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RESEARCH ARTICLE

Extended Kalman Filter–Linear Quadratic Regulator-Based Current Control for Dynamic Response Improvement and Robustness Enhancement of Grid-Forming Inverters

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ABSTRACT This paper proposes an EKF–LQR-based current controller to improve the performance and robustness of the current control loop in grid-forming inverters (GFMI). Since load variations, power-reference changes, and grid-condition variations affect the dynamic characteristics of the output current in GFMI, fast and stable control performance of the current control loop is required. However, conventional fixed-gain current controllers may cause response delay, overcurrent, and oscillations under variations in grid impedance, short-circuit ratio (SCR), and operating conditions. Therefore, this paper combines EKF-based current-state estimation with LQR-based optimal state-feedback control to improve the dynamic performance and robustness of the current control loop. The effectiveness of the proposed EKF–LQR-based current controller is validated through MATLAB/Simulink simulations and hardware-in-the-loop simulation (HILS) experiments under various operating and grid conditions.

INDEX TERMS Current control, dynamic response, extended Kalman filter, grid-forming inverter, linear quadratic regulator, optimal control.

I. INTRODUCTION

Globally, the deployment of renewable energy resources (RESs), such as photovoltaic systems and wind turbines, has been rapidly increasing to address carbon neutrality and climate change issues, leading to a significant growth in inverter-based resources (IBRs) [1]. Accordingly, modern power systems are transitioning from synchronous generator-dominated architectures to IBR-dominated architectures, where IBRs are required to contribute to grid stability and reliability. Most currently installed IBRs operate as grid-following inverters (GFLIs), which extract the grid phase using a phase-locked loop and inject current based on the estimated phase. However, GFLIs may become unstable in

weak grids where the grid voltage is poorly regulated [2]. In contrast, grid-forming inverters (GFMI) independently generate voltage and frequency without relying on the grid, thereby providing virtual inertia and enhancing grid stability [3], [4]. Recent review studies have also emphasized that grid-forming control is becoming a key enabling technology for IBR-dominated power systems because it can provide autonomous voltage and frequency support under high renewable penetration [5].

The stable operation and control performance of a GFMI strongly depend on the dynamic response of its inner current control loop. A GFMI typically employs a dual-loop control structure consisting of an outer voltage control loop and an inner current control loop. The outer voltage control loop generates current references, which are cascaded as control inputs to the inner current controller [6].

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Since the inner current control loop has a higher bandwidth than the outer voltage control loop, sufficient bandwidth separation is essential for stable cascaded-loop operation [7]. In general, the inner-loop bandwidth is designed to be approximately ten times higher than the outer-loop bandwidth; otherwise, loop interaction can degrade control stability [6], [7], [8]. Therefore, fast dynamic response and robustness of the inner current control loop are essential for stable GFMI operation. In prior studies, the inner current control loop has commonly been designed using proportional–integral (PI) control because of its simple structure [9]. However, since PI control is designed based on a linearized small-signal model around a specific operating point, its performance can degrade under varying operating conditions where nonlinear characteristics become significant [10].

To overcome this limitation, nonlinear current-control strategies such as model predictive control (MPC) and H_∞ control have been investigated. However, MPC can be affected by prediction errors caused by parameter variations and external disturbances, which may reduce the robustness of the optimal control action [11]. Although H_∞ control provides robustness against disturbances, its relatively slow dynamic response can degrade control performance during active-power reference variations [12]. Therefore, these approaches still face practical limitations associated with model uncertainties, computational complexity, and real-time implementation. Linear quadratic regulator (LQR) control is a representative optimal control technique that minimizes a quadratic cost function of the state variables and control inputs. By adjusting the weighting matrices Q and R , LQR control can achieve a trade-off among settling time, overshoot, and control effort according to the design specifications [13], [14], [15], [16]. However, when a fixed-gain LQR controller is designed based on the system linearized around a non-equilibrium operating point, the resulting controller tends to drive the system back toward the same unstable operating point, which is not desirable [17]. In addition, since LQR control computes the optimal gain based on state variables, its performance strongly depends on the availability and reliability of the feedback current states [18].

This state-feedback characteristic motivates the use of state estimation in the LQR-based current-control loop. In power electronic converters, measured current signals can be affected by sensor noise, signal delay, switching ripple, and model uncertainties. These effects become more important in IBR-dominated power systems because IBR dynamics are strongly affected by the interaction between converter dynamics and digital controller computations. In this regard, the control-physics dynamic state estimation (DSE) framework in [19] shows that IBR dynamics contain both physical and digital control states, and that measurement-signal and control-signal uncertainties should be explicitly considered when estimating IBR states. In addition, the GFM-oriented DSE study in [20] indicates that internal GFM states, such as virtual voltage angle, virtual frequency, and voltage-control states, are not directly measurable

and therefore require DSE, especially under operating-condition changes such as current-limiting operation. From a power-converter implementation perspective, EKF-based estimation has been shown to enable full-state estimation, sensor reduction, and noise filtering in modular multilevel converters, while supporting estimator-based state-feedback control without requiring all physical states to be directly measured [21].

To address these issues, this paper proposes an extended Kalman filter (EKF)–LQR-based current controller. The EKF is a recursive estimation method for nonlinear systems in which the nonlinear state and measurement equations are locally linearized using a first-order Taylor-series approximation before applying the Kalman-filter prediction and correction procedure [22]. In the proposed method, the EKF is applied to the reduced-order dq -axis current-state model of the inner current control loop. Therefore, the estimator focuses on the filter current dynamics required for LQR feedback control rather than estimating a high-order nonlinear system. The estimated current states are then used as feedback variables for the LQR controller, which determines the state-feedback control action using the predesigned optimal gain. In this structure, the EKF improves the reliability of the feedback current states under measurement noise and operating-condition variations, while the LQR provides optimal state-feedback control based on the reduced current-state model.

The contributions of this paper can be summarized as follows:

- Unlike conventional PI- and pole-placement-based current controllers with fixed gains, this paper proposes an EKF–LQR-based current controller that combines recursive current-state estimation with optimal state-feedback control to improve the dynamic response and robustness of the GFMI current-control loop under operating-condition variations.
- Compared with existing LQR-based inverter control approaches that apply a feedback gain directly to measured current signals, the proposed method applies the LQR control law to EKF-estimated dq -axis current states, thereby improving the dynamic response and enhancing the robustness of the GFMI current-control loop.
- In contrast to recent IBR and GFMI dynamic-state-estimation studies mainly focused on state monitoring or reconstruction, this paper directly integrates EKF-based current-state estimation into the inner-loop LQR current-control law as an estimated-state feedback mechanism.
- The proposed method is verified through MATLAB/Simulink simulations and HILS experiments. The results demonstrate that the proposed EKF–LQR-based current controller maintains stable operation and superior current-quality characteristics under active-power reference changes, phase-jump conditions, and SCR variations.

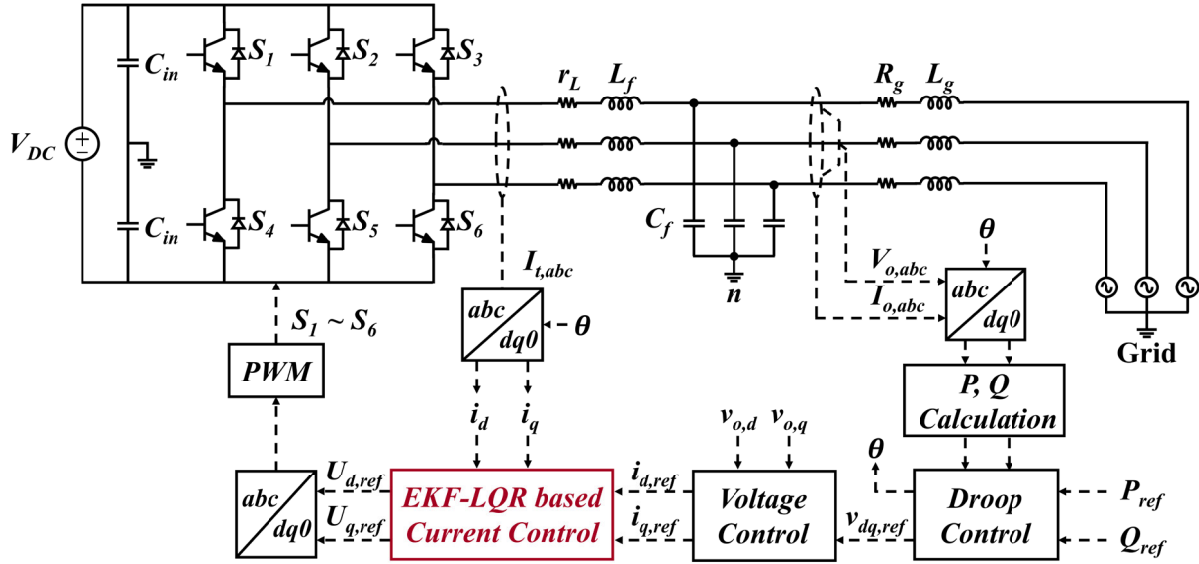


FIGURE 1. Overall system configuration of the GFMI with EKF-LQR-based current control.

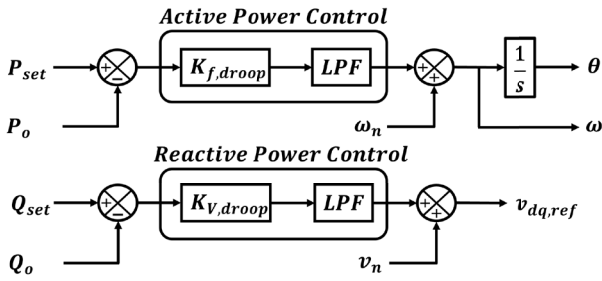


FIGURE 2. Control block diagram of the droop control with LPFs.

The remainder of this paper is organized as follows. Section II presents the system configuration and the proposed EKF-LQR-based current control method. Section III provides the stability analysis of the proposed current-control loop. Section IV presents the MATLAB/Simulink simulation results. Section V describes the HILS experimental setup and experimental results. Finally, Section VI concludes the paper.

II. EKF-LQR-BASED CURRENT CONTROL OF GRID-FORMING INVERTER

A. SYSTEM CONFIGURATION AND CONTROL STRUCTURE OF THE GRID-FORMING INVERTER

Fig. 1 illustrates the overall system configuration of the GFMI incorporating the proposed method. Here, V_{DC} denotes the DC input voltage, C_{in} is the DC-link capacitor, L_f and C_f represent the filter inductor and capacitor, respectively, r_L is the series equivalent resistance, and R_g and L_g denote the grid impedance. $V_{o,abc}$ and $I_{o,abc}$ are the voltage and current at the point of common coupling (PCC) and are used for the calculation of active and reactive power. $I_{t,abc}$ denotes the terminal current and, together with $V_{o,abc}$, is used as an input signal for the voltage and current controllers.

