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Single Sampling Multi Controlling- Model Predicted Control for Single Inverters

Po Li[1, 2], Xiao Tang[2, *], Lei Fu[2], Yibiao Fan [3]

[1]Shenzhen Research Institute of Xiamen University, Shenzhen, China
[2]Department of Instrumental Electrical Engineering, School of Aerospace Engineering, Xiamen University, Xiamen, China
[3]College of Mechanical and Electrical Engineering, Longyan University, Longyan, China

*Corresponding author e-mail: 1024032728@qq.com

Abstract. In this paper, a single sampling multi controlling-model predicted control (SSMC-MPC) scheme is proposed to decrease a considerable part of the computational burden and reduce the dependence on the sampling module. The SSMC-MPC achieves a ratio of control frequency to sampling frequency of N ($N \in Z$). The same control frequency requires only a lower sampling frequency module, which saves hardware costs and has advantages in practical application. By comparing the control effect of traditional FCS-MPC algorithm and SSMC-MPC algorithm, the proposed method and benefits were validated by simulations in MATLAB/Simulink.

1. Introduction

This article mainly studies a model predictive control algorithm for inverter control. With the rapid development of social economy and the ever-increasing population of the world, the demand for energy by human beings is increasing, and electric energy plays an increasingly important role in energy supply. Generally, new energy should be converted into electricity before it can be used by people. For example, DC power generated by wind turbines and photovoltaic panels should be transformed into AC power through inverters before they can be delivered to the grid or users. Therefore, inverters play an important role in the development of new energy sources. The control method of the inverter is of great significance to the safe and reliable operation of the power system. The model predictive control algorithm was first practiced in the petrochemical industry [1]. It can provide solutions for multivariable constraint control problems in the petrochemical industry, and then it is applied in more fields, such as the mechanical industry, communications systems, and aerospace et al [2], the research of model predictive control for inverter circuits is gradually emerging.

The application of model predictive control in power electronic systems is mainly divided into Continuous Control Set-MPC (CCS-MPC) and Finite Control Set-MPC (FCS-MPC) [3]. Because of the discrete nature of the inverter and the limited states of the switch combination, the model prediction control of inverter generally refers to FCS-MPC. In [4], the principle of finite-control-set model predictive control is introduced in detail, a predictive control model based on multi-step predictive finite-control set model is proposed; and a simplified model predictive control based on FCS-MPC is proposed in [5], which can effectively reduce the number of cycle calculations and predictions required for model predictive control and reduce the average switching frequency. In [6], the author proposed a simplified branch and bound method to reduce the MPC calculation of the cascaded H-bridge Static Synchronous Compensator (STATCOM) by selecting the possible values of a variable as branches and enumerating the best integer result of each branch. In [7], the author proposed a fast MPC scheme for multi-level cascaded H-bridge STATCOM. On the analysis of time complexity, the scheme can reduce the total computation of FCS-MPC from exponential time to polynomial time, and the proposed method don't reduce the control performance. In order to realize the application of model predictive control in fast dynamic systems, a number of model predictive control online optimization algorithms have emerged successively, such as interior point method [8], effective set method [9], and gradient descent method [10]. These algorithms can realize the real-time calculation of the model predictive control online optimization problem, greatly reduce the computational burden of the model predictive control, speed up the online calculation speed, and broaden the application scope of model predictive control [11].

Now we propose a single sampling multi controlling-model predicted control (SSMC-MPC) based on FSC-MPC, which can reduce a considerable part of the computational burden and reduce the dependency on the sampling module. The SSMC-MPC achieves a ratio of control frequency to sampling frequency of N ($N \in Z$). The same control frequency requires only a lower sampling frequency module, which saves hardware costs and has advantages in practical application.

This paper mainly studies the inverter current tracking method based on model predictive control, and proposes a comparison between SSMC-MPC and traditional FCS-MPC for simulation experiments to show that SSMC-MPC reduces the calculation and sampling Module dependency advantages.

