This paper addresses the problem of distributed secondary voltage control of an islanded microgrid (MG) from a cyber-physical perspective. An event-triggered distributed model predictive control (DMPC) scheme is designed to regulate the voltage magnitude of each distributed generator (DG) in order to achieve a better trade-off between the control performance and communication and computation burden. By using two novel event triggering conditions that can be easily embedded into the DMPC for the application of MG control, the computation and communication burdens are significantly reduced with negligible compromise of control performance. In addition, to reduce the sensor cost and to eliminate the negative effects of non-linearity, an adaptive non-asymptotic observer is utilized to estimate the internal and output signals of each DG. Thanks to the deadbeat observation property, the observer can be applied periodically to cooperate with the DMPC-based voltage regulator. Finally, the effectiveness of the proposed control method has been tested on a simple configuration with 4 DGs and the modified IEEE-13 test system through several representative scenarios.
1 | INTRODUCTION

A microgrid (MG) is a single controllable entity with interconnected loads and distributed energy resources [1-3]. Combining these physical plants with indispensable measurement and control loops, MG has been investigated as a typical cyber-physical system (CPS) [4]. A MG can connect and disconnect from the grid to operate in either grid-connected or islanded mode [1-5]. When in the islanded mode, MG control architecture can be divided into three parts: primary control, secondary control and tertiary control [6,7]. The primary control is implemented locally, whereas the secondary control and the tertiary control coordinate the controllable distributed generators (DGs) in the MG to achieve respective control objectives: commonly the objective of the secondary control is to regulate the voltage/frequency to its references and to guarantee the accurate power sharing, while the objective of the tertiary control is to achieve the economic dispatch [2,6,8].

This paper focuses on the secondary control of the MGs. Initial research on this topic investigates the centralized control strategies [9], where DGs receive control commands from a center controller. However, due to the fact that the centralized control structure suffers communication delays and requires extensive communication and computation infrastructure, the distributed control strategies, which allow each DG to communicate only with neighboring DGs, have received increasing attention [10,11]. In particular, distributed control strategies such as linear feedback control [12,13,14], finite-time control [15,16], fixed-time control [17], have been applied to improve the secondary control in the MG with sparse communication network. However, most of existing distributed secondary control methods of the MG [15,18,17] are still designed and implemented in a time-triggered fashion, where the sensing and the controlling are conducted periodically. The time-triggered control could lead to inefficient utilization of computation and communication resources as many data transmissions and calculations are not actually essential to guarantee the control performance.

In this context, the event-triggered control has been proposed to achieve a better trade-off between the control performance and communication and computation burden [19,20,21]. This may prolong the lifetime of the battery-powered controllers and keep resilient against reduced communication resources caused by cyber contingency. So far, several event-triggered secondary control methods have been developed in the MG system with droop-based DGs. However, several problems related to the event-triggered MG secondary control need further investigation: (i) the triggering conditions for simultaneously reducing computation and communication have not been fully considered; (ii) practical limitations such as model non-linearity and inevitable Gaussian noise have been largely neglected in the MG control; (iii) the existing event-triggered MG control methods [14,22] are designed with the assumption that the system state information are fully available, which may not be the case for certain system configuration or require continuously running of an observer.

To mitigate the aforementioned problems, a distributed robust voltage control of an islanded MG is designed based on an event-triggered distributed model predictive control (DMPC) and an adaptive non-asymptotic observer. The main contributions of this paper are as follows: (i) a novel distributed event-triggered DMPC framework is proposed to restore the voltage for islanded MGs and two event triggering conditions which can be easily embedded into the DMPC are designed respectively to reduce computation and communication in the cyber layer; (ii) an adaptive non-asymptotic observer is designed to facilitate a cost-effective output-based control framework, which, unlike the Luenberger-like observer [23,24], can operate in an intermittent way due to its deadbeat convergence property; (iii) the integrated control framework that coordinates the proposed DMPC voltage regulator and the non-asymptotic observer is designed from a timing sequence perspective.

The remainder of this paper is organized as follows. Section 2 is concerned with the cyber-physical modelling of the islanded MG and the corresponding problem formulation. In Section 3, the DMPC with specific event-triggered
mechanism and the adaptive non-asymptotic observer are detailed. The corresponding simulation cases are provided in Section 4 and the conclusions are collected in Section 5.

Primary notations and definitions are given as follows. The set of real numbers is denoted by \( \mathbb{R} \). For any vector \( x \), \( \|x\| \) denotes the Euclidean norm and \( \|x\|_Q = \sqrt{x^T Q x} \) stands for \( Q \)-weighted norm, where \( Q \) is a matrix with appropriate dimension. The notation \( Q > 0 \) denotes that \( Q \) is a positive definite matrix. For any set \( N \), \( |N| \) denotes the number of elements in \( N \). For any \( n \)th order differentiable \( y(t) \), \( y^{(n)}(t) \) denotes the \( n \)th order differential value. The notation \( 1_n \in \mathbb{R}^n \) denotes a column vector with all elements being ones, i.e., \( 1_n = [1, 1, \cdots, 1]^T \). The notation \( I_n \) denotes the \( n \)th order identity matrix.

2 | PROBLEM FORMULATION

In this section, the model for designing distributed robust control method of an islanded microgrid is detailed from a cyber-physical coupling system perspective. The physical system contains the electrical topology of the MG and its local controllers, while the cyber layer of the MG can be modeled as a multi-agent system with interconnecting communications, as shown in Figure 1.