The droop control generates the reference voltage $v_{dq,ref}$ for voltage regulation and the phase angle used for frequency control. The voltage and current controllers employ a dual-loop control structure, in which the outer voltage control loop regulates the capacitor-voltage dynamics and generates the current references. The inner current control loop then regulates the terminal current according to these references and produces the PWM reference voltage, $U_{dq,ref}$, which is applied to the PWM modulator to generate the converter switching signals.

Fig. 2 illustrates the control block diagram of the low-pass-filter (LPF)-based droop control adopted in this paper. Droop control originates from the governor operating principle of conventional synchronous generators. It is designed to autonomously share active and reactive power by regulating frequency and voltage when multiple generators or power converters operate in parallel within a power system. Specifically, the fundamental principle of droop control is to proportionally adjust frequency and voltage in response to variations in generator output power, enabling multiple generators to maintain synchronization and actively respond to load changes without relying on communication links [23], [24], [25]. The P - f droop control characteristic can be expressed as follows:

$$\omega = \omega_n + K_{f,droop} \frac{\omega_c}{s + \omega_c} (P_{set} - P_o) \quad (1)$$

where ω_n represents the nominal angular frequency, $K_{f,droop}$ is the frequency droop coefficient, ω_c is the cutoff angular frequency of the LPF, P_{set} denotes the active power reference, and P_o represents the measured active power. The Q - V droop control characteristic can be expressed as follows:

$$v_{dq,ref} = v_n + K_{V,droop} \frac{\omega_c}{s + \omega_c} (Q_{set} - Q_o) \quad (2)$$

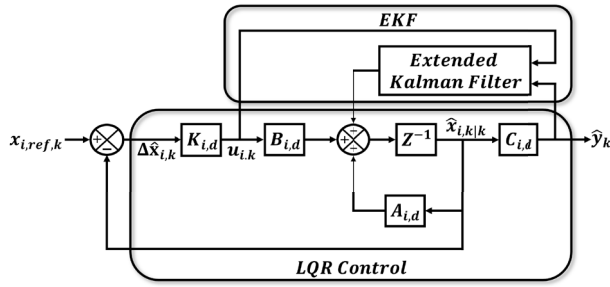


FIGURE 3. Control block diagram of the proposed EKF-LQR current controller.

where v_n represents the nominal voltage, $K_{V,droop}$ represents the voltage droop coefficient, Q_{set} denotes the reactive power reference, and Q_o represents the measured reactive power.

B. STATE-SPACE MODELING AND IMPLEMENTATION OF THE EKF-LQR-BASED CURRENT CONTROL

Fig. 3 illustrates the control block diagram of the proposed EKF-LQR current controller. The EKF estimates the dq-axis current states in real time using the measured current signals and the reduced current-state model. The EKF-based current-state estimate is used to calculate the deviation between the current-reference vector and the estimated current-state vector. Based on this deviation, the LQR controller applies the optimal feedback gain determined by minimizing a quadratic cost function and generates the PWM reference signal. Specifically, the EKF improves the accuracy of current-state estimation under measurement noise and operating-condition variations, whereas the LQR controller improves the dynamic response through optimal feedback-gain-based control. The integration of these two methods improves the dynamic performance and robustness of the inner current-control loop.

The state-space model of the GFMI, which forms the basis for the design of the proposed method, is derived as follows. An LC filter is connected to the output of the three-phase inverter and consists of a filter inductor L_f , a series equivalent resistance r_L , and a filter capacitor C_f . After transforming the voltage and current variables into the dq reference frame, the complete state and input vectors are defined as follows:

$$x = [i_d \ i_q \ v_{o,d} \ v_{o,q}]^T, \quad u = [v_{t,d} \ v_{t,q}]^T. \quad (3)$$

The complete LC-filter dynamics of the GFMI can be derived as follows:

$$\dot{x} = Ax + Bu + Ei_o, \quad y = Cx \quad (4)$$

where $i_o = [i_{o,d} \ i_{o,q}]^T$ represents the output-current vector, A , B , E , and C are given by

$$A = \begin{bmatrix} -\frac{r_L}{L_f} & \omega & -\frac{1}{L_f} & 0 \\ -\omega & -\frac{r_L}{L_f} & 0 & -\frac{1}{L_f} \\ \frac{1}{C_f} & 0 & 0 & \omega \\ 0 & \frac{1}{C_f} & -\omega & 0 \end{bmatrix}, \quad B = \begin{bmatrix} \frac{1}{L_f} & 0 \\ 0 & \frac{1}{L_f} \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

$$E = \begin{bmatrix} 0 & 0 \\ -\frac{1}{C_f} & 0 \\ 0 & -\frac{1}{C_f} \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (5)$$

When the complete state-space model in (4) is expressed in the form of differential equations, it can be written as follows:

$$L_f \frac{di_d}{dt} = v_{t,d} - v_{o,d} - r_L i_d + \omega L_f i_q \quad (6)$$

$$L_f \frac{di_q}{dt} = v_{t,q} - v_{o,q} - r_L i_q - \omega L_f i_d \quad (7)$$

$$C_f \frac{dv_{o,d}}{dt} = i_d - i_{o,d} + \omega C_f v_{o,q} \quad (8)$$

$$C_f \frac{dv_{o,q}}{dt} = i_q - i_{o,q} - \omega C_f v_{o,d}. \quad (9)$$

From (6) and (7), the term $v_{t,dq} - v_{o,dq}$ corresponds to the voltage across the filter inductor. Because the objective of the inner current-control loop is to regulate the dq-axis inductor currents, the proposed LQR controller is designed using a reduced current-state model. It should be noted that the capacitor-voltage dynamics are not neglected in the overall GFMI model; rather, they are included in the complete LC-filter model and are associated with the outer voltage-control dynamics. Therefore, the capacitor-voltage states are not included in the reduced state-space model used for the inner-loop LQR design.

Based on this reduced model, the current-state vector and current-control input vector are defined as follows:

$$x_i = \begin{bmatrix} i_d \\ i_q \end{bmatrix}, \quad u_i = \begin{bmatrix} v_{t,d} - v_{o,d} \\ v_{t,q} - v_{o,q} \end{bmatrix}. \quad (10)$$

The reduced current-state model can be expressed as follows:

$$\dot{x}_i = A_i x_i + B_i u_i, \quad y_i = C_i x_i \quad (11)$$

where A_i , B_i , and C_i are given by

$$A_i = \begin{bmatrix} -\frac{r_L}{L_f} & \omega \\ -\omega & -\frac{r_L}{L_f} \end{bmatrix}, \quad B_i = \begin{bmatrix} \frac{1}{L_f} & 0 \\ 0 & \frac{1}{L_f} \end{bmatrix}, \quad C_i = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}. \quad (12)$$

For digital implementation, the continuous-time reduced current-state model in (11) is converted into its discrete-time representation using the sampling period T_s . In this paper, zero-order-hold discretization is used to obtain the discrete-time matrices from the continuous-time reduced current-state model. Since the output equation directly maps the dq-axis current states to the measured current output, the output matrix is preserved in the discrete-time representation. The discrete-time current-state model is expressed as follows [26]:

$$x_{i,k+1} = A_{i,d} x_{i,k} + B_{i,d} u_{i,k}, \quad y_{i,k} = C_{i,d} x_{i,k} \quad (13)$$

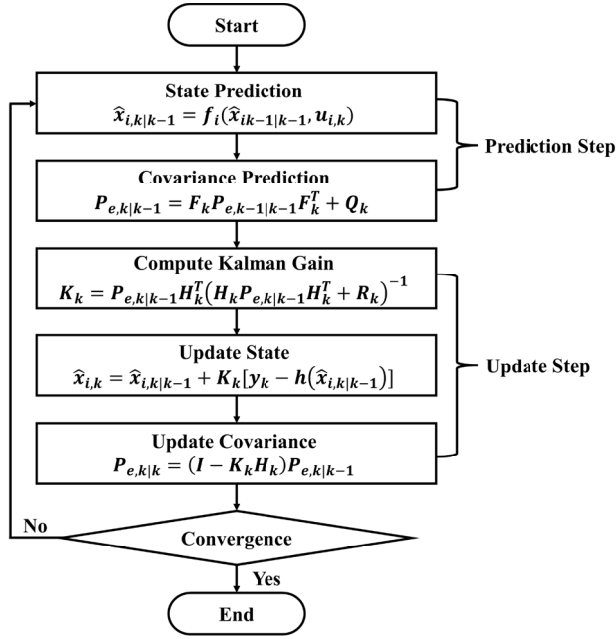


FIGURE 4. Flowchart of the EKF algorithm used in the proposed current controller.

where system matrices are defined as follows:

$$A_{i,d} = e^{A_i T_s}, \quad B_{i,d} = \int_0^{T_s} e^{A_i \tau} B_i d\tau, \quad C_{i,d} = C_i. \quad (14)$$

For the LQR design, the current-state deviation is defined as follows:

$$\Delta x_{i,k} = x_{i,\text{ref},k} - x_{i,k} \quad (15)$$

where $x_{i,\text{ref},k}$ denotes the current-reference vector generated by the outer voltage-control loop. The discrete-time LQR cost function for the inner current-control loop is defined using the current-state deviation and the current-control input as follows [26], [27]:

$$J_{i,d} = \sum_{k=0}^{\infty} \left[\Delta x_{i,k}^T Q_{i,d} \Delta x_{i,k} + u_{i,k}^T R_{i,d} u_{i,k} \right] \quad (16)$$

where $Q_{i,d}$ represents the symmetric positive semi-definite weighting matrix that determines the relative importance of the dq -axis current-state deviations, whereas $R_{i,d}$ is a symmetric positive definite weighting matrix that penalizes the current-control effort.

The discrete-time algebraic Riccati equation is expressed as follows:

$$P_{i,d} = A_{i,d}^T P_{i,d} A_{i,d} - A_{i,d}^T P_{i,d} B_{i,d} \times (R_{i,d} + B_{i,d}^T P_{i,d} B_{i,d})^{-1} B_{i,d}^T P_{i,d} A_{i,d} + Q_{i,d}. \quad (17)$$

By solving (17), the discrete-time optimal feedback gain is obtained as follows:

$$K_{i,d} = (R_{i,d} + B_{i,d}^T P_{i,d} B_{i,d})^{-1} B_{i,d}^T P_{i,d} A_{i,d}. \quad (18)$$

Fig. 4 illustrates the flowchart of the EKF algorithm used in the proposed current controller. The LQR gain is designed based on the discrete-time linear current-state model, whereas

the EKF is formulated using the current-state transition and measurement functions in a general nonlinear stochastic form. This formulation allows the estimator to update the current states through local linearization using the Jacobian matrices under measurement noise and operating-condition variations. The EKF recursively performs the prediction and update steps to obtain the posterior current-state estimate required by the LQR feedback control law.

