Model Predictive Current Control with Online Parameter Estimation for Synchronous Reluctance Machine Controlled by High-Frequency Signal Injection Position-Sensorless

Hyeon-Seong Kim¹, and Kibok Lee², Member, IEEE
¹Department of Mechatronics Engineering, Incheon National University, Incheon 22012, South Korea
²Department of Smart Mobility Engineering, Inha University, Incheon 22212, South Korea

Corresponding author: Kibok Lee (Kibok.lee@inha.ac.kr).

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ABSTRACT Accurate machine parameters and rotor position information are essential in vector-controlled motor drive systems. However, machine parameter variations by various factors such as the current and the temperature degrade the performance of vector control. Also, a position sensor such as an encoder and a resolver increases the drive system cost. This paper proposes model predictive current control (MPCC) with the online parameter estimation for synchronous reluctance machines controlled by a high-frequency signal injection position-sensorless method. This approach removes the need for accurate knowledge about the system and eliminates the need for the position sensor. The proposed method adopts a recursive least-square (RLS) to estimate the electrical machine parameters in real-time. The estimated parameters are used for the deadbeat continuous control set (CCS) MPCC and the position-sensorless control. The high-frequency signal injection method is modified to be suitable for the proposed CCS-MPCC method, ensuring stable operation in the low-speed regions. Simulation and experimental results are provided to verify the performance of the proposed control method.

INDEX TERMS Model predictive current control (MPCC), Recursive-least square (RLS), High-frequency signal injection, Position-sensorless, Synchronous reluctance machines (SynRM).

I. INTRODUCTION
In electric machine drives, the model predictive current control (MPCC) has been applied to various machines such as induction machine (IM) [1], permanent magnet synchronous machine (PMSM) [2], switched reluctance machine (SRM) [3], and synchronous reluctance machine (SynRM) [4]. Although model predictive control (MPC) suffers from intensive computation in real-time, MPC provides high dynamic responses, easy implementation, and a simple control structure [5]. Also, the development of advanced digital microprocessors makes the MPC getting attention in many applications. However, parameter dependency is still a drawback of the MPCC. The machine parameters such as resistance, inductance, and permanent magnet flux are easily varied by the temperature, the current magnitude, and so on [6], [7]. The control performance is affected by variations of machine parameters used to calculate the voltage command or to predict the future stator current.

Various studies to reduce the parameter dependency of the MPCC have been conducted [8]-[11]. In [8], the model-free predictive current control (MFPC) based on the finite control set (FCS) method is introduced. This method does not require any machine parameter information and only utilizes the measured stator current and the current variations by applied voltage vector stored in look-up tables (LUTs). The method in [9] proposes the FCS-MPCC using a recursive least-square (RLS) self-commissioning model. The RLS algorithm adapts the machine parameters used to predict the future currents. The sensitivity of the machine parameter variations is reduced. The FCS-MPCC method in [10] proposes using the predicted slopes of current vectors to select the optimal voltage vectors. This method does not require the motor parameter information and LUTs. However, the FCS methods in [8]-[10] inherently have current ripple issues because only one among eight voltage vectors that can be generated by a voltage source inverter (VSI) is applied in a switching period. Also, the
switching frequency is varied by the applied voltage vector patterns [5]. The method in [11] proposed the ultra-local model based MFPCC, which adopts the deadbeat continuous control set (CCS) method. This method can apply any desired voltage vectors in a switching period, resulting in improved dynamics compared to FCS-MPC and the fixed switching frequency. The methods introduced in [8]-[11] can reduce the parameter dependency of MPC. However, these methods require position sensors, such as resolver or encoder, which increase system cost, size, and reliability issues [12]-[15].

Various strategies were proposed to eliminate the position sensor in the MPCC [16]-[20]. In [16] and [17], the rotor position information is extracted from the back-electromotive force (back-EMF) and the stator current ripples, respectively. Similarly, the method in [18] uses the current variation by the applied dual-voltage vectors to estimate the rotor position. However, the approaches in [16]-[18] are the model-based sensorless method. Thus, the estimation performance is easily degraded by the parameter variations. In [19], the modified finite position algorithm based on the model reference adaptive system (MRAS) was proposed for SynRM drives. This method is relatively robust to the parameter variations. But the stator resistance is still required, which results in the position estimation error, particularly in the low-speed region. The method in [20] proposes the CCS-MPCC without the estimated rotor position for the surface-mounted PMSM (SPMSM). However, this method estimates the back-EMF using machine parameters. Therefore, this method is suitable for the medium and high-speed regions, and the I-F scalar control is adopted in the low-speed region.