2.1 | Physical System

The MG physically contains multiple DGs that are interconnected through the electrical network. If there is a line between DG \( i \) and DG \( j \) with the impedance \( Z_{ij} = R_{ij} + j X_{ij} \), due to the inductive impedance [14][25], the output active

---

**FIGURE 1** Distributed control structure of a cyber-physical coupling MG.
Power and reactive power of DG $i$ can be expressed as follows:

$$P_i = P_{iL} + \sum_{j=1}^{N_i} \frac{V_i V_j}{X_{ij}} \sin(\theta_i - \theta_j)$$  (1)

$$Q_i = Q_{iL} + \sum_{j=1}^{N_i} \left[ \frac{V_i^2}{X_{ij}} - \frac{V_i V_j}{X_{ij}} \cos(\theta_i - \theta_j) \right]$$  (2)

where $P_{iL}$ and $Q_{iL}$ are active and reactive power of the load at bus $i$; and $V_i$ and $\theta_i$ are the bus voltage and the angle at bus $i$. Due to the fact that the phase difference $(\theta_i - \theta_j)$ is small [26], $\sin(\theta_i - \theta_j) \approx (\theta_i - \theta_j)$ and $\cos(\theta_i - \theta_j) \approx 1$, which means the active and reactive power can be controlled by the difference of phase angle and voltage magnitude respectively. Thus, the conventional droop control can be obtained:

$$\omega_i = \omega_{ni} - m_P P_i$$  (3)

$$V_i = v_{odi} = V_{ni} - n_Q Q_i$$  (4)

where $\omega_i$, $V_i$ are the angular frequency and the voltage magnitude provided for the inner control loops. $m_P$, $n_Q$ are droop coefficients and are selected based on the active and reactive power ratings of each DG [7]. $\omega_{ni}, V_{ni}$ are the nominal references of the primary control, which can be generated from the secondary control. It should be noted that each DG is controlled under itself $d$-q (direct-quadrature) axis, which guarantees the voltage magnitude $V_i$ is equivalent to the $d$-axis voltage $v_{odi}$, which means $v_{eqi}^* = 0$. Through the droop control principle, each inverter is controlled with its rotating angular reference. To model the MG in a uniform frame, a specifically chosen DG is considered as the common reference $\omega_{com}$, and the angular frequency difference of the $i$th DG can be denoted by $\delta_i$:

$$\delta_i = \omega_i - \omega_{com}$$  (5)

Combining detailed models in the DG control loops as shown in Figure 2 (including models of inner loops shown in the APPENDIX), the large-signal dynamic model of the $i$th DG can be detailed as the following multi-input multi-output (MIMO) nonlinear system:

$$\dot{x}_i = f_i(x_i) + g_i(x_i)u_i + k_i(x_i)d_i(x_j)$$  (6)

with the state vector

$$x_i = [\delta_i \; P_i \; Q_i \; \phi_{qi} \; \phi_{di} \; \gamma_{di} \; i_{di} \; i_{dj} \; v_{odi} \; v_{odi} \; v_{odi} \; v_{odi} \; i_{odi} \; i_{odi} \; i_{odi}]^T,$$

where the system input is denoted by $u_i = [\omega_i \; V_{ni}]^T$ and $d_i(x_j) = [\omega_{com} \; v_{bdi} \; v_{bqi}]^T$ reflects the interconnection with other DGs, modeled as a disturbance in the single DG system.

2.2 | Cyber System

To realize the implementation of the secondary controllers, we assume each DG is equipped with a transceiver for information exchange among sparsely distributed DGs. Thus, as depicted in Figure 4, the communication network in the multi-DG MG can be modelled as a weighted graph $G_c = (V_c, E_c)$, where $V_c = \{v_1, v_2, \ldots, v_N\}$ is a set of
nodes, $\mathcal{E}_e \subseteq \mathcal{V}_e \times \mathcal{V}_e$ is a set of edges, and $N$ is the number of controllable DG nodes. A edge $(v_j, v_i)$ means that the $i$th node can receive information from the $j$th node and $v_j$ is a neighbour of $v_i$. The set of neighbours of node $i$ is described by $N_i = \{ j : (v_j, v_i) \in \mathcal{E}_e \}$. The corresponding adjacency matrix $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N \times N}$ is denoted by $a_{ii} = 0; a_{ij} > 0$ if $(v_j, v_i) \in \mathcal{E}_e$, otherwise $c_{ij} = 0$. For the graph representing a MG, there exists a virtual leader (reference node), whose adjacency matrix is denoted by $\mathcal{B} = \text{diag} \{ b_i \} \in \mathbb{R}^{m \times m}$, and the Laplacian matrix $\mathcal{L} = \mathcal{D} - \mathcal{A} + \mathcal{B}$, where $\mathcal{D} = \text{diag} \{ \sum_{j \in N_i} a_{ij} \}$.

The objective of the secondary voltage control designed in the cyber system is to regulate the output voltage magnitude $V_i$ of each DG to a unified reference $v_{\text{ref}}$ through a leader-following scheme, in the sense that $v_{\text{ref},1} = v_{\text{ref}}$ and $v_{\text{ref},i} = V_{i-1}, \forall i > 1$. In other words, each DG tracks its neighbors’ voltage to achieve the reference tracking. In the cyber layer design, it is meaningful and desirable to limit the computation and communication, especially with the wireless embedded control systems [19]. From this point of view, this paper proposes an event-triggered control framework, where, as opposed to the conventional control with continuous (or periodic) observation and control of the system, control tasks are executed only when certain conditions are met in order to minimise the computation and communication costs.