The EKF is formulated to estimate the current-state vector used in the LQR control law. For this purpose, the state transition and measurement relations are expressed in a general nonlinear stochastic form as follows:

$$x_{i,k} = f_i(x_{i,k-1}, u_{i,k}) + w_k \quad (19)$$

$$y_k = h_i(x_{i,k}) + v_k \quad (20)$$

where $u_{i,k}$ represents the current-control input vector. In this paper, the measured output vector consists of the measured dq -axis inductor currents and is distinguished from the current-state vector $x_{i,k}$ because it includes the effect of measurement noise, as represented by the measurement model in (20). The functions $f_i(\cdot)$ and $h_i(\cdot)$ represent the nonlinear state-transition and measurement functions, respectively. The terms w_k and v_k denote the process noise and measurement noise, whose covariance matrices are represented by Q_k and R_k , respectively. It should be noted that Q_k and R_k are the EKF noise covariance matrices.

The EKF state vector is selected as follows:

$$x_{i,k} = \begin{bmatrix} i_d \\ i_q \end{bmatrix}_k. \quad (21)$$

The EKF input vector is defined as the voltage applied across the filter inductor as follows:

$$u_{i,k} = \begin{bmatrix} u_d \\ u_q \end{bmatrix}_k = \begin{bmatrix} v_{t,d} - v_{o,d} \\ v_{t,q} - v_{o,q} \end{bmatrix}_k. \quad (22)$$

The Jacobian matrices of the nonlinear state-transition function and measurement function are defined as follows:

$$F_k = \left. \frac{\partial f_i}{\partial x_i} \right|_{\hat{x}_{i,k-1|k-1}, u_{i,k}}, \quad H_k = \left. \frac{\partial h_i}{\partial x_i} \right|_{\hat{x}_{i,k|k-1}} \quad (23)$$

where F_k represents the Jacobian matrix of the state-transition function, and H_k is the Jacobian matrix of the measurement function.

In the prediction step, the current-state estimate and the estimation-error covariance matrix are predicted using the state-transition function and its Jacobian matrix, respectively, as follows:

$$\hat{x}_{i,k|k-1} = f_i(\hat{x}_{i,k-1|k-1}, u_{i,k}) \quad (24)$$

$$P_{e,k|k-1} = F_k P_{e,k-1|k-1} F_k^T + Q_k. \quad (25)$$

In the update step, the Kalman gain is computed as follows:

$$K_k = P_{e,k|k-1} H_k^T (H_k P_{e,k|k-1} H_k^T + R_k)^{-1}. \quad (26)$$

The current-state estimate and the estimation-error covariance matrix are then updated as follows:

$$\hat{x}_{i,k|k} = \hat{x}_{i,k|k-1} + K_k [y_k - h_i(\hat{x}_{i,k|k-1})] \quad (27)$$

$$P_{e,k|k} = (I - K_k H_k) P_{e,k|k-1}. \quad (28)$$

Through this recursive prediction and update process, the EKF provides the estimated current states required by the LQR feedback control law.

As shown in Fig. 3, the proposed EKF–LQR controller generates the current-control input by applying the discrete-time LQR gain to the deviation between the current-reference vector and the EKF-estimated output. The current-reference vector generated by the outer voltage-control loop is defined as follows:

$$x_{i,\text{ref},k} = \begin{bmatrix} i_{d,\text{ref},k} \\ i_{q,\text{ref},k} \end{bmatrix}. \quad (29)$$

The estimated output vector is denoted by $\hat{y}_k$ and is obtained from the EKF-estimated current-state vector as follows:

$$\hat{y}_k = C_{i,d} \hat{x}_{i,k|k} \quad (30)$$

where $\hat{x}_{i,k|k}$ represents the updated EKF current-state estimate. In general, the feedback deviation is defined in terms of the output variable. Therefore, the EKF-based output deviation used in the LQR feedback law is defined as follows:

$$\Delta \hat{y}_{i,k} = x_{i,\text{ref},k} - \hat{y}_k. \quad (31)$$

Since $C_{i,d} = I$ in the proposed reduced current-state model, the estimated output vector is equivalent to the EKF-estimated current-state vector. Accordingly, (31) can be equivalently written as the EKF-based current-state deviation as follows:

$$\Delta \hat{x}_{i,k} = x_{i,\text{ref},k} - \hat{x}_{i,k|k}. \quad (32)$$

Based on the discrete-time optimal feedback gain in (18), the current-control signal applied to the input channel of the reduced current-state model is determined as follows:

$$u_{i,k} = K_{i,d} \Delta \hat{x}_{i,k}. \quad (33)$$

Accordingly, the PWM reference voltage $U_{dq,\text{ref}}$ generated by the current controller is obtained as follows:

$$U_{dq,\text{ref}} = v_{o,dq,k} + u_{i,k} = v_{o,dq,k} + K_{i,d} \Delta \hat{x}_{i,k}. \quad (34)$$

Therefore, the proposed EKF–LQR-based current controller uses the EKF to obtain the more reliable current-state estimate $\hat{x}_{i,k|k}$. Since the measured output directly corresponds to the current-state vector in the reduced current-state model, the output-based feedback deviation can be expressed as the EKF-based current-state deviation $\Delta \hat{x}_{i,k}$. The LQR controller then applies the discrete-time feedback gain to generate the current-control input. As a result, the proposed method improves both the dynamic response and the robustness of the inner current-control loop under operating-condition variations.

III. STABILITY ANALYSIS

Because the proposed current controller uses the EKF-estimated current state as the feedback variable in the LQR control law, the stability of the current-control loop should be evaluated by considering both the current-state deviation and the EKF estimation error. In this analysis, the local stability of the coupled EKF–LQR current-control system is evaluated around the operating point.

The current-state deviation is defined as follows:

$$\Delta x_{i,k} = x_{i,\text{ref},k} - x_{i,k}. \quad (35)$$

The EKF estimation error is defined as follows:

$$\varepsilon_{i,k} = \hat{x}_{i,k|k} - x_{i,k}. \quad (36)$$

From (36), the EKF-estimated current state can be expressed as

$$\hat{x}_{i,k|k} = x_{i,k} + \varepsilon_{i,k}. \quad (37)$$

Therefore, the estimated current-state deviation used in the LQR feedback law can be rewritten as

$$\Delta \hat{x}_{i,k} = \Delta x_{i,k} - \varepsilon_{i,k}. \quad (38)$$

Substituting (38) into the proposed control law in (33), the current-control input becomes

$$u_{i,k} = K_{i,d} \Delta x_{i,k} - K_{i,d} \varepsilon_{i,k}. \quad (39)$$

The discrete-time current-state model is expressed as

$$x_{i,k+1} = A_{i,d} x_{i,k} + B_{i,d} u_{i,k}. \quad (40)$$

Using (35), the current-state deviation at the next sampling instant is

$$\Delta x_{i,k+1} = x_{i,\text{ref},k+1} - x_{i,k+1}. \quad (41)$$

Substituting (40) and (39) into (41) gives

$$\Delta x_{i,k+1} = x_{i,\text{ref},k+1} - A_{i,d} x_{i,k} - B_{i,d} K_{i,d} \Delta x_{i,k} + B_{i,d} K_{i,d} \varepsilon_{i,k}. \quad (42)$$

Since

$$x_{i,k} = x_{i,\text{ref},k} - \Delta x_{i,k}. \quad (43)$$

(42) can be rewritten as

$$\Delta x_{i,k+1} = (A_{i,d} - B_{i,d} K_{i,d}) \Delta x_{i,k} + B_{i,d} K_{i,d} \varepsilon_{i,k} + d_{\text{ref},k} \quad (44)$$

where the reference-variation term is defined as

$$d_{\text{ref},k} = x_{i,\text{ref},k+1} - A_{i,d} x_{i,\text{ref},k}. \quad (45)$$

For the local stability analysis around the operating point, the current reference is assumed to be constant or slowly varying over the current-control sampling interval. Therefore, the reference-variation term is neglected, i.e., $d_{\text{ref},k} \approx 0$. Consequently, the current-state deviation dynamics are obtained as

$$\Delta x_{i,k+1} = (A_{i,d} - B_{i,d} K_{i,d}) \Delta x_{i,k} + B_{i,d} K_{i,d} \varepsilon_{i,k}. \quad (46)$$

For the EKF, the local estimation-error dynamics around the operating point can be approximated as follows:

$$\varepsilon_{i,k+1} \approx \Phi_{e,k} \varepsilon_{i,k} \quad (47)$$

where $\Phi_{e,k}$ denotes the local transition matrix of the EKF estimation error and is given by

$$\Phi_{e,k} = (I - K_k H_k) F_k. \quad (48)$$

In (48), F_k and H_k are the Jacobian matrices of the state-transition and measurement functions, respectively, and K_k is the EKF gain.

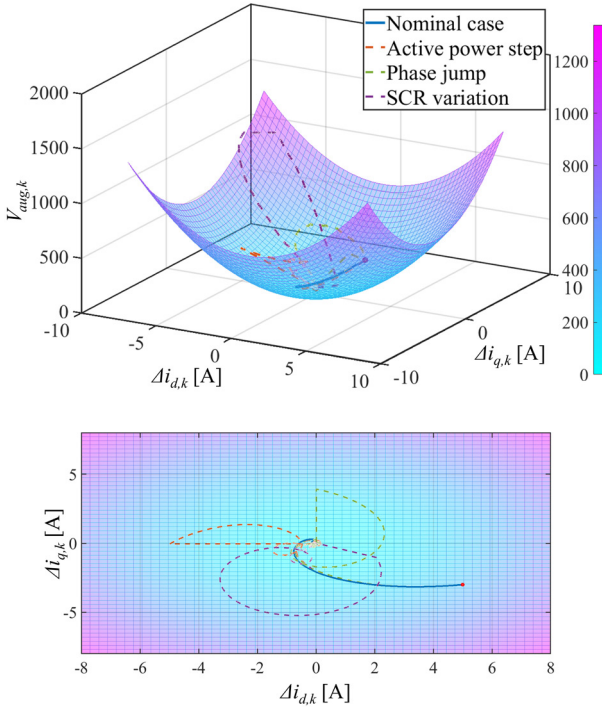


FIGURE 5. Scenario-based augmented lyapunov trajectories.

