Efficient Model Predictive Control Method with Parameter Identification Capability for Three-Level Converters Postprint

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Abstract

Three-level PWM converters have been widely employed in industrial applications, particularly in medium-high voltage and high-power scenarios. During practical operation, system parameters may vary due to environmental conditions and temperature fluctuations, thereby affecting control performance. Model predictive control (MPC) offers excellent multi-objective optimization capabilities and flexible constraint handling, garnering significant attention and research in three-level converter control. However, existing MPC methods for three-level PWM converters require substantial computation for optimal voltage vector selection and depend on precise inductance parameters, resulting in heavy computational burden and poor robustness. To address these issues, this paper proposes an improved MPC methodology that drastically reduces the computational complexity involved in selecting the optimal voltage vector. Furthermore, by incorporating an online inductance identification algorithm based on recursive least squares, the system' s parameter robustness is significantly enhanced. Simulation and experimental results demonstrate that the proposed simplified MPC algorithm achieves favorable dynamic and static performance along with robust parameter adaptation.

Full Text

Preamble

An Efficient Model Predictive Control Method for Three-Level Converters with Parameter Identification

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Abstract

Three-level PWM converters have been widely used in industrial applications, particularly in medium-voltage and high-power scenarios. In practical operation, system parameters may vary due to environmental conditions and temperature fluctuations, which degrades control performance. Model predictive control (MPC) offers excellent multi-objective optimization capabilities and flexible constraint handling, garnering significant attention in three-level converter control. However, existing MPC methods for three-level PWM converters require extensive computations to obtain the optimal voltage vector and rely on precise inductance parameters, resulting in high computational burden and poor robustness. To address these issues, this paper proposes an improved MPC method that substantially reduces the computational effort required for optimal voltage vector selection. Furthermore, by incorporating an online inductance identification algorithm based on the recursive least squares method, the system' s parameter robustness is enhanced. Simulation and experimental results demonstrate that the proposed simplified MPC algorithm exhibits favorable dynamic and static performance as well as robustness against parameter variations.

Keywords: Three-level PWM converters, model predictive control, inductance parameter identification, recursive least squares algorithm

1 Introduction

With the continuous development of power electronics technology, three-level converters have found extensive applications in industrial fields such as flexible DC transmission, variable-frequency speed regulation of AC motors, electric traction, and renewable energy generation [1-3]. Compared with traditional two-level converters, three-level converters offer advantages in high-voltage and high-power applications due to their increased DC-side voltage levels. At the same switching frequency, they produce more sinusoidal grid-side currents with lower harmonic content. Additionally, the increased number of voltage levels reduces the voltage stress on switching devices for a given DC bus voltage, thereby improving system efficiency [4].

Various control theories and methods have been proposed for three-level PWM converters. Among the earliest and most widely adopted is Voltage Oriented Control (VOC) [5], which decouples the three-phase grid currents into active and reactive current components through rotational transformation, enabling closed-loop control of both components. While VOC achieves good dynamic and steady-state performance, it heavily depends on the parameters of the inner-loop Proportional Integral (PI) regulators [6]. With the development of instantaneous power theory, Toshihiko Noguchi proposed Direct Power Control (DPC) in 1998 [7], which attracted widespread attention. Unlike VOC, DPC eliminates the need for current rotational transformation and inner-loop PI regulator design. It directly controls active and reactive power by selecting an appropriate voltage vector from a pre-defined switching table based on grid voltage phase and power error signals, offering advantages such as simple structure and fast dynamic response [8]. However, DPC suffers from high power ripple, significant harmonic content, and non-fixed switching frequency. When applied to three-level topologies, the design of optimal switching tables becomes challenging due to constraints such as neutral point voltage balance and voltage jump limitations [9].

In recent years, with advances in microprocessor and digital signal processing technologies, Model Predictive Control (MPC) theory has gained increasing attention in power electronics and electric drives. MPC predicts future system outputs based on historical information and future inputs, evaluating different voltage vectors through a cost function to select the one that minimizes the objective function and yields the optimal switching sequence [10]. Compared with DPC, MPC exhibits similarly fast dynamic response while providing superior steady-state performance. Nevertheless, traditional three-level PWM converter MPC algorithms require 27 power predictions, resulting in substantial computational load. Moreover, the inductance parameter directly affects the calculation of optimal voltage vectors. Failure to track inductance parameter variations in real-time significantly impacts control performance [11-13]. Therefore, incorporating inductance parameter identification is essential to enhance system robustness.