3 | LINEAR DMPC BASED NOISE-RESILIENT VOLTAGE CONTROL ALGORITHM DESIGN

The proposed control scheme, as shown in Figure 3, is mainly comprised of three parts: distributed model predictive control (DMPC) based voltage regulator, event triggering mechanism design and adaptive non-asymptotic observer. The voltage regulator is designed based on the DMPC framework, where the event-triggered mechanism can be easily embedded to alleviate the computation burden. In addition, the information exchange among agents is also governed by the event trigger scheme in order to reduce communication cost. Finally, to reduce sensor cost, an adaptive non-asymptotic observer is utilized for the reconstruction of internal and output signals. Owing to its fast convergence property, the observer can be operated in an intermittent way, and consequently, it can be integrated into the overall event-triggered control framework.
3.1 | DMPC-Based Voltage Restoration

The system model [6] is a MIMO nonlinear system, but when voltage control is considered, instead of using such a sophisticated model, linearization feedback [12] is utilized to simplify the model into a linearized form:

\[
\begin{align*}
\dot{y}_{i,1} &= v_{odi} = y_{i,2} \\
\dot{y}_{i,2} &= v_{odi} = f_i(x_i) + g_i u_i \\
y_{i,o} &= y_{i,1} = v_{odi}
\end{align*}
\]

\[f_i(x_i) = L_{P_i}^2 h_i(x_i) = \left( -\omega_i^2 - \frac{K_{Pci} K_{Pvi} + 1}{C_{fi} L_{fi}} \right) v_{odi} - \omega_i \frac{K_{Pci} K_{Pvi} n_{oi} Q_i}{C_{fi} L_{fi}} v_{odi} + \frac{R_{ci}}{C_{fi} L_{ci}} i_{odi} - \frac{2\omega_i}{C_{fi}} i_{odi} - \frac{R_{fi} + K_{Pci}}{C_{fi} L_{fi}} v_{odi}
\]

\[g_i = L_{gi} L_{P_i} h_i(x_i) = \frac{K_{Pci} K_{Pvi}}{C_{fi} L_{fi}}
\]

where \(f_i(x_i)\) represents the system non-linearity.

Let us define an auxiliary control variable \(\xi_i = f_i(x_i) + g_i u_i\), then \(u_i = (g_i)^{-1}(\xi_i - f_i(x_i))\) and the dynamic system [7] can be rewritten as

\[
\begin{align*}
\dot{\xi}_i &= A \xi_i + B \xi_i \\
y_{i,o} &= C \xi_i
\end{align*}
\]

\[y_i = \begin{bmatrix} y_{i,1} \\ y_{i,2} \end{bmatrix}, \quad A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \end{bmatrix}
\]

The distributed voltage regulation problem is to find appropriate input \(\xi_i\) to achieve \(y_{i,o} \rightarrow v_{ref,i}\). To implement DMPC,
the discrete-time model of (8) is obtained through Euler discretization:

\[
\begin{align*}
    y_i(k + 1) &= A_z y_i(k) + B_z \xi_i(k) \\
    y_{i,\text{o}}(k) &= C_z y_i(k)
\end{align*}
\]  

(9)

where \( A_z = I + A T_s \), \( B_z = B T_s \), \( C_z = C \) and \( T_s \) denotes the sampling time interval.

At each time-step \( k \), the time-triggered DMPC solves voltage tracking control problem by applying the model-based prediction:

\[
y_{i,\text{o}}(k + h \mid k) = C_z A_z^h y_i(k) + \sum_{i=0}^{h-1} C_z A_z^{h-i} B_z \xi_i(k + i \mid k)
\]

(10)

where \( h = 1, 2, \cdots, H \) denotes the prediction time steps with the horizon length \( H \), and the prediction model (10) also can be expressed in a matrix form:

\[
Y_{i,\text{o}}(k) = \begin{bmatrix}
    y_{i,\text{o}}(k + 1 | k) \\
    y_{i,\text{o}}(k + 2 | k) \\
    \vdots \\
    y_{i,\text{o}}(k + H | k)
\end{bmatrix} = F_i y_i(k) + G_i \Xi_i(k)
\]

(11)

Due to the fact that the proposed DMPC tracking voltage reference by eliminating the difference between local and neighboring DGs’ voltage magnitudes, the objective function is designed as follows:

\[
\min_{\Xi_i(k)} J_i(y_i(k), \Xi_i(k)) = \frac{1}{|N_i|} \sum_{j \in N_i} \| Y_{i,\text{o}}(k) - Y_{j,\text{o}}(k) \|_Q^2 + \| \Xi_i(k) \|_R^2
\]

(12)

where \( |N_i| \) denotes the neighbor number of the \( i \)th DG; the weighting matrix \( Q > 0, R > 0 \) are designed to balance the tracking performance and the control effort. It is noteworthy that when solving the optimization problem, the output of the virtual leader (reference node) is a constant vector \( Y_{0,\text{o}}(k) = 1_H v_{\text{ref}} \). At each time step \( k \), the optimization is repeated and only the first control input \( \xi_i(k | k) \) of the optimal control sequence \( \Xi_i(k) \) is applied to the DG.

### 3.2 Event Triggering Condition Design

Traditionally, the DMPC-based voltage regulation algorithm relies on the iterative finite-horizon optimization and information exchange among DGs at each time step \( k \), which heavily increase the computation and communication burdens. In this connection, an event-triggered scheme is designed and integrated into the DMPC framework to effectively save computation and communication power without sacrificing control performance. The overall scheme of a single DG is shown in Figure 4. To better demonstrate the event triggering mechanisms, two sets of samples, are defined: \( O = \{ k \mid \Phi(k) \} \) collects the time steps when the DMPC optimization is triggered, while \( C = \{ k \mid \Psi(k) \} \)
collects the time steps when the communication is activated, where \( \Phi(k) \) and \( \Psi(k) \) denote the event-trigger rules for optimization and communication, respectively. The design of these rules is introduced next.