In [21], we have proposed a deadbeat MPCC with online parameter estimation for SynRM drives controlled by high-frequency signal injection-based sensorless vector control. This method estimates the machine parameter online and adopts the sensorless method to eliminate the need for the position sensor. In this work, we provide a more detailed review of the state-of-the-art and discuss the implementation of the proposed method in detail. The RLS algorithm for the online machine parameter estimation and the high frequency signal injection sensorless are introduced in section II. In section III, the deadbeat CCS-MPCC applicable to the high frequency signal injection based sensorless method is proposed. This MPCC based sensorless control allows stable operation in low-speed regions, including zero-speed. Simulation and experimental results are provided to validate the performance of the proposed method in sections IV and V.

II. RLS PARAMETER ESTIMATOR WITH A CONVENTIONAL HIGH-FREQUENCY SIGNAL INJECTION POSITION-SENSORLESS

In this section, the RLS estimator and the conventional high-frequency signal injection position-sensorless method are briefly introduced. The parameter estimation performance of the RLS estimator in the drive system controlled by the high-frequency signal injection sensorless method is analyzed.

A. RLS ALGORITHM FOR PARAMETER ESTIMATION

As well known, dq-axis voltage equations of the SynRM in the rotor reference frame are expressed as:

\[
\begin{align*}
\dot{v}_{ds} &= R_s i_d + L_{ds} \frac{di_d}{dt} - \omega r \lambda_{qs} \\
\dot{v}_{qs} &= R_s i_q + L_{qs} \frac{di_q}{dt} + \omega r \lambda_{ds}
\end{align*}
\]

(1)

where \(v_{ds}, v_{qs}\) are the dq-axis voltages, \(i_d, i_q\) are the dq-axis currents, \(R_s\) is the stator resistance, \(L_{ds}, L_{qs}\) are the dq-axis stator inductances, \(\lambda_{ds}, \lambda_{qs}\) are the dq-axis stator flux linkages, and \(\omega r\) is the rotor electrical speed.

Fig. 1 shows the d-axis current by applied d-axis voltages. The round bracket and the square bracket represent the switching period and the sampling number, respectively. The d-axis current variation during one switching period \(\Delta i_{ds}\) calculated at the \([k]\)th sampling time is a result of the d-axis voltage applied during the \((k-1)\)th switching period. The d-axis voltage in (1) is expressed in the discrete form using the Backward-Euler method as:

\[
\dot{v}_{ds}(k) = R_s[k] i_d[k] + L_{ds}[k] \frac{\Delta i_{ds}[k]}{T_s} - \omega r[k] \lambda_{qs}[k] \tag{2}
\]

\[
\frac{\Delta i_{ds}[k]}{T_s} = \dot{i}_d[k] - \dot{i}_d[k-1] \tag{3}
\]

where \(T_s\) means a controller sampling time. The d-axis current derivative (referred as output) can be rewritten as:

\[
\begin{align*}
\frac{\Delta i_{ds}[k]}{T_s} &= \frac{1}{L_{ds}[k]} \left( \dot{v}_{ds}(k-1) + \omega r[k] \lambda_{qs}[k] - R_s[k] i_d[k] \right) \\
&= \phi_{d1}[k] p_{d1}[k] + \phi_{d2}[k] p_{d2}[k]
\end{align*}
\]

(4)

where \(\phi_{d1}, \phi_{d2}\) are the d-axis inputs, and \(p_{d1}, p_{d2}\) are the d-axis parameters. Each term on the right side is the product of the known value (referred as input) and the unknown value
(referred as parameter). Eq. (4) can be simply expressed as the inner vector product as:

$$\frac{\Delta i_d[k]}{T_i} = \begin{bmatrix} \phi_{d1}[k] & \phi_{d2}[k] \end{bmatrix} \begin{bmatrix} p_{d1}[k] & p_{d2}[k] \end{bmatrix}^T$$  \hspace{1cm} (5)

where $\phi_d^j$ is the $d$-axis input vector and $p_d$ is the $d$-axis parameter vector.

This study adopts the RLS algorithm for estimating parameters that is one of the most widespread methods [9]. Two unknown values (parameters) in (4) can be estimated by the below RLS estimator [9].

$$G_d[k] = Q_d[k-1] - \Phi_d^T[k] \Phi_d[k] Q_d[k-1] \Phi_d[k] + \sigma^2 I$$

$$\hat{p}_d[k] = \hat{p}_d[k-1] + G_d[k] (y_d[k] - \Phi_d[k] \hat{p}_d[k-1])$$  \hspace{1cm} (6)

The hat "^\hat{\cdot}\" indicates the estimated values. $\hat{p}_d[k]=[\hat{p}_{d1}[k] \hat{p}_{d2}[k]]^T$ is the estimated $d$-axis parameter vector, $y_d[k]=[\Delta i_d[k]/T_i \ \Delta i_d[k-1]/T_i]^T$ is the $d$-axis output vector, $\Phi_d[k]=[\phi_d^j[k] \ \phi_d^k[k-1]]$ is the $d$-axis regressors matrix, $G_d[k]$ is the $d$-axis $2 \times 2$ gain matrix, $Q_d[k]$ is the $d$-axis $2 \times 2$ estimation error covariance matrix, $I$ is a $2 \times 2$ unit matrix, and $f$ is a forgetting factor. The forgetting factor $f$ is a control factor that determines the weight between the measured and estimated values.