Numerous online parameter identification methods have been proposed by scholars worldwide, building upon offline identification and integrating modern control theory with system identification techniques. Common approaches include the recursive least squares method, model reference adaptive method, and extended Kalman filter method. The least squares method, originally developed by Karl Gauss for planetary orbit prediction, has become a widely used parameter identification technique [14-15]. Its conceptual simplicity, low computational requirements, and favorable statistical properties such as consistency, efficiency, and unbiasedness make it well-suited for online inductance parameter identification in PWM converters [16]. The model reference adaptive method predicts grid-side currents using system mathematical models and estimates grid-side inductance values in real-time based on sampled actual current values, offering fast dynamic response and strong robustness, though its design process is relatively complex [18]. The extended Kalman filter method, as a recursive estimation algorithm [19], requires extensive matrix operations during iteration, making it computationally intensive and impractical for PWM converter inductance parameter identification. Alternative artificial intelligence methods such as neural networks, genetic algorithms, and fuzzy control [20-21] involve extremely complex modeling, complicating the control system and consuming substantial controller resources, rendering them unsuitable for practical inductance parameter identification and confining them to theoretical research.

This paper proposes an improved MPC method that significantly reduces computational burden compared to traditional three-level PWM converter MPC requiring 27 power predictions. Based on deadbeat control principles, the method first calculates a reference voltage vector that eliminates power error, then selects the voltage vector closest to this reference, substantially reducing calculations. Furthermore, to enhance system robustness, an online inductance identification algorithm based on the recursive least squares method is introduced, enabling the PWM converter to maintain good control accuracy and dynamic performance even with inaccurate initial inductance parameters. Simulation and experimental results validate the effectiveness of the proposed method.

2 Model Predictive Control Principle

During PWM converter operation, system parameters may vary due to environmental conditions and temperature factors.

2.1 Traditional Model Predictive Control

Among various MPC methods, Finite Control Set Model Predictive Control (FCS-MPC) has been extensively studied and applied due to its advantages of requiring no modulation strategy, conceptual simplicity, and capability for multi-objective coordinated control. When applied to three-phase PWM converters, FCS-MPC can be categorized into Finite Control Set Model Predictive Power Control (FCS-MPPC) and Finite Control Set Model Predictive Current Control (FCS-MPCC). FCS-MPPC aims to make actual active and reactive power accurately track their reference values.

As shown in Figure 1 [Figure 1: see original paper], three-level topologies additionally require neutral point potential balance control to minimize DC bus capacitor voltage difference. To simultaneously achieve these control objectives, the target function incorporates these terms. Based on the system prediction model, all candidate voltage vectors are enumerated to select the one that minimizes the target function value.

The target function for three-level PWM converters using FCS-MPPC is defined as:

$$G = |p_{ref} - p_{k+1}| + |q_{ref} - q_{k+1}| + K_r|\Delta U_{dc}^{k+1}|$$

where the first two terms represent active and reactive power tracking errors; K_r is the weighting coefficient for neutral point potential balance control; and ΔU_{dc}^{k+1} is the voltage difference between the upper and lower DC bus capacitors. The influence of neutral point potential balance control can be enhanced or reduced by adjusting the weighting coefficient K_r.

The mathematical expression for traditional FCS-MPPC with delay compensation is:

$$G_n = |p_{ref} - p_{k+2}^n| + |q_{ref} - q_{k+2}^n| + K_r|\Delta U_{dc}^{k+2}| \quad n = 1, 2, \dots, 27$$

$$v_{opt} = \min\{G_n\}$$

where v_{opt} is the optimal voltage vector. The overall system control block diagram is shown in Figure 2 [Figure 2: see original paper].

Due to control delay in digital systems, one-step delay compensation is required for active and reactive power prediction between k and $k+1$ moments to obtain power values at $k+1$. Between $k+1$ and $k+2$, the target function values corresponding to 27 voltage vectors are predicted, and the voltage vector minimizing the target function is selected to make active and reactive power as close as possible to their reference values.

