This paper investigates an adaptive control problem for switched cyber-physical systems subject to external disturbances, denial-of-service (DoS) attacks, and false data injection attacks. We consider attackers to be able to threaten the networked system performance, where the DoS depletes the network bandwidth and might randomly block out the transmission signals or produce a significant delay in transmission signals, while the false data injections fabricate the transmission signal as a disturbance. To handle the abrupt occurrence of cyber attacks, the power system is modeled as a switched system. The switched system responds to changing dynamic models and among the states when the system parameters are altered due to disturbances, denial-of-service, and false data injection attacks. The proposed controller unit involves a reliable estimation scheme to estimate and compensate for cyber attacks while sustaining the desired performance and robustness. A distinctive feature of the proposed controller is the introduction of a low-pass filter, which is particularly convenient for attenuating parameter fluctuations and guaranteeing a rapid adaptation rate. The simulation of the closed loop system shows that the proposed $L_1$ controller outperforms the $H_\infty$ controller. A simulation study is established to illustrate the influence and robustness of the developed controller, which can enhance the transient response under different operating conditions.

**INDEX TERMS** $L_1$ adaptive controller, load frequency, state feedback.

**I. INTRODUCTION**

The trend of global power and energy companies is to increase their electric power generation to meet the high requirements of the power supply. Power systems in general are complex, interconnected networks in which power units can exchange power with neighboring units via transmission lines. Distributed power systems suffer from different types of nonlinearities and communication constraints. It should be noted that a change in load frequency would have some series consequences for the entire interconnected system, which could lead to damage to generators and transformers or cause them to deviate from their normal operation. For all of the foregoing reasons, any disturbance that may occur among multi-area units may produce fluctuations in voltage and frequency signals from the standard values. The primary aim of the control system is to automatically regulate power generation and consumption in an interconnected network while sustaining the voltage and frequency at predefined values. To perform continuous regulation and monitoring, large-scale power plants are outfitted with smart measurement and actuation devices that share critical information via various communication channels [1], [2].

Cyber-physical systems are one of the most attractive research areas due to the high integration between a variety of engineering disciplines, namely computing, telecommunications, and control. The performance of physical systems may be intensely degraded by the existence of attacks. With the fast development of attack technologies and programs, using smart transducers with shared communication networks
makes the power system more vulnerable. In general, false data injection and denial-of-service (DoS) attacks are the most commonly reported attacks on power systems. The impact of DoS attacks is introduced as a communication failure or a varying time delay in transmitted signals.

As smart meters on the load end may be influenced by a variety of circumstances, including power theft, equipment malfunction, and cyber attack, those factors could contribute to the inaccurate injection of relevant data for customers. This type of fake data attack typically confuses power efficiency, resulting in incorrect dispatch schemes, increasing economic costs and emission rates, and potentially causing a safety issue. Real system loads and measured data may vary significantly, posing a security concern when the measured data is required immediately to achieve proper operation of interconnected power systems [3]. Also, false data injections in the shared channels are introduced as nonlinear signals or as equipment faults. Because tie lines and communication channels are shared by distributed power areas, attackers can disrupt all connected areas at the same time.

In another research area, switched systems are basically a sort of hybrid dynamical system used quite frequently to deal with complex systems. These systems involve a set of continuous- or discrete-time subsystems where a switching signal manages the switching among the subsystems. The switching signal is a key factor in maintaining the performance and stability of the overall system. Switched systems can form a wide class of systems that exhibit switching features and provide a proper solution for many complex systems that are required to be modeled due to changes in parameters and operating conditions, such as chemical-oil plants, networked control systems, multi-agent systems, and power systems, among others. Additionally, switching controllers can provide a dynamic solution when no special control unit is functional [4], [5]. The most difficult challenge is dealing with significant increases in customer demand while maintaining the quality of delivered power and the reliability of the power system. This quality is accomplished by balancing customer requirements with the utility grids. The consistency and stability of frequency and voltage electric signals are important factors in power quality and safety. Nevertheless, the imperfections of environmental conditions, load variations, generation constraints, nonlinearities, and false data injections might degrade the power system. Due to mismatches between power generation and demand, sudden frequency variations from predefined values can be observed. As a result, the operating points of the power system change quickly. To sustain power quality and frequency stability, various control methodologies have been effectively utilized. The designed controller must be able to maintain power quality and reliability in the face of disturbances such as changes in load, generation, and system uncertainties [1] and [7].

On a different note, load frequency control (LFC) is a critical issue in power systems and has received considerable attention in academia and industry. A load frequency control technique is locally applied to immediately regulate the output real power of distributed power systems in the presence of generation and load demand variations [1]. When a frequency oscillation occurs as a result of mismatching issues, the local droop controller works to restore the power flow and frequency to nominal levels in multi-area networks. As a result, local controllers may cause some fluctuations in power quality and frequency, and they cannot maintain stability on their own. The main idea behind secondary-level control is to use the local control loop to stabilize the power flow and frequency fluctuations in tie lines [7].

Automatic generation control systems of multi-area power systems are powerful tools that have the capability to handle disturbances, unknown constraints, and nonlinearities due to the system dynamics. These factors may cause fluctuations in system stability due to the rapid change of operating points, which may have unfavorable consequences. The controllers must ensure the quality of power and frequency stability in the presence of such problems. The frequency and the networking power are usually sustained at reference values by employing AGC with a feedback control strategy. A load frequency controller is effectively implemented as a secondary-level controller that can deal with small frequency fluctuations caused by the AGC. In this setting, the secondary-level control system can eliminate steady-state errors and enhance the overall performance of multi-area power systems. The area control error (ACE) integral has been used to maintain error in control signals to zero which comprises the frequency fluctuations and the error based on the tie line and regulating the prime movers of the generators [7]. That means designing a robust LFC is necessary to deliver better performance and minimize steady-state error.

To address the aforementioned issues, much research has been published and control strategies have been tested in order to improve the quality of power flow over distributed power lines and provide better dynamic responses. Various types of load frequency problems have been successfully applied, particularly proportional-integral (PI) and proportional integral derivative (PID) controllers [7], [13], optimal control [14], and robust control [15]. In particular, the parameters of classical control systems have been tuned for certain operation conditions, but these conditions may be derived due to load and generation fluctuations. However, these typical schemes have trouble accomplishing the desired performance in the existence of uncertainties and fast-changing operating points. Under these limitations, the classical controller with specified parameters usually fails to offer the desired performance. Recently, many optimization and intelligent algorithms have been effectively utilized to adaptively adjust the parameters with respect to randomly changing operation conditions [1], [2]. Load frequency control is an important part of keeping multi-area power plants that are linked together stable and getting rid of load frequency changes. Proportional-integral controllers have been widely utilized in industry to efficiently balance between the load and generations [1]. In [7], a PID based on a particle swarm algorithm was implemented to tackle the LFC problem for two area systems,
in which a particle algorithm was applied to automatically fix the PID parameters. Reference [24] investigated an LFC by adjusting the PID controller utilizing the linear matrix inequalities. In this sense, the PID parameters are optimized by minimizing the norm of the linear matrix inequality. Moreover, some adaptive control strategies have been effectively utilized to handle uncertainty issues and nonlinearities in LFC systems [16], [17], [18], and [19].

