Robust Model Predictive Flux Control of PMSM Drive Using a Compensated Stator Flux Predictor

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This work was supported in part by the Civil-Military Integration Research Foundation of Shaanxi Province under Grant 17JMR21, in part by the Special Scientific Research Program of Education Department of Shaanxi Province under Grant 17JK0268, and in part by the Talent Foundation of Weinan Normal University under Grant 17ZRRC03.

ABSTRACT In the model predictive control of permanent magnet synchronous motor (PMSM), predictive flux control (PFC) has been widely studied because it does not need the complicated setting of weight factor. In predictive flux control, the prediction of stator flux vector is usually based on the voltage model. However, the mismatched resistance parameter and current sampling errors will lead to stator flux prediction errors, resulting in the degradation of control performance and even the system instability. To solve this problem, this paper proposes a compensated stator flux predictor based-predictive flux control (CSFP-PFC) of permanent magnet synchronous motor. In the proposed method, stator flux vector is firstly expressed at the rotor reference frame. Then, a compensated stator flux predictor is firstly constructed based on stator current prediction error. The accurate prediction of stator flux vector will ensure the selection of optimal voltage vector. Experimental results verify the effectiveness of the proposed algorithm.

INDEX TERMS Model predictive control, permanent magnet synchronous motor, robustness.

I. INTRODUCTION
Permanent magnet synchronous motor (PMSM) is widely used in electric vehicles, wind power generation and high performance servo control theory, because of its high power density, small size and small torque ripple [1], [2]. The control strategies of PMSM mainly include vector control and direct torque control [3]. Vector control realizes static decoupling of excitation current and torque current by coordinate transformation, but it also faces many problems such as difficulty of multi-loop parameter modulation and limited bandwidth design. Direct torque control (DTC) selects voltage vector through voltage vector table to control electromagnetic torque, but it also faces the problems of large torque ripple and stator flux amplitude ripple, especially in low speed region. Recently, finite control set-model predictive control (FCS-MPC) is expected to be applied in the field of high performance PMSM drive due to its fast dynamic response, simple structure and easy handling of multivariable constraints [4]–[7].

However, in the model predictive torque control of permanent magnet synchronous motor, the cost function includes the stator flux amplitude tracking and the electromagnetic torque tracking, where the weighting factor is utilized to balance the importance of both [8]. At present, the setting of weight factor is lack of theoretical basis and needs tedious debugging in practice. In view of this problem, scholars have carried out extensive research. In [9], for model predictive torque and flux control of induction machine, algebraic tuning guidelines are proposed to set the weight factors. In [10], the offline genetic algorithm is applied to the weight factor optimization to realize the cooperative control among multiple control variables. However, in the actual operation of the motor, magnetic circuit saturation and winding temperature rise lead to the variation of motor parameters, so the weight factors of offline optimization are not optimal in practice. In [11], the neural network method is applied to the weight factor optimization, and the weight factor configuration under different torque ripple and flux ripple can be obtained by offline learning. The model predictive flux control takes the stator flux vector as the control variable instead of the stator flux amplitude and electromagnetic torque as the control variables, so there is no weight factor in the cost function, which further simplifies the structure of predictive control.

The state prediction of model predictive control depends on the mathematical model of motor. Mismatched motor
parameters, such as inductance and stator resistance, will cause prediction error and affect the dynamic and robust performances of predictive control [12]. In [13], model predictive current control with model parameter mismatch in a three-phase inverter is analyzed under different operation conditions. In [14], disturbance compensation-based robust predictive torque control is proposed for PMSM drives, where disturbance observer is used to estimate torque tracking error and suppress prediction error. In [15], online parameter identification technology is introduced into model predictive control. Through real-time identification of motor parameters, the prediction accuracy of stator current and electromagnetic torque is improved. In [16], a robust predictive torque control is proposed, in which the stator flux prediction combines voltage model and current model, and the stator current prediction adopts a closed-loop mechanism, which improves the prediction accuracy through feedback. In [17], active disturbance rejection control (ADRC) technology is introduced into the speed loop. The prediction error of the torque loop is regarded as a disturbance. By adding disturbance feedforward compensation technology into the speed loop, the high dynamic response of the speed is realized.

