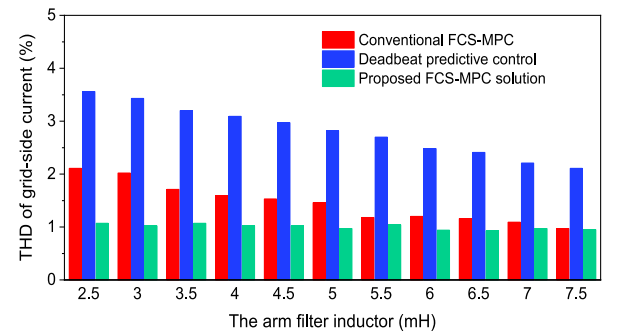


Fig. 12. Robustness of the proposed controller under arm inductance values mismatch ($N=4$).

B. Experimental Result Analysis

The experimental results of the AFE-MMC operation with three different control solutions are depicted in more detail in Figs. 7–9. First, the steady-state control performance of the system is studied using the same experimental conditions. As can be seen from Figs. 7(a) to 9(a), the waveforms of input active and reactive powers are smooth and constant. Second, the

TABLE II
COMPARISON RESULTS BETWEEN THREE DIFFERENT CONTROL SCHEMES

Method	Execution time (μs)					Error (%)	THD (%)
	Number of SM	Optimization	SM voltage estimation	Sorting	Sum		
Conventional FCS-MPC method	N=4	27.324	—	18.939	46.263	0.81	1.46
Deadbeat predictive control method	N=4	10.043	—	19.929	29.972	1.82	2.82
Proposed FCS-MPC solution	N=4	63.313	5.214	20.190	88.717	0.58	0.97

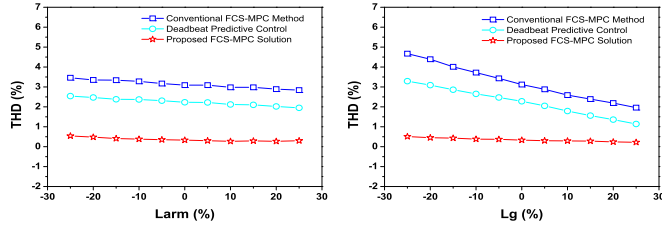


Fig. 13. Robustness of the proposed controller (Arm inductance and grid-side filter inductance values mismatch versus grid-side current THD ($N=10$)).

control performance of input voltage/current and dc-link voltage waveforms is depicted in Figs. 7(b)–9(b). Meanwhile, the performance of measured and estimated SM capacitor voltages can be further confirmed and illustrated in Figs. 7(c)–9(c). The upper and lower arm currents, circulating current, and rectifier dc current are shown in Fig. 9(d), with low ripple in the currents.

Alternatively, as can be seen from Figs. 7(d)–8(d) and 9(e), when the dc-link voltage changes from 500 to 400 V suddenly, they show the good behavior of this control technique, where the input powers and voltage/current have a good dynamic and stationary behavior. Furthermore, the accurate tracking ability of dc-link voltage and estimated SM capacitor voltages can be obtained, as shown in Figs. 7(e)–8(e) and 9(f). Next, the transient-state tracking performance of grid-side reference/actual active and reactive powers can be illustrated in Figs. 7(f)–8(f) and 9(g). Finally, as shown in Fig. 9(h), the estimated active and reactive power values will quickly converge to their real values by the proposed solution in the initialization process. A good tracking performance of the controlled variables can be observed.

C. Robustness Performance Analysis

In this section, theory validation is achieved by comparing the three controllers in different operating conditions. In particular, the control behavior in case of parameter mismatches has been studied. In order to quantify the performance of the proposed solution, a thorough analysis of the effect of parameters mismatch in terms of arm inductance and grid-side filter inductance for three different control schemes is illustrated to ensure robust performance, and as shown in Figs. 10–13. It is clearly appreciated that the proposed design is very robust against parameter uncertainties, and it remains robustness to uncertainty of the system's parameters, while maintaining the satisfactory regulation performance.

Alternatively, a thorough performance evaluation between three different control strategies is conducted, and the THD, execution time, and state-steady tracking error of different control methods are also investigated, and as shown in Table II. As previously mentioned, a challenge presented by this proposal

is that the prohibitive computational cost will be increased due to the fact that the data-driven predictors-based neural network FCS-MPC solution is adopted. In our future work, a possible interesting direction for the future investigations could be to further improve the computationally efficient by deploying a supervised imitation learning technique for power converters without sacrificing the transient behavior [34]–[36]. Furthermore, the authors will also further consider an interesting investigation related to the improvement of the system reliability and robustness by deploying a data-driven-based model-free adaptive predictive control solution to other power converters.