The event-trigger conditions for the DMPC optimization is discussed at first. With the aim of reducing the number of optimization iterations, the DMPC can be made active only when the control performance is not satisfactory. Considering the DMPC is triggered at \( k_m \) th step \( (k_m \in \mathcal{O}) \), then for any \( k > k_m \) the DMPC is disabled unless 1) the prediction of the system behavior based on the previously calculated control is not reliable any more, or 2) the maximum horizon is reached:

\[
\Phi(k) : \quad \| y_{i,o}(k) - y_{i,o}(k|m) \| \geq \epsilon_{opt} \quad \text{OR} \quad k \geq k_m + H \tag{13}
\]

where \( \epsilon_{opt} > 0 \) is the user designed threshold for the prediction error. Assuming the DMPC is reactivated at \( k_m + n \) th step with \( 1 \leq n \leq H \), the control input is not updated by optimization for any steps in between (i.e., \( k_m + m, 1 \leq m < n \)). Without loss of generality, the input sequence \( \Xi_i(k_m + m) \) is updated by

\[
\Xi_i(k_m + m) = \begin{bmatrix} \xi_i(k_m + m|k_m) & \cdots & \xi_i(k_m + H - 1|k_m) \end{bmatrix}^T, \quad 1 \leq m < n \leq H \tag{14}
\]

and based on (14) the output predictions are reevaluated by (11).

On the other hand, to eliminate unnecessary data exchange, the communication between DGs is also regulated by an event-triggered mechanism. Considering the fact that the communication is not required when the consensus among voltage signals of each DG is achieved, the communication is enabled only when the control signal meets the following condition:

\[
\Psi(k) : \quad \| \Xi_i(k) \|^2 \geq \epsilon_{com} \tag{15}
\]

as the local control signal is driven by the local voltage tracking error and tends to be very small when voltage signals are
TABLE 1  Event-triggered voltage regulation algorithm

| Event-triggered DMPC iterations in time step $k$ for each DG $i$ |
|---|
| 1: given $k$, $y_i(k)$, $Y_{i,o}(k)$, $j \in N_i$, $\Xi(k - 1)$: |
| 2: if $13$ holds |
| 3: solve $12$ to update the control input sequence $\Xi_i(k)$ and the voltage magnitude output sequence $Y_{i,o}(k)$ |
| 4: else |
| 5: update $\Xi_i(k)$, $Y_{i,o}(k)$ according to $14$ and $11$ respectively |
| 6: end if |
| 7: apply $\xi_i(k|k)$ to DG $i$ |
| 8: if $15$ holds |
| 9: update $Y_{i,o}(k)$ in the communication network |
| 10: end if |

synchronized across all DGs. As such, if the condition $15$ is triggered at $k_j$th time step ($k_j \in C$), the voltage predictions $Y_{i,o}(k_j)$ are updated through the communication network.

Since the threshold $e_{com}$ is tracking error dependent, the following offline optimization derived from $12$ can be formulated to find a virtual input sequence $\Xi_e$ that guides the threshold selection:

$$\begin{aligned}
&\min_{\Xi_e} J_e(y_e, \Xi_e) = \|Y_{e,o} - 1_{[y_{ref}]} \|_Q^2 + \|\Xi_e\|_R^2 \\
e_{com} = \|\Xi_e\|_R, y_e = [y_{ref} + d_0 \ 0]^T
\end{aligned}$$

(16)

where $d_0$ is the user designed voltage tracking error and $Y_{e,o}$ is obtained from $11$ with the initial state $y_e$.

Based on the discussion above, the event-triggered DMPC-based voltage regulation algorithm is illustrated in Table 1. The impacts of the event triggering thresholds $e_{opt}$ and $e_{com}$ on the system behavior will be numerically investigated in Section 4 to provide further insights into the selection of the thresholds.

3.3  Finite-time Adaptive Observer Design for Enhancing Noise-Resilience

The mismatch between the continuous-time system [8] and the discretized system [9] is highly influenced by the non-linearity $f_i(x_i)$ embedded in $\xi_i$ due to the variation of $f_i$ within two samples. As such, the evaluation of the $y_i(k+1)$ based on the given control input at $k+1$ may be inaccurate, and in turn, affects the upcoming optimization and prediction. In addition, after generating the auxiliary control variable $\xi_i$, the actual control input $u_i$ is obtained by $u_i = (g_i)^{-1}(\xi_i - f_i(x_i))$, where the term $f_i(x_i)$ need to be evaluated and additional sensors may be required to monitor the internal states, such as $v_{odi}$, $v_{oqi}$. In fact, to obtain the state $y_i$ and the term $f_i(x_i)$, a more cost-effective solution is to use a system observer for reconstructing the real-time state $y_i$ and the time-varying variable $f_i(x_i)$, where the influence of measurement noise can also be highly attenuated [24].

In the sequel, to streamline the notation, let us consider $y_i(t) = z(t) = [z_0(t) \ z_1(t)]^T$ and $y_{i,o}(t) = y(t)$. Then, the
single DG system [7] can be rewritten in the following observer-canonical form:

\[
\begin{align*}
\dot{z}(t) &= A z(t) + B u(t) + B_w w(t) \\
y(t) &= C z(t)
\end{align*}
\]

with \(A = \begin{bmatrix} a_1 & 1 \\ a_0 & 0 \end{bmatrix}, B = \begin{bmatrix} b_1 \\ b_0 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \end{bmatrix}, B_w = \begin{bmatrix} a_1 \\ a_0 \end{bmatrix} = \begin{bmatrix} 0 \\ f(x(t)) \end{bmatrix}, w(t) = 1
\]

Motivated by a recently proposed deadbeat adaptive observer [28], which offers nearly instantaneous convergence property with high noise immunity, the intermittent (over short time-interval) state and parameter estimation can be enabled to cooperate with the proposed DMPC algorithm. Assuming the short time-interval can guarantee that \(f(x(t))\) can be seen as a constant parameter, we can convert the linear time-varying (LTV) system [17] to a linear time-invariant system (LTI) with an unknown parameter \(a_0 = f\).