This chapter is organized as follows: The first chapter is introduction, explains the research objects and the significance of research, introduces the related research status of model predictive control; Chapter 2 describes the problem statement and system description, introduces the single-phase H-bridge inverter circuit topology, establishes discrete Mathematical model; The third chapter is the control algorithm design, design cost function, control flow chart; The fourth chapter is the simulation experiment of single-phase H bridge inverter circuit, comparing the control effect of traditional FCS-MPC algorithm and SSMC-MPC algorithm. The fifth chapter is a summary of the research work of this paper, as well as the expectations of future research.

2. System Description and Problem Statement

Figure 1 shows the topology of a typical single-phase H-bridge inverter circuit. It consists of a DC power supply, four MOSFET switches, four diodes, a resistive and inductive load, and the grid's counter electromotive force. The inverter circuit can output three levels in total, that is, high level U_{dc}, low level $-U_{dc}$, and zero level. The output level of the inverter is controlled by controlling the drive signal of the switch tube so as to track the reference current, so that the output current meets the grid requirements.

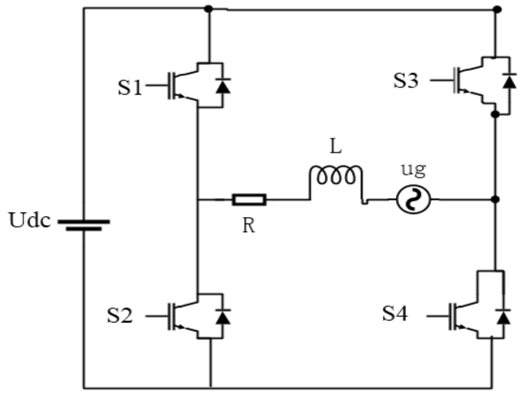


Figure 1. Single-phase H-bridge inverter circuit.

The state equation of the H-bridge inverter circuit is as follows:

$$\mathrm{L}\frac{di(t)}{dt} = -Ri(t) + \mathrm{aU}_{dc} - u_g \quad (1)$$

Where $\mathrm{i(t)}$ is the output current, L is the load inductance value, R is the load resistance value, U_{dc} is the DC power supply, u_g is the grid's counter electromotive force, a is the output voltage coefficient of the inverter circuit, and $\mathrm{a} \in \{1,0,-1\}$, where a = 1 represents a high level, a = 0 represents a zero level, and a = -1 represents a low level. The design of the model predictive control algorithm is based on a discrete model, so the state equation (1) is discretized to equation (2) by using Euler's method.

$$\mathrm{L}\frac{di(t)}{dt} = L \ \frac{i(k+1) - i(k)}{T_s} \quad (2)$$

Where $\mathrm{T_s}$ is the sampling period, and $\mathrm{i(k)}$ is the value of controlled variables in the current state and $\mathrm{i(k+1)}$ is the value of controlled variables in the next state. The combination of equations (1) and (2) becomes the discrete model of a single-phase H-bridge inverter circuit as.

$$i(k+1) = \left(1 - \frac{R}{L}Ts\right)i(k) + \frac{Ts}{L}\left(\mathrm{a}U_{dc} - u_g\right) \quad (3)$$

3. Controller Design

The control block diagram of MPC is shown in Fig. 2. The control variables is current, $\mathrm{i(k)}$ is fed back to the predictive model, then the cost function is calculated based on the predictive current, and then select the combination of switching function which involves the minimum value of the cost function to control the inverter circuit. The traditional multi-step FCS-MPC calculates the predictive currents and the cost functions for all steps at a time, and then compares them. Then, the first switch combination state with the minimum cost function is selected to control the circuit until the arrival of the next sampling period, regardless of the prediction step size, the control is always performed using only the switch combination in the first prediction, and the control frequency and the sampling frequency are always equal. Although the control effect is good, computational burden is very large, and the frequency of the sampling module limits the control frequency. The SSMC-MPC is simplified on the traditional FCS-MPC. Let $\mathrm{N}=\frac{f_c}{f_s}$, which means in single sample period the number of control period, where f_c is the control frequency, f_s is the sampling frequency, and SSMC-MPC performs N times of control during each sampling period. The best combination of switching function predicted each time is used for control. The local optimization of SSMC-MPC means that each time the prediction is performed, it is controlled once. The predicted value of next moment is used again instead of the measured value to be predicted and controlled again until the arrival of the next sampling period. The SSMC-MPC global optimization means that the predictive values of all N times are calculated once and then control N times in sequence. All "global optimization" in this paper refers to the global optimization within a single sampling period, which is different from the global optimization problem in multi-step predictive control.