The augmented state vector of the coupled EKF-LQR current-control system is defined as follows:

$$z_k = \begin{bmatrix} \Delta x_{i,k} \\ \varepsilon_{i,k} \end{bmatrix}. \quad (49)$$

Using (46) and (47), the augmented error dynamics are expressed as follows:

$$z_{k+1} = A_{aug,k} z_k \quad (50)$$

where

$$A_{aug,k} = \begin{bmatrix} A_{i,d} - B_{i,d}K_{i,d} & B_{i,d}K_{i,d} \\ \mathbf{0} & \Phi_{e,k} \end{bmatrix}. \quad (51)$$

A quadratic Lyapunov function is selected for the augmented EKF-LQR error system as follows:

$$V_{aug,k} = z_k^T P_{aug} z_k \quad (52)$$

where P_{aug} is a symmetric positive definite matrix. Because the numerical verification is performed at each sampling instant $t_k = kT_s$, the time-domain Lyapunov trajectory shown in the simulation results is calculated as

$$V_{aug}(t_k) = V_{aug,k} = z_k^T P_{aug} z_k. \quad (53)$$

Therefore, $V_{aug}(t_k)$ represents the Lyapunov energy of the coupled current-state deviation and EKF estimation error along the actual discrete-time trajectory.

The Lyapunov difference is defined as follows:

$$\Delta V_{aug,k} = V_{aug,k+1} - V_{aug,k}. \quad (54)$$

From (50), the Lyapunov function at the next sampling instant is

$$V_{aug,k+1} = z_k^T A_{aug,k}^T P_{aug} A_{aug,k} z_k. \quad (55)$$

TABLE 1. Eigenvalue verification of the EKF-LQR error dynamics.

Matrix	Eigenvalues	Spectral radius
$A_{i,d} - B_{i,d}K_{i,d}$	$0.8532 \pm j0.0322$	0.8538
A_{aug}	$0.8532 \pm j0.0322,$ $0.9789 \pm j0.0369$	0.9796

Substituting (52) and (55) into (54), the Lyapunov difference can be rewritten as follows:

$$\Delta V_{aug,k} = z_k^T (A_{aug,k}^T P_{aug} A_{aug,k} - P_{aug}) z_k. \quad (56)$$

If symmetric positive definite matrices P_{aug} and Q_{aug} exist such that

$$A_{aug,k}^T P_{aug} A_{aug,k} - P_{aug} = -Q_{aug}, \quad Q_{aug} > 0 \quad (57)$$

then the Lyapunov difference becomes

$$\Delta V_{aug,k} = -z_k^T Q_{aug} z_k < 0, \quad z_k \neq 0. \quad (58)$$

Therefore, in the deterministic local error model without persistent measurement noise and model mismatch, the Lyapunov function $V_{aug,k}$ decreases along the augmented error dynamics. This indicates that the augmented state z_k , including both the current-state deviation and the EKF estimation error, asymptotically converges to the origin near the operating point. Thus, the local stability of the proposed EKF-LQR-based current-control loop is verified.

To provide numerical evidence for the local discrete-time stability, the eigenvalues of the nominal LQR current-state deviation dynamics and the augmented EKF-LQR error dynamics were calculated at the nominal operating point, as summarized in Table 1. The matrix $A_{i,d} - B_{i,d}K_{i,d}$ represents the nominal closed-loop dynamics of the LQR-based current-state deviation, whereas A_{aug} represents the augmented local error dynamics that include both the current-state deviation and the EKF estimation error. The eigenvalues of $A_{i,d} - B_{i,d}K_{i,d}$ are $0.8532 \pm j0.0322$, with a spectral radius of 0.8538. In addition, the eigenvalues of A_{aug} are $0.8532 \pm j0.0322$ and $0.9789 \pm j0.0369$, with a spectral radius of 0.9796. Since all eigenvalues are located inside the unit circle, the nominal augmented EKF-LQR error dynamics are locally stable in the discrete-time domain. This eigenvalue-based verification supports the local Lyapunov stability analysis and complements the scenario-based Lyapunov trajectory results under representative operating-condition variations.

For visualization of the Lyapunov function, the augmented state is explicitly written as follows:

$$z_k = \begin{bmatrix} \Delta i_{d,k} \\ \Delta i_{q,k} \\ e_{d,k} \\ e_{q,k} \end{bmatrix}. \quad (59)$$

Because z_k is four-dimensional, the complete augmented Lyapunov function in (52) cannot be directly represented as a three-dimensional surface including all state variables.

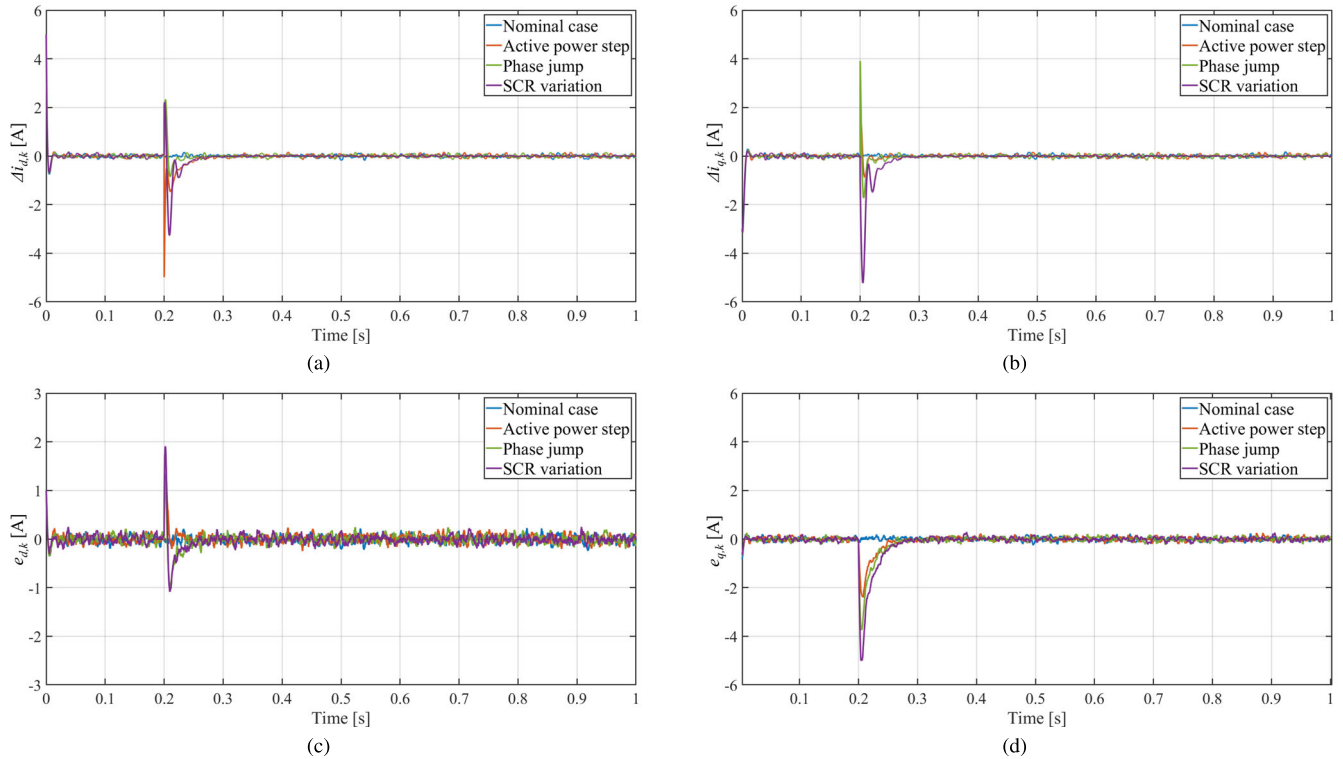


FIGURE 6. Scenario-based current-state deviations and EKF estimation-error responses under the nominal case, active-power step, phase jump, and SCR variation: (a) d -axis current-state deviation, (b) q -axis current-state deviation, (c) d -axis EKF estimation error, and (d) q -axis EKF estimation error.

Therefore, the actual augmented Lyapunov value is computed from the full augmented state vector along the simulated trajectory and visualized by projecting the trajectory onto the plane whose horizontal axes are $\Delta i_{d,k}$ and $\Delta i_{q,k}$. In this visualization, the two horizontal axes represent the current-state deviations $\Delta i_{d,k}$ and $\Delta i_{q,k}$, whereas the vertical axis represents the full augmented Lyapunov value $V_{\text{aug},k}$.

Although the EKF estimation-error components $e_{d,k}$ and $e_{q,k}$ are not directly displayed as the horizontal axes of Fig. 5, their effect is included in the plotted z -axis value, $V_{\text{aug},k}$. This is because $V_{\text{aug},k}$ is computed from the full augmented state vector in (59), which includes both the current-state deviation and the EKF estimation error. To clarify this point, P_{aug} can be partitioned as follows:

$$P_{\text{aug}} = \begin{bmatrix} P_x & P_{xe} \\ P_{xe}^T & P_e \end{bmatrix}. \quad (60)$$

Then, the augmented Lyapunov function can be decomposed as follows:

$$V_{\text{aug},k} = \Delta x_{i,k}^T P_x \Delta x_{i,k} + 2\Delta x_{i,k}^T P_{xe} \varepsilon_{i,k} + \varepsilon_{i,k}^T P_e \varepsilon_{i,k}. \quad (61)$$

In (61), the first term represents the quadratic contribution of the current-state deviation, the second term represents the cross-coupling contribution between the current-state deviation and the EKF estimation error, and the third term represents the quadratic contribution of the EKF estimation error. Therefore, the plotted z -axis value, $V_{\text{aug},k}$, reflects the combined effect of the current-state deviation, the EKF

estimation error, and their cross-coupling. The plotted trajectory is expressed as follows:

$$(\Delta i_{d,k}, \Delta i_{q,k}, V_{\text{aug},k}). \quad (62)$$

It should be noted that this three-dimensional plot is not the complete four-dimensional Lyapunov surface. Instead, it is a projected visualization of the actual augmented Lyapunov trajectory evaluated using the full augmented state vector. This representation allows the convergence behavior of the coupled EKF–LQR current-control system to be evaluated using a single scalar Lyapunov value.

