Adaptive Fuzzy Dynamic Surface Control for Multi-Machine Power System Based on Composite Learning Method and Disturbance Observer

GUOQIANG ZHU 1,2, LINLIN NIE 1,2, MIAOLEI ZHOU 3, (Member, IEEE), XIUYU ZHANG 1,2, (Member, IEEE), LINGFANG SUN 1, AND CHENG ZHONG 4

1 School of Automation Engineering, Northeast Electric Power University, Jilin City 132012, China
2 Jilin Province International Research Center of Precision Drive and Intelligent Control, Jilin City 132012, China
3 Department of Control Science and Engineering, Jilin University, Changchun 130012, China
4 Tangshan Power Supply Company, State Grid Jibei Electric Power Company, Tangshan 063000, China

Corresponding author: Xiuyu Zhang (zhangxiuyu80@163.com)

This work was supported in part by the NSF of China under Grant 61673101 and Grant 61304015, in part by the Natural Science Foundation of Jilin Province under Grant 20180201009SF and Grant 20180101069JC, in part by the Thirteenth Five Year Science Research Plan of Jilin Province under Grant JJKH20200119KJ, and in part by the Jilin Technological Innovation Development Plan under Grant 201831719.

ABSTRACT A composite learning dynamic surface control is proposed for a class of multi-machine power systems with uncertainties and external disturbances by using fuzzy logic systems (FLSs) and disturbance observer (DOB). The main characteristics of the proposed strategy are as follows: (1) The approximation ability of FLSs for nonlinear model of multi-machine power systems is enhanced considerably by using the composite learning method and providing additional correction information for the FLSs. These findings differ considerably from previous designs that focus directly on the system’s tracking performance. (2) The filtering errors caused by the utilizations of the first-order low-pass filters in dynamic surface control (DSC) are compensated effectively by designing the compensating signals in the control law design process. (3) The compound disturbances including the FLSs’ approximation error and external disturbances are estimated and mitigated by constructing DOB. Finally, the proposed control algorithm is verified on the StarSim Hardware-in-loop experimental platform, and the experimental results validate the effectiveness of the proposed control strategy in suppressing disturbances and enhancing the robustness of the controller.

INDEX TERMS DSC, multi-machine power system, SVC, DOB, StarSim.

I. INTRODUCTION

With the expansion of the power grid’s scale, modern power systems have gradually formed a strong coupling dynamic nonlinear system. Power systems are more likely to encounter oscillations because of its complex nonlinear characteristics and some accidents, such as three phase voltages short circuit fault; maintaining a safe and stable operation is also more difficult [1]–[4]. Therefore, improving the control ability of multi-machine excitation system has aroused considerable concern among researchers. An increasing number of nonlinear control methods have been applied to multi-machine power systems [5]–[9].

The traditional excitation control strategy usually adopts the PID control method [10]. However, this strategy is no longer suitable for a highly nonlinear multi-machine power system. Backstepping control method provides a systemic framework for tracking and regulating problem of nonlinear systems, which are utilized widely in the excitation control field. In [11], stability sensitive parameters are brought into the multi-machine power system model and a robust adaptive backstepping excitation controller that can which overcome the over-parameterization problem of stability sensitive parameters was design. In [12], by introducing the sliding mode surface into the dynamic surface controller,
the robustness and anti-interference ability of the system are improved. Fuzzy logic systems (FLSs) and neural networks (NNs) are usually used to approximate the system’s uncertainties because of their good approximation capabilities [13]–[21]. In [22], FLSs and NNs are introduced into the design of backstepping controllers to provide feedback unknown information. However, there is an inherent “explosion of complexity” problem exists in backstepping method. With the increases of system order, the derivative times of virtual control law increases, causing a sharp increase in the complexity of the control law. Dynamic surface control introduces the first-order low-pass filter into backstepping control, and filters the virtual control law to avoid the expansion of its terms [23]–[25]. Therefore, DSC method have been utilized in control multi-machine power system [26]–[30]. In [26], NNs and tracking error transformed functions are used in the design of an adaptive DSC scheme for the SIMS. In [28], an approximation-based adaptive controller for uncertain stochastic nonlinear system with dead-zone and output constraint was proposed, where NNs are utilized to approximate the uncertainties. Although great progress has been made in DSC strategy based on FLSs/NNs, it is designs directly to address the system’s tracking performance but ignores how the FLSs/NNs work as an approximator and the approximated FLSs/NNs models are not accurate and interpretable.

The multi-machine power system is affected easily by external disturbance, which can influence the tracking performance. For the parameters uncertainty and disturbance problem, various solutions, such as robust control [31]–[33], online policy iteration [34], [35], adaptive control [36]–[39], parametric based dynamic compensator [40] and active disturbance rejection control [41]. In [31], a discrete-time sliding mode controller is designed for a class of conic-type systems, and the disturbance attenuation level achieved the prescribed performance. In [34] and [35], by using the neural network technique, a novel online policy iteration scheme has been developed, compared with the previous offline method, this method obtained an excellent calculation accuracy while retaining the nonlinear characteristics of the system. Reference [41] designed an active disturbance rejection controller for hydraulic servo systems, where the problem of difficult combination of parametric adaptive control and disturbance observer was solved. Also in [38], a multilayer NNs based RISE controller was designed for hydraulic system with various disturbances, and obtained a dynamic tracking accuracy of 0.2% through experiments. However, controller design based on disturbance observer (DOB) has caused some concerns in recent years [42]–[47]. In [43], a backstepping control in combination with a DOB to estimate the complex disturbance for a class of uncertain strict-feedback nonlinear system with unknown external disturbance was proposed. In [48], DOB was combined with fuzzy logic systems to realize the composed estimation for a class of uncertain nonlinear system in the presence of actuator saturation and external disturbances. In [49], an extended sliding mode disturbance observer was proposed to compensate the strong disturbances of permanent magnet synchronous motor servo system and achieve high tracking performance. In [50], an adaptive DOB control scheme was proposed to overcome the frequent incompatibility and harmonic interference in the distributed static compensator systems.

Previous works have focused on system uncertainties and external disturbances. However, the works usually focused on the system’s progressive tracking stability, while the accuracy of the approximated models was neglected. In this article, the main contributions are listed as follows.

1) The approximation ability of FLSs for nonlinear model of multi-machine power systems is enhanced by introducing the composite learning method and providing additional correction information. This is achieved by introducing a serial—parallel estimation model (also called a state predictor in some literature) to provide prediction errors, which is designed in the composite learning of FLSs as an additional adjustment information to update the weight vector.