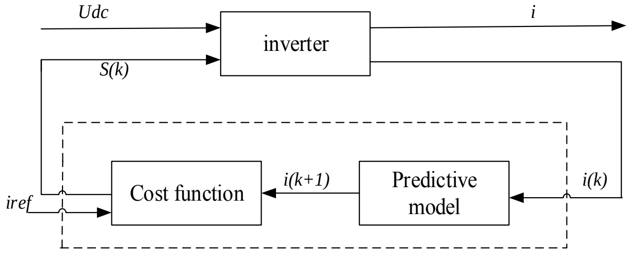


Figure 2. The control block diagram of MPC.

3.1. Cost Function Design

In order to track the reference current, the cost function designed as follow:

$$cost_n(k+1) = (i_n(k+1) - i_{\text{ref}}) * (i_n(k+1) - i_{\text{ref}}) \tag{4}$$

Where $n \in \{1,2,3\}$, i_{ref} is a given reference current and is a periodic sine wave. The a has three values, so the corresponding $\mathrm{i}(\mathrm{k}+1)$ and $\mathrm{cost}(\mathrm{k}+1)$ also have three values, select the smallest $\mathrm{cost}(\mathrm{k}+1)$value, and then output the corresponding switch signal.

When N≥2, the total cost function is the sum of the cost functions of each step. Take N=2 as an example.

$$cost_n(k+2) = cost_{1i}(k+1) + cost_{2n}(k+2) \tag{5}$$

Where $i \in \{1,2,3\}$, $n \in \{1,2,3,4,5,6,7,8,9\}$, when N increases, the total number of cost functions increases exponentially.

3.2. Control Flow Design

(1) The global optimization control flow for SSMC-MPC with N=2 is shown in Figure 3. The details are as follows:

Step 1: Initialize the value of the variables.

Step 2: Measure the control variable $\mathrm{i}(k)$ through the current sensor.

Step 3: Calculate the predicted current $\mathrm{i}_{1n}(k+1)$, $n \in \{1,2,3\}$

Step 4: Calculate the cost function $\mathrm{cost}_{1n}(k+1)$ corresponding to each predicted current

Step 5: Calculate the predicted current $\mathrm{i}_{2n}(k+2)$, $n \in \{1,2,3,4,5,6,7,8,9\}$ by using $\mathrm{i}_{1n}(k+1)$ instead of $\mathrm{i}(k)$in the discrete model formula

Step 6: Calculate the cost function $\mathrm{cost}_{2n}(k+2)$ corresponding to each predicted current value through the cost function formula. $n \in \{1,2,3,4,5,6,7,8,9\}$

Step 7: Add the cost function in first and second step to get the total cost function $\mathrm{cost}_n(k+2)$

Step 8: Compare the cost function and select the switch state corresponding the minimal cost function.

Step 9: Output the first controlled switch signal.

Step 10: Output the second controlled switch signal.

When N>2, the SSMC-MPC global optimization control flow is similar to the control flow of N=2.