Fig. 5 shows the scenario-based augmented Lyapunov trajectories visualized on the $(\Delta i_{d,k}, \Delta i_{q,k})$ current-state deviation plane. The nominal case is used as the reference operating condition without an external disturbance. In this case, the augmented Lyapunov trajectory remains close to the low-energy region after the initial transient, which confirms the local convergence property of the nominal EKF–LQR current control loop around the operating point.

For the active-power step case, the Lyapunov trajectory moves mainly along the $\Delta i_{d,k}$ axis. This is because the active-power command variation directly changes the d -axis current reference, thereby producing an instantaneous d -axis current-state deviation. After the transient event, the trajectory returns toward the low-Lyapunov-energy region. This result indicates that the proposed EKF–LQR current-control loop remains stable against active-power reference variation.

TABLE 2. System parameters.

Parameter	Symbol	Value
Rated power	P_{rated}	10 kW
DC-link voltage	V_{dc}	800 V
Filter inductance	L_f	2 mH
Filter resistance	r_L	0.1 Ω
Filter capacitance	C_f	27 μF
Nominal frequency	f_0	60 Hz
Switching frequency	f_{sw}	10 kHz
LQR state-weighting matrix	$Q_{i,d}$	$10I_2$
LQR input-weighting matrix	$R_{i,d}$	I_2
EKF process-noise covariance	Q_k	$1.0 \times 10^{-4}I_2$
EKF measurement-noise covariance	R_k	$0.25I_2$

For the phase-jump case, the trajectory exhibits a dominant $\Delta i_{q,k}$ axis excursion. This behavior is physically consistent with the effect of a sudden phase-angle variation, which causes a transient mismatch in the dq -axis reference frame. Due to the cross-coupling terms in the dq -axis current dynamics, the recovery path appears as a curved trajectory rather than a purely single-axis response. Nevertheless, the trajectory remains bounded and returns toward the low-energy region, confirming stable operation under the phase-angle disturbance.

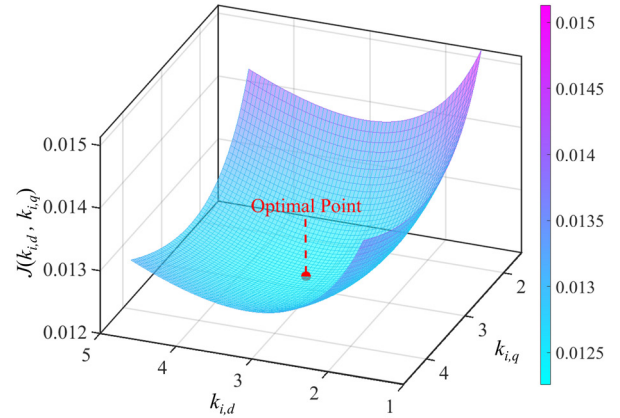
For the SCR-variation case, the Lyapunov trajectory shows the largest excursion among the tested scenarios. This is expected because the transition from a strong-grid condition to a weak-grid condition changes the grid impedance and increases the mismatch between the operating-point model used to construct the Lyapunov function and the actual post-event system dynamics. However, the trajectory remains bounded after the disturbance and moves back toward the low-Lyapunov-energy region. This confirms that the proposed EKF–LQR current control loop maintains stable operation even under grid-strength variation.

To further clarify the underlying state components associated with the augmented Lyapunov trajectories and to evaluate the EKF estimation behavior under nonideal conditions, Fig. 6 presents the time responses of the current-state deviations and EKF estimation errors. In this scenario-based verification, EKF measurement noise and model-mismatch perturbations are included in the estimator-error response.

Fig. 6(a) shows the current-state deviation of the d -axis current, $\Delta i_{d,k}$. The active-power step case exhibits the largest transient in $\Delta i_{d,k}$ because the active-power command change is mainly reflected in the d -axis current reference. After the event, $\Delta i_{d,k}$ is rapidly attenuated and remains bounded around zero.

Fig. 6(b) shows the current-state deviation of the q -axis current, $\Delta i_{q,k}$. The phase-jump case has the dominant transient in $\Delta i_{q,k}$, which is consistent with the transient dq -frame mismatch caused by the phase-angle disturbance. In the SCR-variation case, both current-state deviations are affected by the grid-impedance variation, but the deviations are damped after the transient period.

Figs. 6(c) and 6(d) show the EKF estimation errors of the d -axis and q -axis currents, respectively. The estimation

**FIGURE 7.** Cost surface and optimal LQR gain point, where $k_{i,d}$ and $k_{i,q}$ denote the d -axis and q -axis feedback gains, respectively.

errors temporarily increase at the disturbance instant due to the injected measurement noise and model-mismatch terms. However, they do not diverge; instead, they decrease and remain bounded near the origin. This behavior confirms that the EKF estimation errors remain within a limited range around zero under noisy measurements and operating-condition variations, rather than converging exactly to zero as in the deterministic local Lyapunov analysis.

Therefore, the Lyapunov equation verifies the local asymptotic stability of the linearized augmented error dynamics around the operating condition. In addition, the scenario-based trajectories provide complementary verification of the stable response behavior under active-power reference variation, phase-angle disturbance, SCR variation, measurement noise, and model mismatch. The augmented Lyapunov trajectory, current-state deviations, and EKF estimation errors demonstrate that the proposed EKF–LQR current control loop maintains stable behavior under the tested representative operating-condition changes.

IV. SIMULATION RESULTS

In this paper, the performance of the proposed method is validated through simulations conducted in the MATLAB/Simulink environment. The main system parameters used for the simulation are summarized in Table 2. The table also includes the LQR weighting matrices and the EKF covariance matrices used in the proposed current controller to improve the reproducibility of the controller design. For the EKF-based current-state estimator, the process-noise covariance matrix and measurement-noise covariance matrix are set to $Q_k = 1.0 \times 10^{-4}I_2$ and $R_k = 0.25I_2$, respectively. The measurement-noise covariance matrix R_k is determined from the assumed current-measurement noise standard deviation of $\sigma_i = 0.5$ A, and Q_k is selected as a small value because the reduced-order current model provides an adequate representation of the filter inductor-current dynamics. Therefore, the EKF is conservatively tuned to provide more reliable current estimates for the LQR current controller.

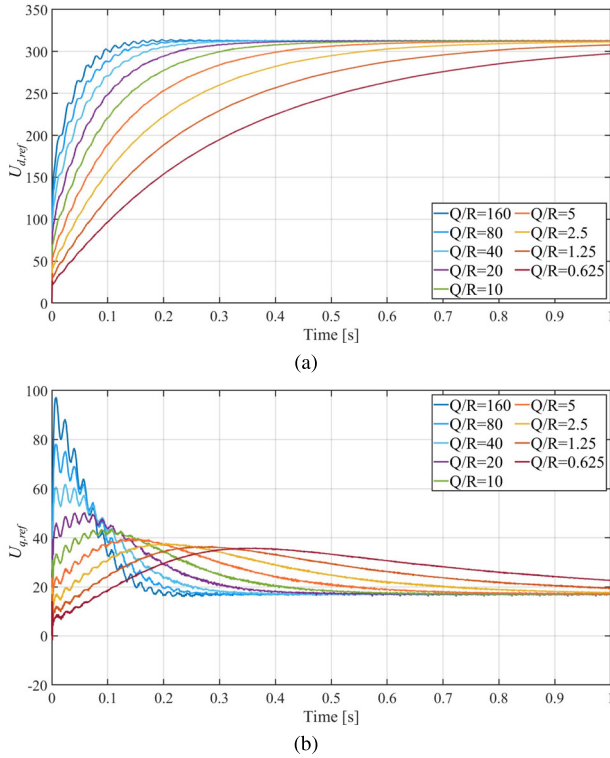


FIGURE 8. Current-controller output responses according to the LQR weighting ratio Q/R : (a) d -axis current-controller output $U_{d,ref}$ and (b) q -axis current-controller output $U_{q,ref}$.

For fair benchmarking, the PI-based, pole-placement-based, and proposed EKF-LQR-based current controllers are evaluated under the same GFMI parameters, current-control sampling condition, and operating scenarios. The pole-placement-based current controller is designed in the discrete-time domain using the same reduced current-state model as the proposed EKF-LQR controller. With the sampling period of $T_s = 100 \mu s$, the desired discrete-time closed-loop poles of the pole-placement controller are selected as $0.9851 \pm j0.0049$.

To evaluate the performance of the proposed method, four simulation analyses are considered. First, the LQR gain-selection characteristic is analyzed in Section IV-A. The cost surface is presented to verify that the EKF-LQR-based current controller determines the optimal feedback gain by minimizing the quadratic cost function. In the cost-surface analysis, $k_{i,d}$ and $k_{i,q}$ represent the feedback gain components associated with the d - and q -axis current-state deviations, respectively. In addition, the current-controller output responses are compared under different Q/R ratios to examine how the LQR weighting ratio affects the transient response. Section IV-B presents the current control loop response under step changes in the active-power reference. Section IV-C presents the current control loop response under phase-jump conditions. Section IV-D presents the analysis results of the GFMI output current response and the corresponding output-current THD under SCR variations.

TABLE 3. Current control loop response under active power reference step changes.

Name	PI-based		Pole-placement-based		EKF-LQR-based	
Axis	d	q	d	q	d	q
Maximum overshoot [%]	1.68	23.6	0.44	6.68	0.15	5.2
Maximum settling time [s]	0.16	0.18	0.09	0.14	0.08	0.13

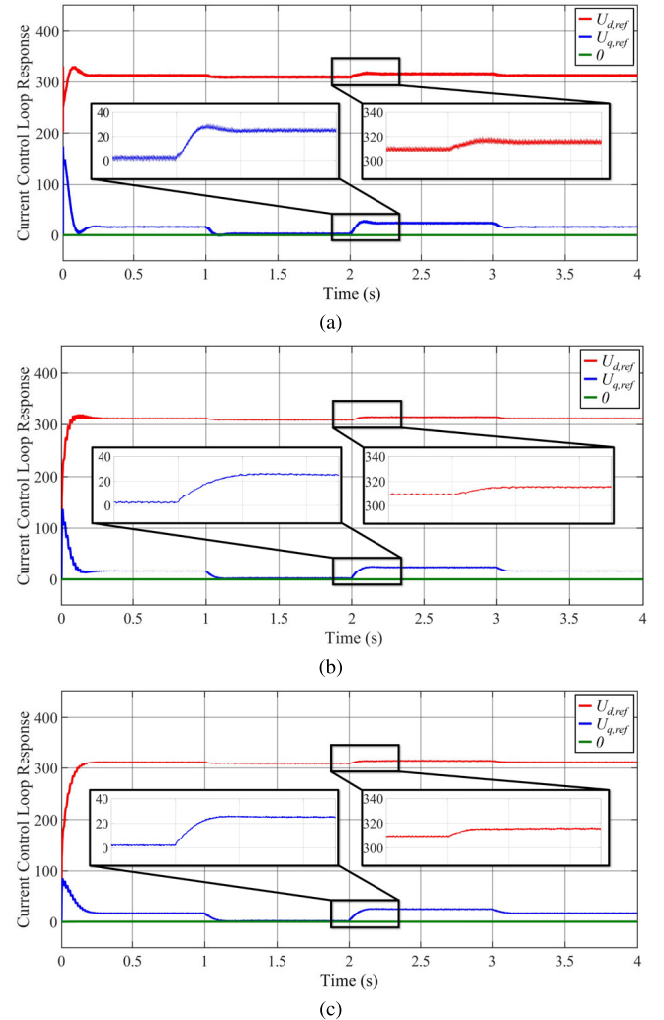


FIGURE 9. Current control loop responses under active power reference step changes: (a) PI-based current control, (b) pole-placement-based current control, and (c) EKF-LQR-based current control.