An adaptive control scheme is a sort of nonlinear control system that is widely utilized to compensate for nonlinear uncertainties in physical plants. The theory of adaptive control has received considerable attention due to the benefits it can provide for vast engineering problems. The theoretical results of adaptive control, in particular, are proven using the Lyapunov theory. It is well known that adaptive control can automatically adjust uncertainties and estimate the unknown parameters while sustaining stability and desired performance in the presence of unknown uncertainties. Correspondingly, adaptive control schemes can be divided into two methods: direct and indirect adaptive control. The former estimates only the actuation parameters, whereas the latter estimates system parameters and determines the actuation parameters using Lyapunov theory (see Hovakimyan 10). Decoupling identification from control loops allows for fast adaptation and uniform performance in the presence of nonlinear uncertainties. The distinctive feature of the $L_1$ control scheme is the introduction of a low-pass filter (LPF), which is particularly convenient for attenuating parameter fluctuations by waiving high-frequency parts within the bandwidth of the low-pass filter [20], [21], [22].

In this paper, an improved $L_1$ adaptive control scheme is developed to solve the problems arising from uncertainties, disturbances, and cyber attack problems in networked power systems. The proposed controller makes it possible to employ a high adaptation gain, which allows for fast adaptation and estimation of nonlinear uncertainties and unknown disturbances. The multi-area system shares information through a tiered communication network with distributed measuring devices, which makes it accessible to many cyber attacks. The $L_1$ adaptive controller significantly improves tracking, transit response, and robustness. In general, a decoupled controller from an estimation scheme is utilized in $L_1$ designs to estimate and compensate for cyber attacks while sustaining the desired performance and robustness. $L_1$ adaptive theory is well known for incorporating a high-gain observer in the adaptation procedure to maintain a fast response and cancel the disturbance without losing robustness. To solve this problem, low-pass filtering is mainly integrated into the control structure to tackle disturbance effects and meet the desired tracking response with increased robustness. The high-frequency components of the transit response can completely filter out of the control channel in this configuration [22].

To deal with the abrupt existence of attackers, the power system is modeled as a switched system, in which the switched system performs changing dynamic models among the states when the system parameters have altered due to disturbances, denial-of-service, or false data injection attacks. The utilization of $L_1$ LFC plays a vital role in minimizing high frequency components in the control channel. Compared with [5], [20], and [23], the main contributions of this paper are concluded as follows:

1) An improved $L_1$ adaptive controller for multi-area LFC is proposed. It constructs a MIMO $L_1$ adaptive controller for a switched power system susceptible to denial-of-service attacks and false data injection. The adaptive controller is developed to estimate the unknown parameters and manipulate the control signal according to the estimate.

2) In view of the noisy and cyber-attack sensing information, adaptive state estimation is developed to estimate the unknown parameters and manipulate the control signal according to the estimation. When an attack exists, the observation residual error goes large, and it is ignored using associated low-pass filtering.

3) In the case of an unreliable communication link where the transmission signals are subjected to different attacks, measurements and actuation are frequently altered, completely blocked (dropped), or delayed by the attacker. In addition, the probabilities of cyber attacks are modeled as independent Bernoulli-distributed white sequences [8], [9], [10], [11].

4) Develop a state feedback $L_1$ adaptive control problem of cyber-physical power systems (CPPS) in order to sustain closed-loop stability in the occurrence of attacks.

5) A switched system is used to model the time-varying transmission power plant and to ensure the system’s stability by switching the state according to the change in the operating conditions.

The remainder of this paper is as follows: Section II depicts the multi-area model, and Section III develops an $L_1$ adaptive control scheme for the LFC area. In section IV, the main result and the stability condition are analyzed and proven. In section V, the results are demonstrated in the occurrence of nonlinear uncertainties and cyber attacks. Finally, in section VI, the paper is concluded.

II. MODELING LOAD FREQUENCY PROBLEM

Automatic generation controllers have utilized feedback systems to minimize the error between the nominal values and the measured values to an accepted one. Figure (1) depicts the general structure of two-area load frequency control with cyber attacks. Communication networks at both measurement and controller units are disturbed by DoS attacks and false data injection attacks. In fact, the power flow is exchanged over a tie line between the distributed areas. The power flow and frequency are frequently constrained due to the fluctuations of generation and consumption power and the systems’ nonlinearities as well. The control design utilizes the feedback signals to equalize the area control error to zero [7].
The integral control scheme for multi-area control are given
in the area control error for Kirchhoff’s voltage and current laws on multi-area systems, generation units and a local load, as shown in Fig. 1. Using Kirchhoff’s voltage and current laws on multi-area systems, the area control error for \( n^{th} \) is represented by

\[
ACE_{1} = B_{1} \Delta f_{1} + \Delta P_{tl1}
\]

\[\vdots\]

\[
ACE_{n} = B_{n} \Delta f_{n} + \Delta P_{tln}
\]

where \( ACE_{1} \) and \( \ldots ACE_{n} \) are the area control errors of area-1 to area-n respectively. \( \Delta f_{n} \) represents load disturbance, \( \Delta P_{tln} \) tie-line power error, and \( B_{n} \) frequency bias element. The integral control scheme for multi-area control are given as:

\[
\Delta P_{c1} = -K_{1} \int (B_{1} \Delta f_{1} + \Delta P_{tl1})
\]

\[\vdots\]

\[
\Delta P_{cn} = -K_{n} \int (B_{n} \Delta f_{n} + \Delta P_{tln})
\]

\( K_{1} \) and \( \ldots K_{n} \) are the integral gain for both the areas. \( \Delta P_{c1} \), and \( \ldots \Delta P_{cn} \) are control signals of the two areas.