2) The compensating signals are introduced to overcome the filtering error caused by using a first-order low-pass filter in DSC, thereby enabling the compensated tracking error to be obtained. The compensated tracking error signal is introduced together with the prediction error to update the weight vectors of the FLSs.

3) The DOB is employed to estimate compound disturbances that include the approximation error of the FLSs and the external disturbances in the multi-machine power systems. Thus, in addition to the system’s external disturbances, the approximation error of FLSs is also considered, which further improves the accuracy of the multi-machine power systems.

The rests of this article are as follows. Section 2 expounds on the mathematical model of power generator excitation system and fuzzy logical systems. In Section 3, the composite learning dynamic surface control is designed and the stability analysis of the entire control system discussed. The experimental results of the proposed control strategy are given in Section 4. Section 5 concludes this article.

II. PROBLEM STATEMENT AND PRELIMINARIES

A. MODEL DYNAMICS AND PROBLEM FORMULATION

A large-scale power system consists of $n$ generators connected by transmission lines and equipped with SVC. The mathematical model is expressed as follows [26], [51]:

$$\dot{\delta}_i = \omega_i$$
$$\dot{\omega}_i = -\frac{D_i}{2H_i}\omega_i - \frac{\alpha_0}{2H_i}\Delta P_{ei} + d_i$$
$$\Delta P_{ei} = \frac{1}{T_{d0i}}\Delta P_i + \frac{1}{T_{d0i}}u_i + h_i(\delta, \omega)$$
$$\dot{B}_{Li} = \frac{1}{T_{Ci}}(-B_{Li} + B_{Ci} + u_{Bi})$$

Therein, $u_i$ is the control signals of the generator with

$$u_i = I_q E_{fi} - (x_{di} - x'_{di})I_{di}I_{qi} - P_{mi} - T_{d0i}Q_e\omega_i$$

$$VOLUME 8, 2020$$
According to [51], the interconnection term \( h_i(\delta, \omega) \) represents:

\[
\begin{align*}
&h_i(\delta, \omega) = E_i' n \sum_{j=1}^{n} E_j' B_{ij} \sin(\delta_j - \delta_i) \\
&- E_{ij} n \sum_{j=1}^{n} E_j' B_{ij} \cos(\delta_j - \delta_i) \omega_j. \quad (3)
\end{align*}
\]

According to [51], the interconnection term \( h_i(\delta, \omega) \) satisfies:

\[
\begin{align*}
|h_i(\delta, \omega)| &\leq \frac{\sum_{j=1}^{n} (h_{1ij}|\sin \delta_i| + h_{2j} |\omega_j|)}{|P_{el}|_{\max}} \\
&\leq \frac{\sum_{j=1}^{n} (h_{1ij}|\delta_j| + h_{2j} |\omega_j|)}{|P_{el}|_{\max}}, \quad (4)
\end{align*}
\]

where

\[
\begin{align*}
h_{1ij} &= \frac{4p_{1ij}}{|T_{d0ij'}|_{\min}} |P_{el}|_{\max} \quad \text{when } j = i, \\
h_{2ij} &= \frac{4p_{2ij}}{|T_{d0ij'}|_{\min}} |P_{el}|_{\max} \quad \text{when } j \neq i
\end{align*}
\]

and \( p_{1ij}, p_{2ij} \) are constants with values either 1 or 0.

The notation for the power systems is given as follow. \( \delta_i \) is the rotor angle of the \( i \)th generating machine, \( \omega_i = 2\pi f_0 \) is the synchronous speed of the \( i \)th generating machine, \( P_m \) is the mechanical power, \( P_{el} \) is the electromagnetic power, \( D_i \) is the damping constant, \( H_i \) is the inertia constant(s), \( E_{el} \) is the transient electromotive force of the \( i \)th generating machine, \( T_{d0} \) represent the direct axis transient short-circuit time constant(s), \( T_{Ci} \) is the time constant of adjusting system and SVC(s), \( Q_{el} \) is the reactive power, \( u_i \) is the control voltage of excitation equipment, \( u_{Bi} \) is the input of SVC, \( B_L \) is the adjustable equivalent susceptance in SVC, \( B_{Ci} \) is the initial value of the adjustable susceptance, \( \delta_j \) is the rotor angle of the \( j \)th row and \( j \)th column element of nodal susceptance matrix at the internal nodes after eliminating all physical buses, and \( d_i \) is the position bound torque interference of the rotor.

Let \( x_1 = \delta_i - \delta_{0i}, x_2 = \delta_i - \omega_i, x_3 = P_{el} - P_{m0}, x_4 = V_{mi} - V_{refi}, \) where \( V_{mi} \) is the accessing point voltage and \( V_{refi} \) is the reference voltage. According to [26], (1) can be expressed as following two subsystems:

\[
\begin{align*}
\dot{x}_1 &= x_2, \\
\dot{x}_2 &= -g_{21} x_1 + f_{21}(x_2) + d_{11}, \\
\dot{x}_3 &= g_{31} u_i + f_{31}(x_3) + h_i(\delta, \omega), \\
y_1 &= x_1, \\
\dot{x}_4 &= g_{41} u_{Bi} + f_{41}(x_4), \\
y_2 &= x_4, \quad (5)
\end{align*}
\]

where \( f_{ij}(x_{1j}, x_{2j}, \ldots, x_{ij}) \) are the input variables, \( y_{1j} \) and \( y_{2j} \) are the outputs of the large-scale power systems and the SVC equipment, where

\[
\begin{align*}
g_{ij} &= \omega_{0i}, \\
g_{12} &= \frac{1}{2H_i}, \\
g_{21} &= \frac{1}{T_{d0i}}, \\
g_{41} &= \frac{-x_{3i}}{T_{d0i}}, \\
g_{4u} &= -x_{4u}, \\
f_{21}(x_2) &= \sin x_1, \\
f_{31}(x_3) &= -\frac{x_{3i}}{T_{d0i}}, \\
&- x_{3i}, \\
f_{41}(x_4) &= -\frac{x_{4u}}{T_{d0i}}, \\
&- \frac{x_{4u}}{T_{d0i}}.
\end{align*}
\]

with \( X_{i1} = x_{0i} + X_{I1}, X_{I1} = x_{0i} + X_{I1}, X_{dS1} = X_{dS1} + X_{d21} + X_{d32} + X_{d43}, X_{dS1} = X_{dS1} + X_{d21} + X_{d32} + X_{d43} \), where \( X_{i1}, X_{d1}, X_{d2} \) are transmission line reactances, \( X_{d1} \) is the direct axis reactance, \( X_{dS1} \) is the direct axis reactance of the generator, \( X_{d1} \) is the transformer reactance. Define following assumptions:

**Assumption 1:** The external disturbances \( d(t) \) satisfy

\[
\begin{align*}
&|d_i(t)| \leq \kappa_{0i}, \quad \text{and} \quad |d_f(t)| \leq \kappa_{1i},
\end{align*}
\]

where \( \kappa_{0i} \) and \( \kappa_{1i} \) are positive constants.

