Constant switching frequency predictive control scheme for three-level inverter-fed sensorless induction motor drive

D. STANDO¹,² and M.P. KAZMIERKOWSKI¹,²

¹Electrotechnical Institute, ul. Pożaryskiego 28, 04-703 Warsaw, Poland
²Warsaw University of Technology, ul. Koszykowa 75, 00-662 Warsaw, Poland

Abstract. The paper presents a novel model predictive flux control (MPFC) scheme for three-level inverter-fed sensorless induction motor drive operated in a wide speed region, including field weakening. The novelty of the proposed drive lies in combining in one system a number of new solutions providing important features, among which are: very high dynamics, constant switching frequency, no need to adjust weighting factors in the predictive cost function, adaptive speed and parameter (stator resistance, main inductance) estimation. The theoretical principles of the optimal switching sequence predictive stator flux control (OSS-MPFC) method used are also discussed. The method guarantees constant switching frequency operation of a three-level inverter. For speed estimation, a compensated model reference adaptive system (C-MRAS) was adopted while for IM parameters estimation a Q-MRAS was developed. Simulation and experimental results measured on a 50 kW drive that illustrates operation and performances of the system are presented. The proposed novel solution of a predictive controlled IM drive presents an attractive and complete algorithm/system which only requires knowledge of nominal IM parameters for proper operation.

Key words: model predictive control (MPC), induction motor (IM), direct torque and flux control (DTFC), sensorless control, MRAS, three-level VSI.

1. Introduction

The model based predictive control (MPC) methods have been recently developed for control in power electronics and drives mainly thanks to advances in digital signal processors (DSP) and field-programmable gate array (FPGA) technologies, allowing to implement even most sophisticated algorithms in real time. Many MPC methods have been developed lately [1–6], however only a few MPC systems are related to the induction motor (IM) drives supplied from three-level inverters [7–12] and, additionally, with speed sensorless operation [13–19].

In this study, we have formulated the following set of practical requirements to facilitate the application of MPC methodology in IM industrial drives and transportation [20]:

- development of a control algorithm operating at inverter constant switching frequency,
- high dynamics of torque control over the entire operating range of the drive, including flux weakening,
- elimination of a speed sensor (increased reliability),
- compensation sensitivity to IM parameters uncertainty.

The research intended to study two groups: the control structure based on the optimal switching sequence (OSS-MPC) (see Fig. 1) and speed/parameter estimation based on the MRAS approach (see Fig. 6). The result of research is an innovative model predictive flux control (OSS-MPFC) method which, in contrast with OSV-MPC, guarantees constant switching frequency of the inverter (Fig. 3). It meets the requirements set, both in the constant torque region and in the flux weakening region, where in order to increase the torque dynamics it generates dynamic flux weakening. For speed estimation, compensated C-MRAS (Fig. 7) has been proposed, which shows good results in the range from very low speed (10 rpm = 0.5% \( \Omega_{mN} \)) to high speed in the weakened flux region. Finally, for IM parameters estimation, Q-MRAS (Fig. 11) has been selected. The whole structure (Fig. 3) creates a novel complete predictive control system for IM drive operating in a wide speed range without a mechanical motion sensor.

2. Modelling induction motor and three-level inverter

2.1. Model of IM. The model is based on the cage rotor IM complex space vectors dynamic equation [21, 22]:

\[
\mathbf{V}_s = \mathbf{I}_s \cdot R_s + \frac{d\mathbf{\Psi}_s}{dt},
\]  

(1a)
2.2. Model of three-level inverter. Figure 2 depicts the three-phase, three-level neutral point clamped (3L-NPC) voltage source inverter (VSI). Each of the inverter legs can generate three voltage levels: \( V_{dc}/2 \), 0, and \(-V_{dc}/2\). This is accomplished by means of three combinations of switch states assigned the number 2, 1 or 0, where: State 2: \( V_s = V_{dc} \), State 1: \( V_s = V_{dc}/2 \), and State 0: \( V_s = 0 \), for \( x = A, B, C \).

Taking into account the available combinations of switch states of individual legs, a three-phase, three-level converter generates 27 basic vectors: 3 zero (000, 111, 222), 12 short (100, 211, 110, 221, 010, 121, 011, 122, 001, 112, 101, 212), 6 medium (210, 120, 021, 012, 102, 201) and 6 long (200, 220, 020, 022, 002, 202) ones.