The DC bus capacitor voltage difference ΔU_{dc}^{k+1} at $k+1$ moment can be predicted by:

$$\Delta U_{dc}^{k+1} = \Delta U_{dc}^{k} + \frac{t_{sc}}{C} i_{np}^{k}$$

where t_{sc} represents the control period; the superscript "*"denotes the conjugate of a complex vector; and $C_1 = C_2 = C$ are the DC bus capacitors.

The predicted complex power at $k+1$ moment can be expressed as:

$$S_{k+1} = S_k + \frac{3t_{sc}}{2} v_k^* e_k - \frac{3t_{sc}}{2}(R - j\omega L) i_k^2$$

For unity power factor operation, the reactive power reference q_{ref} is set to zero. Therefore, the target function simplifies to:

$$G = |p_{ref} - p_{k+1}| + |q_{k+1}| + K_r|\Delta U_{dc}^{k+1}|$$

where $p_{k+1} = \mathrm{Re}(S_{k+1})$ and $q_{k+1} = \mathrm{Im}(S_{k+1})$.

2.2 Improved Model Predictive Control

For three-level PWM converters, traditional FCS-MPPC requires 27 power prediction calculations. While conceptually straightforward, the computational burden becomes significant when selecting the optimal voltage vector, with this drawback becoming more pronounced in higher-level topologies. To reduce computational load, this paper proposes an Efficient Model Predictive Control (E-MPPC) method that uses a reference voltage vector v_{ref} instead of power tracking error for optimal voltage vector selection, eliminating the need for 27 power predictions and substantially reducing program computational requirements.

In E-MPPC, the reference voltage vector v_{ref} is calculated using the deadbeat power control method. By replacing S_{k+2} in equation (6) with the reference complex power S_{ref} and rearranging, the reference voltage vector calculation becomes:

$$v_{ref} = e_{k+1} - \frac{S_{ref} - S_{k+1}}{\frac{3t_{sc}}{2} i^*_{k+1}}$$

If the converter-side output voltage vector at $k+2$ moment equals v_{ref}, the complex power S_{k+2} will perfectly track the reference value S_{ref}, achieving precise deadbeat control. However, traditional deadbeat control struggles to consider system constraints and implement other control objectives. Therefore, this paper still employs target function minimization after obtaining v_{ref} to determine the optimal voltage vector.

The E-MPPC target function is defined as:

$$G = |v_{ref} - v_{k+2}| + K_r|\Delta U_{dc}^{k+2}|$$

The mathematical expression for optimal voltage vector selection in E-MPPC is:

$$G_n = |v_{ref} - v_n| + K_r|\Delta U_{dc}^{k+2}| \quad n = 1, 2, \ldots, 27$$

$$v_{opt} = \min\{G_n\}$$

Substituting equation (6) into equation (10) and rearranging yields:

$$G_n = K|p_{ref} - p_{k+2}^n| + K|q_{ref} - q_{k+2}^n| + K_r|\Delta U_{dc}^{k+2}| \quad n = 1, 2, \ldots, 27$$

where $K = \frac{2}{3t_{sc}|e_{(k+1)}|}$.

Comparing equations (7) and (11) reveals that the improved E-MPPC and traditional FCS-MPPC are formally similar, with the improved method having an additional positive gain factor K. If the first term on the right side of equation (9) is divided by gain factor K (i.e., $K_r' = K_r/K$), minimizing equation (11) becomes equivalent to minimizing equation (7), meaning both methods will select the same optimal voltage vector. However, equation (7) shows that the improved method eliminates 27 power prediction calculations, achieving higher computational efficiency. Furthermore, this method can be extended to two-level or higher-level topologies.

3 Parameter Identification

3.1 Recursive Least Squares Method

The least squares method is fundamental in system identification but requires batch processing of all test data, demanding significant memory and making it suitable only for offline parameter identification. For online parameter identification, the computational burden limits its widespread application. To address this, the recursive least squares method was proposed, which requires minimal system memory and is suitable for online parameter identification. The basic principle is: based on sampled measurements and previous parameter estimates, the current parameter estimate is corrected through iterative formulas, significantly reducing computational complexity and making it a practical online parameter identification method.

For a single-variable linear time-invariant system with n input and output variables, the equation can be expressed as:

$$Y(N) = \Phi(N)\theta(N) + \eta(N)$$

where $Y(N)$ is the system output sequence; $\Phi(N)$ is the input-output sequence; $\theta(N)$ is the parameter vector to be identified; and $\eta(N)$ is the noise sequence.