Fig. 2 shows the block diagram of the RLS estimator for the parameter estimation. The output vector and the regressors matrix are determined by the input voltage and the measured current as:

$$\Phi_d[k] = \begin{bmatrix} \phi_d^j[k] \ \phi_d^k[k-1] \end{bmatrix}$$

$$y_d[k] = \begin{bmatrix} \Delta i_d[k]/T_i \ \Delta i_d[k-1]/T_i \end{bmatrix}$$  \hspace{1cm} (7)

The initial value of the parameter vector $\hat{p}_d[0]$ and the estimation error covariance matrix $Q_d[0]$ are required, which are generally determined by experiments [9], [15]. In this work, the initial values of first parameters $\hat{p}_{d1}[0]$ are set to 1, the second parameters $\hat{p}_{d2}[0]$ are set to zero, and the estimation error covariance matrix $Q_d[0]$ are set to $2 \times 2$ unit matrix, experimentally.

With this RLS estimator, the parameters $\hat{p}_d$ used in the MPCC can be estimated. Also, the $q$-axis parameters can be estimated with the same process. Next, the performance of the RLS for the machine controlled by the conventional high-frequency signal injection sensorless method is analyzed.

B. RLS ESTIMATOR WITH A CONVENTIONAL HIGH-FREQUENCY SINUSOIDAL VOLTAGE SIGNAL INJECTION METHOD [12]

If the injected high-frequency is sufficiently faster than the electrical rotor speed, the resistance voltage drops and the back-EMF terms in (1) can be neglected. Considering only high-frequency components, the high-frequency impedances can be obtained as:

$$z_{dh} \approx v_{dh} \ i_{dh}^{-1}, \ z_{qh} \approx v_{qh} \ i_{qh}^{-1} = \alpha \omega L_{dh}$$  \hspace{1cm} (8)

where $\omega$ is the injected high-frequency, $L_{dh}$, $L_{qh}$ are the $dq$-axis stator inductances at the injected high-frequency, $z_{dh}$, $z_{qh}$ are the $dq$-axis high-frequency impedances, $v_{dh}$, $v_{qh}$ and $i_{dh}$, $i_{qh}$ are the $dq$-axis high-frequency components of voltages and currents, respectively.

To obtain the position error information, the high-frequency voltage is injected only in the estimated $\gamma$-axis.

$$v_{\gamma} = V_{\gamma} \cos \omega t, \ \ v_{\delta} = 0$$  \hspace{1cm} (9)

where the superscript "^*" indicates the command and $V_{\gamma}$ is the amplitude of the high-frequency sinusoidal voltage injected in the estimated $\gamma$-axis. The relationship between the real $dq$-axis and the estimated $\gamma\delta$-axis is described in Fig. 3.

When the high-frequency sinusoidal voltage is injected in the $\gamma$-axis, the high-frequency component of the $\delta$-axis current can be obtained as:

$$i_{dh} = \frac{V_{\gamma}}{z_{dh} z_{qh}} \left( i_{\delta} \ \frac{1}{2} \ z_{d}\sin 2\delta \right)$$  \hspace{1cm} (10)
where $\theta_i$ is the rotor position estimation error between the real rotor position $\theta_r$ and the estimated rotor position $\hat{\theta}_r$, and $\delta_{dq}$ is the difference of dq-axis high-frequency impedances.

In (10), the high-frequency component of the $\delta$-axis current includes the information of the rotor position estimation error. Assumed that the estimation error $\hat{\theta}_r$ is sufficiently small, the input error $\text{Err}$ can be obtained by a demodulation process in Fig. 4 as:

$$
\text{Err} \approx \frac{V_{\gamma \delta} (L_{\gamma \delta} - L_{\delta \delta})}{2\omega L_{\delta \delta} L_{\gamma \delta}} \frac{\hat{\theta}_r}{K_{\text{err}}}
$$

(11)

where $K_{\text{err}}$ is determined by stator inductance which is varied by the operating condition.

In Fig. 4, $i_{\delta \delta}$ is the $\delta$-axis stator current, the BPF is a band-pass filter, the LPF is a low-pass filter, and $K_\gamma$ and $K_\delta$ denote the proportional and integral gain, respectively, of the observer. The electrical rotor speed and position are estimated with the demodulation process and the state filter type observer. In this sensorless method, the cross-coupling inductance can cause a small position estimation error [22]-[24]. But this work ignored the cross-coupling inductance for the sake of simplification.