A. OPTIMAL GAIN OF THE EKF-LQR-BASED CURRENT CONTROLLER

Fig. 7 illustrates the cost surface of the objective function for the EKF-LQR-based current controller and the corresponding optimal point. In this figure, J denotes the quadratic cost function, and $k_{i,d}$ and $k_{i,q}$ denote the d -axis and q -axis diagonal feedback-gain components of the current controller,

respectively, which are obtained from the LQR gain matrix in (18). The cost surface shows that the objective function has a minimum value at the optimal gain point. As the feedback gains move away from this optimal point, the value of the cost function increases, indicating that the current-control performance becomes less optimal in terms of the LQR design criterion. This result confirms that the proposed EKF-LQR current controller determines the feedback gain through an optimization process based on the minimization of the quadratic cost function.

To further examine the effect of the LQR weighting ratio on the controller behavior, the current-controller output responses are compared under different Q/R ratios, as shown in Fig. 8. Fig. 8(a) shows the d -axis current-controller output $U_{d,ref}$, and Fig. 8(b) shows the q -axis current-controller output $U_{q,ref}$. Since the LQR gain is determined by the relative weighting between the state-error penalty Q and the control-input penalty R , the Q/R ratio directly affects the transient response and control-output smoothness of the current controller. Therefore, the Q/R -ratio sensitivity analysis confirms the trade-off between transient response speed and control-output smoothness. Based on this sensitivity analysis, the LQR weighting matrices were selected as $Q_{i,d} = 10I_2$ and $R_{i,d} = I_2$, corresponding to $Q/R = 10$. This selection provides a suitable balance between improved transient response, reduced oscillatory behavior, and smooth controller-output characteristics for the proposed EKF-LQR current-control loop.

B. CURRENT CONTROL LOOP RESPONSE UNDER ACTIVE POWER REFERENCE STEP CHANGES

Fig. 9 illustrates the current control loop responses of the proposed method and conventional methods under step changes in the active power reference, where the reference decreases from 10 kW to 1 kW at 1 s, increases from 1 kW to 15 kW at 2 s, and decreases from 15 kW to 10 kW at 3 s. Fig. 9(a) corresponds to the current control loop based on PI control, Fig. 9(b) represents the current control loop based on pole placement control, and Fig. 9(c) shows the current control loop based on EKF-LQR control. In both the d -axis and q -axis current control loop responses, the proposed method exhibits reduced overshoot and shorter settling time compared to PI control and pole placement control, indicating improved dynamic performance. Table 3 summarizes the quantitative performance comparison among the control methods. The maximum overshoot of the proposed method is 0.15% for the d -axis current and 5.2% for the q -axis current, which corresponds to reductions of 1.53 and 18.4 percentage points compared to PI control, and reductions of 0.29 and 1.48 percentage points compared to pole placement control, respectively.

Moreover, the maximum settling time is reduced to 0.08 s for the d -axis current and 0.13 s for the q -axis current, representing reductions of 0.08 s and 0.05 s compared to PI control, and a reduction of 0.01 s compared to pole placement control. These results demonstrate that the proposed method

TABLE 4. Current control loop response under phase-jump conditions.

Name	PI-based		Pole-placement-based		EKF-LQR-based	
	d	q	d	q	d	q
Maximum overshoot [%]	4.06	112.94	2.98	109.4	2.62	68.82
Maximum settling time [s]	0.13	0.22	0.11	0.18	0.08	0.17

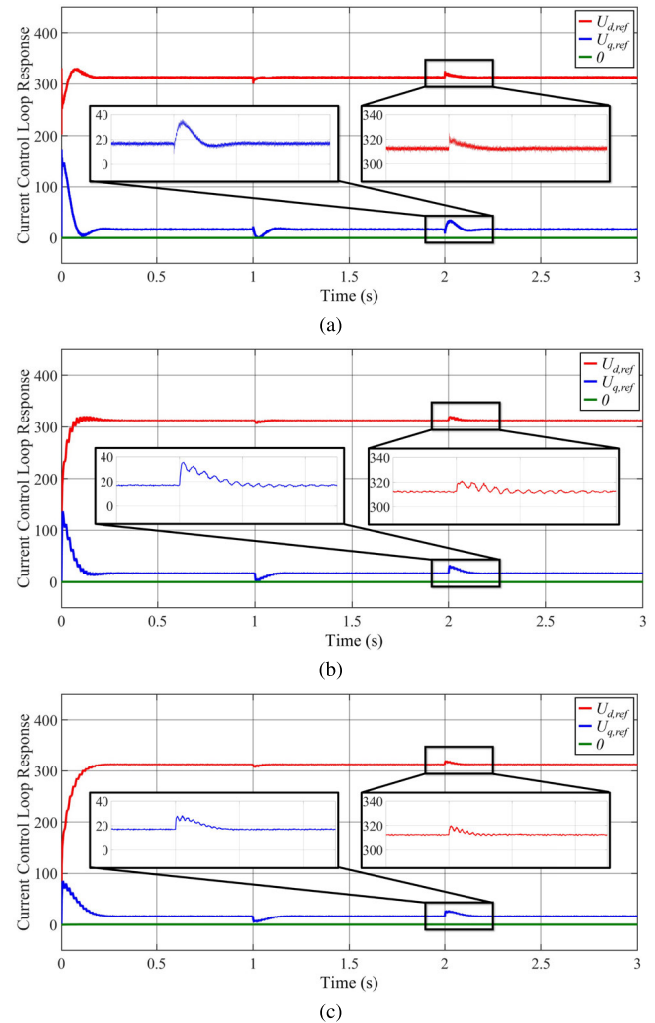


FIGURE 10. Current control loop responses under phase-jump conditions: (a) PI-based current control, (b) pole-placement-based current control, and (c) EKF-LQR-based current control.

is effective in improving the dynamic characteristics and enhancing the control stability of the current control loop under active power reference variations.

C. CURRENT CONTROL LOOP RESPONSE UNDER PHASE JUMPS

Fig. 10 shows the current control loop responses of the proposed method and the conventional methods under phase

jump conditions of 0° to 10° at 1 s and 10° to 0° at 2 s. Fig. 10(a) corresponds to the current control loop based on PI control, Fig. 10(b) corresponds to the current control loop based on pole placement control, and Fig. 10(c) corresponds to the current control loop based on EKF-LQR control. In the case of PI control, a larger overshoot was observed during the transient response under phase jump conditions compared to the proposed method, and oscillations were particularly evident in the q -axis current control loop. Under the pole placement control-based current control loop, the d -axis overshoot and settling time exhibited results similar to those of the proposed method; however, a relatively larger overshoot was observed in the q -axis response.

In contrast, the proposed method rapidly attenuated the oscillatory components after the phase jump, ensuring stable convergence to the steady state. Table 4 summarizes the quantitative performance comparison under phase jump conditions. The maximum overshoot of the proposed method was 2.62% for the d -axis current and 68.82% for the q -axis current. Compared with PI control, whose maximum overshoot was 4.06% for the d -axis current and 112.94% for the q -axis current, the proposed method achieved reductions of 1.44 and 44.12 percentage points, respectively. In addition, compared with pole placement control, which exhibited maximum overshoots of 2.98% for the d -axis current and 109.4% for the q -axis current, reductions of 0.36 and 40.58 percentage points were obtained, respectively. In addition, the maximum settling time was 0.08 s for the d -axis current and 0.17 s for the q -axis current, which are reduced by 0.05 s compared to those of PI control at 0.13 s and 0.22 s, respectively, and reduced by 0.03 s and 0.01 s compared to those of pole placement control at 0.11 s and 0.18 s. These results indicate that the proposed method ensures stable current control even under conditions involving abrupt phase variations such as phase jumps.

D. DISTORTION CHARACTERISTICS OF GFMI OUTPUT CURRENT UNDER SCR VARIATIONS

Fig. 11 shows the output current waveforms of the GFMI under SCR variation. In this scenario, the SCR increases from 2 to 15 at 2 s, representing the transition from a weak-grid condition to a strong-grid condition, and subsequently decreases from 15 to 2 at 3 s, representing the transition from a strong-grid condition back to a weak-grid condition. Therefore, this scenario evaluates whether each current control method can maintain stable current-regulation performance under both strong-grid and weak-grid operating conditions.