For the classical model predictive torque control (MPTC), in order to avoid the cumbersome setting of weight factors in the cost function, scholars proposed predictive flux control of induction motor and permanent magnet synchronous motor. In [18], predictive flux control of induction machine is firstly proposed, where stator flux vector is regarded as control variable instead of electromagnetic torque and stator flux amplitude. Compared with MPTC, predictive flux control has no weight factors and reduce the control complexity significantly. In [3], for PMSM drives, predictive flux control of PMSM is proposed, where the computation equation of stator flux vector reference is established. However, in the traditional predictive flux control, the predictive equation of stator flux vector is based on voltage model. The prediction equation is actually an open-loop prediction mode. The mismatched stator resistance, the sampling error of stator current and the dead-time of actual voltage vector will lead to the prediction error of stator flux vector [19]. In order to improve the prediction accuracy of stator flux linkage vector, a compensated stator flux predictor based-predictive flux control is proposed in this paper. The design principle of compensated stator flux vector prediction is that firstly, the discrete equation of stator flux linkage is expressed in dq reference frame system, and then the compensation term is introduced into this discrete equation. The compensation term is composed of the product of stator current prediction error and the proportional coefficient. Thirdly, the stability of CSFP and the design method of proportional coefficient are analyzed based on linear control theory.

The basic structure of this paper is as follows. The second part introduces the mathematical model of PMSM and the classical model predictive torque control. In the third part, the model predictive flux control of PMSM based on compensated predictive flux vector model is described in detail. Firstly, the mechanism of stator flux vector prediction error caused by mismatched parameters is analyzed, and then the compensated stator flux vector predictor is introduced. In the fourth part, the dynamic performance, steady-state performance and robust performance of the proposed algorithm are compared with the traditional predictive torque control. The fifth part summarizes the paper.

II. MATHEMATICAL MODEL OF PMSM AND TRADITIONAL PREDICTIVE TORQUE CONTROL

In the three-phase stator reference frame, the mathematical model of PMSM based on space vector theory is presented in (1)-(4), where \( v_s \), \( i_s \), and \( \psi_s \) are stator voltage vector, stator current vector and stator flux vector, respectively. \( \psi_f \) is permanent magnet flux and \( R_s \) is stator resistance. \( L_s \) denotes the excitation magnet flux [20], [21]. The electromagnetic torque of PMSM can be regarded as the result of the interaction between stator flux and permanent flux. Therefore, the electromagnetic torque \( T_e \) can be expressed as equation (4).

\[
\begin{align*}
    v_s &= R_s i_s + \frac{d\psi_s}{dt} \\
    \psi_s &= L_s i_s + \psi_f e^{j\theta} \\
    v_s &= R_s i_s + L_s \frac{di_s}{dt} + j\omega_r \psi_f e^{j\theta} \\
    T_e &= \frac{3}{2L_s} \psi_f e^{j\theta} \times \psi_s
\end{align*}
\]

The traditional predictive torque control consists of predictive model and cost function, as shown in Fig. 1. Generally, the prediction model is obtained by the first-order Euler discretization of the continuous equations as shown in (5)-(7). The cost function is presented in (8), which consists of two parts, the electromagnetic torque tracking and stator flux amplitude tracking. \( \lambda_\psi \) is the weight factor to adjust the importance of the two.

\[
\begin{align*}
    \psi_s (k + 1) &= T_s \left( v_s (k) - R_s i_s (k) \right) + \psi_s (k) \\
    i_s (k + 1) &= i_s (k) + \frac{T_s}{L_s} \left( v_s (k) - R_s i_s (k) \right) + j\omega_r \psi_f e^{j\theta} (k)
\end{align*}
\]
\[ T_e (k + 1) = \frac{3}{2L_s} \psi_f e^{j\theta_r (k+1)} \times \psi_s (k + 1) \]
\[ g_i = \left| T_e^* - T_e (k+1) \right| + \lambda \psi \left| \psi_3^* - \psi_s (k+1) \right| \]

In the traditional predictive torque control, the predictive model depends on the motor parameters, and the mismatched motor parameters will produce predictive errors, which reduce the control performance of the system. In addition, the setting of weight factors is lack of theoretical guidance, and the trial and error method is often used, which not only increases the debugging time, but also cannot obtain the optimal value.