**Assumption 2:** The control gain functions \( g_{ij}, j = 2, 3, 4, \) can be written as known part \( g_{ijN} \) and unknown part \( \Delta g_{ij}, \) where \( \Delta g_{ij} = g_{ij} - g_{ijN} \), \( f_{21}(x_2), f_{31}(x_3), \) and \( f_{41}(x_4) \) are unknown continuous functions.

**Assumption 3:** The reference signals \( y_{refi} \) are smooth and bounded functions. Its first and second derivatives are exist and satisfy \( \sum_{i=1}^{N} y_{refi}^2 + \sum_{i=1}^{N} y_{refi}^2 \leq \chi \) for positive real number \( \chi \).

Remark 1: The controlled object system includes two subsystems, which are excitation subsystem (6) and Static var compensator subsystem (7). There is coupling between the two controllers: the SVC subsystem (6) includes the state variables \( x_{1i}, x_{2i}, x_{3i} \) and control signal \( u_i \) of the excitation system. Therefore, considering the coupling effect, the target system in this article is defined as a multi-machine power system with SVC.

**B. FUZZY LOGIC SYSTEMS (FLSs)**

An FLS is composed of a fuzzy rule base as following form:

\[
\begin{align*}
&\text{IF } x_1 \text{ is } A_1^m \text{ and } x_2 \text{ is and } A_2^m \ldots \text{ and } x_n \text{ is } A_n^m, \quad \text{THEN } y \text{ is } B^m, \quad (m = 1, 2, \ldots , M)
\end{align*}
\]

where \( x_i (i = 1, 2, \ldots , n) \) are the input variables, \( A_1^m \) and \( B^m \) are fuzzy sets in \( R \), and \( \mu_{A_1^m}(x_l) \) and \( \mu_{B_1^m}(y) \) are fuzzy membership functions. With singleton fuzzifier, product inference, centroid defuzzifier, the FLS can be constituted in the follow-
ing form [52]:

\[ y(x) = \frac{1}{M} \sum_{i=1}^{M} \mu_{A_i}^{m} (x_i) \]

where \( \mu_{A_i}^{m} = \alpha_i^m \exp \left[ -\frac{1}{2} \left( \frac{x_i - \mu_i}{\sigma_i} \right)^2 \right] \) is Gaussian membership function and \( x = (x_1, x_2, \ldots, x_n) \), \( m \) is point which maximizes \( \mu_{B_m}(y) \). Define the fuzzy basis functions as

\[ \Psi^m(x) = \frac{1}{M} \sum_{i=1}^{M} \mu_{A_i}^{m} (x_i) \]

Then, FLS can be expressed as

\[ Y = \omega^T \Psi(x) \]

where \( \omega \in \mathbb{R}^M \) is the adjustable weight vector and \( \Psi(x) = [\Psi^1(x), \Psi^2(x), \ldots] \).

**Lemma 1** [52], [53]: Let continuous function \( f(x) : \mathbb{R}^n \rightarrow \mathbb{R} \) defined on compact set \( \Omega_x \subset \mathbb{R}^n \), and any constants \( \epsilon > 0 \), an FLS exists such that the following formula hold,

\[ \sup_{x \in \Omega_x} |f(x) - Y(x)| < \epsilon. \]

Then, \( f(x) \) can be approximated by FLS in the compact set \( \Omega_x \), described as

\[ f(x) = \omega^T \Psi(x) + e^x, \quad x \in \Omega_x, \]

where \( e^x \) is the approximate error and satisfying \( |e^x| \leq \epsilon_M \). The \( \omega \) is unknown, which needed to design adaptive law online estimates.

**Assumption 4**: \( \omega^a \) is bounded and satisfying \( \| \omega^a \| \leq \omega_M \), \( j = 2, 3, 4 \), where \( \omega_M \) is a known positive number; \( e^x_j \) is bounded and satisfying \( |e^x_j| \leq \epsilon_M, j = 2, 3, 4 \).

### III. DESIGN OF ADAPTIVE FUZZY DYNAMIC CONTROLLER BASED ON COMPOSITE LEARNING AND DISTURBANCE OBSERVER

According to (6) and (7), the difficulty of controller design lies in the unknown nonlinear functions \( f_{12}(\bar{x}_{12}), f_{33}(\bar{x}_3), f_{44}(\bar{x}_4) \), multi-machine interconnection coupling term \( h_i(\delta, \omega) \), and external disturbance \( d_1 \). The algorithm structure diagram is shown in FIGURE 1. The controller design process consists of four steps, the alternative variables are show in TABLE 1.

In TABLE 1, \( e_{ij} \), \( j = 1, \ldots, 4 \) represents the \( j \)th surface error, where \( y_{ri} \) is the desired power angle, \( V_{ref_i} \) is the reference voltage, and \( \alpha_i^a \) and \( \alpha_i^b \) are the virtual control in step 1 and step 2, respectively. (T1.3) and (T1.8) are the first-order low-pass filter, where \( \tau_2 \) and \( \tau_3 \) are the time constants. To compensate the filtering error, define the compensated tracking error as (T1.5), (T1.10), (T1.17), and (T1.24). Then, design the compensation signals as (T1.4), (T1.9), (T1.16), and (T1.23). (T1.13), (T1.20), and (T1.27) are weight vector updating law of FLSs. According to the composite learning method, prediction error \( e_{i2p} \) and compensated tracking error \( E_2 \) are introduced in the design of weight vector of FLSs, thereby updating law. Prediction error \( e_{i2p} \) are designed as (T1.11), (T1.18), (T1.25), and the prediction signals are