To proceed with the analysis, the state-space system [17] is expressed as the combination of the input-output derivatives:

\[
y^{(n)}(t) = \sum_{i=0}^{n-1} a_i y^{(i)}(t) + \sum_{i=0}^{n-1} b_j u^{(i)}(t) + \sum_{i=0}^{n-1} \alpha_i w^{(i)}(t) \\
z_r(t) = y^{(r)}(t) - \sum_{j=0}^{r-1} a_{n-r+j} y^{(i)}(t) - \sum_{j=0}^{r-1} b_{n-r+j} u^{(i)}(t) - \sum_{j=0}^{r-1} \alpha_{n-r+j} w^{(i)}(t)
\]

where \(n = r = 2\) and \(\sum_{j=0}^{k} \{ \cdot \} = 0, k < 0, y^{(i)}(t)\) denotes the \(n\)th differential value of \(y(t)\) and \(z_r(t)\) denotes the \(r\)th element of the state in [17].

Let us introduce the Volterra integral operator \(V_K\) induced by a bivariate function \(K(t, \tau)\) to the output and its derivatives:

\[
[V_K y^{(i)}](t) \triangleq \int_0^t K(t, \tau) y^{(i)}(\tau) d\tau, \forall i \in \{0, \cdots, n\}
\]

where \(K(t, \tau)\) is the \(n\)th order non-asymptotic kernel [29] subject to

\[
k^{(i)}(t, 0) = 0, \forall i \in \{0, \cdots, n\}
\]

After some algebra, we get:

\[
[V_K y^{(i)}](t) = \sum_{j=0}^{i-1} (-1)^{j-1} y^{(j)}(t) K^{(i-j-1)}(t, t) + (-1)^i [V_{K^{(i)}} y](t)
\]

which can be obtained by applying the integral by parts and [21]. If \(i = 1\),

\[
[V_{K^{(1)}} y](t) = y(t) K(t, t) - [V_{K^{(1)}} y](t)
\]
Replacing \( y(t) \) with \( y^{(n-1)}(t) \), (23) becomes

\[
[V_{K(t)} y^{(n-1)}](t) = y^{(n-1)}(t)K(t, t) - [V_{K} y^{(n)}](t)
\]

which can be further expanded by substituting (18)

\begin{equation}
(-1)^{n-1}[V_{K(t)} y](t) = - \sum_{j=0}^{n-2} (-1)^{n-2-j} y^{(j)}(t) K^{(n-j-1)}(t, t) + y^{(n-1)}(t) K(t, t)
\end{equation}

\begin{equation}
\hspace{0.5cm} - \sum_{i=0}^{n-1} a_i [V_{K} y^{(i)}](t) - \sum_{i=0}^{n-1} b_i [V_{K} u^{(i)}](t) - \sum_{i=0}^{n-1} \alpha_i [V_{K} w^{(i)}](t)
\end{equation}

Substituting (22) and its same forms with \( u(t), w(t) \) into (24), we obtain

\begin{equation}
(-1)^{n-1}[V_{K(t)} y](t) + \sum_{i=0}^{n-1} (-1)^i a_i [V_{K} y^{(i)}](t) + \sum_{i=0}^{n-1} (-1)^i b_i [V_{K} u^{(i)}](t)
\end{equation}

\begin{equation}
\hspace{0.5cm} = - \sum_{i=0}^{n-1} (-1)^i \alpha_i ([V_{K(t)} w](t) + \sum_{r=0}^{n-1} (-1)^{n-r-1} K^{(n-r-1)}(t, t) z_r(t)
\end{equation}

where the state variables \( z_r(t) \) and the unknown parameters \( \alpha_i \) appear explicitly, and can be obtained by the casual filtering of the signals \( y(t), u(t) \).

Considering the specific parameters of (17), the following expression can be inferred from (25):

\begin{equation}
(-1)[V_{K(t)} y](t) + [V_{K} u](t) = f [V_{K} w](t) + (-1)K^{(1)}(t, t) z_0(t) + K(t, t) z_1(t)
\end{equation}

To estimate the state and unknown parameter, let us define

\begin{equation}
\lambda(t) \triangleq (-1)[V_{K(t)} y](t) + [V_{K} u](t)
\end{equation}

\begin{equation}
\gamma(t) \triangleq [V_{K} w](t), (-1)K^{(1)}(t, t), K(t, t)
\end{equation}

Then, (26) can be rewritten as

\begin{equation}
\lambda(t) = \gamma(t) \begin{bmatrix} f \\ z(t) \end{bmatrix}
\end{equation}

To find the estimates of \( \begin{bmatrix} f \\ z(t) \end{bmatrix} \) (of dimension 3), we can apply three different non-asymptotic kernel functions to augment (29) into three linearly independent equations

\begin{equation}
\Lambda(t) = \Gamma(t) \begin{bmatrix} f \\ z(t) \end{bmatrix}
\end{equation}

where \( \Lambda(t) = [\lambda_0(t), \lambda_1(t), \lambda_2(t)]^T \) and \( \Gamma(t) = [\gamma_0^T(t), \gamma_1^T(t), \gamma_2^T(t)]^T \), and \( \lambda_0(t), \gamma_0(t), \lambda_1(t), \gamma_1(t), \lambda_2(t), \gamma_2(t), h \in (0, 1, 2) \) are (27) and (28).

FIGURE 5 Time-sequence cooperation between the event-triggered DMPC and the non-asymptotic observer.

induced with the kernel functions respectively. The three kernel functions are designed as follows [29]:

\[ K_h(t, \tau) = e^{-\omega_h(t-\tau)}(1 - e^{-\omega \tau})^2, \ h \in \{0, 1, 2\} \tag{31} \]

which meets the non-asymptotic condition [21]. Finally, the estimates are obtained by:

\[ \begin{bmatrix} \hat{f} \\ \hat{z} \end{bmatrix} = \Gamma^{-1}(t) \Lambda(t), \forall t_e < t < t_e + \Delta t \tag{32} \]

where \( t_e \) is the observer initialization time to guarantee the invertibility of \( \Gamma(t) \) (\( \Gamma(0) = 0 \)) and \( \Delta t \) is the observation time that ensure the transient invariant characteristic of \( f \).