It is known that multistep finite control set-model predictive control has excellent performances than one-step-ahead model predictive control. Research conducted by Professor Tobias Geyer showed that for long prediction horizons and a low switching frequency, the total harmonic distortion of the current is significantly lower than for space vector modulation, making direct MPC with long horizons an attractive and computationally viable control scheme [22]–[24]. Therefore, multi-step model predictive control is suitable for high-performance motor drive systems, because multi-step predictive control requires a lot of computation, where the control chip needs FPGA or other high-performance processors. In electric vehicles or servo drive systems, the C2000 series microprocessors of Texas Instruments are often used in order to reduce costs. However, due to the limited computing power of the microprocessors, it is difficult to realize multistep predictive control. Therefore, in this paper, single-step predictive control is adopted, which means that the control horizon and the prediction horizon is one.

III. COMPENSATED STATOR FLUX PREDICTOR-PREDICTIVE FLUX CONTROL

A. CALCULATION OF STATOR FLUX VECTOR REFERENCE VALUE

In order to realize model predictive flux control, the reference value of stator flux vector \( \psi_s^* \) must be calculated firstly. In traditional model predictive torque control, stator flux amplitude \( |\psi_s| \) and electromagnetic torque \( T_e^* \) are used as control variables. The reference value of stator flux amplitude \( |\psi_3| \) is given directly, and the reference value of electromagnetic torque \( T_e^* \) is given by the speed loop. Therefore, in model predictive flux control, the amplitude of stator flux vector reference value \( |\psi_s^*| \) is equal to the reference value of stator flux amplitude \( |\psi_3| \) in traditional predictive flux control.

\[ |\psi_s^*| = |\psi_3| \]

In addition, the angle of stator flux vector reference value \( \psi_s^* \) needs to be solved. The electromagnetic torque at \( k + 1 \) sampling time can be rewritten as (10), where \( \delta_{sr} \) is the difference of stator flux vector and permanent magnet flux linkage vector. \( \theta_r (k + 1) \) denotes the position of permanent magnet at \( k + 1 \) sampling time, which can be calculated by (11).

\[ \delta_{sr} = \arcsin \left( \frac{2T_e^*}{3p\psi_f |\psi_s (k+1)|^2} \right) \]

Therefore, the angle \( \theta_r^*(k + 1) \) of stator flux vector can be calculated by (13), and stator flux vector reference can be expressed as (14).

\[ \theta_r^* (k + 1) = \theta_r (k) + \omega_r (k) T_s + \delta_{sr} \]
\[ \psi_s^* (k + 1) = |\psi_s (k+1)| e^{j\theta_r^* (k+1)} \]
The orthogonal rotation matrix $J$ and inductance matrix $L$ are defined as

$$ J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}; \quad L = \begin{bmatrix} L_d & 0 \\ 0 & L_q \end{bmatrix} \quad (18) $$

Based on equation (15) and the first-order Euler discretization method, the prediction equation of stator flux vector can be obtained as shown in (19), where $T_s$ is the sampling period.

$$ \psi_{dqs} (k+1) = T_s [u_{dqs}(k) - R_i i_{dqs}(k)] - T_s \omega_m \psi_{dqs}(k) + \psi_{dqs}(k) \quad (19) $$

However, the above equation is still an open-loop prediction model, and the mismatch of stator resistance will lead to the stator flux vector prediction error. In order to compensate the prediction error, the compensation term is introduced and added into the stator flux vector prediction equation, and the expression is shown in (20), where $i_{dqs}(k)$ is the prediction error of stator current and can be calculated by (21).

$$ \psi_{dqs} (k+1) = T_s [u_{dqs}(k) - R_i i_{dqs}(k)] - T_s \omega_m J \psi_{dqs}(k) + \psi_{dqs}(k) + K \tilde{i}_{dqs}(k) \quad (20) $$

$$ \tilde{i}_{dqs}(k) = \hat{i}_{dqs}(k) - i_{dqs}(k) \quad (21) $$

In (21), $i_{dqs}(k)$ is the stator current sampled by the current sensor, and $\hat{i}_{dqs}(k)$ is the stator current calculated by the predicted stator flux $\psi_{dqs}(k)$.

$$ \hat{i}_{dqs}(k) = L^{-1} \left[ \psi_{dqs}(k) - \psi_{pm}(k) \right] \quad (22) $$