Fig. 2. Circuit of a three-level inverter (top) and representation of output voltage as space vectors and division of the \(\alpha\beta\) plane into sectors by long vectors and regions by short and medium vectors (bottom).

\[ 0 = I_r \cdot R_r + \frac{d\Psi_r}{dt} - j \cdot p_b \cdot \Omega_m \cdot \Psi_r, \]  
\[ \Psi_s = I_s \cdot L_s + I_r \cdot L_M, \]  
\[ \Psi_r = I_r \cdot L_r + I_r \cdot L_M, \]  
\[ \frac{d\Omega_m}{dt} = \frac{3}{T_e} \left[ \frac{3}{2} p_b \cdot Im(\Psi_s \cdot I_s) - T_L \right], \]

where \( V_s = (V_{αβ}, V_{βα}) \), \( I_s = (I_{αβ}, I_{βα}) \), \( \Psi_s = (\Psi_{αβ}, \Psi_{βα}) \) are the stator voltage vector, the stator current vector and stator flux vector, respectively. \( I_s = (I_{αβ}, I_{βα}) \), \( \Psi_r = (\Psi_{αβ}, \Psi_{βα}) \) are the rotor current vector and rotor flux vector, respectively. \( \Omega_m \) denotes the rotor electrical angular speed. \( R_s, R_r, L_s, L_r, L_M \) are the stator resistance, rotor resistance, stator inductance, rotor inductance and main inductance, respectively. Lastly, \( p_b \) denotes the pair of poles, \( J \) – the moment of inertia, \( \Psi_s^* \) – the conjugate stator flux vector, and \( T_L \) is the load torque.

3. Predictive stator flux vector control with optimal switching sequence (OSS-MPFC)

The optimal switching sequence-model predictive flux control (OSS-MPFC) control structure developed is implemented in accordance with the algorithm presented in Fig. 3 and Fig. 5. In this system, the control is based on a predictive model and one controller in the form of a cost function with optimization block. In the optimization block, the optimal sector and then the region of inverter voltage plane (Fig. 2) with the reference voltage are selected. Then the switching sequence \( T_A, T_B, T_C \) of the three nearest inverter voltage vectors which minimize the cost function (13) are calculated.

3.1. Predictive model. The bases of predictive control are models of the IM and the 3L-VSI. The predictive model of the IM was formulated on basis of the IM equations in a stationary \(\alpha\beta\) system (1) transformed into the state equations of the stator flux and current.

\[ \frac{d\Psi_s}{dt} = V_s - R_s I_s. \]

After transformation using the Euler method, a discrete form of (6) was obtained as:

\[ \Psi_s(k + 1) = \Psi_s(k) + [V_s(k) - R_s I_s(k)] T_s \]

where: \( k \) – sampling step, \( T_s \) – sampling time.
Taking into account set (1) one obtains the predictive model of the IM:

\[
\Psi_s(k+1) = \Psi_s(k) + \left[ \frac{R_l L_m}{\sigma L_s L_r} \Psi_s(k) - \frac{R_s}{\sigma L_s} \Psi_s(k) + V_s(k) \right] T_s, \quad (7a)
\]

\[
\Psi_r(k+1) = \Psi_r(k) + \left[ \frac{R_s L_s}{L_m} I_s(k) - \frac{R_r}{L_m} \Psi_s(k) + j \phi_m \Psi_r(k) \right] T_r \quad (7b)
\]

where \( \sigma = 1 - \frac{L_r^2}{L_r L_s} \) is the total leakage factor.

### 3.2. Cost function and optimization procedure.

One of the most important advantages of predictive control is the possibility to use a cost function as a regulator. In the case being discussed, it can be defined as:

\[
J = (\Psi_{sac}(k+1) - \Psi_{sc}(k+1))^2 + (\Psi_{\alpha\beta c}(k+1) - \Psi_{\alpha\beta}(k+1))^2. \quad (8)
\]

In this form it is used to determine the optimal sector and then the region. In the first step, the set of stator flux in the \( \alpha\beta \) stationary system is determined. For this purpose, the dependence of the phase angle between the stator and rotor flux (so-called torque angle \( \delta \)) was used. During no-load operation, the torque angle is equal to zero, whereas when the torque appears on the motor shaft, it is directly proportional to the second component of (10). The first part of (10) results from the currently estimated position of the rotor flux \( \gamma_{sr}(k) \). It is also necessary to take into account the effect of prediction, and therefore the desired position of the rotor flux at the application instant of the predicted switch states. This was done according to (9) bearing in mind that the time constant of the rotor circuit is much greater than the stator circuit time constant. Thanks to this, it can be assumed that the increment of the rotor flux angle is the same as in the previous period.