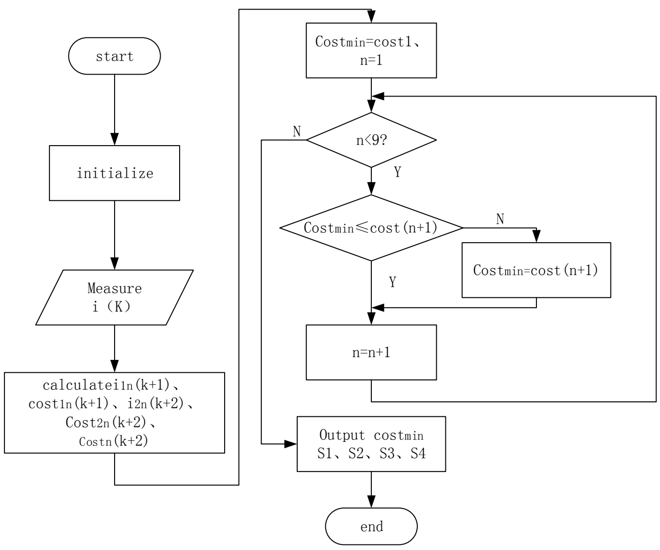


Figure 3. SSMC-MPC Global Optimization Control Flowchart when N=2.

(2) The local optimization control flow for SSMC-MPC with N=x is shown in Figure 4. The details are as follows:

Step 1: Initialize the value of the variables.

Step 2: Measure the control variable $\mathrm{i}(k)$ through the current sensor.

Step 3: Calculate the predicted current $\mathrm{i}_{1n}(k+1)$, n ∈ {1,2,3}

Step 4: Calculate the cost function $\mathrm{cost}_{1n}(k+1)$ corresponding to each predicted current

Step 5: Compare the cost function and select the switch state corresponding the minimal cost function, and store the $\mathrm{i}_{1n}(k+1)$

Step 6: Output the first controlled switch signal.

Step 7: Use the stored $\mathrm{i}_{1n}(k+1)$ as the measured value at time K+1. Repeat steps 3, 4, 5, and 6

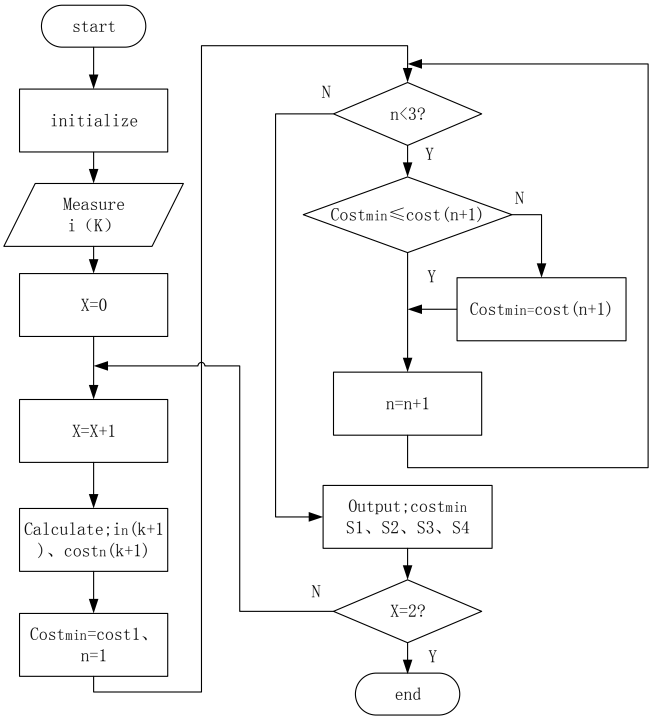


Figure 4. SSMC-MPC Local Optimization Control Flowchart when N=x.

4. Simulation

In order to verify the effectiveness of the designed algorithm and control flow, we use MATLAB/Simulink for simulation, which is divided into three parts. The first part is the comparison of the SSMC-MPC local optimum control output effect as the N increases. The second part is the local optimization of the SSMC-MPC Compare with the global optimization SSMC-MPC as the control frequency increases when N=2 or N=3. The simulation parameters are set as shown in the following table:

Table 1. Simulation Parameters of SSMC-MPC

Descriptions	Parameters	Numerical value
Input voltage	Vdc/V	36
inductance	L/H	3.3e-3
resistance	R/Ω	2.2
period	Ts/s	T_S

4.1. Change N in the local optimization SSMC-MPC

Ts is set as (5e-5)s. That is, the control frequency is 20 *KHz*, which is equivalent to the sampling frequency is (20/N) *KHz*. The tracking control effect of N=1 and N=5 is shown in Figure 5 (a) and Figure 5 (b), in which the output current can track the reference current. As shown in Figure 6 (a) and Figure 6 (b), at the same control frequency, with the increase of N, the variance of the output current and the THD both fluctuate irregularly. It also shows that with the increase of the N, the local optimization SSMC-MPC control effect is not always bad than the traditional FCS-MPC, which means the same control frequency only requires a lower frequency module to match.