V. CONCLUSION

In this article, a new approach, which has a good potential to effectively solve the undesired effect of the uncertainties and to flexibly take multiple control objectives into account in regulated AFE-MMC, is proposed by incorporating a data-driven predictor-based neural network solution into a Lyapunov-based cost function. The novelty of the proposed methodology is that the uncertainties can be alleviated from the system, which largely improves the robustness, but also appropriately deals with the design procedure of complex multiobjective optimization control since no parameters information and weighting factor combinations are required. To illustrate the feasibility of our innovative proposal, the benefits of the proposed design solution are validated both theoretically and experimentally for regulated AFE-MMC. The obtained experimental results showed good tracking and robustness performances with low harmonic distortion values in comparison to other two different control strategies, which validate the interest of the proposal.

REFERENCES

- [1] S. Vazquez *et al.*, "Model predictive control: A review of its applications in power electronics," *IEEE Ind. Electron. Mag.*, vol. 8, no. 1, pp. 16–31, Mar. 2014.
- [2] X. Liu *et al.*, "Neural predictor-based low switching frequency FCS-MPC for MMC with online weighting factors tuning," *IEEE Trans. Power Electron.*, vol. 37, no. 4, pp. 4065–4079, Apr. 2022.
- [3] J. Rodríguez *et al.*, "State of the art of finite control set model predictive control in power electronics," *IEEE Trans. Ind. Informat.*, vol. 9, no. 2, pp. 1003–1016, May 2013.
- [4] T. Dragičević, "Model predictive control of power converters for robust and fast operation of AC microgrids," *IEEE Trans. Power Electron.*, vol. 33, no. 7, pp. 6304–6317, Jul. 2018.
- [5] S. Vazquez, J. Rodríguez, M. Rivera, L. G. Franquelo, and M. Norambuena, "Model predictive control for power converters and drives: Advances and trends," *IEEE Trans. Ind. Electron.*, vol. 64, no. 2, pp. 935–947, Feb. 2017.
- [6] H. Makhamreh, M. Sleiman, O. Kükrer, and K. Al-Haddad, "Lyapunov-based model predictive control of a PUC7 grid-connected multilevel inverter," *IEEE Trans. Ind. Electron.*, vol. 66, no. 9, pp. 7012–7021, Sep. 2019.