\[
\gamma_{sr}(k+1) = \gamma_{sr}(k) + \alpha \gamma_{sr} T_s \quad (9)
\]

\[
\gamma_{sc}(k+1) = \gamma_{sr}(k+1) + \arcsin \left( \frac{2(\gamma_{sr} - L_m^2) T_c(k)}{\gamma_{sc}(k) \gamma_{sr}(k)} \right). \quad (10)
\]

\[
\Psi_{sc}(k+1) = |\Psi_{sc}(k)| e^{j \gamma_{sc}(k+1)} \quad (11)
\]

This gives the command values of the stator flux \( \alpha\beta \) components:

\[
\Psi_{sac}(k+1) = \Psi_{sc} \cos (\gamma_{sc}(k+1)), \quad (12a)
\]

\[
\Psi_{\alpha\beta c}(k+1) = \Psi_{sc} \sin (\gamma_{sc}(k+1)). \quad (12b)
\]
In the next step, the optimal sector is set, in which there is a wanted vector minimizing the cost functions. As a result, the number of calculated values of the cost function is reduced from 18 of available vectors (excluding redundant vectors) to only 10. This is accomplished by pre-determining the cost function for the longest vectors, and then finding the minimum sum of the cost functions of two neighboring vectors. Each pair of vectors represents one of the six sectors, as shown in Fig. 2 (bottom). After identifying the optimal sector in the next step, the cost functions are calculated to give the remaining medium and short vectors within it. Then the optimal region is determined, i.e. the one in which the wanted vector is located. This process is similar to the selection of the optimal sector by the force of the fact that in this case a minimum of the sum of three cost functions for neighboring vectors representing the respective regions is sought.

After determining the region in which the voltage vector is located, that we were looking for, we can calculate the switching times (15)–(17):

\[ J = \left( \Psi_{\alpha \beta c}(k+1) - \Psi_{\alpha \beta c}(k) - \Delta_{\alpha c} \Delta_{\alpha c} T_A - \Delta_{\alpha \beta} T_B \right) \]
\[ \left. + \Delta_{\alpha c} \Delta_{\alpha c} (1 - T_A - T_B) \right)^2 \]
\[ + \left( \Psi_{\alpha \beta c}(k+1) - \Psi_{\alpha \beta c}(k) - \Delta_{\beta c} \Delta_{\beta c} T_A - \Delta_{\beta \beta} T_B \right) \]
\[ \left. + \Delta_{\beta c} \Delta_{\beta c} (1 - T_A - T_B) \right)^2. \]

(13)

After calculating partial derivatives with respect to \( T_A \) and \( T_B \) in accordance with condition (14), we obtain formulas for optimal switching times (15)–(17):

\[ \frac{\partial J}{\partial T_A} = 0, \]
\[ \frac{\partial J}{\partial T_B} = 0, \]

(14)

4. MRAS based speed and IM parameters estimation

To implement vector control of IM, it is necessary to know such directly not measurable state variables as: stator and/or rotor flux, electromagnetic torque and – in sensorless drives – rotor speed/position. Therefore, in recent years a number of state variable estimation methods have been studied and investigated, and among them adaptive systems based on the reference and the adjustable MRAS model (Fig. 6) [23–29] constitute an im-

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**Fig. 4. Changes in the \( \alpha-\beta \) components of the stator flux as a result of the application of three voltage vectors during one sampling period**

**Fig. 5. Flow diagram of the OSS-MPFC algorithm**
important group. The attractiveness of the MRAS methodology results from the fact that it can be used both for estimating speed as well as identifying IM parameters [30–33].

### 4.1. Speed estimation

In this study, the compensated C-MRAS version is used (Fig. 7) [26]. It employs the real IM as the reference model and the full voltage-speed (V-Ωm) model of the IM [22, 34] as the adaptive model. The C-MRAS, like other variants of MRASs – is parameter-dependent, however it is more robust thanks to real time correction with measured currents.