The proposed non-asymptotic observer [32] has to cooperate with the proposed event-triggered DMPC voltage regulation from a timing sequence perspective, as shown in Figure 5. At the time step \( k \), the estimates in [32] should be ready for the voltage regulator. Assuming the time at the step \( k \) is \( t_k \), the proposed observer is operated at \( t_k - \Delta t - t_e \). After that, the observation is activated at \( t_k - \Delta t \) and stopped at time instant \( t_k \), when the observed \( \hat{f}_i \) and \( \hat{y}_i \) are available to the voltage regulator.

4 | SIMULATION RESULTS

In this section, the proposed event-triggered robust control method is tested on a simple MG configuration with 4 DGs and on the modified IEEE-13 test system.

4.1 | Case 1: 4-DG MG system

The single line diagram of the 4-DG MG and its communication topology is shown in Figure 6. The parameters of the tested MG system and the proposed controllers is shown in Table 2. The simulation test involves a few representative scenarios by which the effectiveness of the proposed methodology can be reflected.

4.1.1 | Scenario 1: Load Change and Plug-and-Play Capability Test

In this Scenario, the control performance of the proposed control is illustrated under load change and DG’s plug-and-play operation: in the beginning, Load2 is disconnect from the system and only primary control is applied; at \( t = 1s \), the proposed secondary control is activated; Load2 and half of Load3 are connected and disconnected at \( t = 2s \) and \( t = 3s \) respectively, and DG4 is disconnected and re-connected at \( t = 4s \) and \( t = 5s \) respectively. The performance of voltage
FIGURE 6  Diagram of the tested 4-bus MG system.

TABLE 2  Parameters of the tested 4-bus MG system.

|                      | DG1    | DG2    | DG3 & DG4 |
|----------------------|--------|--------|-----------|
| $m_p$                | $6.28 \times 10^{-5}$ | $9.42 \times 10^{-5}$ | $12.56 \times 10^{-5}$ |
| $n_Q$                | $0.5 \times 10^{-3}$  | $0.75 \times 10^{-3}$ | $1 \times 10^{-3}$    |
| $R_f$                | 0.1 Ω  | 0.1 Ω  | 0.1 Ω     |
| $L_f$                | 1.35 mH | 1.35 mH | 1.35 mH   |
| $C_f$                | 47 μF  | 47 μF  | 47 μF     |
| $R_c$                | 0.02 Ω | 0.02 Ω | 0.02 Ω    |
| $L_c$                | 2 mH   | 2 mH   | 2 mH      |
| $K_{PV}$             | 0.05   | 0.05   | 0.1       |
| $K_{IV}$             | 390    | 390    | 420       |
| $K_{PC}$             | 10.5   | 10.5   | 15        |
| $K_{IC}$             | $1.6 \times 10^4$   | $1.6 \times 10^4$   | $2 \times 10^4$       |
| Lines                | Line1  | $R = 0.23 \Omega, L = 318 \mu H$ |          |
| Lines                | Line2  | $R = 0.35 \Omega, L = 1847 \mu H$ |          |
| Lines                | Line3  | $R = 0.23 \Omega, L = 318 \mu H$ |          |
| RL Loads             | Load1  | $R = 2 \Omega, L = 6.4 \mu H$      |          |
| RL Loads             | Load2  | $R = 4 \Omega, L = 9.6 \mu H$      |          |
| RL Loads             | Load3  | $R = 6 \Omega, L = 12.8 \mu H$     |          |
| RL Loads             | Load4  | $R = 6 \Omega, L = 12.8 \mu H$     |          |
| DMPC                 | $v_{ref} = 311(220\sqrt{2})$, $Q = 10I_N$, $R = 0.15I_N$, $H = 10$ |
| Control Parameters   | Event Triggering Thresholds | $e_{opt} = 0.1$, $e_{com} = 2.30$ |
| Observer             | $\varpi = 2.5$, $[\omega_0, \omega_1, \omega_2] = [1, 2, 3]$ |
By using the event-triggered mechanism, the sacrifice of control performance is limited, whereas the computation and communication are both considerably reduced. It should be noted that the dynamics of the voltage regulation at $t = 5s$ is worse than any other time, due the the fact that the re-connection of the DG leads to the re-synchronization of the AC MG system.

By employing the proposed non-asymptotic observer, the negative effects of the disturbance can be eliminated, as shown in Figure 8. The performance of the proposed observer is emphasized by the comparisons among true values, observed values and disturbance contaminated values that are obtained from indirect measurement in the noisy environment. Compared to the previous Luenberger-like extended state observer [24], the proposed non-asymptotic observer benefits from its intermittent operating characteristic. The performance comparisons between intermittent operating Luenberger-like observer and the proposed non-asymptotic observer is shown in Figure 7, where we can see that Luenberger-like Observer cannot estimate the state precisely when the system responses to the physical events. If the Luenberger-like extended state observer is working intermittently as the proposed non-asymptotic observer, the voltage tracking performance will degrade as Figure 7(b).