In (4), the RLS estimator output is set to the derivative of the current. Therefore, the estimation of the $\gamma \delta$-axis parameters $\hat{p}_{\gamma \delta}$ can be failed if the current change in one switching period is too small. The $\gamma$-axis current has sufficient difference during one switching period by the high-frequency sinusoidal voltage injected in the $\gamma$-axis. However, the $\delta$-axis current change is too small in the steady-state, so the RLS estimator can be failed to estimate the parameters.

Fig. 5 shows the simulation results for an RLS estimator with a conventional high-frequency signal injection in the $\gamma$-axis. The SynRM parameters are listed in Table 1. The $\gamma$-axis parameter $p_{\gamma 1}$ is estimated well due to the injected high-frequency signal. On the other hand, the $\delta$-axis parameter $p_{\delta 1}$ maintains the initial value due to no current variation in the $\delta$-axis, and the parameter estimation is failed. Therefore, an additional signal is required to estimate $\delta$-axis parameters.

### III. PROPOSED DEADBEAT MPCC BASED ON HIGH-FREQUENCY SIGNAL INJECTION POSITION-SENSORLESS CONTROL

#### A. PROPOSED SQUARE-PULSE CURRENT INJECTION IN THE $\delta$-AXIS

The proposed method additionally injects the high-frequency square-pulse current in the $\delta$-axis for estimating $\delta$-axis parameters by the RLS estimator.

$$
i_{\delta p}^* [k] = I_{\delta p}^* \Pi[k]
$$

$$
\Pi[k] = \begin{cases} +1, & k = 1, 3, 5, \ldots \\
-1, & k = 2, 4, 6, \ldots 
\end{cases}
$$

(12)

The subscript “p” indicates the square-pulse component, $\Pi$ is the square-pulse function, and $I_{\delta p}$ is the amplitude of the injected $\delta$-axis square-pulse current command. In this study, the frequency of the $q$-axis injected pulse is set to half of the switching frequency. On the other hand, the frequency of $d$-axis sinusoidal voltage is set to 800 Hz. If the signal having a similar or same frequency is injected in the $q$-axis, the $q$-axis current in (10) for the sensorless control is affected, which may cause the failure of the sensorless control. To minimize interference, the frequency of the $q$-axis pulse current is set to be much faster than that of the $d$-axis sinusoidal voltage.

The $\delta$-axis current consists of a main component $i_{\delta \delta \text{on}}$, the square-pulse component $i_{\delta p}$, and the high-frequency component $i_{\delta \delta h}$ caused by the high-frequency sinusoidal voltage injected in $\gamma$-axis.

$$
i_{\delta \delta} = i_{\delta \delta \text{on}} + i_{\delta p} + i_{\delta \delta h}
$$

(13)

where the command component of the $\delta$-axis current $i_{\delta \delta \text{on}}$ is defined as the current components except for the current component caused by the $\gamma$-axis high-frequency sinusoidal voltage.

#### B. PROPOSED DEADBEAT MPCC
This section presents the proposed deadbeat MPCC for the voltage command calculation considering the injected high-frequency signals. In the estimated coordinate, \([k]th\) \(\delta\)-axis current can be obtained from (3) and (4) as:

\[
i_{\delta}[k] = i_{\delta}[k-1] + T \cdot v_{\delta}[k-1] \cdot p_{\delta1}[k] + T \cdot p_{\delta2}[k]
\]

where \(v_{\delta}, i_{\delta}\) are the \(\delta\)-axis stator voltage and current, and \(p_{\delta1}, p_{\delta2}\) are the \(\delta\)-axis first and second parameter, respectively.

Most predictive control methods suffer from the delay by the controller calculation time. The general solution is that the controller calculates a voltage command one switching period earlier [25]. In the proposed method, the \((k+1)th\) voltage command is also calculated in the \((k+1)th\) switching period.

Substituting \(k+2\) to \(k\) in (14), the \((k+1)th\) \(\delta\)-axis voltage can be obtained as:

\[
v_{\delta}(k+1) = \frac{i_{\delta}(k+2) - i_{\delta}(k+1) - T \cdot p_{\delta2}(k+2)}{T \cdot p_{\delta1}(k+2)}
\]

The voltage command to generate the command current component defined in (13) is rewritten as:

\[
v_{\delta}^*(k+1) = \frac{i_{\delta}(k+2) - i_{\delta}(k+1) - T \cdot p_{\delta2}(k+2)}{T \cdot p_{\delta1}(k+2)}
\]

Actually, the RLS estimator acts as a time-varying low-pass filter [26]. The forgetting factor in the RLS estimator is similar to the time constant of the low-pass filter. If the forgetting factor is sufficiently large, the RLS estimator attenuates the high-frequency component \(\hat{p}_{\delta1}\) and estimates the low-frequency component \(\hat{p}_{\delta1}\). With this in mind, assuming the estimated parameters are almost constant during two switching periods, the \([k+1]\) and \([k+2]\) estimated parameters are set to the \([k]\)th values.