**A. CASE OF TWO AREA GENERATION UNITS**

Assuming a two-area system exists, the distributed systems of automatic generation control include two areas: The state space variables of the system are represented by:

\[
x_i = \begin{bmatrix} x_{i1} \\ x_{i2} \end{bmatrix}
\]

\[
x_{i1} = \begin{bmatrix} \Delta f_{1} \\ \Delta P_{t1} \\ \Delta P_{g1} \\ \Delta f_{2} \end{bmatrix} + \int ACE_{1} dt + \int ACE_{2} dt
\]

\[
x_{i2} = \begin{bmatrix} \Delta P_{g2} \\ \Delta P_{tie(1,2)} \end{bmatrix}
\]

To simplify the control design procedure, the dynamical equations (3) should be transformed to thedq-frame as:

\[
x_{1} = \frac{1}{T_{p1}} x_{1} + \frac{K_{p1}}{T_{p1}} x_{2} - \frac{K_{p1}}{T_{p1}} y_{1} - \frac{K_{p1}}{T_{p1}} d_{1}
\]

\[
x_{2} = \frac{1}{T_{t1}} x_{2} + \frac{1}{T_{t1}} x_{3}
\]

\[
x_{3} = \frac{1}{R_{1} T_{g1}} x_{1} - \frac{1}{T_{g1}} x_{3} + \frac{1}{T_{g1}} \dot{u}_{1}
\]

\[
x_{4} = \frac{1}{T_{p2}} x_{4} + \frac{K_{p2}}{T_{p2}} x_{5} + \frac{K_{p2}}{T_{p2}} x_{7} - \frac{K_{p2}}{T_{p2}} d_{2}
\]

\[
x_{5} = \frac{1}{T_{t2}} x_{5} + \frac{1}{T_{t2}} x_{6}
\]

\[
x_{6} = -\frac{1}{T_{g2}} x_{4} - \frac{1}{T_{g2}} x_{6} + \frac{1}{T_{g2}} \dot{u}_{2}
\]

\[
x_{7} = 2\pi T_{0} x_{1} - 2\pi T_{0} x_{4}
\]

\[
x_{8} = B_{1} x_{1} + x_{7}
\]

\[
x_{9} = B_{2} x_{4} - x_{7}
\]

(3)

where \( ACE_{1} \) and \( ACE_{2} \) show errors in the control area, \( R_{1} \) and \( R_{2} \) are speed governor parameters, \( T_{g1}, T_{g2}, T_{t1} \) and \( T_{t2} \) denote time constants of the governor’s speed, and turbines, respectively, \( T_{p1}, T_{p2}, K_{p1} \) and \( K_{p2} \) denote time constants and gains of the power system respectively, \( \Delta P_{tie}, \Delta f_{1} \) and \( \Delta f_{2} \) denote fluctuations in the tie-power, frequency of each area 1,2, respectively, \( \Delta P_{d1} \) and \( \Delta P_{d2} \) denote variations in local load of each area 1,2. \( T_{0}, B_{1}, \) and \( B_{2} \) represent constants of tie-synchronizing and frequency bias in the two-area [7]. The state space equation of the reheated thermal power system can be modeled as follow:

\[
\dot{x}(t) = Ax(t) + Bu(t), \quad y(t) = Cx(t)
\]

where \( x(t) \in \mathbb{R}^{n} \) denotes the state, \( u(t) \in \mathbb{R}^{m} \), denotes the control signal, and the measured output is represented by \( y(t) \in \mathbb{R}^{p} \). \( A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, \) and \( C \in \mathbb{R}^{m \times n} \) denote known dynamic, control, and measurement matrices of the power plant, respectively. The parameter values are stated in reference [7]. Equation A, as shown at the bottom of the next page.

\[
B = \begin{bmatrix} 0 & 0 \\ \frac{1}{T_{g1}} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{1}{T_{g2}} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad C^{T} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}
\]

the dynamics of the networked multi-area switched power plant can be obtained as:

\[
\dot{x}(t) = \sum_{i=1}^{N} \sigma_{i}[A_{1} x(t) + B_{1} (u_{p}(t) + d(t))]}
\]
\[\sigma_i(t+) = \delta(t, \sigma_i(t), x(t)), \quad \delta : N \times \mathbb{R}^n \rightarrow N\]
\[y(t) = \sum_{i=1}^{N} \sigma_i C x(t)\]

where \(x(t), y(t)\) and \(u_p(t)\) denote the system state, output, and control (actuation) signal, respectively. \(\delta(.)\) is commonly defined as the partitioning of a continuous sequence, \(\sigma(t+) = \lim_{t \to t+} \sigma(s)\), where \(t+ = t \geq 0\). It should be observed that model (4) represents the continuous (state) portion of linear hybrid systems. \(\sigma_i(t) : [0, \infty) \rightarrow \{N\} = \{1, 2, \ldots, N\}\) is the switching signal that excites a particular mode at any given time instant. For any \(\sigma(t) = i \in N, A_i \in \mathbb{R}^{n \times n}\).

It may be determined via a selective procedure leading to a partition of the continuous state space, see [8]. Letting \(N\) denotes the set of all selective rules. Therefore, the linear hybrid system under consideration is composed of \(N\) subsystems, each of which is activated at a particular switching instant. The associated matrices for a switching mode \(i \in N\) are \(A_1, \ldots, C_i\). As a result, we obtain the indication function \(\sigma_i(t) = \{\sigma_i(t), \ldots, \sigma_N(t)\}\).

\[\sigma_i(t) = \begin{cases} 1, & i \in \{N\} \\ 0, & \text{otherwise} \end{cases}\]

Note that \(d(t)\) denotes uncertainties due to generation/demand variations. Assuming \(A \equiv A_1 \in \mathbb{R}^{n \times n}, B \equiv B_1 \in \mathbb{R}^{n \times m}, C \equiv C_1 \in \mathbb{R}^{p \times n}\), with \((A, B)\) is controllable [22]. \(\sigma_i\) denotes a piecewise constant switching signal among the states.

**Assumption 1:** The pair \((A_1, B_1)\) is controllable.

**Assumption 2:** The switching signal is a piecewise constant function \(\sigma_i(t) = \sigma_i(t - \tau_d)\), which has a bounded dwell time, \(\tau_d > 0\), i.e. the switching signal satisfies the foregoing inequality \(t_k + 1 - t_k \geq \tau_d\) for all \(k\). The deriving of the dwell-time signal is hold here, for more details see [12].

The benefits may be described in the subsequent facets: initially, for denial-of-service (DoS), fake data injection assaults, and load disturbances in the switching CPSs, \(L_1\) controller has been designed so that the error is acceptable with required and necessary for robustness.

An adaptive control problem has been developed to ensure the stability and operation of multi-measuring devices employing a switching signal. The switching scheme can provide a smooth swap between the measuring devices to achieve the desired performance. So, the dynamic attitude of the multi-area power systems is determined by the switching scheme and the communication constraints. Fig. (2) represents a system (4) that is continuously monitored by distributed sensors for recording the system parameters of interest. Also, it assumes communication channels facilitate unidirectional information flow. The networked control signal might be represented as follows:

\[u_p(t) = \sum_{i=1}^{N} \sigma_i \{[1 - \alpha(t)]u_d(t - \tau_d) + \gamma(t)\tilde{y}(t, x_i(t))\}
+ \alpha(t) \left(u_d(t) - \mu_0 u_d(t)\right)\]

where \(\alpha(t)\) is unrelated Bernoulli distributed white sequences stand for the probability of DoS attacks that can completely block (drop) or delay the sending actuation signals, i.e., \(\alpha(t) \in \{0, 1\}\). Note that \(\alpha(t) = 1\) indicates the backward actuation signal is dropped, whereas

\[P\{\alpha(t) = 1\} = E\{\alpha(t)\} = \tilde{\alpha}(t), P\{\alpha(t) = 0\} = 1 - \tilde{\alpha}(t)\]

\[P\{\gamma(t) = 1\} = E\{\gamma(t)\} = \tilde{\gamma}(t), P\{\gamma(t) = 0\} = 1 - \tilde{\gamma}(t)\]