FIGURE 7 Voltage control performance by using event-triggered mechanism: (a) voltage tracking performance with time-triggered mechanism; (b) voltage tracking performance with event-triggered mechanism; (c) event-triggered time of DMPC optimization; (d) event-triggered time of neighbouring communication.
### Table 3: Computation and communication reductions by using event-triggered mechanism

|               | DG1  | DG2  | DG3  | DG4  | Average |
|---------------|------|------|------|------|---------|
| Computation Reduction | 67.15% | 56.26% | 47.19% | 45.01% | 53.90%  |
| Communication Reduction | 86.93% | 82.58% | 79.13% | 78.04% | 81.67%   |

**Figure 8** Non-asymptotic observer performance.

### 4.1.2 Scenario 2: Control Performance with Different Event Triggering Thresholds

The control performance of proposed event-triggered mechanism may be influenced by the selection of thresholds for both computation and communication event generators. Therefore, in Scenario 2, case studies as Scenario 1 are carried out with different triggering thresholds.

The control performance with fixed $e_{com}$ ($e_{com} = 2.30$) but different thresholds $e_{opt}$ is detailed in Figure 10 and Table 4. As $e_{opt}$ increases, the optimization computation of each DG controller decreases largely, but from Figure 10 we can also see the control performance will clearly degrade when $e_{opt} = 0.2$ and $e_{opt} = 0.3$. Thus, the selection of $e_{opt}$ is a trade-off between the tracking performance and the computation reduction.

The control performance with fixed $e_{opt}$ ($e_{opt} = 0.1$) but different thresholds $e_{com}$ is detailed in Figure 11 and Table 5. By choosing $d_0 = 0.01$, $d_0 = 0.1$, $d_0 = 0.2$ and $d_0 = 0.3$, we can obtain four different thresholds $e_{com}$. As $e_{com}$ increases, the communication among DGs is reduced with the gradually degraded control performance.

### 4.1.3 Scenario 3: Communication Topology Change

In Scenario 3, we consider communication interruptions which may occur in the distributed operation, and the physical and cyber events is shown in Figure 12. In the cyber layer, the communication change mimics the failure and recovery of
**FIGURE 9** Voltage control performance with intermittent operating Luenberger-like observer.

**FIGURE 10** Event-triggered condition with fixed $e_{\text{com}}$ ($e_{\text{com}} = 2.30$) but different thresholds $e_{\text{opt}}$: (a) $e_{\text{opt}} = 0.05$; (b) $e_{\text{opt}} = 0.1$; (c) $e_{\text{opt}} = 0.2$; (d) $e_{\text{opt}} = 0.3$.

cyber links. The corresponding control performance is shown in Figure 13 and Table 6. The voltage tracking performance is maintained during the whole event, although DG4 has a voltage tracking error during the time period $2 < t < 4$ (DG4
TABLE 4 Computation and communication reductions with fixed $e_{\text{com}}$ ($e_{\text{com}} = 2.30$) but different thresholds $e_{\text{opt}}$.

| $e_{\text{opt}}$ | DG1  | DG2  | DG3  | DG4  | Average |
|------------------|------|------|------|------|---------|
| 0.05             | 4.54%| 6.53%| 10.16%| 12.34%| 8.39%   |
| Computation Reduction |
| 0.1              | 67.15%| 56.26%| 47.19%| 45.01%| 53.90%  |
| 0.2              | 83.85%| 80.58%| 77.13%| 78.04%| 79.90%  |
| 0.3              | 85.66%| 83.30%| 80.04%| 79.85%| 82.21%  |
| Communication Reduction |
| 0.05             | 87.66%| 84.03%| 76.41%| 78.58%| 81.67%  |
| 0.1              | 86.93%| 82.58%| 79.13%| 78.04%| 81.67%  |
| 0.2              | 85.12%| 82.58%| 76.59%| 74.41%| 79.67%  |
| 0.3              | 84.57%| 79.31%| 75.68%| 72.41%| 77.99%  |

FIGURE 11 Event-triggered condition with fixed $e_{\text{opt}}$ ($e_{\text{opt}} = 0.1$) but different thresholds $e_{\text{com}}$: (a) $e_{\text{com}} = 0.006$; (b) $e_{\text{com}} = 0.57$; (c) $e_{\text{com}} = 2.30$; (d) $e_{\text{com}} = 5.17$.

operates only with primary control due to lack of neighbouring information). However, this error is eliminated after the cyber reconfiguration.

4.2 | Case 2: Modified IEEE-13 bus system

A real MG system is utilized to further test the effectiveness of the proposed method. The electrical and communication topology of the modified IEEE-13 bus test system [30] is shown in Figure 14 where there is a breaker between node 671 and 692. The simulation test focuses on the scalability and especially the resilience against potential system reconfiguration.
### TABLE 5
Computations and communication reductions with fixed $e_{opt}$ ($e_{opt} = 0.1$) but different thresholds $e_{com}$.

| $e_{com}$ | DG1 | DG2 | DG3 | DG4 | Average |
|-----------|-----|-----|-----|-----|---------|
| 0.006     | 58.80% | 51.00% | 36.30% | 44.10% | 47.55% |
| 0.57      | 62.98% | 56.44% | 41.74% | 43.56% | 51.18% |
| 2.30      | 67.15% | 56.26% | 47.19% | 45.01% | 53.90% |
| 5.17      | 62.98% | 54.99% | 44.28% | 36.12% | 49.59% |

### Computation Reduction

### Communication Reduction

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### FIGURE 12
Physical and cyber events of the 4-DG MG system.