**FIGURE 1.** The algorithm structure diagram.

**TABLE 1.** Adaptive fuzzy dynamic control based on composite learning and disturbance observer.
designed as (T1.12), (T1.19), (T1.26). In addition, \( k_{ij} (j = 1, \ldots, 4) \) and \( \eta_{ij}, \gamma_{ij}, \gamma_{ij} \) (\( l = 2, 3, 4 \)) are positive design parameters. \( \hat{\omega}_{ij} (j = 2, 3, 4) \) is the estimation of \( \omega_{ij}^* \). \( \omega_{ij}^T \) and \( \Psi_{ij}(\hat{x}_{ij}) \) are the ideal weight vector and fuzzy basis function vector of FLSs. \( \hat{D}_{ij}, (j = 2, 3, 4) \) are the observed value of the DOBs. In this article, DOB is designed as following:

\[
\hat{D}_{ij} = \hat{\xi}_{ij} + K_{ij}p(\hat{x}_{ij}),
\]

\[
\dot{\hat{\xi}}_{ij} = -K_{ij}\hat{\xi}_{ij} - K_{ij}(L_{ij}^{-1} \hat{\omega}_{ij}^T \Psi_{ij}(\hat{x}_{ij}) - g_{ij}x_{ij}) + K_{ij}p(\hat{x}_{ij})) + \hat{E}_{ij} + \gamma_{ij}\epsilon_{ij},
\]

where \( p(\hat{x}_{ij}) \) is nonlinear function to be observed, \( K_{ij} > 0 \) are positive design gain of DOBs, and it should meet \( K_{ij}x_{ij} = dp(\hat{x}_{ij})/dt \). The observation error of DOB is defined as \( \hat{D}_{ij} = \hat{D}_{ij} - D_{ij} \).

**Remark 2:** According to Assumption 2, \( |D_{ij}| \leq \phi_{ij} \), \( |\hat{D}_{ij}| \leq \phi_{ij}, j = 2, 3, 4 \), where \( \phi_{ij0} \) and \( \phi_{ij} \) are positive parameters.

### IV. STABILITY ANALYSIS

The proof of the control system stability will be discussed in this section. Select the Lyapunov function as

\[
V = \sum_{i=1}^{4} V_i,
\]

with

\[
V_1 = \sum_{i=1}^{2} \frac{1}{2} E_{i1}^2,
\]

\[
V_2 = \sum_{i=1}^{2} \frac{1}{2} \left( E_{i2}^2 + \gamma_{i2}\epsilon_{i2}^2 + \hat{\omega}_{i2}^T \gamma_{i2}^{-1} \hat{\omega}_{i2} + D_{i2}^2 \right),
\]

\[
V_3 = \sum_{i=1}^{2} \frac{1}{2} \left( E_{i3}^2 + \gamma_{i3}\epsilon_{i3}^2 + \hat{\omega}_{i3}^T \gamma_{i3}^{-1} \hat{\omega}_{i3} + D_{i3}^2 \right),
\]

\[
V_4 = \sum_{i=1}^{2} \frac{1}{2} \left( E_{i4}^2 + \gamma_{i4}\epsilon_{i4}^2 + \hat{\omega}_{i4}^T \gamma_{i4}^{-1} \hat{\omega}_{i4} + D_{i4}^2 \right),
\]

where \( \hat{\omega}_{ik} = \hat{\omega}_{ik} - \omega_{ik}^* \) (\( k = 2, 3, 4 \)).

**Theorem 1:** Consider a closed-loop control system consisting of the object power systems (6), (7) and the actual controllers (T1.15), (T1.22). If assumptions 1-4 are satisfied and the initial conditions satisfy \( V(0) \leq p, (p > 0) \), adjustment parameters \( k_{i1}, k_{i2}, k_{i3}, k_{i4}, \eta_{i2}, \eta_{i3}, \eta_{i4}, \gamma_{i2}, \gamma_{i3}, \gamma_{i4}, c_{i2}, c_{i3}, c_{i4}, K_{i2}, K_{i3}, K_{i4} \) exist, which can make all signals of the closed-loop system semi-global become bounded uniformly and the system tracking error can converge to arbitrarily small residual set.

**Proof:** The proof is given in the Appendix.

**Remark 3:** To make it easy for readers to understand, the parameters of the controller proposed in this article can be determined by the following steps: Step 1, according to the actual application, the time constants \( \tau_j (i = 1, 2; j = 2, 3) \) in (T1.3) and (T1.8) can be selected in the range of 0.001 to 0.1.

Step 2, when the values of \( L_{ij} \), \( L_{ij} \) are determined by (47) and (48), the value of \( r \) can be obtained according to (50) and (51). Step 3, according to (52) (53) and the value of \( r \), the values of \( k_{i1}, k_{i2}, k_{i3}, k_{i4}, \eta_{i2}, \eta_{i3}, \eta_{i4} \) can be obtained.

**Remark 4:** The improved FLSs are used as universal approximators to deal with systems’ uncertainties. As shown in (T1.13), (T1.20) and (T1.27), the additional adjustment term prediction error \( \epsilon_{ij} \) is added when designing the weight update law of FLS. The compensated tracking error \( E \) guarantees the output tracking performance of the system, and the prediction error \( \epsilon_{ij} \) guarantees the authenticity of FLSs approximation. Furthermore, DOB is introduced to handle the external disturbances. In addition to observing the external disturbances, DOB also observes the approximation error of FLS. DOB and FLS work together to solve all unknown nonlinear functions of the system. Through the Lyapunov stability analysis, the stability of the control system is ensured.

**Remark 5:** The fuzzy logic system is used as a general approximator to approximate unknown nonlinear functions in the system (1), i.e. [16], [19], [21]–[23], [47] and [48]. It is worth noting that the fuzzy system does not need to accurately approximate the unknown functions, but to make the system output accurately track the desired signal. In other words, the estimated values of the norm of fuzzy weight vector will be updated online as the output error of the system changes.

### V. EXPERIMENTAL RESULTS

The StarSim Hardware-in-loop testing platform is used to demonstrate the performance of the proposed control scheme. The experiment environment consists of four parts: Host Computer, MT RTS (Real-Time Simulator), Adapter plate and MT RCP (Rapid Control Prototype), and the structure of the test platform is shown in FIGURE 2. The hardware configuration is listed in TABLE 2.