\[
v_{\delta}(k+1) = \frac{i_{\delta}(k+2) - i_{\delta}(k+1) - T \cdot \hat{p}_{\delta2}[k]}{T \cdot \hat{p}_{\delta1}[k]}
\]

In (17), the \(\delta\)-axis \([k+1]th\) current \(i_{\delta}(k+1)\) can be predicted by adding the predicted \([k+1]th\) current variation \(\Delta i_{\delta}(k+1)\) to the \([k]th\) current \(i_{\delta}(k)\). The current \(i_{\delta}(k)\) can be obtained from the sampled current \(i_{\delta}(k)\). A low-pass filter is adopted to remove the high-frequency components in the sampled current as follows.

\[
i_{\delta}(k+1) = i_{\delta}(k) + \frac{\omega_1}{D + \omega_1} \cdot i_{\delta}(k) + \Delta i_{\delta}(k+1)
\]

The superscript “P” indicates the predicted values, \(\omega_1\) is an angular cutoff frequency of the low-pass filter, and \(D\) means the differential operator.

During the \((k)th\) switching period, the \(\delta\)-axis \([k+1]th\) current variation \(\Delta i_{\delta}(k+1)\) can be predicted by substituting \(k+1\) to \(k\) in (5) as follows.

\[
\Delta i_{\delta}(k+1) = T_s (\phi_{\delta}^{*}(k+1) \cdot \hat{p}_{\delta1}(k))
\]

In (19), the \([k+1]th\) input vector \(\phi_{\delta}(k+1) = [v_{\delta}(k) - 1] \) is a known value during the \((k)th\) switching period, and the \([k]th\) estimated parameters are used to predict the command component of the \(\delta\)-axis \([k+1]th\) current variation.

Finally, assuming the current command is almost constant during two switching periods, the \([k+2]\)th current in (17) is set as the \([k]\)th current command. The \(\delta\)-axis voltage command is expressed as:

\[
v_{\delta}(k+1) = \frac{i_{\delta}(k) - i_{\delta}(k+1) - T \cdot \hat{p}_{\delta2}[k]}{T \cdot \hat{p}_{\delta1}[k]}
\]

Fig. 6 shows the block diagram of the proposed deadbeat MPCC to calculate the \(\delta\)-axis voltage command.

Next, the \(\delta\)-axis current by the square-pulse current command is analyzed. The \(\delta\)-axis current generated by the applied voltage is obtained by substituting (20) into (14) as:

\[
i_{\delta}(k) \approx i_{\delta}^{*}(k-2) + \frac{-\omega_1}{D + \omega_1} i_{\delta}(k-2) + \frac{D}{D + \omega_1} \cdot i_{\delta}(k-2)
\]

The voltage command for the \(\delta\)-axis square-pulse current injection is:
The detailed equation expansion is described in Appendix. In (21), the actual current tracks the current command with two sampling periods delay and contains the high-frequency components.

Fig. 7 shows the simulation results for an RLS estimator with the proposed square-pulse current injection method. The high-frequency sinusoidal voltage is injected in the γ-axis, and the high-frequency square-pulse current is injected in the δ-axis. The downward arrows represent the controller sampling instance, where the current is measured. The simulation results show that the δ-axis first parameter \( p_{δ1} \) is estimated well, unlike the case with only the sinusoidal voltage injection shown in Fig. 5. Notably, although the square-pulse is commanded, the resulted current has the trapezoidal form due to the voltage pulses applied by the SVPWM based VSI.

Next, the γ-axis voltage command is calculated. As previously mentioned in section II, the high-frequency sinusoidal voltage is injected in the γ-axis to estimate the rotor position and speed. Fig. 8 shows the block diagram to calculate the γ-axis voltage command in the proposed deadbeat MPCC. The command voltage generated by the MPCC is added with the injected high-frequency sinusoidal voltage.

\[
v_{γs}(k) = v_{γs1}(k) + v_{γsh}(k)
\]

Similar to the δ-axis voltage in (16), the γ-axis voltage command is calculated as:

\[
v_{γs}(k+1) = \frac{i_{γs1}(k) - i_{γs1}(k+1) - T_s \hat{p}_{γs1}(k)}{T_s \hat{p}_{γs1}(k)}
\]

This voltage command \( v_{γs} \) is used as the input vector \( \phi_{γ} \) to predict the low frequency component of the current variation \( \Delta i_{γs1}^{\text{sc}} \) as follows.

\[
\phi_{γ}^r[k+1] = [v_{γs}(k) 1]
\]

Similar to the derivation of the δ-axis current in (21), the γ-axis current generated by the applied voltage is derived as:

\[
i_{γs}[k] \approx i_{γs1}[k - 2] + i_{γsh}[k - 1] + T_s \left( p_{γsh} [k] + v_{γsh}(k-1) p_{γsh} [k] \right)
\]

\[
i_{γsh}[k-2] + \frac{D}{D + \omega} i_{γsh}[k-2]
\]

In (25), the actual current tracks the current command with two sampling periods delay and includes the high-frequency components.