In the compensated stator flux prediction equation (20), the coefficient matrix $K$ should be designed to ensure the stability of the prediction equation. In this paper, $K$ can be design as (23)-(25) [25], [26], where $\beta = \frac{(L_d - L_q)\omega_m}{\psi}\frac{(L_d - L_q)\omega_m}{\psi}$, $\beta = 0$ for SPMSM, $b > 0$ and $c > 0$. 

$$ K = \begin{bmatrix} R_s + L_d k_{11} & L_q k_{12} \\ L_q k_{21} & R_s + L_d k_{22} \end{bmatrix} \quad (23) $$

$$ k_{12} = -\beta k_{11}; \quad k_{22} = -\beta k_{21} \quad (24) $$

$$ k_{11} = \frac{b + \beta (c/\omega_m - \omega_m)}{\beta^2 + 1}; \quad k_{12} = \frac{\beta b - c/\omega_m + \omega_m}{\beta^2 + 1} \quad (25) $$

The stator flux vector predictor is essentially a stator flux observer, which is utilized to predict the stator flux vector at $k + 1$ sampling instant, based on the state variables of PMSM at $k$ sampling instant. For high-speed digital control system, the stability of stator flux predictor can be proved in discrete domain or continuous domain.

With this gain selection, the characteristic polynomial of stator flux predictor (20)-(25), after linearization, can be expressed as (26), which is a second-order polynomial [27].

$$ s^2 + bs + c \quad (26) $$

According to linear control theory, the stability of stator flux predictor can be guaranteed for all positive values of $b, c$ [28], where $b = 0.05$ and $c = 0.1$ based on empirical results in this paper.

C. THE COST FUNCTION OF CSFP-PFC

In the proposed CSFP-PFC, the stator flux vector is regarded as the control variable, so the cost function is also the difference between the predicted value and the reference value. The cost function is designed as (27). Compared with (8), the cost function (27) has no weight factor, so there is no tedious weight factor debugging.

$$ g = |\psi_{dqs}^r(k+1) - \psi_{dqs}(k+1)| \quad (27) $$

D. THE BLOCK DIAGRAM OF CSFP-PFC

The block diagram of the proposed CSFP-PFC for PMSM drives is shown in Fig.3, which mainly includes stator flux vector reference calculation, stator flux observation, compensated stator flux vector prediction and the cost function.

The flow chart of the proposed CSFP-PFC is presented in Fig.4. Firstly, the stator current $i_s(k)$ and the rotor speed $\omega_r(k)$ are measured. Then, the motor state variables at $k + 1$ are estimated and the reference value of stator flux vector is calculated by (12). Thirdly, the predicted stator flux vectors of each voltage vector are calculated based on the prediction equation (20). Finally, the optimal voltage vector is obtained based on the cost function (27) and applied at the next time.

IV. THE EXPERIMENTAL VERIFICATION

A. THE EXPERIMENTAL PLATFORM

The proposed CSFP-PFC is verified on the experimental platform of PMSM, which is shown in Fig.5. The experimental platform consists of two permanent magnet synchronous motors, and one is controlled motor and the other is load motor. The parameters of PMSM are presented in Table 1. The motor controller consists of a control board and a
drive board. In the control board, digital signal processor (TMS320F28335) is used to implement the proposed CSFP-PFC. The drive board consists of a two-level voltage source inverter. The state variables of PMSM are collected by the oscilloscope and drawn in MATLAB.

### B. THE DYNAMIC-STATE EXPERIMENT

The dynamic-state experimental results of the traditional predictive torque control (T-PTC) and the proposed CSFP-PFC is presented in Fig.6. From top to bottom are the rotor speed $n$, the electromagnetic torque $T_e$, stator flux amplitude $|\psi_s|$ and stator current $i_a$, respectively. It is seen that T-PTC and CSFP-PFC have fast dynamic response of electromagnetic torque, which is due to the direct selection of voltage vector by FCS-MPC through the cost function. From Fig.6, compared with T-PTC, the proposed CSFP-PFC has smaller electromagnetic torque ripple and the Total Harmonic Distortion (THD) of stator current. During the period of 2.5-4.0 s, the THD of stator current for T-PTC is 13.27%, while that of the proposed CSFP-PFC is 11.21%. The ripple of $T_e$ for T-PTC is 2.2 Nm, while that of the proposed CSFP-PFC is 1.2 Nm.