\(\alpha(t) = 0\) indicates the actuation signal is delayed. The scale factor \(\mu > 0\) represents DoS attacks that completely block the control signal. \(\gamma(t) \in \{0, 1\}\) is the indicator of false data injection attacks. It should be noted that \(\gamma(t) = 1\) indicates that the backward actuation signal has been falsified, whereas \(\gamma(t) = 0\) indicates that no false data has been injected [8].

\[
A = 
\begin{pmatrix}
-1 & K_{p1} & 0 & 0 & 0 & 0 & -K_{p1} & 0 & 0 \\
T_{p1} & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & T_{p1} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 0 & T_{g1} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & T_{p2} & -1 & K_{p2} & 0 & K_{p2} & 0 \\
B_1 & 0 & 0 & T_{p2} & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
2\pi T^o & -2\pi T^o & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & B_2 & 0 & 0 & 0 & -1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\]
Remark 1: From (5), this paper assumes that the denial of service attack causes an actuation signal to be dropped if \( \alpha(t) = 1 \) and it causes a delay in the signal if \( \alpha(t) = 0 \), while the deception attack is represented by a bounded nonlinearity signal if \( \gamma(t) = 1 \).

Remark 2: \( L_1 \) employs fast adaptation, an estimator, low pass filtering, and a control unit. Implementing a filter in the control architecture decouples it from the estimator. The control architecture decouples it from the estimator. The proposed \( L_1 \) method may overcome uncertainty and communication constraints by reducing the bandwidth of the reference signal and deleting outliers. \( L_1 \) controller design alters the controller to improve system performance and robustness. Low-pass filtering is essential to reduce high-frequency control components because it acts as a barrier. High adaptation gains allow for quick estimation of unknown variables’ values.

In comparison to existing adaptive strategies, this \( L_1 \) adaptive controller using a concurrent estimate method may not only result in a straightforward design approach but could also detect disturbance signs and remove the outliers. This advantage gives it an advantage over other adaptive methodologies. As a result, the estimating strategy does not need any previous information about the disturbance signal in order to function properly.

III. CYBER-PHYSICAL ATTACKS ON LOAD FREQUENCY CONTROL

Considering cyber-physical networks, a networked control model of a two-area reheat thermal system in the presence of the power demand and generation constraints and stealth attacks are considered. In addition, the backhand DoS attacks are represented by nonstationary time delays in the actuation path. channel, see Figure (2):

\[
\dot{x}(t) = \sum_{i=1}^{N} \sigma_i [Ax(t) + B(\alpha(t)(u_d(t) - \mu u_d(t))) + (1 - \alpha(t))u_d(t) - \tau_a + \gamma(\ell(f(t, x_i(t)) + d(t)))]
\]

\[
y(t) = \sum_{i=1}^{N} \sigma_i Cx(t), \quad x(0) = x_0
\]

where \( f(t, x_i(t)) = K\hat{f}(t, x_i(t)) \). The initial condition \( x_0() \) is assumed to be known within a pre-specifies set, i.e. \( \|x_0(\cdot)\|_\infty \in \varnothing_0 \).

Assumption 3: It is considered that the nonlinearity function for cyber attacks, denoted by \( f(t, x(t)) \), satisfies the preceding condition:

\[
||f(t, x(t))||_2 \leq ||G_cx(t)||_2
\]

in which \( G_c \) is a fixed matrix that represents the maximum allowable value of the nonlinear dynamics.

Assumption 4: Let the external disturbance \( d(t) \) to be bounded such as

\[
||d(t) - \hat{d}(t)|| \leq L(\varnothing_1)||d(t) - \hat{d}(t)||_\infty
\]

Where \( \varnothing, \varnothing_1 > 0, L(\varnothing) > 0, L(\varnothing_1) > 0 \) and \( F \in \mathbb{R}^{m \times n} \) are positive constants and constant matrix respectively.

Assumption 5: The unknown parameters \( \alpha(t), \gamma(t) \), \( \tau_a \) fit into given compact convex sets \( \Theta_1, \Theta_2, \Theta_3 \) respectively, where \( \alpha(t) \in \Theta_1, \gamma(t) \in \Theta_2, \tau_a \in \Theta_3 \). Let \( \alpha_{max} \) \( \gamma_{max} \) \( \tau_{max, a} \) fit into given compact convex sets. The initial condition \( x(0) \) is assumed to be known within a pre-specifies set, i.e. \( x(0) \in \varnothing_0 \).

The impact of DoS attacks is introduced as a communication failure (packet drops) or a nonstationary time delay in the backward actuation channel. Also, false data injections in the shared channels are introduced as nonlinear signals. In particular, the tie line and communication channels are shared by distributed power areas, resulting in all the connected areas being concurrently disturbed by attackers.

IV. \( L_1 \) CONTROL DESIGN

In this section, an \( L_1 \) adaptive controller for switched cyber-physical systems in the occurrence of external disturbances, DoS and false data injection attacks. Fig. 2 demonstrates a general \( L_1 \) control topology for a power system with a shared communication channels, in which the forward and backward channels are frequently subjected to various attacks. \( L_1 \) LFC controller is designed to deal with communication constraints and disturbances to ensure better performance and fast transient response. In this approach, the control system for (6) may be written as

\[
u(t) = u_1(t) + u_{ac}(t)
\]

where \( u_1(t) = -Kx(t), \) \( u_{ac}(t) \) denote state feedback, and adaptive control response, respectively. \( K \in \mathbb{R}^{m \times n} \) represents optimal gain to provide \( A_1 = A - BK \) is Hurwitz matrix. \( Q_1 \geq 0 \) and \( R_1 > 0 \) denote states and inputs weight matrices for a linear quadratic, and \( J_{ad} \geq 0 \) denotes the cost function.

\[
J_{ad} = 2 \sum_{t=0}^{\infty} \sum_{i=1}^{N} \sigma_i [x^T(t)P_1x(t) + u^T(t)R_1u(t)]
\]

Assume there exist a symmetric matrix \( P_1 = P_1^T > 0 \) and \( Q_1 \in \mathbb{R}^{m \times n} \) such that:

\[
A_1^TP_1 + P_1A_1 = -Q_1
\]

Remark 3: We have observed that matrix \( A_1 \) is Hurwitz. The strategy described in this study is generalizable to any dynamic matrix \( A_1 \) as provided that \( (A_1, B_1) \) is controllable. Since \( (A_1, B_1) \) is controllable, the gain \( K \in \mathbb{R}^{m \times n} \), exists so that \( A_1 = A - B_1K \) is Hurwitz matrix.