- [7] H. Makhamreh, M. Trabelsi, O. Kükrer, and H. Abu-Rub, "An effective sliding mode control design for a grid-connected PUC7 multilevel inverter," *IEEE Trans. Ind. Electron.*, vol. 67, no. 5, pp. 3717–3725, May 2020.
- [8] X. Liu, D. Wang, and Z. H. Peng, "Cascade-free fuzzy finite control-set model predictive control for nested neutral point-clamped converters with low switching frequency," *IEEE Trans. Control Syst. Technol.*, vol. 27, no. 5, pp. 2237–2244, Sep. 2019.
- [9] M. Mehreganfar, M. H. Saeednia, S. A. Davari, C. Garcia, and J. Rodríguez, "Sensorless predictive control of AFE rectifier with robust adaptive inductance estimation," *IEEE Trans. Ind. Informat.*, vol. 15, no. 6, pp. 3420–3431, Jun. 2019.
- [10] H. A. Young, M. A. Perez, and J. Rodríguez, "Analysis of finite-control-set model predictive current control with model parameter mismatch in a three-phase inverter," *IEEE Ind. Electron.*, vol. 63, no. 5, pp. 3100–3107, May 2016.
- [11] J. X. Liu, S. Vazquez, L. G. Wu, A. Marquez, H. J. Gao, and L. G. Franquelo, "Extended state observer-based sliding-mode control for three-phase power converters," *IEEE Trans. Ind. Electron.*, vol. 64, no. 1, pp. 22–31, Jan. 2017.
- [12] W. J. Wu *et al.*, "Model-free sequential predictive control for MMC with variable candidate set," *IEEE Trans. Emerg. Sel. Topics Power Electron.*, to be published, doi: [10.1109/JESTPE.2021.3130262](https://doi.org/10.1109/JESTPE.2021.3130262).
- [13] X. Liu *et al.*, "Predictor-based neural network finite-set predictive control for modular multilevel converter," *IEEE Trans. Ind. Electron.*, vol. 68, no. 11, pp. 11621–11627, Nov. 2021.
- [14] J. J. Duan, Z. H. Yi, D. Shi, C. Lin, X. Lu, and Z. W. Wang, "Reinforcement-learning-based optimal control of hybrid energy storage systems in hybrid AC-DC microgrids," *IEEE Trans. Ind. Electron.*, vol. 15, no. 9, pp. 5355–5364, Sep. 2019.
- [15] M. Schenke, W. Kirchgässner, and O. Wallscheid, "Controller design for electrical drives by deep reinforcement learning: A proof of concept," *IEEE Trans. Ind. Inform.*, vol. 18, no. 7, pp. 4650–4658, Jul. 2020.
- [16] X. Liu *et al.*, "Event-triggered neural predictor-based FCS-MPC for MMC," *IEEE Trans. Ind. Electron.*, vol. 69, no. 6, pp. 6433–6440, Jun. 2022.
- [17] X. Liu *et al.*, "Neural predictor-based dynamic surface predictive control for power converters," *IEEE Trans. Ind. Electron.*, to be published, doi: [10.1109/TIE.2022.3146643](https://doi.org/10.1109/TIE.2022.3146643).
- [18] J. J. Huang *et al.*, "Priority sorting approach for modular multilevel converter based on simplified model predictive control," *IEEE Trans. Ind. Electron.*, vol. 65, no. 6, pp. 4819–4830, Jun. 2018.
- [19] X. Liu, L. Qiu, Y. T. Fang, K. Wang, Y. D. Li, and J. Rodríguez, "A fuzzy approximation for FCS-MPC in power converters," *IEEE Trans. Power Electron.*, vol. 37, no. 8, pp. 9153–9163, Aug. 2022.
- [20] F. Z. Peng and J. S. Lai, "Generalized instantaneous reactive power theory for three-phase power systems," *IEEE Trans. Instrum. Meas.*, vol. 45, no. 1, pp. 293–297, Feb. 1996.
- [21] X. Liu, D. Wang, and Z. H. Peng, "A computationally efficient FCS-MPC method without weighting factors for NNPCs with optimal duty cycle control," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 5, pp. 2503–2514, Oct. 2018.
- [22] T. Dragičević and M. Novak, "Weighting factor design in model predictive control of power electronic converters: An artificial neural network approach," *IEEE Trans. Ind. Electron.*, vol. 66, no. 11, pp. 8870–8880, Nov. 2019.
- [23] X. Liu *et al.*, "Event-triggered ESO-based robust MPC for power converters," *IEEE Trans. Ind. Electron.*, to be published, doi: [10.1109/TIE.2022.3167135](https://doi.org/10.1109/TIE.2022.3167135).
- [24] Z. F. Song, Y. J. Tian, Z. Yan, and Z. Chen, "Direct power control for three-phase two-level voltage-source rectifiers based on extended-state observation," *IEEE Trans. Ind. Electron.*, vol. 63, no. 7, pp. 4593–4603, Jul. 2016.
- [25] J. Moon, J. Gwon, J. Park, D. Kang, and J. Kim, "Model predictive control with a reduced number of considered states in a modular multilevel converter for HVDC system," *IEEE Trans. Power Del.*, vol. 30, no. 2, pp. 608–617, Apr. 2015.
- [26] J. Y. Wang, Y. Tang, P. F. Lin, X. Liu, and J. Pou, "Deadbeat predictive current control for modular multilevel converters with enhanced steady-state performance and stability," *IEEE Trans. Power Electron.*, vol. 35, no. 7, pp. 6878–6894, Jul. 2020.
- [27] Z. H. Peng, D. Wang, and J. Wang, "Predictor-based neural dynamic surface control for uncertain nonlinear systems in strict-feedback form," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 9, pp. 2156–2167, Sep. 2017.
- [28] H. Wang, Y. Tian, and H. L. Xu, "Neural adaptive command filtered control for cooperative path following of multiple underactuated autonomous underwater vehicles along one path," *IEEE Trans. Syst. Man, Cybern., Syst.*, vol. 52, no. 5, pp. 2966–2978, May 2022.
- [29] N. Gu, D. Wang, Z. H. Peng, T. S. Li, and S. C. Tong, "Model-free containment control of underactuated surface vessels under switching topologies based on guiding vector fields and data-driven neural predictors," *IEEE Trans. Cybern.*, to be published, doi: [10.1109/TCYB.2021.3061588](https://doi.org/10.1109/TCYB.2021.3061588).
- [30] H. K. Khalil, *Nonlinear Systems*. 3rd ed. Englewood Cliffs, NJ, USA: Prentice-Hall, 2002.
- [31] H. Makhamreh, M. Trabelsi, O. Kükrer, and H. Abu-Rub, "A Lyapunov-based model predictive control design with reduced sensors for a PUC7 rectifier," *IEEE Trans. Ind. Electron.*, vol. 68, no. 2, pp. 1139–1147, Feb. 2021.
- [32] X. Liu, L. Qiu, Y. T. Fang, Z. H. Peng, and D. Wang, "Finite-level-state model predictive control for sensorless three-phase four-arm modular multilevel converter," *IEEE Trans. Power Electron.*, vol. 35, no. 5, pp. 4462–4466, May 2020.
- [33] P. Cortés, J. Rodríguez, C. Silva, and A. Flores, "Delay compensation in model predictive current control of a three-phase inverter," *IEEE Trans. Ind. Electron.*, vol. 59, no. 2, pp. 1323–1325, Feb. 2012.
- [34] S. Zhao, F. Blaabjerg, and H. Wang, "An overview of artificial intelligence applications for power electronics," *IEEE Trans. Power Electron.*, vol. 36, no. 4, pp. 4633–4658, Apr. 2021.
- [35] M. Novak and T. Dragičević, "Supervised imitation learning of finite-set model predictive control systems for power electronics," *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 3402–3412, Apr. 2021.
- [36] D. M. Wang *et al.*, "Model predictive control using artificial neural network for power converters," *IEEE Trans. Ind. Electron.*, vol. 69, no. 4, pp. 3689–3699, Apr. 2022.



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