For each new set of sampled data, there corresponds a new output:

$$Y(N+1) = \begin{bmatrix} Y(N) \\ y(n+N+1) \end{bmatrix}, \quad \Phi(N+1) = \begin{bmatrix} \Phi(N) \\ \varphi^T(N+1) \end{bmatrix}$$

where $\varphi^T(N+1) = [y(n+N), \dots, y(N+1), u(n+N), \dots, u(N+1)]$.

In the basic least squares method, the identified parameter value is:

$$\hat{\theta}(N) = [\Phi^T(N)\Phi(N)]^{-1}\Phi^T(N)Y(N)$$

The updated parameter estimate $\hat{\theta}(N+1)$ can be obtained through:

$$\hat{\theta}(N+1) = [\Phi^T(N+1)\Phi(N+1)]^{-1}\Phi^T(N+1)Y(N+1)$$

Substituting equation (13) into equation (15) yields:

$$\hat{\theta}(N+1) = [\Phi^T(N)\Phi(N)+\varphi(N+1)\varphi^T(N+1)]^{-1}[\Phi^T(N)Y(N)+\varphi(N+1)y(n+N+1)]$$

For convenience, define:

$$L(N) = \Phi^T(N)\Phi(N)$$

$$L(N+1) = \Phi^T(N+1)\Phi(N+1) = L(N) + \varphi(N+1)\varphi^T(N+1)$$

Further simplification leads to:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + H(k)[y(k) - \varphi^T(k)\hat{\theta}(k-1)]$$

$$H(k) = \frac{L(k-1)\varphi(k)}{1 + \varphi^T(k)L(k-1)\varphi(k)}$$

$$L(k) = [I - H(k)\varphi^T(k)]L(k-1)$$

where $L(0) = \alpha I$ and $\hat{\theta}(0) = \beta$, with L_e being the initial inductance value. Initial values $L(0)$ and $\hat{\theta}(0)$ are assigned before identification. Based on sampled data, $H(k)$, $L(k)$, and $\hat{\theta}(k)$ are calculated, with the identified parameters serving as initial values for the next sampling period. This iteration repeats every sampling cycle, outputting the identified values.

The system control principle of the improved E-MPPC with parameter identification is shown in Figure 3 [Figure 3: see original paper]. Using the initial values from equation (22) and the iterative formulas (19)-(21), the system parameters can be identified.

3.2 Identification Model Establishment for Three-Level PWM Converter

To identify the grid-side inductance of a three-level PWM converter, the system mathematical model must be transformed into the standard form of the least squares method, as shown in equation (12). In the two-phase dq coordinate system, the mathematical model of the three-level PWM converter is:

$$\begin{bmatrix} e_d \\ e_q \end{bmatrix} = R\begin{bmatrix} i_d \\ i_q \end{bmatrix} + L\frac{d}{dt}\begin{bmatrix} i_d \\ i_q \end{bmatrix} + \begin{bmatrix} v_d \\ v_q \end{bmatrix}$$

Under steady-state conditions, the current derivative term becomes zero, and equation (23) simplifies to:

$$\begin{bmatrix} e_d - v_d \\ e_q - v_q \end{bmatrix} = R\begin{bmatrix} i_d \\ i_q \end{bmatrix} + \omega L\begin{bmatrix} -i_q \\ i_d \end{bmatrix}$$

4 Simulation Results

This paper incorporates inductance parameter identification based on the recursive least squares method into the improved MPC for simulation verification. The simulation parameters are listed in the table below.

Table: System and Control Parameters

Parameter	Value
Grid-side resistance R	0.3 Ω
Inductance L	5 mH
DC bus capacitance C	2200 F
Load resistance R_L	100 Ω
Line voltage U_N	220 V
Grid frequency f	50 Hz
Sampling frequency f_s	10 kHz
DC bus voltage U_{dc}	600 V
Weighting coefficient K_r	0.01
Gain constant K	1000

Figure 4a shows simulation results with inductance identification using the recursive least squares method. The curves from top to bottom are: inductance set value and identified value, active power, reactive power, converter-side line voltage, DC-side neutral point potential, and grid phase voltage/current. The initial inductance set value is 30 mH, and the parameter identification algorithm is not enabled before 0.075 s. When the inductance set value is larger than the actual value, significant power ripple and increased grid-side current harmonic content are observed, with chaotic converter-side line voltage waveforms. At 0.075 s, the parameter identification algorithm is activated, demonstrating that the least squares algorithm can accurately and rapidly identify the actual inductance value, with substantial improvements in both power ripple and current THD. Figure 4b [Figure 4: see original paper] shows a magnified view of the inductance identification waveform, revealing an identification error of approximately 2% and a dynamic response time of about 1 ms.