Remark 4: In that, it clearly differentiates efficiency and resilience, the \( L_1 \) adaptive controller has significant advantages over all other adaptive control procedures, including model-free control. The use of a low-pass filter not only ensures a bandwidth-limited input signal but, permits an arbitrarily high adaption rate that is only restricted by existing computer capabilities. This divides the controller design issue into two extremely practical restrictions and limitations: transducer bandwidth and applicable performance arithmetic.
Remark 5: The gain $K$ is computed using a continuous-time linear quadratic method that computes the new eigenvalues of the dynamic matrix $(A-BK)$, which is located on the left half of the s-plane.

According to (6) and (9), the state estimator is defined by

$$
\begin{align*}
\hat{x}(t) &= \sum_{i=1}^{N} \sigma_i [A \hat{x}(t) + B (\hat{\alpha}(t) + M u_d(t) - \mu_d(t))] + (1 - \hat{\alpha}(t) u_d(t - \tau_0) + \gamma(t) f(t, \hat{x}(t)) + \hat{d}(t)), \\
\hat{y}(t) &= \sum_{i=1}^{N} \sigma_i C \hat{x}(t), \quad \hat{x}(0) = x_0
\end{align*}
$$

where $\hat{x}(t) \in \mathbb{R}^n$ is the estimated state vector, $\hat{y}(t) \in \mathbb{R}^n$ is the estimated output.

**FIGURE 2.** $L_1$ adaptive controller.

A. ADAPTATION LAW

The estimation of unknown parameters is governed by employing projection-operator, which enables to realize within known bounds: let $\hat{x}(t) = x(t) - \hat{x}(t)$ is tracking error.

$$
\begin{align*}
\hat{\alpha}(t) &= \Gamma \text{Proj}(\hat{\alpha}(t), -\hat{x}^T(t) \sum_{i=1}^{N} \sigma_i (P_1 B u_d(t))], \\
\hat{y}(t) &= \Gamma \text{Proj}(\hat{y}(t), -\hat{x}^T(t) \sum_{i=1}^{N} \sigma_i (P_1 B \|x\|_\infty)), \\
\hat{d}(t) &= \Gamma \text{Proj}(\hat{d}(t), -\hat{x}^T(t) \sum_{i=1}^{N} \sigma_i P_1 B),
\end{align*}
$$

where $\Gamma$, $\text{Proj}(\cdot, \cdot)$ denote adaptive gain, the projection operator, respectively [22], [25]. Given that $\hat{\alpha}(0) = 0$, $\hat{y}(0) = 0$, and $\hat{d}(0) = 0$.

Remark 6: Project operation $\text{Proj}(\cdot, \cdot)$ is a kind of adaptation tool that widely employs to sustain robustness and to produce a rapid identification of unknown uncertainties within limited bounds. Additionally, this adaptive controller can effectively alter the time varying gain of the closed-loop system based on Lyapunov theory, more detailed information can be found in [29].

Remark 7: Provided a convex compact set with a uniform border provided by $\Theta_1 \triangleq \{\tilde{\alpha}(t) \in \mathbb{R}^n \mid S(\tilde{\alpha}(t)) \leq c_0\}$, $0 \leq c_0 \leq 1$ in which the preceding defines $S : \mathbb{R}^n \rightarrow \mathbb{R}$ indicated a convex compact set with a smooth boundary. Smooth function $S(\tilde{\alpha}(t)) = \frac{(\alpha(t) \tilde{\alpha}(t) - \alpha_{max}(t))}{\delta_{max}(t)}$, $\alpha_{max}(t)$ is the norm constraint placed on the vector, and $\alpha_0 > 0$ is the projection tolerance bound, the projection operator [29], $\text{Proj}(\tilde{\alpha}(t), \tilde{x}^T(t))$, as shown at the bottom of the next page.

Remark 8: In general, introducing a high adaptation rate of $\Gamma$, enhances the performance and transit response. On the other hand, the occurrence of unwanted high frequency components in the control loop due to a high value of $\Gamma$ can hurt the system’s robustness. A low-pass filter is commonly utilized to limit the communication bandwidth and can absolutely block the high-frequency parts. In the event of nonlinear uncertainties and disturbances, the integration of control and adaptive law sustains tracking and robustness.

The adaptive control signal can be represented by

$$
\begin{align*}
u_{ac}(t) &= \sum_{i=1}^{N} \sigma_i \hat{K} g(t) \left[ K_f r_f(t) - \gamma(t) f(t, x(t)) \right. \\
&- \left. \alpha(t) [u_d(t) - \mu u_d(t)] - d(t) - (1 - \alpha(t)) u_d(t - \tau_0) \right]
\end{align*}
$$

where $\hat{K} > 0$, $g(t)$ is a time domain function, which has a strictly proper transfer function, one simple selection is $G(s) = s^{\frac{1}{2}}$. For simplification, $K_f \triangleq \frac{1}{C A B^2}$ denotes a feedforward reference model gain that yields unit DC gains, and $\gamma(t)$ denotes the bounded piecewise reference signal, wherein-frequency the sound of the reference signal $\|r_f(t)\|_\infty$. Assume $\Psi_1(t) \triangleq (1 - \alpha(t)) u_d(t - \tau_0) + \gamma(t) f(t, x(t)) + \alpha(t) [u_d(t) - \mu u_d(t)] + d(t)$

B. CONTROL LAW

Calculating Laplace transforms (12), we deduce:

$$
\begin{align*}
\hat{X}(s) &= \sum_{i=1}^{N} \sigma_i [A_1 \hat{X}(s) + B (\hat{\alpha}(t) U(s) - \mu U(s)) \\
&+ (1 - \hat{\alpha}(t) U(s) e^{-ts} + \hat{\gamma}(t) F(s, \hat{X}(s)) + \hat{D}(s))] \\
\hat{X}(s) &= -\sum_{i=1}^{N} \sigma_i [A_1 \hat{X}(s) + B (C(s) - 1) \left( \hat{\alpha}(t) U(s) \\
&- (1 - \hat{\alpha}(t) U(s)) e^{-ts} + \hat{\gamma}(t) F(s, \hat{X}(s)) + \hat{D}(s) \right) - C(s) K_f r_f(t)] \\
\hat{X}(s) &= \sum_{i=1}^{N} \sigma_i [s I - A_1]^{-1} B (C(s) - 1) \left( \hat{\alpha}(t) U(s)
\right.
\end{align*}
$$
generating a stable low pass filter controllable and the transfer function $G$ and integral, respectively. In particular, since $(A_r \in \mathbb{R}^{n \times n})$ is strictly proper and bounded input bounded output subject to the following

\[
\lim_{t \to \infty} (\hat{x}(t) - x(t)) = 0.
\]

Consider the following switching control law in the frequency domain $u(s)$:

\[
u(s) = \sum_{i=1}^{N} \sigma_i \bar{K} G(s) \left[ K_f r_f(s) - (1 - \alpha) U_d(s)e^{-\tau_d s} - \gamma(t) F(t, x_i(s)) - \alpha [U_d(s) - \mu U_d(s)] - D(s) \right]
\]

where $r_f(s)$ and $G(s)$ denote transfer functions of the reference and integral, respectively. In particular, since $(A_1, B_1)$ is controllable and the transfer function $G(s)$ is a strictly proper generating a stable low pass filter $C(s)$ given as follows:

\[
C(s) \triangleq \frac{\bar{K} G(s)}{1 + \bar{K} G(s)}
\]

$C(s)$ is strictly proper and bounded input bounded output stable, $C(0) = I$, $\bar{K} > 0$ presents feedback gain.