Fig. 11(a) presents the results obtained with the PI control-based current control loop. During the SCR variation intervals, noticeable distortion appears in the output current waveforms, particularly when the grid condition changes abruptly. This result indicates that the PI-based current controller is sensitive to grid impedance variation, and its dynamic current-regulation performance is degraded when the grid strength changes. Fig. 11(b) shows the results

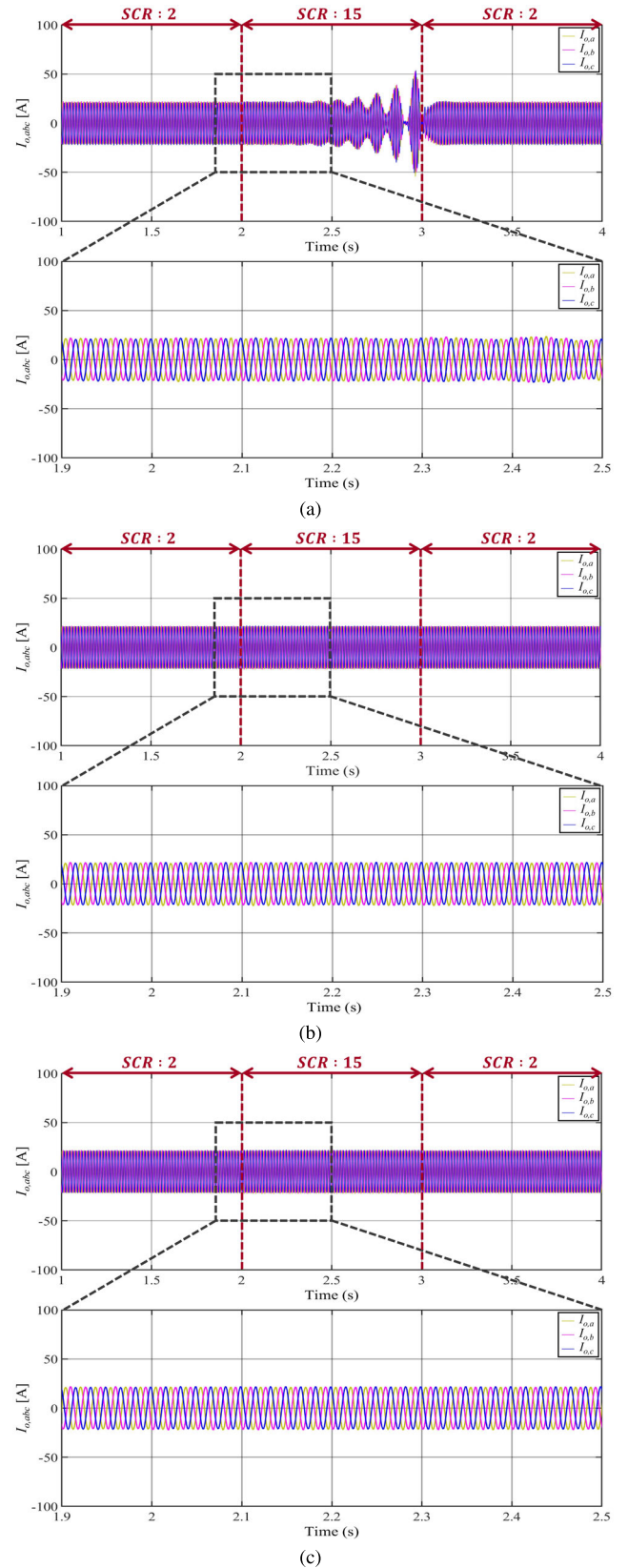


FIGURE 11. Output current waveforms of the GFMI under SCR variations: (a) PI-based current control, (b) pole-placement-based current control, and (c) EKF-LQR-based current control.

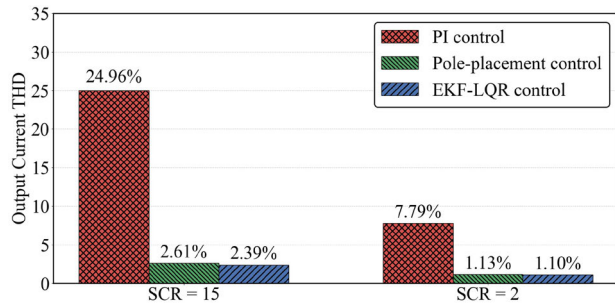


FIGURE 12. Current THD comparison under SCR variations.

obtained with the pole placement-based current controller. Compared with the PI controller, the output current waveforms are maintained more stably during the SCR variation, which indicates improved robustness against grid-strength variation. Fig. 11(c) shows the results obtained with the proposed EKF-LQR-based current controller. The output current waveforms are robustly maintained during both the weak-to-strong grid transition and the strong-to-weak grid transition. This demonstrates that the proposed method preserves stable current-control performance and favorable dynamic characteristics under both strong-grid and weak-grid conditions.

Fig. 12 presents the quantitative current THD results for each control method under the strong-grid and weak-grid conditions. To evaluate the output current harmonic characteristics for each SCR condition, the THD was calculated using a 60-cycle analysis window from 2 s to 3 s for the strong-grid condition with $SCR = 15$ and from 3 s to 4 s for the weak-grid condition with $SCR = 2$. Since each 60-cycle analysis window begins at the corresponding SCR transition instant, the calculated THD values include the transient response immediately after the grid-strength change as well as the subsequent waveform behavior over the entire one-second interval. Therefore, six THD values are compared: the strong-grid and weak-grid THD values of the PI, pole placement, and EKF-LQR current controllers.

Under the strong-grid condition with $SCR = 15$, the THD values of the PI, pole placement, and EKF-LQR current controllers were measured as 24.96%, 2.61%, and 2.39%, respectively. The PI controller exhibits a significantly higher THD. In particular, the THD of 24.96% obtained with the PI controller reflects the sustained oscillatory behavior observed throughout the strong-grid interval in Fig. 11(a), rather than only the short-duration transient occurring immediately after the SCR transition. A similar sustained oscillatory tendency is also observed in the corresponding HILS waveform shown in Fig. 16(a). In contrast, the pole-placement and EKF-LQR controllers maintain much lower THD values under the same strong-grid condition. In particular, the proposed EKF-LQR controller achieves the lowest THD of 2.39%, which is 0.22 percentage points lower than that of the pole-placement controller. In contrast, the pole placement and EKF-LQR controllers maintain much



FIGURE 13. HILS-based experimental setup for validating the proposed EKF-LQR-based current controller.

lower THD values under the same strong-grid condition. In particular, the proposed EKF-LQR controller achieves the lowest THD of 2.39%, which is 0.22 percentage points lower than that of the pole placement controller.

Under the weak-grid condition with $SCR = 2$, the THD values of the PI, pole placement, and EKF-LQR current controllers were measured as 7.79%, 1.13%, and 1.10%, respectively. Although the THD of the PI controller decreases compared with the strong-grid interval, it remains higher than those of the other two controllers. The pole placement controller achieves a low THD of 1.13%, indicating stable current-control performance under the weak-grid condition. However, the proposed EKF-LQR controller achieves the lowest THD of 1.10%, showing the best harmonic performance among the three methods.

These results confirm that the proposed EKF-LQR current controller maintains stable output current waveforms and low THD under both strong-grid and weak-grid conditions. This improved performance is attributed to the EKF-based real-time current-state estimation, which provides more reliable current-state estimates under grid-impedance variation, and the LQR-based optimal feedback gain, which enhances the dynamic current-regulation performance. Consequently, the proposed EKF-LQR current controller achieves superior waveform quality and robust dynamic characteristics during SCR variation.

V. HARDWARE-IN-THE-LOOP SYSTEM EXPERIMENT SETUP AND RESULTS

A. HARDWARE-IN-THE-LOOP SYSTEM EXPERIMENT SETUP

To verify the real-time implementability and control performance of the proposed EKF-LQR-based current controller,

hardware-in-the-loop system (HILS) experiments were conducted. Fig. 13 illustrates the HILS-based experimental setup developed in this study. The GFMI system model is implemented on a real-time simulator (OPAL-RT OP-5707) and controlled by an external controller (Texas Instruments TMS320F28377). To experimentally validate the dynamic performance and robustness of the proposed controller, the HILS environment was configured to reproduce the same scenarios as those used in the simulation studies in Section IV, including active-power reference step changes, phase-jump operation, and SCR variations. The experimental results were measured using an oscilloscope. Figs. 14 and 15 show the current control loop responses under active-power reference step changes and phase-jump operation, respectively, while Fig. 16 shows the GFMI output current waveforms under SCR variations.

The proposed EKF–LQR routine was implemented using floating-point arithmetic on the TMS320F28377 DSP with a 10-kHz current-control interrupt. Therefore, the available computation time for one control period is 100 μ s. To satisfy this real-time constraint, the implementation of the proposed controller is based on the reduced two-state current model. The discrete-time LQR gain is computed offline from the reduced current-state model and the selected weighting matrices. Thus, the DSP does not solve the Riccati equation during real-time operation. At each sampling instant, the DSP only evaluates the LQR control law using the precomputed gain matrix, which reduces the control-input computation to a fixed 2×2 matrix-vector multiplication.

The additional computational burden is mainly introduced by the EKF prediction and update steps. However, the EKF is formulated only for the dq -axis inductor-current states. Therefore, the covariance matrix, process-noise covariance, measurement-noise covariance, and innovation covariance are all limited to 2×2 matrices. In addition, because the measurement matrix is $C = I_2$, the innovation covariance is obtained as a 2×2 matrix, and its inverse can be implemented using a closed-form 2×2 inverse. This reduced-order structure decreases the computational overhead compared with a full 4×4 EKF implementation.

The execution time of the implemented EKF–LQR routine was measured in the 10-kHz current-control interrupt by toggling a GPIO pin before and after the EKF–LQR routine. The corresponding pulse width was measured using an oscilloscope. The measured execution time was 18.3 μ s, which is lower than the available 100 μ s computation time per control period. Therefore, the proposed EKF–LQR current controller can be executed within one sampling period on the TMS320F28377 DSP with sufficient timing margin.

B. HARDWARE-IN-THE-LOOP SYSTEM EXPERIMENT RESULTS

Fig. 14 shows the HILS experimental results of the current control loop response under active-power reference step changes. This experiment verifies the dynamic response of the current controller when the operating point of the

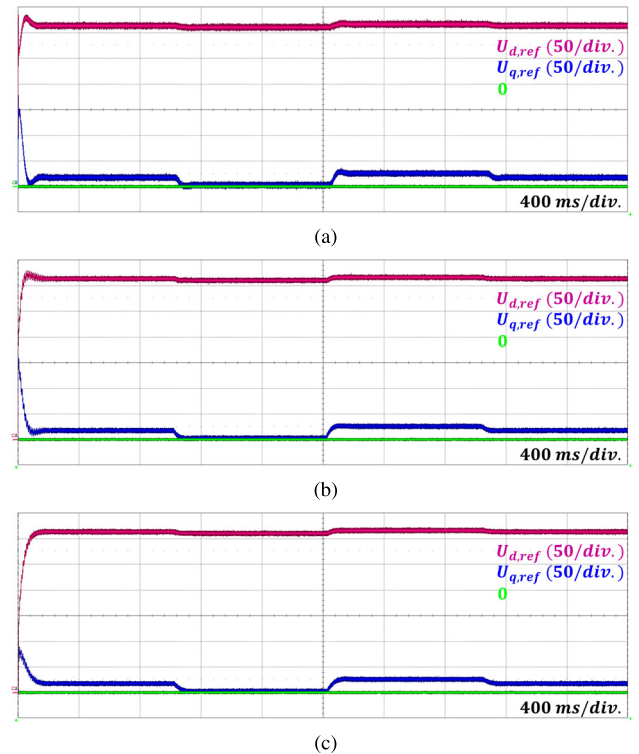


FIGURE 14. HILS experimental results of the current control loop response under active-power reference step changes: (a) PI-based current control, (b) pole-placement-based current control, and (c) EKF–LQR-based current control.