### TABLE 6
Computations and communication reductions in cyber and physical events.

|                | DG1   | DG2   | DG3   | DG4   | Average |
|----------------|-------|-------|-------|-------|---------|
| Computation Reduction | 67.15% | 56.62% | 49.36% | 63.88% | 59.26% |
| Communication Reduction   | 93.28% | 89.84% | 87.11% | 83.48% | 88.43% |

### 4.2.1 Scenario 1: Scalability Test

In this Scenario, the breaker between nodes 671 and 692 is always switched on, and the scalability of the proposed control is illustrated by load change and DG’s plug-and-play scenario: loads at bus 645 and bus 675 are decreased and increased at $t = 2\text{s}$, $3\text{s}$ respectively; and DG4 is disconnected and re-connected at $t = 4\text{s}$ and $t = 5\text{s}$ respectively. The voltage tracking performance is shown in Figure 15 and the average reductions of computation and communication are 46.64% and 83.61%.
4.2.2 | Scenario 2: Resilience Illustration with System Reconfiguration

To evaluate the resilience of the proposed voltage regulation method when the system reconfiguration occurs on both physical and cyber layers, we design the physical and cyber events (including breaker switched off and on) as shown in Figure 13. The corresponding control performance is shown in Figure 14. Although there are tracking errors caused by cyber events and tracking dynamics due to both physical and cyber events, the voltage tracking performance is guaranteed by using event-triggered DMPC method, and the average reductions of computation and communication are 54.70% and 84.91%. The dynamics at $t = 5s$ are caused by the re-synchronization after the break is switched on.

**FIGURE 13** Voltage control performance with cyber and physical events by using event-triggered mechanism.

**FIGURE 14** Diagram of modified IEEE-13 bus MG system
**FIGURE 15** Voltage control performance of modified IEEE-13 bus MG system: (a) voltage tracking performance with time-triggered mechanism; (b) voltage tracking performance with event-triggered mechanism; (c) event-triggered time of DMPC optimization; (d) event-triggered time of neighbouring communication.

**FIGURE 16** Physical and cyber events of modified IEEE-13 bus MG system
In this paper, an event-triggered distributed secondary voltage control scheme that considers the model non-linearity and the system noise-resilience has been presented for a cyber-physical coupled MG system. In the control design, based on the event-triggered DMPC, two thresholds are designed to trigger the local DMPC computation and neighboring communications among DGs. To facilitate a cost-effective and noise-resilient control, an adaptive observer that features the non-asymptotic convergence characteristic is utilized, and this designed adaptive non-asymptotic observer can be coordinated with the DMPC voltage regulator in a timing sequence. Finally, the effectiveness of the proposed control method is verified on a 4-DG MG system and the modified IEEE-13 system.
APPENDIX

| Dynamic models of DG inner loops |

As shown in Figure 2, the instantaneous active and reactive powers are generated through a low-pass filter with the cutoff frequency \( \omega_{ci} \ll \omega_i \):

\[
P_i = -\omega_{ci} P_i + \omega_{ci} (v_{odi} i_{odi} + v_{oqi} i_{oqi})
\]
\[
Q_i = -\omega_{ci} Q_i + \omega_{ci} (v_{oqi} i_{odi} - v_{odi} i_{oqi})
\]

(33) (34)

where \( v_{odi}, v_{oqi} \) and \( i_{odi}, i_{oqi} \) are \( d-q \) voltage and current of the \( i \)th DG output respectively. Apart from the droop control, the inner control loops (the voltage control loop and the current control loop) are modelled as:

\[
\begin{align*}
\phi_{di} &= v_{odi}^* - v_{odi} \\
\phi_{qi} &= v_{oqi}^* - v_{oqi} \\
i_{odi}^* &= f_i i_{odi} - \omega_b C_f v_{oqi} + K_{PV} (v_{odi}^* - v_{odi}) + K_{IV} \phi_{di} \\
i_{oqi}^* &= f_i i_{oqi} + \omega_b C_f v_{odi} + K_{PV} (v_{oqi}^* - v_{oqi}) + K_{IV} \phi_{qi} \\
\dot{y}_{di} &= i_{odi}^* - i_{odi} \\
\dot{y}_{qi} &= i_{oqi}^* - i_{oqi} \\
\psi_{odi}^* &= -\omega_b L_f i_{oqi} + K_{PC} (i_{odi}^* - i_{odi}) + K_{IC} \dot{y}_{di} \\
\dot{v}_{oqi}^* &= \omega_b L_f i_{odi} + K_{PC} (i_{oqi}^* - i_{oqi}) + K_{IC} \dot{y}_{qi}
\end{align*}
\]

(35)

where \( \phi_{di}, \phi_{qi}, \gamma_{di}, \gamma_{qi} \) are auxiliary variables for the voltage controller and the current controller respectively; \( K_{PV}, K_{IV}, \) and \( K_{PC}, K_{IC} \) are \( P-I \) control parameters for the voltage controller and the current controller; \( \omega_b \) represents the rated frequency of the MG; \( F_i \) is the parameter for \( d-q \) frame compensation. The dynamics of the LC filter and the output impedance also can be expressed as

\[
\begin{align*}
i_{odi} &= -\frac{R_f}{L_f} i_{odi} + \frac{1}{L_f} v_{odi} - \frac{1}{C_f} i_{odi} \\
i_{oqi} &= -\frac{R_f}{L_f} i_{oqi} - \frac{1}{L_f} v_{oqi} - \frac{1}{C_f} i_{oqi} \\
v_{odi} &= \omega_b i_{odi} + \frac{1}{C_f} i_{odi} - \frac{1}{C_f} i_{odi} \\
v_{oqi} &= -\omega_b i_{oqi} + \frac{1}{C_f} i_{oqi} - \frac{1}{C_f} i_{oqi} \\
\dot{i}_{odi} &= -\frac{R_c}{L_c} i_{odi} + \omega_b i_{odi} + \frac{1}{L_c} v_{odi} - \frac{1}{L_c} v_{odi} \\
\dot{i}_{oqi} &= -\frac{R_c}{L_c} i_{oqi} - \omega_b i_{oqi} + \frac{1}{L_c} v_{oqi} - \frac{1}{L_c} v_{oqi}
\end{align*}
\]

(36)

where \( i_{odi}, i_{oqi} \) denote currents at the LC filter inductance; \( v_{odi}, v_{oqi} \) denote the voltages at the connection bus in Figure 2.
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