The $L_1$ adaptive control comprises of (2), (12) and (16), subject to the following $L_1$ norm condition.

\[
\text{Proj}(\hat{x}, \bar{x}^T) \triangleq \begin{cases} 
\bar{x}^T & \text{if } S(\hat{x}) < 0 \\
\bar{x}^T - \frac{\nabla S}{\|\nabla S\|} & \text{if } S(\hat{x}) \geq 0 \land \nabla S^T \leq 0 \\
\bar{x}^T S(\hat{x}) & \text{if } S(\hat{x}) \geq 0 \land \nabla S^T > 0
\end{cases}
\]

The goal of designing a control system, according to [22], is to have the controlled output $Y_s$ follow a desired signal $r_f(s)$.

\[
Y(s) \approx G(s)r_f(s)
\]

where $C_{ad}(s) = \frac{m_u}{\sigma_{\gamma_{\max}}} > 0$ is a minimum-phase stable transfer function, $m_u$ is positive real number, and $r_f(s)$ is the reference of the minimum model.

This work contributes to switched systems with $L_1$ controller design. Neither rapid nor slow switching limitations exist. Hurwitz switching is the sole need. This approach doesn’t specifically incorporate switching stability or uncertain input parameters.

1) STABILITY ANALYSIS OF THE REFERENCE MODEL

Consider a reference model of distributed generation system such as:

\[
\begin{align*}
\dot{x}_r(t) &= \sum_{i=1}^{N} \sigma_i [A x_r(t) + B (\alpha(t) (u_r(t) - \mu u_r(t))) \\
&+ (1 - \alpha(t)) u_{r1}(t - \tau_a) + \gamma(t) f(t, x_r(t)) + d(t)]
\end{align*}
\]

\[
\begin{align*}
y_r(t) &= \sum_{i=1}^{N} \sigma_i C x_r(t),
\end{align*}
\]

\[
\begin{align*}
u_r(t) &= \sum_{i=1}^{N} \sigma_i \bar{K} g(t) \left[ K_f r_f(t) + \gamma(t) \bar{K} f_1(t, x_r(t)) \\
&- (1 - \alpha(t)) K x_r(t - \tau_a) + \alpha(t) [K x_r(t) \\
&- \mu K x_r(t)] + d(t) \right]
\end{align*}
\]

where $x_r(t) \in \mathbb{R}^n$, $y_r(t) \in \mathbb{R}^p$, and $u_r(t) \in \mathbb{R}^m$ are state vector, measured output, and the control input of the reference model respectively. The Laplace function of law pass filter:

\[
C_{r1}(s) \triangleq \frac{\bar{K} G_{r1}(s)}{1 + \bar{K} G_{r1}(s)}
\]

The $L_1$ adaptive framework comprises of (12), (13), and (17) conditionally upon the $L_1$ norm condition.

\[
\|G(s)\|_{L_1} (\alpha_{\max}, \gamma_{\max}, \tau_{\max,a}) < 1
\]

where $H(s) \triangleq (\xi - A)^{-1} B$, and $G(s) \triangleq H(s) (C(s) - 1)$.

Lemma 1: If the $L_1$ norm condition holds, then the reference model in (17) and its control law are BIBO stable with respect to reference signal.
2) PREDICTION ERROR ANALYSIS
The error dynamics can be derived:

\[
\dot{\tilde{x}}(t) = \sum_{i=1}^{N} \sigma_i [A\tilde{x}(t) + B\left(\tilde{a}(t)u_d(t) - \mu u_d(t)\right) + (1 - \tilde{a}(t))u_d(t - \tau_a) + \tilde{\gamma}(t)\tilde{y}(t, \tilde{x}_i(t)) + \tilde{d}(t)],
\]

\[
\tilde{y}(t) = \sum_{i=1}^{N} \sigma_i C\tilde{x}(t), \quad \tilde{x}(0) = x_0 \tag{18}
\]

where (\cdot) represents the error between actual and estimated parameter such \(\tilde{x}(t) = \hat{x}(t) - x(t)\), in the same sequence, there are \(\tilde{a}, \tilde{\gamma}, \tilde{x}, \text{ and } \tilde{f}\). Assume that, \(\tilde{\Psi}_1(t) \triangleq \tilde{\Psi}_r(t) + K_f r_f(t)\), then the transfer function of the prediction error is given as:

\[
\tilde{x}(s) = (sI - A)^{-1}B\tilde{\Psi}_1(t) \tag{19}
\]

The following result holds

**Lemma 2:** Regarding the system (6) and control law (5), we have

\[
\|\tilde{x}(t)\|_{\infty} \leq \sqrt{\frac{\Pi}{\lambda_{\min}(P_{1})\Gamma}} \tag{20}
\]

where \(\Pi \triangleq 4 \sum_{i=0}^{m} \max_{x \in \Xi} \|\Pi\|_{2}^{2} + 4\Delta_{2}^{2} + (\alpha_{1} - \alpha_{2})^{2} + \frac{4\lambda_{\max}(P)\max_{x \in \Xi} \|\Pi\|_{2}}{\lambda_{\min}(Q)} + d_{\Pi}\Delta\).

where \(\lambda_{\min}(S), \lambda_{\max}(S)\) denote, respectively, the smallest and largest eigenvalues of matrix \(S\).