### C. THE STEADY-STATE EXPERIMENT

The steady-state performances of the T-PTC and CSFP-PFC are shown in Fig.7. The THD of stator current for T-PTC is 17.49%, while that of the proposed CSFP-PFC is 11.56%, which is reduced by 33.91%. The electromagnetic torque ripple of CSFP-PFC is 1.4 Nm, and that of T-PTC is 2.1 Nm. It is seen that the proposed CSFP-PFC has better steady performance, because the compensated stator flux predictor can suppress prediction errors caused by mismatched parameters and improve the prediction accuracy in the CSFP-PFC algorithm. The compensated stator flux predictor uses the compensation term to eliminate the prediction errors caused by mismatched parameters.

### D. THE ROBUSTNESS EXPERIMENT

The robust performances of the T-PTC and CSFP-PFC are shown in Fig.8-10. $R_s$, $L_s$ and $\psi_f$ are actual stator resistance, stator inductance and permanent magnet flux. $R^*_s$, $L^*_s$ and $\psi^*_f$ denote the mismatched parameters, which are used in the T-PTC and the proposed CSFP-PFC algorithms. When $R^*_s = 2.0 R_s$, the THD of T-PTC is 13.79%, and the THD of the proposed CSFP-PFC is 10.85%, which is 21.32% lower. The ripples of the electromagnetic torque for T-PTC and CSFP-PFC are 1.9 Nm and 1.1 Nm, respectively. This is because in T-PTC of PMSM, the mismatched parameters will lead to the prediction errors, and then the selected voltage vector is not optimal, so the torque ripple increases. However, the proposed CSFP-PFC can effectively eliminate the prediction errors. Saturation of the magnetic circuit will cause
FIGURE 6. The dynamic performance evaluation of the T-PTC and CSFP-PFC for PMSM drives, (a) the traditional predictive torque control, (b) the proposed CSFP-PFC.

FIGURE 7. The steady performance evaluation of the T-PTC and CSFP-PFC for PMSM drives, (a) the traditional predictive torque control, (b) the proposed CSFP-PFC.

FIGURE 8. The robust performance evaluation of the T-PTC and CSFP-PFC with $R_s^* = 2.0R_s$ for PMSM drives, (a) the proposed CSFP-PFC, (b) the traditional predictive torque control.

the excitation inductance $L_s$ to decrease. When $L_s^* = 0.5L_s$, the THD of T-TPC is 14.25%, while that of CSFP-PFC is only 11.13%. The ripple of the electromagnetic torque ripple for T-PTC is 2.2 Nm, and that of CSFP-PFC is 1.3 Nm. High temperature will cause the permanent magnet to demagnetize. When $\psi_f^* = 0.5\psi_f$, the THD of stator current for CSFP-PFC
FIGURE 9. The robust performance evaluation of the T-PTC and CSFP-PFC with $L_s^* = 0.5L_s$ for PMSM drives, (a) the proposed CSFP-PFC, (b) the traditional predictive torque control.

FIGURE 10. The robust performance evaluation of the T-PTC and CSFP-PFC with $\psi_f^* = 0.5\psi_f$ for PMSM drives, (a) the proposed CSFP-PFC, (b) the traditional predictive torque control.

is 11.28%, which is 18.61% lower than that of T-TPC. And, the THD of stator current for T-TPC is 13.86%. The ripple of the electromagnetic torque ripple for T-PTC is 2.0 Nm, and that of CSFP-PFC is 1.2 Nm.

The detailed comparison of T-PTC and CSFP-PFC is illustrated in Table 2. It can be seen that the proposed CSFP-PFC has better dynamic-state, steady-state and robust performances than those of the T-PTC.

V. CONCLUSION
In finite control set-model predictive control, for the problem of prediction errors caused by mismatched parameters, this paper proposes a compensated stator flux predictor based-predictive flux control of permanent magnet synchronous motor. The proposed CSFP-PFC algorithm improves the prediction accuracy of stator flux vector by the compensation term of stator current prediction error. In addition, taking the stator flux vector as the control variable, the weight factor can be cancelled, which further simplifies the predictive control. Experimental results show that the proposed CSFP-PFC algorithm has better dynamic performance and steady-state performance than traditional predictive torque control. Especially, when the motor parameters are mismatched, the proposed CSFP-PFC algorithm can suppress the prediction errors caused by the mismatched parameters.

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