The adaptive (V-Ωm) model is derived from the IM model (1) and is described by the following equations:

\[
\frac{d\hat{\Psi}_{\alpha}}{dt} = \frac{V_s}{R_s} - R_s \hat{I}_{\alpha}, \quad (18a)
\]

\[
\frac{d\hat{\Psi}_{\beta}}{dt} = \frac{V_s}{R_s} - R_s \hat{I}_{\beta}, \quad (18b)
\]

where \( \sigma \) is the total leakage factor, and symbol \( \hat{\cdot} \) denotes estimated values.

As can be seen in Fig. 7, both models are supplied by the same reference voltage \( V_s \). It is important to consider the delay between the application time and acquisition time. The adaptive system is additionally tuned by two closed loops. The first one considers error between measured current \( I_s \) and calculated form (20), while the second one concerns the adaptively estimated speed (22). The first closed loop is responsible for the compensation of offsets which have the main source in current sensors. The mechanism of offset compensation is realized by two PI controllers, one for each of \( \alpha, \beta \) components. Inputs of these controllers are the current errors \( (I_s - \hat{I}_s) \) while the outputs are the offset compensation signals added to the right side of (18).

For the proper compensation in the whole range of the IM rotor speed, the controller time constant is tuned proportionally to the speed value. What is more, the controllers operate very slowly, for two reasons: to ensure lack of influence on the estimation in transients and because they integrate errors from sinusoidal signals. The second closed loop delivers the mechanical speed \( \Omega_m \) which is estimated based on the error between measured \( I_s \) and estimated \( \hat{I}_s \) currents multiplied by estimated stator flux vector \( \Psi \), according to Eq. (21).

\[
\Omega_m = \frac{\text{Im}(\hat{\Psi}_s \cdot \Delta I_s)}{\psi_{r0}} G, \quad (21)
\]

\[
\frac{d\hat{\Psi}_{\alpha}}{dt} = \frac{R_s}{L_m} \left( \frac{1}{\sigma} - 1 \right) \hat{\Psi}_{\alpha} - \frac{1}{\sigma L_r} \hat{\Psi}_{r\alpha} - p_b \hat{\Omega}_m \hat{\Psi}_{r\beta}, \quad (19a)
\]

\[
\frac{d\hat{\Psi}_{\beta}}{dt} = \frac{R_s}{L_m} \left( \frac{1}{\sigma} - 1 \right) \hat{\Psi}_{\beta} - \frac{1}{\sigma L_r} \hat{\Psi}_{r\beta} - p_b \hat{\Omega}_m \hat{\Psi}_{r\alpha}, \quad (19b)
\]

where \( \sigma \) is the total leakage factor, and symbol \( \hat{\cdot} \) denotes estimated values.

![Fig. 6. Classification of IM state variables estimation techniques (MRAS – model reference adaptive system)](image)

![Fig. 7. Block scheme of speed estimation using compensated C-MRAS](image)
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parameters of the PI controller calculated according to the online methods, like e.g. ANN [28, 35] or fuzzy logic [10, 36]. In this study, speed adaptation is performed by the PI regulator (22). This is a steady state of 50 rpm and 1000 rpm speed as well as loads of Rs windings are heated by the high current flow. This directly impacts changes in Rs, rotor resistance (Rs) as well as magnetizing (Lm) and leakage (Ls) inductances in the range of 50% and 150% of the nominal value, where Lm = Ls - Lm = Lr - Lm. All changes in Figs. 9 and 10 were expressed in pu in percent according to the rules of Δx = x - x0 100% and Δy = y - y0 100%.

Fig. 8. Voltage-speed flux IM model used as ADAPTIVE SYSTEM (Fig. 7) in C-MRAS

\[ e_\Omega = \text{Im} \left( \hat{\Psi}_s \Delta I_s \right) = \hat{\Psi}_{s\beta} (I_{s\alpha} - \hat{I}_{s\alpha}) - \hat{\Psi}_{s\alpha} (I_{s\beta} - \hat{I}_{s\beta}), \quad (21) \]

\[ \hat{\Omega}_m = K_p e_\Omega + \frac{K_p}{T_i} \int e_\Omega dt. \quad (22) \]

Speed adaptation is performed by the PI regulator (22). This is a fundamental method used for this purpose in MRAS, which ensures intuitive tuning of only two parameters. In the literature, we can also find other mechanisms of speed adaptation, like e.g. ANN [28, 35] or fuzzy logic [10, 36]. In this study, parameters of the PI controller calculated according to the optimum symmetry criterion, using a simplified model of speed estimation loop [20], were set to Kp = 0.31 and Ti = 1.5 ms. However, in the field weakening region the proportional gain is adapted.