GFMI changes according to the active-power reference variation. Fig. 14(a) corresponds to the case with PI-based current control. Among the three control methods, the PI-based controller exhibits the largest transient deviation and oscillatory components during the initial response and after the active-power reference transitions.

Fig. 14(b) presents the HILS experimental results obtained using pole-placement-based current control. Compared with the PI-based case, the pole-placement-based controller reduces the transient deviation and improves the dynamic response of the current control loop. However, residual oscillatory components are still observed around the transient intervals. This result shows that the pole-placement-based controller improves the current-control-loop dynamics, but its response can still be affected by practical implementation factors such as delay, signal noise, and real-time measurement conditions in the HILS setup.

Fig. 14(c) shows the HILS experimental results obtained using the EKF–LQR-based current control. The proposed controller exhibits the smallest transient deviation and the most damped current-control-loop response among the three control methods. In particular, the response remains smooth after each active-power reference transition, indicating that the EKF-estimated current states and the LQR control law effectively improve the dynamic regulation capability of the current control loop. Therefore, the HILS results confirm that the proposed EKF–LQR-based current controller enhances

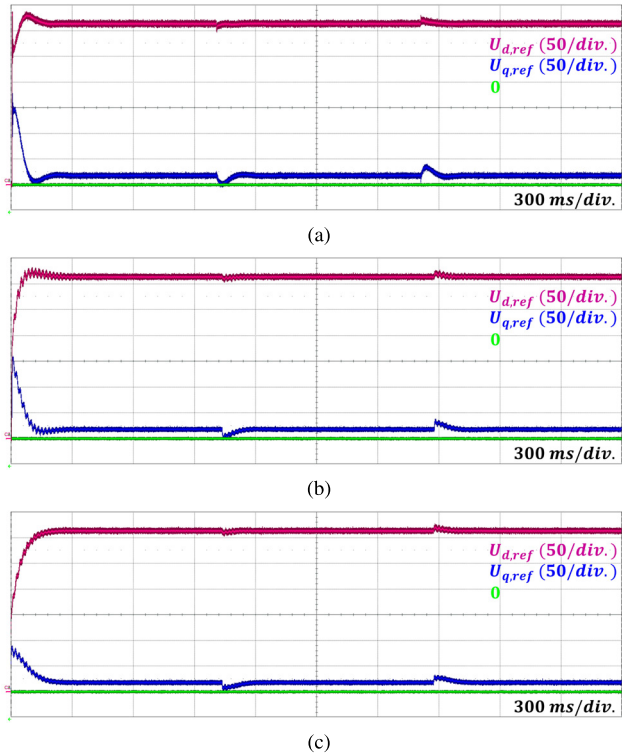


FIGURE 15. HILS experimental results of the current control loop response under phase-jump operation: (a) PI-based current control, (b) pole-placement-based current control, and (c) EKF-LQR-based current control.

the dynamic response and maintains robust current-control performance under active-power reference variations.

Fig. 15 shows the HILS experimental results of the current control loop response under phase-jump operation. Fig. 15(a) corresponds to the PI-based current control case. During the phase-jump intervals, the PI-based controller exhibits relatively large transient deviations and oscillatory components among the three control methods. In particular, the q -axis current response is more sensitive to the phase-angle variation, resulting in a larger transient fluctuation after the phase jump. This result indicates that the PI-based current controller has relatively limited transient-response performance when the grid-voltage phase changes abruptly.

Fig. 15(b) presents the HILS experimental results obtained using pole-placement-based current control. Compared with the PI-based case, the pole-placement-based controller reduces the transient deviation caused by the phase jump and improves the current-control-loop response. However, residual oscillatory components and ripple still remain around the phase-jump instants, particularly during the transient area. This result indicates that pole placement improves the dynamic characteristics of the current control loop compared with PI control, but its transient response is still affected by abrupt phase-angle variations and practical HILS implementation factors such as delay, measurement noise, and real-time signal processing.

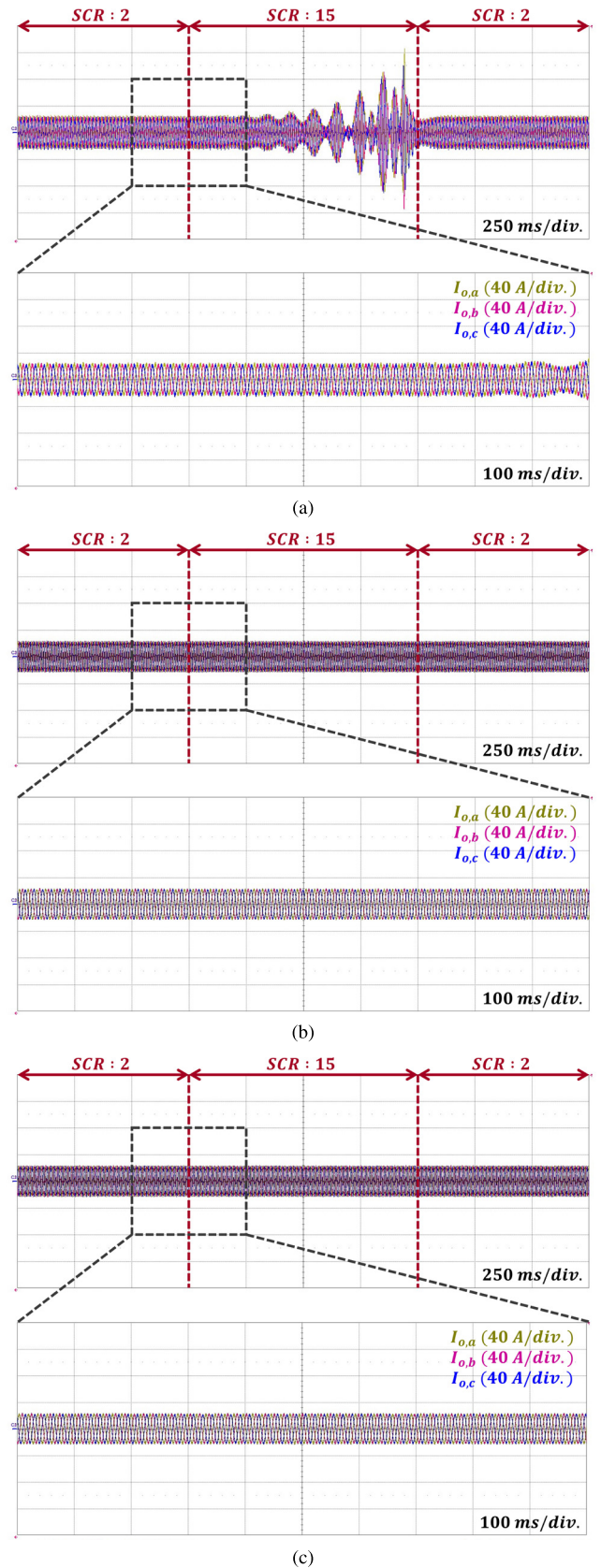


FIGURE 16. HILS experimental results of the GFMI output current under SCR variations: (a) PI-based current control, (b) pole-placement-based current control, and (c) EKF-LQR-based current control.

Fig. 15(c) corresponds to the case with EKF-LQR-based current control. Compared with the PI-based and pole-placement-based controllers, the proposed EKF-LQR-based controller exhibits smaller transient deviations and reduced oscillatory components during phase-jump operation. In particular, both the d - and q -axis current responses show improved transient recovery after the phase-angle disturbance. This result indicates that the EKF-estimated current states provide more reliable feedback information to the LQR controller, while the LQR control law improves the transient regulation capability of the current control loop. Therefore, the HILS experimental results verify that the proposed EKF-LQR-based current controller enhances the dynamic response and robustness of the current control loop under abrupt phase-angle variations.

Fig. 16 shows the GFMI output current waveforms obtained from the HILS experiments under the same SCR variation conditions as those in Fig. 11, when different current control strategies are applied. Fig. 16(a) corresponds to the case with PI-based current control. In this case, distortion appears in the output current waveform during SCR variations. In particular, when the SCR increases from 2 to 15, relatively large oscillatory components are observed in the output current waveform. In addition, compared with the simulation results presented in Section IV, the HILS experiments exhibit oscillatory components with larger amplitudes due to practical implementation factors such as signal noise, interface delay, and real-time measurement conditions. These results indicate that the PI-based current controller is relatively sensitive to grid impedance variations in the practical HILS environment.

Fig. 16(b) presents the experimental results obtained using pole-placement-based current control. Compared with the PI-based case, the output current waveform is significantly improved under the same SCR variation conditions. The pronounced distortion and amplitude variation observed in the PI-based case are not clearly observed, and the output current remains well regulated during both weak-grid and strong-grid intervals. This result is consistent with the simulation results in Section IV, where the pole-placement-based controller also maintained stable output current waveforms under SCR variations. Therefore, the pole-placement-based current controller improves the robustness of the current control loop against grid impedance variations compared with the PI-based controller.

Fig. 16(c) corresponds to the case with EKF-LQR-based current control. In this case, the output current waveform also remains stable without noticeable amplitude variations or pronounced distortion despite SCR changes. Similar to the simulation results, the HILS waveform shows that the proposed EKF-LQR-based current controller maintains stable output current performance under both SCR = 2 and SCR = 15 conditions. This behavior results from the EKF-based current-state estimation and the LQR-based control law, which improve the robustness of the current control loop against grid impedance variations. Therefore, the HILS

experimental results verify that the proposed EKF-LQR-based current controller can maintain stable current-control performance in practical hardware environments under SCR variations.

VI. CONCLUSION

This paper proposed an EKF-LQR-based current control loop to improve the dynamic response and robustness of a grid-forming inverter. The proposed method estimates the dq -axis current states using the EKF and applies them to the LQR control law, thereby enhancing the current-control performance under operating-condition variations. Under active-power reference step changes, the proposed controller showed smaller transient deviations and faster settling behavior than the PI-based and pole-placement-based controllers. Under phase-jump operation, it reduced the transient oscillatory components and improved the response characteristics of the current control loop, particularly in the q -axis current response. Under SCR variations, the proposed controller maintained stable output current waveforms under both weak-grid and strong-grid conditions, confirming its robustness against grid impedance variations. The MATLAB/Simulink-based simulations and HILS experiments verified that the proposed EKF-LQR-based current controller effectively enhances the dynamic characteristics and robustness of the GFMI current control loop under operating-condition variations. Therefore, the proposed method provides a practical current-control solution for improving the transient performance and robust operation of grid-forming inverters.

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