The injected δ-axis square-pulse current can cause any effect in position-sensorless control in Fig. 4. However, if the frequency of the square-pulse current is significantly faster than that of the injected sinusoidal voltage, the effect of the injected square-pulse current in the demodulation process is negligible.

Fig. 9 shows a block diagram of the proposed control scheme, which consists of the RLS estimator, the speed and the current controller, and the high-frequency position-sensorless control. The rotor speed is controlled by the conventional proportional integral (PI) controller.

### IV. SIMULATION RESULTS

Simulation tests were conducted to validate the performance of the proposed method. The machine parameters are listed in Table 1. The amplitude and the frequency of the injected high-frequency γ-axis voltage are set to 50 V and 800 Hz. The amplitude of the injected δ-axis current is set to 0.1 A and 5 kHz, so the δ-axis voltage to make the high-frequency square-pulse current has 24 V amplitude at the nominal parameters. The forgetting factor is set to \( ζ=0.99 \). The bandwidth of the observer and the speed controller in Fig. 4 is set to 5 Hz and 2 Hz, respectively. The proposed method injects the high frequency sinusoidal and pulse signals for the sensorless control.
controller and the parameter estimation, which causes the torque and speed ripples. To minimize the response of the speed controller to the speed ripple, the bandwidth of the speed controller and the observer is set to low values.

Fig. 10 shows the simulation results of the proposed method. Initially, the \( \gamma \delta \)-axis current commands set to zero. The high-frequency sinusoidal voltage and the square-pulse current are injected. The rotor position and speed, the machine parameters, and \( \hat{K}_{err} \) are estimated at the initialization time. The \( \gamma \)-axis current increases to 50% of the rated current to make the stator flux, and the rotor speed increases to 1,200 [r/min]. The error of the rotor position estimation \( \hat{\theta}_r \) is small in all speed regions.

In the simulation, the stator inductance is estimated by the RLS estimator, and the \( K_{err} \) is calculated as:

\[
\hat{K}_{err} = \frac{2\omega_L}{V_{ph}^2} \left( \hat{\rho}_{\gamma \delta} - \rho_{\gamma \delta} \right) + \frac{2\omega_L}{V_{ph}^2} \left( \hat{\rho}_{\gamma \delta} - \rho_{\gamma \delta} \right)
\]

where \( \omega_L \) is the cutoff angular frequency of the low-pass filter. The low-pass filter is used to remove the ripple components in the estimated stator inductance. The \( K_{err} \) in Fig. 4 is updated to maintain the constant bandwidth of the speed observer in the position-sensorless control. The cutoff angular frequency of the low-pass filter for the estimated parameters is set to 5 rad/s, and the \( \hat{K}_{err} \) is initially set to -1.

Fig. 11 shows the simulation results for the estimation of the stator inductance and \( \hat{K}_{err} \) when the \( dq \)-axis currents are varied at a fixed rotor speed of 1,200 [r/min] under no load condition. From \( t = 10 \) to 11 [sec.], the \( dq \)-axis stator inductances are intentionally reduced by half of the nominal parameters. The stator inductance estimated by the RLS estimator tracks well the actual inductance. Also, the estimated \( \hat{K}_{err} \) tracks the correct value although the delay by the low-pass filter exists.

Fig. 12 shows the estimation of the parameters \( \hat{\rho}_{\gamma \delta} \) under different speed and load conditions. At \( t = 2 \) [sec.], the step load of 9 [Nm] is applied at zero-speed. From \( t = 4 \) to 6 [sec.], the speed increases to 1,200 [r/min]. In the whole operating conditions, the estimated second parameters \( \hat{\rho}_{\gamma \delta} \) track well the actual values.
V. EXPERIMENTAL RESULTS

Experimental tests were conducted with a 5.5kW SynRM to validate the performance of the proposed method. In Fig. 13, the experimental setup consists of the tested SynRM and an IM as a load motor. The SynRM nominal parameters are given in Table 1. The digital signal processor (TMS-320F28346) embedded VSI is used to drive the test and load motors. An encoder sensor is used to monitor the actual rotor position so as to validate the proposed method.

Fig. 14 shows the step load test results of the proposed method at zero-speed condition. A step load of 9 [Nm] is applied from $t = 6$ to $t = 14$ [sec.]. The estimated $\hat{K}_{err}$ is matched with the actual value of $-4.168$, even in the step load condition. The maximum position error at the instant of the step load change is about $-0.1$ [rad.].

Fig. 15 shows the speed control performance of the proposed high-frequency signal injection position-sensorless method. From $t = 4$ to $t = 6$ [sec.], the rotor speed increases to 1,200 [r/min], which is over the medium speed. The rated speed of the tested motor is 1,500 [r/min]. A step load of 9 [Nm] is applied from $t = 8$ to $t = 14$ [sec.]. The rotor speed $n_r$ and the $\delta$-axis current $i_{\delta}$ show good performances. Also, the $\hat{K}_{err}$ is estimated well. The position error $\hat{\gamma}_r$ is sufficiently small in all operating ranges, and the maximum position error at the step load is about $-0.1$ [rad.].