The RTS is utilized to run large-scale power electronic system controlled object. The RTS is built by Simulink or StarSim software on FPGA chips. It can simulate the characteristics of the controlled object and send the response signals to the controller box in real-time. The RCP is used to run

| TABLE 2. Hardware configuration of the testing platform. |
|--------------------------------------------------------|
| **Hardware-in-loop Testing Platform**                  |
| NI PXIe-1082, FPGA chip: Kintex-7 325T FPGA @Xilinx;   |
| Synchronous analog output: 26 channels, 1MS/s, 16 bits; |
| the MT RTS                                            |
| Synchronous analog input: 14 channels, 1MS/s, 16 bits; |
| FPGA real-time simulation step size: 250ns-1.5us.      |
| NI PXIe-1071, FPGA chip: Kintex-7 325T FPGA @Xilinx;   |
| Synchronous analog output: 16 channels, 1MS/s, 16 bits;|
| the MT RCP                                            |
| Synchronous analog input: 16 channels, 500ks, 16 bits; |
| FPGA real-time simulation step size: 250ns-1.5us.      |

| Related accessories | Adapter plate, Host computer, Electric wire. |
The traditional tracking error-based NNs method was used as a comparison. The design parameters of the controllers are chosen as $K_1 = 22, K_2 = 42, K_3 = 42, K_4 = 42$, the design parameters chosen as: $L_{fi2} = 10, L_{fi3} = 2, L_{fi4} = 10$. The fuzzy membership function are adopted as: $\mu_{A_l}(\xi_k) = \exp\left(-\frac{(\xi_k - \bar{\xi}_l)^2}{\gamma_k^2}\right)$, where $l = 1, \ldots, 5$ and $k = 1, \ldots, 4$, with $\bar{\xi}_1 = \xi_{11}, \bar{\xi}_2 = \xi_{12}, \bar{\xi}_3 = \xi_{13}, \bar{\xi}_4 = \xi_{14}$. Further, $\mu_1 = 40, \mu_2 = 314, \mu_3 = 2, \mu_4 = 1, b_1 = 3.5, b_2 = 9, b_3 = b_4 = 1$. The interference signal is chosen as smooth function, $d_{11} = 0.01 \cos(t)$.

**Case 1:** Control response to fault

In this case, assume that a three-phase voltage short-circuit fault occurs at $t = 8.14s$ and the fault lasts for 0.4 seconds. The operating points are selected as: $\delta_{10} = 0.733$ rad, $\omega_{10} = 100.04\pi$ rad/s, $P_{m10} = 1.02$ p.u., $V_{ref1} = 1.08$ p.u., $\delta_{20} = 0.740$ rad, $\omega_{20} = 100.05\pi$ rad/s, $P_{m20} = 1.018$ p.u., $V_{ref2} = 1.00$ p.u..

The experimental results are shown inFIGUREs 4-12. FIGURE 4 shows the tracking error of the power angle of the proposed method (denoted as “DOB-CL”) and the general tracking error based NNs adaptive DSC control method (denoted as “Error-NNs”). FIGURE 5 shows the response curves of power angle, both methods can track the reference power angle. However, the proposed control method can suppress the disturbance better and obtain a better tracking performance, while the response under Error-NNs is with oscillation. Define the generalized disturbances as $\Gamma_i = f_i(x_i(t)) + d_i$ and define the compound estimation as $\hat{\Gamma}_i = L_{fi2} \omega_{i2} \Psi_i(x_i(t)) + D_{i2}$. FIGUREs 6 and 7 show that the compound estimation $\hat{\Gamma}_i$ with DOB and FLSs can better “comprehend” the true unknown information $\Gamma_i$. The FLSs...
Case 2: Control response to change of operation point

In this case, the system is running steadily and the equilibrium point (EP) is changed at $t = 8s$. The equilibrium point $EP_1$ changes to the $EP_2$. $EP_1$ and $EP_2$ are selected as following:

$$
\begin{align*}
EP_1: & \quad x'_{11} = 0.698 \text{ rad}, \quad x'_{12} = 100.03\pi \text{ rad/s}, \\
& \quad x'_{13} = 1.01 \text{ p.u.}, \quad x'_{14} = 1.01 \text{ p.u.}, \\
& \quad x'_{21} = 0.703 \text{ rad}, \quad x'_{22} = 100.04\pi \text{ rad/s}, \\
& \quad x'_{23} = 1.02 \text{ p.u.}, \quad x'_{24} = 1.00 \text{ p.u.}
\end{align*}
$$

is designed with composite learning that adds the prediction error to the new-type update laws. FIGUREs 8 and 9 show the response curves of rotating speed and the electrical power angles. FIGURE 10 shows the access point voltage response curves of SVC equipment. FIGUREs 11 and 12 show the control input signals for the two generators and the two SVC equipment, respectively.
The experimental results are shown in FIGUREs.13-20. FIG-
URe.s.13-16 show the response curves of system state, and
indicates that the proposed method achieved faster adaption
and improved tracking performance. FIGURE.s.17 and 18
illustrate the estimation of unknown information $0_i$. Obvi-
ously, with FLs approximation and DOB disturbance esti-
mation, the proposed method can tracking the unknown infor-
mation closely. FIGURE.s.19 and 20 are the control inputs and
SVC equipment inputs, respectively.

Remark 6: It is worth noting that the occurrence of power
system failures is difficult to predict, and most of them occur
when the power system is in a stable working state. In order
to make the experimental results in this article closer to
the actual working conditions of the power system, the two
cases selected in the experimental section are the random
faults that occur when the power system is stable. Therefore,
the tracking error of power angle in FIGURE 4 is zero at the
beginning of the simulation.

Remark 7: In the experiment, the measurement noise is
introduced into the system when the signals are transmitted
between MT RTS and MT RCP. The presence of the noise in
the actual control signal makes it difficult to select the design
parameters of the controller, and it also has an adverse effect
on the entire control system. In order to solve this problem,
the control algorithm to reduce the measurement noise will
be considered in the next research work, such as the control
algorithm.
scheme combining the desired compensation technique [36] and the adaptive dynamic surface.

**Remark 8:** It is worth noting that the verification of the algorithm in this article is carried out on the semi-physical experimental platform of our laboratory. Due to the particularity of the experimental conditions, only the improved FLSs DSC method and the general NNs DSC method are compared. It is verified that the proposed method in this article has better tracking performance. Furthermore, comparing experiments with other researchers’ advanced control algorithms is one of our future research works.

**VI. CONCLUSION**

In this article, an adaptive fuzzy dynamic surface control method based on composite learning and DOB is proposed for large-scale power systems with uncertainties and external disturbances. The approximation capability of the FLSs is influenced considerably when employing the composite learning method. In addition, compensating signals are introduced in the design of the control law and the filtering error caused using the first-order low-pass filter in the DSC was eliminated. Furthermore, DOB is applied to estimate the generalized disturbance, which includes not only external disturbances but also the FLSs’ approximation error. Consequently, the accuracy of the control system is improved further. The effectiveness of the proposed method is verified on a Hardware-in-the-loop Testing Platform.