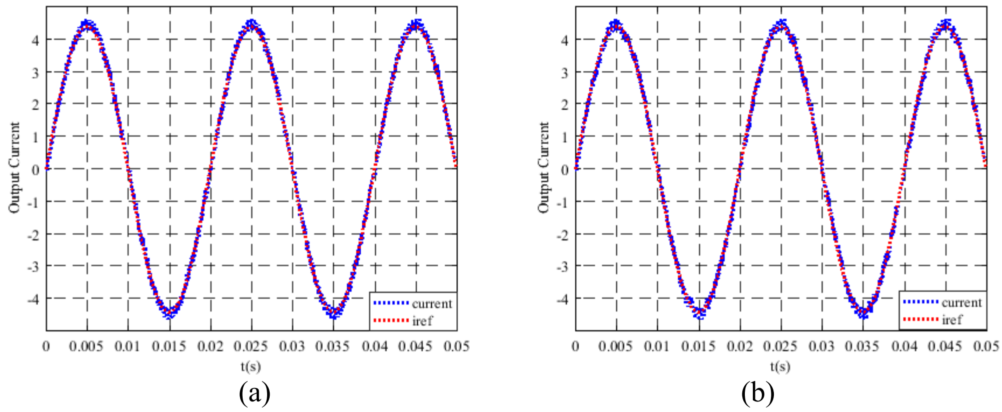


Figure 5. Output current tracking waveform. (a) N=1. (b) N=5

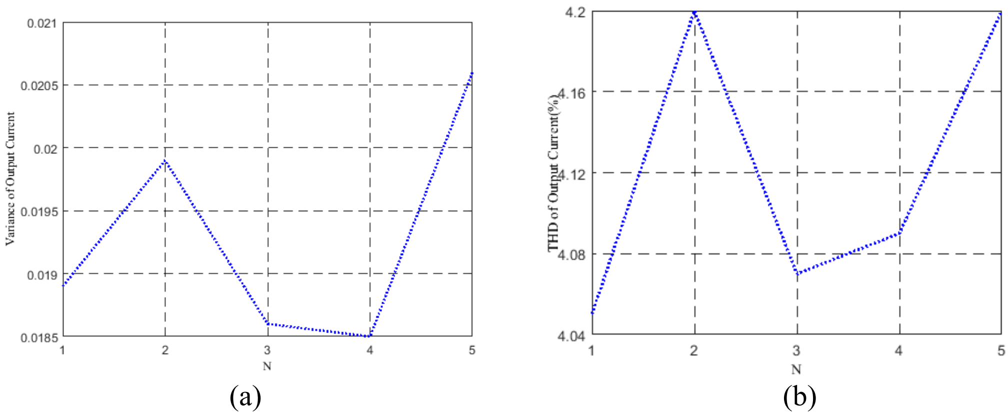
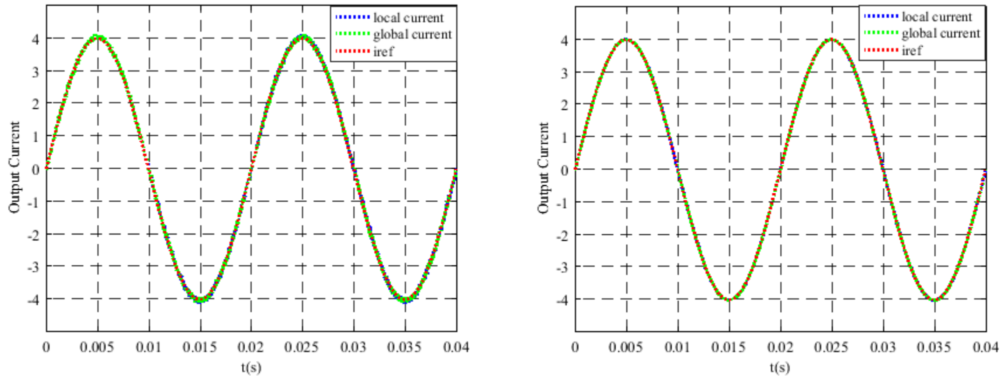