Fig. 16 shows the four-quadrant operation of the proposed method. The numbers below the figure denote the corresponding quadrant. Initially, the rotor speed is $-600$ [r/min] in steady state. The step-type 600 [r/min] speed command is applied from $t = 2$ to $7.5$ [sec.]. The estimated $\hat{K}_{err}$ tracks the actual value of $-4.168$ with the delay by the LPF. The maximum position error $\hat{\gamma}_r$ is about $-0.6$ [rad.] during the transient condition.

Fig. 17 shows the estimated $\gamma\delta$-axis first parameters $\hat{p}_{\gamma\delta}$ by the RLS estimator while the $\gamma$-axis stator current is varied under the zero-speed condition. The $\delta$-axis current command is set to zero while injecting the $\delta$-axis square-pulse. Before the high-frequency signals are injected, the estimated $\gamma\delta$-axis first parameters $\hat{p}_{\gamma\delta}$ are set to the initial value 1. From $t = 2$ [sec.], the parameters are estimated by the RLS estimator. The
γ-axis current increases to 10 [A] from \( t = 4 \) to 6 [sec.], and decreases to 0 [A] from \( t = 14 \) to 16 [sec.]. The estimated γδ-axis first parameter \( \hat{p}_{γ1} \) (≈ 1/\( L_{dq} \)) and \( p_{\theta1} \) (≈ 1/\( L_{qs} \)) are matched well with the actual parameters \((p_{γ1}=35.09 \text{ and } p_{\theta1}=83.33)\) even if the stator current is varied.

Fig. 18 shows the estimated γδ-axis second parameters \( \hat{p}_{γ2} \) by the RLS estimator under the rotor speed and the stator current variations. Initially, the estimated γδ-axis second parameters \( \hat{p}_{γ2} \) are set to zero. From \( t = 2 \) [sec.], the parameters are estimated by the RLS estimator with high-frequency signals injection. From \( t = 4 \) to 4.5 [sec.], although it is not shown in the figure, the γ-axis current increases to 50% of the rated current to generate the γ-axis rotor flux, so the second parameter \( \hat{p}_{γ2} \) is decreased. From \( t = 6 \) [sec.], a step load of 9 [Nm] is applied. The δ-axis current increases, so the δ-axis second parameter \( \hat{p}_{δ2} \) is decreased. From \( t = 10 \) to 16 [sec.], as the rotor speed increases to 1,200 [r/min.], the estimated γδ-axis second parameters \( \hat{p}_{γ2} \) and \( \hat{p}_{δ2} \) are significantly changed due to the back-EMF terms. This test results show that the γδ-axis second parameters \( \hat{p}_{γ2} \) and \( \hat{p}_{δ2} \) are estimated by the injected high-frequency signals even under the rotor speed variation conditions.

![FIGURE 18. Experimental results: second parameters \( \hat{p}_{γ2} \) estimation of proposed method: rotor speed (orange line), δ-axis current (green line), and estimated γδ-axis second parameters by the RLS estimator, \( \hat{p}_{γ2} \) (purple line) and \( \hat{p}_{δ2} \) (cyan line).](image)

![FIGURE 19. Experimental results: position estimation error of the proposed sensorless method under 1,200 [r/min] rotor speed and 9 [Nm] load conditions. (a) real and estimated rotor position, and position error \( \hat{θ}_r \).](image)

Fig. 19 shows the position estimation error of the proposed position-sensorless method under 1,200 [r/min.] rotor speed and 9 [Nm] load conditions. Fig. 19 shows the real and estimated rotor position, and position error \( \hat{θ}_r \). In the proposed high-frequency signal injection sensorless method, the δ-axis square-pulse current is additionally injected for δ-axis parameters estimation unlike the conventional sensorless methods. The maximum position error \( \hat{θ}_r \) is below −0.1 [rad.]. Experimental results confirm that the rotor position is estimated well although the square-pulse current is injected in the δ-axis.

Fig. 20 shows the comparison of the conventional methods and the proposed method. The blue line is the sensorless FCS-MPCC [27], the red line is the sensored deadbeat MPCC [2], and the yellow line is the proposed position-sensorless MPCC. The tests are conducted with 100% dq-axis stator inductance errors (2-\( L_{ds} \) and 2-\( L_{qs} \)) at 1,200 [r/min] rotor speed. The rotor speed is controlled by the load motor (IM), and the test motor (SynRM) is in the current control mode. From \( t = 1 \) to 2 [sec.], the dq-axis current commands increase to 10 [A]. The ripple of dq-axis currents in the proposed method is smaller than that of other conventional MPCC methods. This is because the RLS estimator in the proposed method adjusts the stator inductance. The dq-axis current in the proposed method tracks well the command. But the current error in the conventional MPCC methods has a small offset component due to the inductance error.