Furthermore, in spirit of the previous works, the designing a discrete-time dynamic surface control [31], online policy iteration control [34], [35] and multilayer NNs based active disturbance rejection control [38], [41] for multi-machine power system will be considered in the future works.

**APPENDIX**

**Proof of Theorem 1:** Differentiating the Lyapunov function $V$ in (16) yields,

$$
\dot{V} = \sum_{i=1}^{4} \dot{V}_i.
$$

The time derivative of $V_1$ is

$$
\dot{V}_1 = \sum_{i=1}^{2} E_{i1} \dot{E}_{i1}.
$$

From (T1.2), (T1.4) and (T1.5), the time derivative of $E_{i1}$ is obtained as

$$
\dot{E}_{i1} = \dot{e}_{i1} - \dot{q}_{i1} - \dot{x}_{i1} - \dot{y}_{i1} - \dot{q}_{i1} = e_{i2} + \alpha_{i2}^\delta - \alpha_{i2}^\Delta - k_{i1} e_{i1} - \dot{q}_{i1} = -k_{i1} E_{i1} + E_{i2}.
$$
Then, time derivative of $V_1$ can be written as,

$$
\dot{V}_1 = \sum_{i=1}^{2} -k_i E_i^2 + E_i \dot{E}_i.
$$

(21)

Using the FLS to approximate nonlinear function $F_2(\tilde{x}_2) = L_{fl2} f_2(\tilde{x}_2)$, where $L_{fl2}$ is the positive design parameter, then,

$$
f_2(\tilde{x}_2) = L_{fl2}^{-1}(\omega_2^T \Psi_2(\tilde{x}_2) + \varepsilon_2).
$$

Therefore, $\dot{x}_2$ can be written as

$$
\dot{x}_2 = L_{fl2}^{-1} \omega_2^T \Psi_2(\tilde{x}_2) + D_2 - g_{i2N} x_3.
$$

(22)

where $\tilde{x}_2 := (x_1, x_2) \in \Omega_{x2} \subset \mathbb{R}^2$, $D_2 = L_{fl2}^{-1} \varepsilon_2 + d_1 - \Delta g_{i2} x_3$ is the compound disturbance, with $\Delta g_{i2} = g_{i2} - g_{i2N}$. Define $\dot{\omega}_2$ is the estimation of $\omega_2^T$, and $\dot{\omega}_2 = \dot{\tilde{\omega}}_2 - \dot{\tilde{\omega}}_2^T$ is the estimation error of $\omega_2^T$, $\tilde{D}_2$ is the estimation of $D_2$, and $\dot{D}_2 = \dot{\tilde{D}}_2 - \dot{D}_2$ is the estimation error.

By differentiating $V_2$ yields,

$$
\dot{V}_2 = \sum_{i=1}^{2} E_i \dot{E}_i + \gamma_{i2} e_{i2p} \dot{e}_{i2p} + \dot{\omega}_2^T \gamma_{i2} \dot{\tilde{\omega}}_2 + \tilde{D}_2 \dot{D}_2.
$$

(23)

From (T.1.7), (T.1.9) and (T.1.10), the time derivative of $E_i$ is obtained as

$$
\dot{E}_i = -L_{fl2}^{-1} \omega_i^T \Psi_2(\tilde{x}_2) - \tilde{D}_2 - g_{i2N} E_i - k_i E_i - \varepsilon_i.
$$

(24)

From (T.1.11) and (T.1.12), the time derivative of $e_{i2p}$ is obtained as

$$
\dot{e}_{i2p} = -L_{fl2}^{-1} \omega_i^T \Psi_2(\tilde{x}_2) - \tilde{D}_2 - \eta_i e_{i2p}.
$$

(25)

According to (15), the time derivative of $\tilde{D}_2$ is

$$
\dot{\tilde{D}}_2 = \dot{\tilde{D}}_2 + K_2 \tilde{x}_2
$$

$$
= -K_2(L_{fl2}^{-1} \omega_i^T \Psi_2(\tilde{x}_2) + \tilde{D}_2) + E_i + \gamma_{i2} e_{i2p}.
$$

(26)

where $K_2$ is positive design parameter. $\dot{\tilde{D}}_2$ can be obtained, $\tilde{D}_2 = \tilde{D}_2 - \dot{\tilde{D}}_2$

$$
\dot{D}_2 = \dot{\tilde{D}}_2 - \dot{\tilde{D}}_2
$$

$$
= -K_2(L_{fl2}^{-1} \omega_i^T \Psi_2(\tilde{x}_2) + \tilde{D}_2) + E_i + \gamma_{i2} e_{i2p} - \dot{D}_2.
$$

(27)

Substituting (24), (25), (27) and (T.1.13) into (23), $\dot{V}_2$ can be written as

$$
\dot{V}_2 = \sum_{i=1}^{2} -k_i E_i - \eta_i \gamma_{i2} e_{i2}^2 - K_2 \tilde{D}_2^2 - c_{i2} \omega_i^T \omega_i - \dot{\tilde{D}}_2 \tilde{D}_2 - L_{fl2} K_2 \tilde{D}_2 \omega_i^T \Psi_2(\tilde{x}_2)
$$

$$
= \eta_i g_{i2N} E_i - E_i \dot{E}_i.
$$

(28)

Similar to (22)-(28), approximate the unknown function $F_3(\tilde{x}_3) = L_{fl3} f_3(\tilde{x}_3)$ with FLSs, where $L_{fl3}$ is the positive design parameter, then,

$$
f_3(\tilde{x}_3) = L_{fl3}^{-1}(\omega_3^T \Psi_3(\tilde{x}_3) + \varepsilon_3).
$$

where $\tilde{x}_3 := (x_1, x_2, x_3) \in \Omega_{x3} \subset \mathbb{R}^3$. Therefore, $\dot{\tilde{x}}_3$ can be written as

$$
\dot{\tilde{x}}_3 = L_{fl3}^{-1} \omega_3^T \Psi_3(\tilde{x}_3) + D_3 + g_{i3N} u_i.
$$

(29)

where $D_3 = L_{fl3} \varepsilon_3 + h_i + \Delta g_{i3} u_i$ is the compound disturbance with $\Delta g_{i3} = g_{i3} - g_{i3N}$. Define $\dot{\omega}_3 = \dot{\tilde{\omega}}_3 - \dot{\tilde{\omega}}_3^T$, $\tilde{D}_3 = \tilde{D}_3 - D_3$, with $\dot{\omega}_3$ and $\tilde{D}_3$ are the estimation of $\omega_3^T$ and $D_3$, respectively.