3) STABILITY ANALYSIS

**Proof:** To prove that the input and state are bound, we introduce a candidate Lyapunov function:

\[
V(t) = \tilde{x}^T(t) P_{1}\tilde{x}(t) + \frac{1}{\Gamma}tr\left(\tilde{f}^T(t, x(t))\tilde{f}(t, x(t))\right)
\]

By taking the derivative of the Lyapunov function:

\[
\dot{V}(t) = \tilde{x}^T(t) P_{1}\tilde{x}(t) + \tilde{x}^T(t) P_{1}\tilde{x}(t) + \frac{2}{\Gamma}tr\left(\tilde{f}^T(t, x(t))\tilde{f}(t, x(t))\right)
\]

\[
= \tilde{x}^T(t) (A^T P_{1} + P_{1}A)\tilde{x}(t) + 2\tilde{x}^T(t) P_{1}\tilde{f}(t, x(t))
\]

\[
+ \frac{2}{\Gamma}tr\left(\tilde{f}^T(t, x(t))\tilde{f}(t, x(t))\right)
\]

\[
= -\tilde{x}^T(t) Q_{1}\tilde{x}(t) + 2\tilde{x}^T(t) P_{1}\tilde{f}(t, x(t))
\]

\[
+ 2tr\left(\tilde{f}^T(t, x(t))\text{Proj}\tilde{f}(t, x(t)) - \tilde{x}^T(t) P_{1}B)\right)
\]

\[
= -\tilde{x}^T(t) Q_{1}\tilde{x}(t) + 2tr(\tilde{f}^T(t, x(t))(\text{Proj}\tilde{f}(t, x(t)), -\tilde{x}^T(t) P_{1}B) - \tilde{x}^T(t) P_{1}B) \leq -\tilde{x}^T(t) Q_{1}\tilde{x}(t)
\]

\[
= -\|\tilde{x}(t)\|_{\lambda_{\min}(Q)} \|\tilde{x}(t)\|_{\Gamma} \tag{21}
\]

Therefore, \(\dot{V}(t) \leq 0\), if the output error and state error are bounded, which implies that \(\tilde{x}(t)\) and \(\tilde{f}(t, x(t))\) are uniformly bounded. Since \(\tilde{x}(0) = 0\), it follow that for more analysis see [22].

V. NUMERICAL STUDIES
This section considers an LFC problem for multi-area power systems subject to DoS and false data injection attacks; see Fig. 2.

We investigate a \(L_1\) adaptive controller with state feedback to handle system disturbances caused by load, generation fluctuations, and nonlinearities. The independent Bernoulli parameters \(\alpha(t)\) and \(\delta(t)\) that stand for DoS attacks over communication channels are depicted in Figure 4. For this purpose, a state space model of two-area systems with system disturbances and nonlinearities is given in equations (6). The model parameters of the power system are provided [7].

To see the influence of load/generation variations and nonlinearities on the system performance, we consider a sudden load disturbance of 0.01 p.u. MW. The relevant results are illustrated in Figs. 5–6. The controller design is based on the continuous-time characteristics of the regulated physical process. The collection of operations arising from the controller architecture might not have been functional with the minimal available computational resources. Although the supplied collection of processes is complete, the overall
system performance might not be optimum in the respect that does not effectively make use of computers. Especially in comparison with discrete-time scheme $L_1$ adaptive techniques, the continuous-time scheme $L_1$ adaptive techniques provide more accurate estimations and tracking of both rapid and slow behaviors in power grids that are much less susceptible to disturbances. In this case, the proposed $L_1$ controller is compared to the adaptive $H_\infty$ controller in the occurrence of nonlinear uncertainties, denial-of-service attacks, false data injection attacks, and system dynamics disturbance represented by $f(t,x(t)) \triangleq V_{mg} \sin(\omega t + \mu f)$. The adaptation rate is selected to be $\Gamma_j = 1000$. In the simulation, DoS attacks introduce a nonstationary time delay and false data injection attacks introduce nonlinearity in the communication channel. It can be recognized by figs. 5–6. The $L_1$ scheme outperforms the $H_\infty$ control method in terms of transient response.

In this case, the preferred low pass filter is:

$$C(s) = \frac{1}{0.1 \ s + 1}$$

The comparison results obviously demonstrate that $L_1$ adaptive control can bring a remarkable enhancement in the system’s performance in the existence of nonlinear uncertainties, load variations, and cyber attacks, while the performance of traditional adaptive $H_\infty$ is usually affected under varying time delays. From Fig. 5–6, it is seen that $L_1$ controller provides rapid response without fluctuations comparing with adaptive $H_\infty$ control. Thus, the validity of the proposed $L_1$ control scheme has been demonstrated yields rapid tracking response in the existing dynamic and communication constraints.

$$P_1 = \begin{bmatrix} P_1 & P_{1/2} \\ \bullet & P_{1/3} \end{bmatrix}$$

$$P_{1/1} = \begin{bmatrix} 2.871 & -2.504 & -8.397 & 18.8 & 8.43 \\ -2.50 & 47.87 & -78.34 & -35.11 & 78.19 \\ -8.39 & -78.34 & 195.85 & -5.17 & -195.65 \\ 18.77 & -35.11 & -5.17 & 176.14 & 5.39 \\ 8.43 & 78.19 & -195.65 & 5.39 & 195.56 \end{bmatrix}$$

$$P_{1/2} = \begin{bmatrix} -18.68 & -8.57 & 18.82 & -8.40 & 18.6 \\ 34.75 & -73.05 & -36.75 & -78.29 & -35.07 \\ 5.59 & 186.93 & -2.38 & 195.79 & -5.19 \\ -175.51 & -7.61 & 176.82 & -5.21 & 176.04 \\ -5.57 & -186.76 & 2.61 & -195.61 & 5.41 \end{bmatrix}$$
VI. CONCLUSION
This paper investigates an implementation of $L_1$ adaptive control based on state feedback for load frequency problems. $L_1$ adaptive controller is a robust controller that controls and ensures the network stability of a multi-area in the presence of load and generation change and nonlinearities and cyber attacks in the controller-actuator communication channel. We tested the proposed controller against the $H_{\infty}$ controller and the results demonstrate that the proposed $L_1$ adaptive control provides a remarkable enhancement in steady state error and transient performance of the load frequency in terms of system nonlinearities.

REFERENCES
[1] S. K. Pandey, S. R. Mohanty, and N. Kishor, “A literature survey on load–frequency control for conventional and distribution generation power systems,” Renew. Sustain. Energy Rev., vol. 25, pp. 318–334, Sep. 2013.

[2] R. Shankar, S. R. Pradhan, K. Chatterjee, and R. Mandal, “A comprehensive state of the art literature survey on LFC mechanism for power system,” Renew. Sustain. Energy Rev., vol. 76, pp. 1185–1207, Sep. 2017.

[3] H. Zhang, D. Yue, C. Dou, X. Xie, K. Li, and G. P. Hancke, “Resilient optimal defense strategy of TSK fuzzy-model-based microgrid’s system via a novel reinforcement learning approach,” IEEE Trans. Neural Netw. Learn. Syst., early access, Aug. 31, 2021, doi: 10.1109/TNNLS.2021.3105668.

[4] J. Fu and R. Ma, “Stabilization and $H_{\infty}$ control of switched dynamic systems,” in Studies in Systems, Decision and Control, Cham, Switzerland: Springer, 2021.

[5] N. M. Alyazidi and M. S. Mahmoud, “Distributed $H_2$/ $H_{\infty}$ filter design for discrete-time switched systems,” IEEE/CAA J. Autom. Sinica, vol. 7, no. 1, pp. 158–168, Jan. 2020.