Fig. 21 shows the phase current of the proposed MPCC under 1,200 [r/min] rotor speed and 9 [Nm] load conditions. Fig. 21(a) shows the a-phase current waveform, and Fig. 21(b) shows fast Fourier transform (FFT) results. In this test, the operating frequency is 40 [Hz], the frequency of the sinusoidal voltage injected in the γ-axis is 800 [Hz], the frequency of the
injects the sinusoidal signal in the $y$-axis to estimate the rotor position and the pulse signal in the $\delta$-axis to estimate the machine parameters. The proposed sensorless method ensures stable operation at low-speed regions, including zero-speed. Simulation and experimental results are provided to validate the performance of the proposed method.

**APPENDIX**

The $\delta$-axis current by the voltage command in (20) can be obtained with substituting (20) to (14) as:

$$i_{is}[k] = i_{is}[k-1] + T_p p_{22}[k]$$

As previously mentioned in section III, the estimated parameters are considered as almost constant value during two switching periods. Therefore, the $[k-2]$th estimated parameters are set to [k]th values.

$$i_{is}[k] = i_{is}[k-1] + T_p p_{22}[k]$$

If the estimated parameters by the RLS estimator are accurate, (28) is rewritten as:

$$i_{is}[k] = i_{is}[k-2] + i_{is}[k-1] - i_{is}^p[k-1] + T_p p_{22}[k]$$

Substituting (18) to (29) yields the following.

$$i_{is}[k] = i_{is}[k-2] + i_{is}[k-1] - T_p p_{22}[k]$$

The $\delta$-axis current in (30) is rewritten by substituting (13) into (30) as:

$$i_{is}[k] = i_{is}[k-2] + i_{is}[k-1] + T_p p_{22}[k]$$

It is supposed that the predicted variation of the $\delta$-axis current $\Delta i_{isc}$ is accurate. Then, (31) is rewritten using (3) as:

$$i_{is}[k] = i_{is}[k-2] + i_{is}[k-1] + T_p p_{22}[k]$$

**Table 2. Measured computation time of proposed algorithms.**

| Control block          | Computation time [μsec.] |
|------------------------|--------------------------|
| PI speed controller    | 2.35                     |
| Current control (MPCC) | 8.77                     |
| Parameter estimation (RLS) | 35.3                  |
| High-freq. sensorless  | 6.65                     |

square-pulse current injected in the $\delta$-axis is 5,000 [Hz], and the switching frequency is 10,000 [Hz]. The total harmonic distortion (THD) of the $a$-phase current is 2.15%.

In addition, the computation time of the proposed algorithms in Fig. 10 is measured, which is listed in Table 2. The computation time for the RLS and the MPCC takes a relatively long time. It might not be easy to implement with a low-cost chip. But motor drives are used in various applications ranging from high to low-cost appliances. There are applications where the online parameter estimation and the position-sensorless control would outweigh the cost of implementation, justifying the increase in hardware cost.

**VI. CONCLUSION**

This paper proposes CCS-MPCC with the online parameter estimation for SynRMs controlled by high-frequency signals injection-based position-sensorless method. This method does not require accurate knowledge about the machine parameters and eliminates the need for the position sensor. The proposed method adopts the RLS algorithm for the online machine parameter estimation. Therefore, this method is robust to the parameter variations. In addition, this study proposes the modified high-frequency signal injection method, which
Eq. (32) can be simplified as:

$$i_{ds}[k] = i_{dsc}[k-2] + i_{dsc}[k-1] + T_{i} p_{d2h}[k]$$

$$+ \frac{-\omega}{D + \omega} i_{ds}[k-2] + \frac{D}{D + \omega} \hat{i}_{sc}[k-2]$$

(33)

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Hyeon-Seong Kim received the B.S. and M.S. degrees in mechatronics engineering from Incheon National University, Incheon, South Korea, in 2019 and 2021, respectively. His current research interests include motor drives for AC machines and power conversion systems.
KIBOK LEE (S'13–M’15) received the B.S. and M.S. degrees in electrical engineering from Korea University, Seoul, South Korea, in 2005 and 2007, respectively, and the Ph.D. degree in electrical engineering from North Carolina State University, Raleigh, NC, USA, in 2016. From 2007 to 2011, he was a Research Engineer with LG Electronics R&D Center, Seoul, South Korea. From 2016 to 2018, he was a Senior Motor Control Engineer with the General Motors Powertrain Center, Pontiac, MI, USA. From 2018 to 2021, he was an Assistant Professor, Incheon National University, Incheon, South Korea. He is currently an Assistant Professor with the Department of Smart Mobility Engineering, Inha University, Incheon, South Korea. His current research interests include motor drives, power conversion system, and wireless power transfer system.