By differentiating $V_3$ yields,

$$
\dot{V}_3 = \sum_{i=1}^{2} E_i \dot{E}_i + \gamma_{i3} e_{i3p} \dot{e}_{i3p} + \dot{\omega}_3^T \gamma_{i3} \dot{\tilde{\omega}}_3 + \tilde{D}_3 \dot{D}_3.
$$

(30)

From (T.1.15), (T.1.16) and (T.1.17), the time derivative of the compensated tracking error $E_i$ is obtained as

$$
\dot{E}_i = -L_{fl3}^{-1} \omega_i^T \Psi_3(\tilde{x}_3) - \tilde{D}_3 - k_i E_i + g_{i3N} u_i.
$$

(31)

From (T.1.18) and (T.1.19), the time derivative of $e_{i3p}$ can be written as

$$
\dot{e}_{i3p} = -L_{fl3}^{-1} \omega_i^T \Psi_3(\tilde{x}_3) - \tilde{D}_3 - \eta_i e_{i3p}.
$$

(32)

According to (15), the time derivative of $\tilde{D}_3$ is obtained as

$$
\dot{\tilde{D}}_3 = \dot{\tilde{D}}_3 + K_3 \tilde{x}_3
$$

$$
= -K_3(L_{fl3}^{-1} \omega_i^T \Psi_3(\tilde{x}_3) + \tilde{D}_3) + E_i + \gamma_{i3} e_{i3p}.
$$

(33)

where $K_3$ are positive design parameters. Then, $\tilde{D}_3$ can be written as,

$$
\dot{\tilde{D}}_3 = \dot{\tilde{D}}_3 - \dot{\tilde{D}}_3
$$

$$
= -K_3(L_{fl3}^{-1} \omega_i^T \Psi_3(\tilde{x}_3) + \tilde{D}_3) + E_i + \gamma_{i3} e_{i3p}.
$$

(34)

Substituting (31), (32), (34) and (T.1.20) into (30), $\dot{V}_3$ can be written as

$$
\dot{V}_3 = \sum_{i=1}^{2} -k_i E_i^2 - \eta_i \gamma_{i3} e_{i3}^2 - K_3 \tilde{D}_3^2 - c_{i3} \omega_i^T \omega_i
$$

$$
= \eta_i g_{i3N} E_i - E_i \dot{E}_i.
$$

(35)

Similarly, define $F_{4}(\tilde{x}_4) = L_{fl4} f_4(\tilde{x}_4)$, where $L_{fl4}$ is the positive design parameter. Using FLSs to approximate the unknown function $F_{4}(\tilde{x}_4)$, then,

$$
f_4(\tilde{x}_4) = L_{fl4}^{-1}(\omega_{i4}^T \Psi_4(\tilde{x}_4) + \varepsilon_{i4})
$$

where $\tilde{x}_4 := (x_1, \ldots, x_4) \in \Omega_{x4} \subset \mathbb{R}^4$. Then, $\dot{\tilde{x}}_4$ can be written as

$$
\dot{\tilde{x}}_4 = L_{fl4}^{-1} \omega_{i4}^T \Psi_4(\tilde{x}_4) + D_4 + g_{i4N} u_{Bi}.
$$

(36)

$D_4 = L_{fl4} \varepsilon_{i4} + \Delta g_{i4} u_{Bi}$ is the compound disturbance with $\Delta g_{i4} = g_{i4} - g_{i4N}$. Define $\dot{\omega}_{i4} = \dot{\tilde{\omega}}_{i4} - \dot{\tilde{\omega}}_{i4}^T$, $\tilde{D}_4 = \tilde{D}_4 - D_4$, $\dot{\omega}_{i4}$ and $\tilde{D}_4$ are the estimation of $\omega_{i4}^T$ and $D_4$. 

163172
VOLUME 8, 2020
By differentiating $V_4$ yields,

$$\dot{V}_4 = \sum_{i=1}^{2} E_{i4} \dot{E}_{i4} + \gamma_{i4} e_{i4} \dot{e}_{i4}$$

$$+ \omega_{i4}^T \gamma_{i4}^{-1} \dot{\omega}_{i4} + \dot{D}_{i4} \dot{D}_{i4}. \quad (37)$$

From (T1.22), (T1.23) and (T1.24), the time derivative of $e_{i4}$ can be obtained as

$$\dot{E}_{i4} = -L_{ji}^0 \omega_{i4}^T \Psi_{i4}(\bar{x}_{i4}) - \dot{D}_{i4} - k_{i4} E_{i4}. \quad (38)$$

From (T1.25) and (T1.26), the time derivative of $e_{i4}$ can be written as

$$\dot{e}_{i4} = -L_{ji}^{-1} \omega_{i4}^T \Psi_{i4}(\bar{x}_{i4}) - \dot{D}_{i4} - \eta_{i4} e_{i4}. \quad (39)$$

According to the DOB (15), the time derivative of $\dot{D}_{i4}$ can be written as

$$\dot{D}_{i4} = \dot{\xi}_{i4} + K_{i4} \dot{x}_{i4}$$

$$\quad = K_{i4}(-L_{ji}^0 \omega_{i4}^T \Psi_{i4}(\bar{x}_{i4}) - \dot{D}_{i4})$$

$$\quad + E_{i4} + \gamma_{i4} e_{i4}. \quad (40)$$

where $K_{i4}$ are positive design parameters. And $\dot{D}_{i4}$ can be obtained,

$$\dot{D}_{i4} = \dot{\xi}_{i4} + K_{i4} \dot{x}_{i4}$$

$$\quad = K_{i4}(-L_{ji}^0 \omega_{i4}^T \Psi_{i4}(\bar{x}_{i4}) - \dot{D}_{i4})$$

$$\quad + E_{i4} + \gamma_{i4} e_{i4}. \quad (41)$$

Substituting (38), (39), (41) and (T1.27) into (37), $\dot{V}_4$ can be written as

$$\dot{V}_3 = \sum_{i=1}^{2} \sum_{j=1}^{4} -k_{i4} E_{ij}^2 - \eta_{i4} \gamma_{i4} e_{i4} e_{i4}$$

$$\quad - k_{ij} \dot{D}_{ij}^2 - c_{ij} \omega_{ij} \dot{\omega}_{ij} - L_{ji}^0 \omega_{i4}^T \Psi_{i4}(\bar{x}_{i4})$$

$$\quad - L_{ji}^0 K_{ji} \dot{D}_{i4} \dot{\omega}_{i4} \Psi_{i4}(\bar{x}_{i4}) \quad (42)$$