4.2. Influence of parameters uncertainty. A very important criterion characterizing flux/speed estimators is their sensitivity to parameters uncertainty. All algorithmic methods are more or less sensitive to their variation during operation of a drive or their inaccurate identification. There are three main parameters: Rs, Rr, and Lm, which influence IM control performance. During standard operation of an IM drive, both stator and rotor windings are heated by the high current flow. This directly impact changes of Rs and Rr, under extreme conditions, even up to 100%. Imprecise knowledge of Lm also has a major impact on the proper operation of the drive. It changes with the state of saturation, according to the magnetization characteristics of the IM. Within the operating range defined by the nominal motor parameters, most drives operate in the linear part of the magnetization characteristic curve. Therefore, the largest changes of Lm occur during operation in the flux weakening region. The presented C-MRAS estimator has been tested by simulation in a steady state of 50 rpm and 1000 rpm speed as well as loads of 0 Nm and 150 Nm. To avoid any negative impact on the properties of the control algorithm in the test, IM was controlled by the actual values from the simulation model and the IM parameters were changed only in the estimator. The changes include: stator (Rs) and rotor resistance (Rr) as well as magnetizing (Lm) and leakage (Ls) inductances in the range of 50% and 150% of the nominal value, where Lm = Ls - Lm = Lr - Lm. All changes in Figs. 9 and 10 were expressed in pu in percent according to the rules of Δx = x - x0 100% and Δy = y - y0 100%.

Fig. 9. Influence of 150% Rr (top) and Rr (bottom) uncertainty

As can be seen, most estimation errors are caused by Rr, but only in the low speed range where voltage drop on resistance is close to the generated voltage. The errors are visible on all tested variables and increase with increased load. Similarly, the errors generated by Rr are visible in the low speed range. It influences the speed estimation but only when the drive is running under a load, which is visible in Fig. 9. Lm’s greatest impact is noticeable on reactive power, but it also affects flux and torque errors in a similar range as Rr. As the speed increases, the error of investigated variables decreases, except for the reactive power error, which remains at a similar level throughout the whole considered range. It can also be noticed that load changes have no impact on errors generated in this case. The last pa-
The parameter \( L_M \) has the least effect on the correct operation of the estimator as compared to other IM parameters and therefore, on-line estimation of \( L_M \) will be not considered.

4.3. On-line IM parameters estimation. The analysis presented in the above subsection (Figs. 9 and 10) shows that if \( \hat{Q} \) is calculated on the basis of measured voltage and estimated current \( \hat{I} \), then it shows strong sensitivity to changes of \( \hat{R}_s \) and \( L_M \). This feature can be used for online estimation of these parameters. Because \( \hat{Q} \) differs from \( Q \) calculated directly from measured voltage and current, it is possible to formulate the reference model (23) and adaptive system (24).

\[
Q_{\text{ref}} = V_{\alpha}\hat{I}_{\alpha} - V_{\beta}\hat{I}_{\beta}, \quad (23)
\]
\[
\hat{Q}_{\text{ref}} = V_{\alpha}\hat{I}_{\alpha} - V_{\beta}\hat{I}_{\beta}. \quad (24)
\]

The greatest flux and torque errors are caused by \( \hat{R}_s \) but only in the low speed range, while \( L_M \) influence is significant across the entire speed and torque range. Therefore, it was assumed that a reactive power error \( \varepsilon_Q \) will be used to correct \( \hat{R}_s \) within the range under 15% \( \Omega_m \) and above 15% \( \Omega_m \) to correct \( L_M \). It should be noted that incorrect knowledge of \( L_M \) in this situation will affect the estimation of \( \hat{R}_s \). However, it can be assumed that if the initial value of \( L_M \) is not burdened by more than a 10% error, then this fact can be considered insignificant. Moreover, \( R_s \) errors will not affect the estimation of \( L_M \). It was also assumed that the limit value above which resistance estimation will be performed is 10% \( T_{\text{ref}} \). Figure 11 shows a diagram of the reactive power Q-MRAS estimator.