[6] J. Liu, Y. Gu, L. Zha, Y. Liu, and J. Cao, “Event-triggered $H_{\infty}$ load frequency control for multiarea power systems under hybrid cyber attacks,” IEEE Trans. Syst., Man, Cybern., Syst., vol. 49, no. 8, pp. 1665–1678, Aug. 2019.

[7] Y. L. Abdel-Magid and M. A. Abido, “AGC tuning of interconnected reheat thermal systems with particle swarm optimization,” in Proc. 10th IEEE Int. Conf. Electron., Circuits Syst. (ICECS), Dec. 2003, pp. 376–379.

[8] Y. Ali, Y. Xia, L. Ma, and A. Hammad, “Secure design for cloud control system against distributed denial of service attack,” Control Theory Technol., vol. 16, no. 1, pp. 14–24, Feb. 2018.

[9] Y.-S. Ma, W.-W. Che, C. Deng, and Z.-G. Wu, “Observer-based event-triggered containment control for MASs under DoS attacks,” IEEE Trans. Cybern., vol. 52, no. 12, pp. 13156–13167, Dec. 2022.

[10] Y.-S. Ma, W.-W. Che, and C. Deng, “Dynamic event-triggered model-free adaptive control for nonlinear CPSs under aperiodic DoS attacks,” Inf. Sci., vol. 589, pp. 790–801, Apr. 2022.

[11] G. Guo, J. Kang, R. Li, and G. Yang, “Distributed model reference adaptive optimization of disturbed multiaut system with intermittent communications,” IEEE Trans. Cybern., vol. 52, no. 6, pp. 5464–5473, Jun. 2022.

[12] S. M. Magdi, Switched Time-Delay Systems: Stability and Control, New York, NY, USA: Springer, 2010.

[13] A. Khodabakhshian and R. Hooshmand, “A new PID controller design for automatic generation control of hydro power system,” Electr. Power Energy Syst., vol. 32, pp. 375–382, Jun. 2010.

[14] C. Zhao, U. Topcu, and S. H. Low, “Optimal load control via frequency measurement and neighborhood area communication,” IEEE Trans. Power Syst., vol. 28, no. 4, pp. 3576–3587, Nov. 2013.

[15] C. Bouchchauy, “Improving regulation service based on adaptive load frequency control in LMP energy market,” IEEE Trans. Power Syst., vol. 29, no. 2, pp. 988–989, Mar. 2014.

[16] C. Peng, J. Zhang, and H. Yan, “Adaptive event-triggering $H_{\infty}$ load frequency control for network-based power systems,” IEEE Trans. Ind. Electron., vol. 65, no. 2, pp. 1685–1694, Feb. 2018.

[17] A. S. Mir and N. Senroy, “Adaptive model predictive control scheme for application of SMES for load frequency control,” IEEE Trans. Power Syst., early access, Jun. 18, 2019, doi: 10.1109/TPWRS.2017.2720751.

C. Mu, Y. Tang, and H. He, “Improved sliding mode design for load frequency control of power system integrated an adaptive learning strategy,” IEEE Trans. Ind. Electron., vol. 64, no. 8, pp. 6742–6751, Aug. 2017.

H. A. Yousef, K. Al-Kharusi, M. H. Albadi, and N. Hosseinizadeh, “Load frequency control of a multi-area power system: An adaptive fuzzy logic approach,” IEEE Trans. Power Syst., vol. 29, no. 4, pp. 1822–1830, Jul. 2014.

N. M. Alyazidi and M. S. Mahmoud, “$L_1$ adaptive networked controller for islanded distributed generation systems in a microgrid,” Int. J. Syst. Sci., vol. 49, no. 12, pp. 2507–2524, Sep. 2018.

I. Petros and B. Fidan, Adaptive Control Tutorial, Philadelphia, PA, USA: SIAM Society for Industrial and Applied Mathematics, 2006.

N. Hovakimyan and C. Cao, $L_1$ Adaptive Control Theory: Guaranteed Robustness With Fast Adaptation, Philadelphia, PA, USA: Society for Industrial and Applied Mathematics, 2010.

A. Alhejri, “$L_1$ adaptive load frequency control of single-area electric power system,” in Proc. 4th Int. Conf. Control. Decis. Inf. Technol. (CoDIT), Apr. 2017, pp. 0595–0598.

V. P. Singh, N. Kishor, and P. Samuel, “Improved load frequency control of power system using LMI based PID approach,” J. Franklin Inst., vol. 354, no. 15, pp. 6805–6830, 2017.

J.-B. Pomet and L. Praly, “Adaptive nonlinear regulation: Estimation from the Lyapunov equation,” IEEE Trans. Autom. Control, vol. 37, no. 6, pp. 729–740, Jun. 1992.

M. Yazdianian and A. Mehrizi-Sani, “Distributed control techniques in microgrids,” IEEE Trans. Smart Grid, vol. 5, no. 6, pp. 2901–2909, Nov. 2014.

N. Chuang, “Robust $H_{\infty}$ load-frequency control in interconnected power systems,” IET Control Theory Appl., vol. 10, no. 1, pp. 67–75, 2016.

E. Yesılı, M. Güzelkaya, and I. Eksin, “Self tuning fuzzy PID type load and frequency controller,” Energ. Convers. Manage., vol. 45, no. 3, pp. 377–390, 2004.

N. Hovakimyan and C. Cao, $L_1$ Adaptive Control Theory: Guaranteed Robustness With Fast Adaptation, Philadelphia, PA, USA: Society for Industrial and Applied Mathematics, 2010.

M. S. Mahmoud and N. M. Alyazidi, “Quantized $H_{\infty}$ estimator over communication networks for distributed generation units,” IEEE Trans. Syst., Man, Cybern., Syst., vol. 50, no. 3, pp. 1134–1146, Mar. 2020.

NEZAR M. ALYAZIDI received the B.Sc. degree in electronics and communication engineering from the Hadhramout University of Science and Technology, Hadhramout, Yemen, and the M.Sc. and Ph.D. degrees in systems and control engineering from the Department of Systems Engineering, King Fahd University for Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia, in 2012 and 2016, respectively. Since 2013, he has been a Research Fellow at the Distributed Control Research Group, KFUPM. He worked as a Lecturer-B at the Department of Systems Engineering, KFUPM, from 2013 to 2016. He worked as a Postdoctoral Fellow at the Department of Systems Engineering, KFUPM, from 2017 to 2018. He is currently an Assistant Professor with the Department of Control and Instrumentation Engineering, KFUPM. He is also a Research Fellow of the Acting Director Interdisciplinary Research Center, Smart Mobility and Logistics, KFUPM. He is also a Research Group Deputy Coordinator dealing with control and estimation of wireless networked control systems. His research interests include optimal control, adaptive control, reinforcement learning, intelligent algorithms, distributed generation units, time delay systems, wireless communication networks, and secure control systems.