Figure 5a [Figure 5: see original paper] presents simulation waveforms with an initial model inductance value of 1 mH. Before 0.075 s, the model inductance is set to 1 mH without inductance identification, showing large active/reactive power ripple, inaccurate reference tracking, high grid-side current harmonic content, and phase misalignment between voltage and current. At 0.075 s, the identification algorithm is enabled, demonstrating accurate reference tracking, in-phase voltage and current, and significantly reduced power ripple and current harmonic content, validating the effectiveness of the parameter identification algorithm. The magnified inductance identification waveform is shown in Figure 5b.

5 Experimental Results

To verify the effectiveness of the improved E-MPPC, experiments were conducted to compare the performance of traditional FCS-MPC and improved E-MPPC. Experimental parameters are listed in Table 1 . In the experimental waveforms, voltage and current are measured directly using probes, while other internal variables are obtained through DA converters on the control board, recorded using a DL850 oscilloscope, and then exported to MATLAB for plotting and analysis.

Figure 6 [Figure 6: see original paper] shows steady-state experimental waveforms with a 1 kW load, displaying from top to bottom: active power reference, actual active power, actual reactive power, DC-side neutral point potential, and phase current. The results indicate that the improved E-MPPC exhibits lower power ripple compared to traditional FCS-MPPC, along with smaller DC-side neutral point potential fluctuations.

Grid-side THD and spectrum analysis are shown in Figure 7 [Figure 7: see original paper], revealing that the improved E-MPPC achieves slightly lower current THD than traditional FCS-MPPC.

Figure 8 [Figure 8: see original paper] presents experimental waveforms of grid-side phase voltage U_a, grid-side phase current I_a, and grid-side line voltage V_{ab}. Both methods avoid excessive voltage amplitude jumps, maintain phase alignment between grid voltage and current, and achieve unity power factor control.

Figure 9 [Figure 9: see original paper] shows dynamic experimental waveforms for a power step from 600 W to 1000 W. Both methods demonstrate similar dynamic characteristics with accurate reference tracking. However, the improved method exhibits lower power ripple and smaller current distortion. It should be noted that since the improved E-MPPC uses the reference voltage vector v_{ref} instead of power tracking error for optimal voltage vector selection, it eliminates the complex multiple power prediction calculations required in traditional FCS-MPPC, significantly reducing system complexity and computational load. Experimental measurements of program execution time show that the improved E-MPPC requires 29.67 s, while traditional FCS-MPPC requires 42.56 s, demonstrating the superior execution efficiency of the improved method.

This paper also combines system parameter identification with the improved MPC algorithm to enhance robustness against parameter variations. Figure 10a [Figure 10: see original paper] shows experimental waveforms with an initial model inductance set value of 50 mH. The curves from top to bottom are: identified inductance value, initial set inductance value, active/reactive power, and grid phase voltage/current. The parameter identification algorithm is enabled after approximately 0.05 s. Without parameter identification, significant power ripple and grid-side current harmonic content are observed. After enabling the identification algorithm, both power ripple and current THD are substantially improved, with the identified inductance value approaching the actual model inductance. Figure 10b shows experimental waveforms with an initial inductance set value of 1 mH, demonstrating similar results to the simulation: large power ripple before identification and improved control performance after algorithm activation.

6 Conclusion

Based on the analysis of improved model predictive control for three-level PWM converters and the principle of least squares parameter identification, this paper applies the recursive least squares method to inductance parameter identification for three-level PWM converters and integrates it with the improved MPC algorithm that selects optimal voltage vectors using reference voltage vectors. Experimental results demonstrate that the identified inductance parameter values are close to (though not exactly equal to) the actual values. Using the identified inductance values for system control significantly reduces power ripple and current THD. These results confirm the feasibility and effectiveness of the model predictive control method incorporating recursive least squares inductance parameter identification.

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Note: Figure translations are in progress. See original paper for figures.