As in the case of speed estimation, the PI regulator was also used as an adaptation mechanism in the Q-MRAS estimator. In addition, the direction of rotation and the torque sign had to be taken into account, as the \( \varepsilon_Q \) sign depends on these values. Therefore, the adaptation mechanism is extended to include additional conditions which are listed in Table 1. These relationships are empirically defined. The estimation of \( \hat{R}_s \) depends directly on the speed and torque signs, while the estimation of \( L_M \) depends only on the direction of rotation.

<table>
<thead>
<tr>
<th>( \Omega_m )</th>
<th>( \varepsilon_Q )</th>
<th>( \hat{R}_s )</th>
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The parameter that is not estimated on-line and plays an important role under load is \( \hat{R}_s \). Due to the fact that it changes under the influence of temperature, like \( R_s \), it is assumed that it will be corrected in proportion to the changes of \( \hat{R}_s (\Delta R_s \approx \Delta R) \). In addition, the temperature coefficient of the materials used for cage construction can be taken into account.

5. Simulation and experimental results

In this section, because of limited space, only some selected important oscillograms, illustrating operation of the developed IM drive, are presented.

5.1. Flux and torque control dynamics under OSS-MPFC. The excellent dynamics of stator flux magnitude and torque control illustrate oscillograms in Fig. 12. Additionally, in Fig. 13 the comparison of dynamic performance of the OSS-MPFC and conventional DTC-SVM is presented. Although the prefilter in torque reference path of the DTC-SVM method is
5.2. On line $R_s$ and $L_M$ estimation. An example of the process of estimating $R_s$ and $L_M$ parameters is presented in Figs. 14 and 15, respectively. Oscillograms shown at bottom and marked b) and c) are a zoom of the upper part of the oscillograms before and after the starting point of estimation. This makes it possible to observe how the correct knowledge of $R_s$ and $L_M$ affects the current shape. Waveforms of errors in reactive power and mechanical speed are also shown in both figures. Each of them confirms the correct operation of the estimation process because errors of these auxiliary variables were reduced to zero.

5.3. Speed sensorless operation. The test of speed control at slow speed reversal $\pm 60$ rpm during 6 seconds at no-load operation is presented in Fig. 16. The control algorithm passes

disabled, the dynamics of the OSS-MPFC is much better. This is the result of potential generation of the opposite voltage vector, like in the classical DTC [37], which is visible during a temporary change of the inverter voltage sector from 1 to 4 in Fig. 13 (left). In the case of the PI torque controller in the DTC-SVM method, the voltage sector cannot be changed (see Fig. 13 right) or can move only to a neighboring sector, depending on the initial voltage vector’s location and proportional controller gain.

Fig. 12. Dynamic of flux and torque control in OSS-MPTC system. Left: Step in the magnitude of stator flux $0.7 \rightarrow 0.8 \rightarrow 0.7$ Wb: $|\Psi_s|$ – reference stator flux, $|\hat{\Psi}_s|$ – estimated stator flux, $I_{sa}$ – phase current. Right: Step in the torque $-200 \rightarrow 200$ Nm: $|\hat{\Psi}_{sat}|$ – estimated stator flux, $\hat{T}_e$ – estimated torque, $\Omega_m$ – mechanical speed, $I_{sa}$ – phase current.

Fig. 13. Comparison of proposed OSS-MPFC (left) and DTC-SVM (right) respond to $-200/200$ Nm commanded torque step $T^*_e$ – commanded torque, $\hat{T}_e$ – torque, sec – voltage sector.
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Fig. 14. $R_s$ estimation from 35 mΩ to 71 mΩ at constant −100 rpm and under load torque 10 Nm – generator mode; $\hat{R}_s$ – estimated stator resistance, $Q - \hat{Q}$ – reactive power error, $\hat{\Omega}_m - \Omega_m$ – mechanical speed error, $I_A$ – phase current

Fig. 15. $L_M$ estimation from 35 mH to 23.4 mH at constant speed 400 rpm and under load torque 110 Nm – motor mode; $\hat{L}_M$ – estimated stator resistance, $Q - \hat{Q}$ – reactive power error, $\hat{\Omega}_m - \Omega_m$ – mechanical speed error, $I_A$ – phase current