Figure 6. Tracking effect of output current with changing N. (a) variance. (b) THD

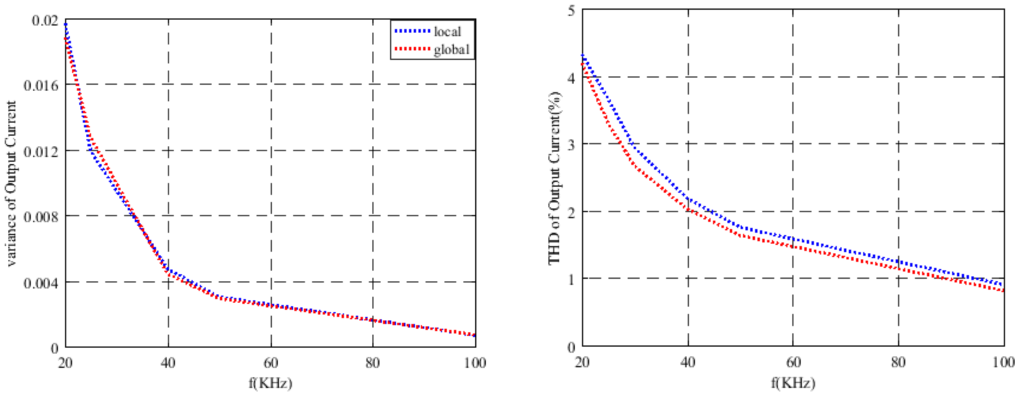
4.2. A Comparison of SSMC-MPC between Local Optimization and Global Optimization at N=2

With the increase of control frequency from 20 *KHz* to 100 *KHz*, record the waveform of the output current at the corresponding frequency, and calculate the variance and THD of the output current based on the data. The simulation waveforms of 40 *KHz* and 100 *KHz* are shown in Figure 7 (a) and Figure 7 (b). The variance of output current and THD trend are shown in Figure 8 (a) and Figure 8 (b).



(a) (b)

Figure 7. Comparison of output current waveforms. (a) f_s=40*KHz*. (b) N=100 *KHz*.



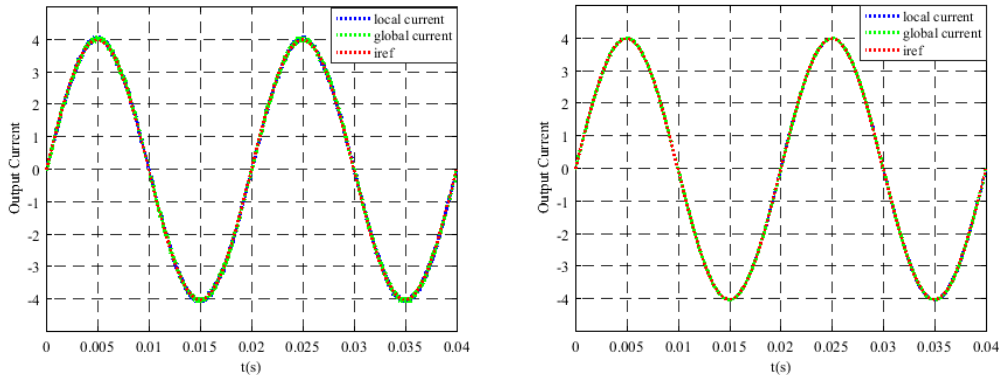
(a) (b)

Figure 8. Output current with changing frequency. (a) Variance. (b) THD.