Fig. 16. Sensorless slow speed reversal ±60 rpm without load torque. Top: experimental; Bottom: simulation. $\hat{\Psi}_s$ – estimated stator flux, $\Omega_m$ – measured mechanical speed, $\hat{\Omega}_m$ – estimated mechanical speed, $I_A$ – phase current

Fig. 17. Sensorless speed reversal from −200 rpm to 10 rpm under 200 Nm load torque, $\hat{T}_e$ – estimated torque, $\Omega_m$ – measured mechanical speed, $\hat{\Omega}_m$ – estimated mechanical speed, $I_A$ – phase current
the tests, which is confirmed by good tracking of the measured speed as well as proper shape of the phase current. In Fig. 17 a cycle of speed reversal from −200 rpm to 10 rpm under 200 Nm load torque is shown. Beginning from the left side, the drive works with constant speed of −200 rpm. After two seconds the load of 200 Nm is applied and the IM starts to work as a generator. Next, the commanded speed is set to 10 rpm and the drive changes the mode from generator to motor until the load is switched off in the eighth second.

5.4. Operation in field weakening range. The oscillograms in Fig. 18 show cycles of speed reversal between 1850 rpm and 2250 rpm under ±170 Nm change of commanded torque. The drive operates with good dynamic and the flux weakening control works properly. It can be noticed that during torque steps the flux is dynamically changed. This is due to the DC-link voltage changes. In the first torque step (170 Nm) the \( U_{DC} \) decreases along with the flux magnitude because of increased DC-link current and weak power grid. In the second step (−170 Nm), the drive operates as the generator and decreases the \( U_{DC} \) voltage, so the reaction of the flux weakening algorithm is to increase the commanded flux.

Finally, the start-up of the drive up to the field weakening region is shown in Fig. 19. In the field weakening region torque is limited according to the formula including the maximum permitted current [20]:

\[
T_c \leq \frac{3}{2} p_b \Psi_s \sqrt{I_s^{2} - I_{st}^{2}}
\]

where: \( I_{st} \) – stator magnetizing current.

![Fig. 19. Start up to 2700 rpm including flux weakening. Top: experimental, Bottom: simulation. \( \Psi_{st} \) – estimated stator flux, \( \hat{T}_c \) – estimated torque, \( \hat{\Omega}_m \) – estimated mechanical speed](image)

6. Conclusions

Main features of the presented model predictive flux controlled (MPFC) scheme for three-level inverter-fed sensorless induction motor drive include:

- very high dynamics; changes of 400 Nm were achieved within just two samplings \( T_c \) (see Fig. 13),
- constant inverter switching frequency,
- no need to adjust weighting factors in the predictive cost function, thanks to torque control via direct stator flux adjustment – see (9),
- adaptive speed and parameters (stator resistance, main inductance) estimation, in the range from very low speed \( (10 \text{ rpm} = 0.5\% \Omega_{MN}) \) to high speed in the flux weakening region.

The theoretical principles of the optimal switching sequence predictive control (OSS-MPFC) used and of the compensated C-MRAS-based estimation methods are discussed. The simu-
lational and experimental results measured on the 50 kW drive, which illustrate operation and performances of the system, are presented.

The proposed novel solution of the predictive controlled IM drive presents an attractive and complete algorithm/system which for proper operation requires only the knowledge of the nominal IM parameters without the necessity of weights factors selection using the “trial and error method”. It also presents methodology of how to combine many innovative solutions in one system to provide excellent, high performance IM drives. In the authors’ opinion, this approach can be used in design of modern drives for industry and transportation.

Appendix

Parameters of the three-level NPC inverter: 

\[ S_N = 200 \text{ kVA}; \quad I_N = 300 \text{ A}; \quad V_N = 3 \times 400 \text{ V}. \]

Parameters of the IM type STDA 200LU:

\[ P_N = 50 \text{ kW}; \quad V_N = 3 \times 380 \text{ V}; \quad I_N = 88 \text{ A}; \]

\[ f_N = 65 \text{ Hz}; \quad T_{N}\text{IN} = 249 \text{ Nm}; \quad p_b = 2; \]

\[ R_s = 69.5 \text{ m}\Omega; \quad R_r = 46.3 \text{ m}\Omega; \quad L_s = 25.217 \text{ mH}; \]

\[ L_r = 25.137 \text{ mH}; \quad L_M = 24.75 \text{ mH}; \quad J = 10 \text{ gm}^2. \]

REFERENCES