As shown in Figure 8 (a) and Figure 8 (b), the blue line is the output current variance and THD under local optimization SSMC-MPC, and the red line is the output current variance and THD under the global optimization SSMC-MPC. In terms of THD, the global optimization control effect is better, but the difference between the two is not large, in terms of variance, the control effect of the two methods is almost the same, no one is always lead. However, in terms of calculation amount, the global optimization control needs to calculate the predicted current value and the cost function value of the nine kinds of switch combination functions at a time, so its computational burden is large than the local optimization control which only needs to calculate the predicted current value and the cost function value of the six switch combination functions. Considering comprehensively, the algorithm and control flow of the local optimization SSMC-MPC are feasible and effective.

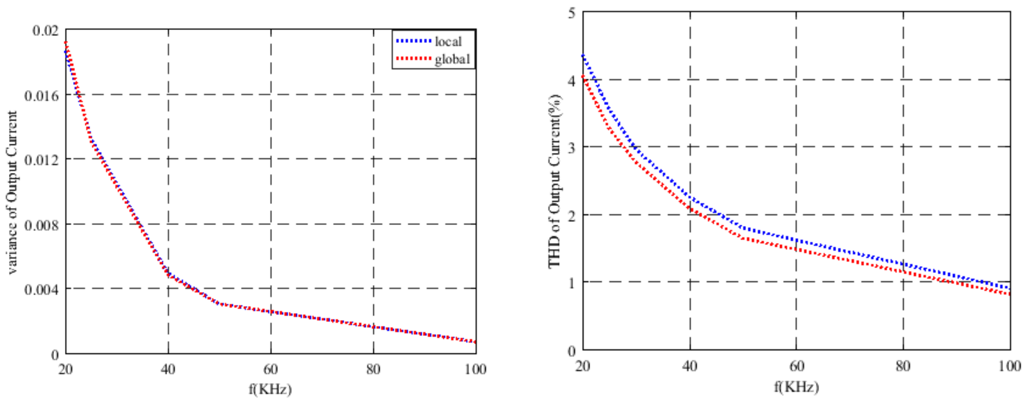
4.3. A Comparison of SSMC-MPC between Local Optimization and Global Optimization at N=3

With the increase of control frequency from 20 KHz to 100 KHz, record the waveform of the output current at the corresponding frequency, and calculate the variance and THD of the output current based on the data. The simulation waveforms of 40 KHz and 100 KHz are shown in Figure 9 (a) and Figure 9 (b). The variance of output current and THD trend are shown in Figure 10 (a) and Figure 10 (b).



(a) (b)

Figure 9. Comparison of output current waveforms. (a) f_s=40*KHz*. (b) N=100*KHz*.



(a) (b)

Figure 10. Output current with changing frequency. (a) Variance. (b) THD.

As shown in Figure 10(a) and Figure 10(b), the control effect of N=3 is almost the same as when N=2. In terms of THD and variance, the global optimization SSMC-MPC is more advantageous, but in terms of calculation amount, the global optimization SSMC-MPC needs to consider 27 kinds of switch combination functions, which is much larger than the local optimization SSMC-MPC which only needs to consider 9 kinds of switch combination functions. Similarly, as N increases, the advantage of local optimization SSMC-MPC in terms of calculation amount becomes more obvious.

5. Conclusion

The focus of this study is the use of a single sampling multi controlling-model predicted control (SSMC-MPC) based on finite-control-set model prediction in inverters. Take Phase H-bridge inverters as example, firstly, the topological structure and control principle of single-phase H-bridge inverter are respectively described and the corresponding mathematical model is deduced; secondly, the control principle and design of SSMC-MPC are described; then, the control algorithm of SSMC-MPC is studied and proposed, which using the current prediction value as the next-time sampling value to participate in the calculation, so the number of calculation state quantities is changed from 3^N to 3N, thereby reducing the computational burden and reducing the requirements of the control module to the sampling module Frequency. Then through the MATLAB/Simulink modeling simulation, the proposed SSMC-MPC method is verified by simulation, comparing the traditional FCS-MPC and SSMC-MPC tracking performance of the reference current, and the local optimization of SSMC-MPC and the global optimization of the SSMC- MPC in the tracking performance of the reference current, thus confirming the rationality and effectiveness of the proposed method.

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