Then, substituting (21), (28), (35) and (42) into (18), it follows that,

$$\dot{V} = \sum_{i=1}^{2} \sum_{j=1}^{4} (E_{ij}^T \dot{E}_{ij} + \gamma_{ij} e_{ij} \dot{e}_{ij})$$

$$\quad + \omega_{ij}^T \gamma_{ij}^{-1} \dot{\omega}_{ij} + \dot{D}_{ij} \dot{D}_{ij}$$

$$\quad = \sum_{i=1}^{2} \sum_{j=1}^{4} \left[ \sum_{i=1}^{4} k_{ij} E_{ij}^2 + \sum_{j=2}^{4} \left( -\eta_{ij} \gamma_{ij} e_{ij}^2 \right) \right.$$

$$\quad - k_{ji} \dot{D}_{ji}^2 - c_{ij} \omega_{ij} \dot{\omega}_{ij} - L_{ji}^0 K_{ji} \dot{D}_{i4} \dot{\omega}_{i4} \Psi_{i4}(\bar{x}_{i4})$$

$$\quad - \dot{D}_{ji} \dot{D}_{ji} \right] \quad (43)$$

Consider the following Yang’s inequality

$$- L_{ij}^0 K_{ij} \dot{D}_{ij} \omega_{ij} \Psi_{ij}(\bar{x}_{ij})$$

$$\quad = - L_{ij}^0 K_{ij} \Psi_{ij}(\bar{x}_{ij}) \sqrt{\omega_{ij}^T \dot{\omega}_{ij}}$$

$$\quad \leq \frac{1}{2} a_{ij} w_{ij} \dot{D}_{ij}^2 + \frac{1}{2 a_{ij}} \omega_{ij}^T \dot{\omega}_{ij}. \quad (44)$$

where $w_{ij} = \left( L_{ij}^{-1} K_{ij} \right)^2 \| \Psi_{ij} \|^2$, $a_{ij}$ are positive design parameters, here we choose $a_{ij} = 2$.

$$- c_{ij} \omega_{ij} \dot{\omega}_{ij} \leq - \frac{c_{ij}}{2} \omega_{ij}^T \dot{\omega}_{ij} + \frac{c_{ij}}{2} \| \omega_{ij} \|^2,$$

$$- \dot{D}_{ij} \dot{D}_{ij} \leq \frac{1}{2} \dot{D}_{ij}^2 + \frac{1}{2} \dot{\omega}_{ij}^T \dot{\omega}_{ij}. \quad (45)$$

where $| \dot{D}_{ij} | \leq \mu_{ij}$. Then, the $\dot{V}$ can be further obtained as

$$\dot{V}_i \leq \sum_{i=1}^{2} \left[ \sum_{j=1}^{4} -k_{ij} E_{ij}^2 + \sum_{j=2}^{4} \left( -\eta_{ij} \gamma_{ij} e_{ij}^2 \right) \right.$$

$$\quad - \left( -c_{ij} \omega_{ij} \dot{\omega}_{ij} - (K_{ij} - \frac{1}{2} a_{ij} w_{ij}) \right)$$

$$\quad - \frac{1}{2} \dot{D}_{ij}^2 + \frac{1}{2} \dot{\omega}_{ij}^T \dot{\omega}_{ij} + \frac{c_{ij}}{2} \| \omega_{ij} \|^2 \right]. \quad (46)$$

By selecting the parameters to make

$$L_{\dot{\omega}_{ij}} = \frac{c_{ij}}{2} - \frac{1}{2} a_{ij} > 0,$$

$$L_{\dot{D}_{ij}} = K_{ij} - \frac{1}{2} a_{ij} w_{ij} - \frac{1}{2} > 0. \quad (48)$$

Then, (46) can be rewritten as

$$\dot{V}_i \leq \sum_{i=1}^{2} \left[ \sum_{j=1}^{4} -k_{ij} E_{ij}^2 + \sum_{j=2}^{4} \left( -\eta_{ij} \gamma_{ij} e_{ij}^2 \right) \right.$$

$$\quad - L_{\dot{\omega}_{ij}} \omega_{ij} \dot{\omega}_{ij} - L_{\dot{D}_{ij}} \dot{D}_{ij} + C^*$$

$$\quad \leq -2r V + C^*, \quad (49)$$

where $C^* = \sum_{j=2}^{4} \left( \frac{c_{ij}}{2} \| \omega_{ij} \|^2 + \frac{1}{2} \dot{\omega}_{ij}^T \dot{\omega}_{ij} \right)$, and design parameters satisfy

$$L_{\dot{\omega}_{i2}} \geq r, L_{\dot{\omega}_{i3}} \geq r, L_{\dot{\omega}_{i4}} \geq r, \quad (50)$$

$$L_{\dot{D}_{i2}} \geq r, L_{\dot{D}_{i3}} \geq r, L_{\dot{D}_{i4}} \geq r, \quad (51)$$

$$k_{i1} \geq r, k_{i2} \geq r, k_{i3} \geq r, k_{i4} \geq r, \quad (52)$$

$$\eta_{i2} \geq \frac{r}{\gamma_{i2}}, \eta_{i3} \geq \frac{r}{\gamma_{i3}}, \eta_{i4} \geq \frac{r}{\gamma_{i4}}. \quad (53)$$

Choose $r$ satisfies $r \geq C^*/(2p)$. Then, $\dot{V} \leq -2r V + C^* \leq 0$ when $V = p$, which shows that $V \leq p$ is an invariant set, that is, if $V(0) \leq p$, then $V(t) \leq p$ is set up for all $t \geq 0$. Solve this inequality (49), it follows that

$$0 \leq V(t) \leq \frac{C^*}{2r} + \left( V(0) - \frac{C^*}{2r} \right) e^{-2rt}, \quad t \geq 0. \quad (54)$$

Distinctly, all signals in the closed loop system are bounded in the following compact set $\Phi = \{ E_{i1}, E_{i2}, E_{i3}, E_{i4}, e_{i2p}, e_{i3p}, e_{i4p}, \dot{v}_{ij}, \dot{\omega}_{ij}, \dot{D}_{ij}, \dot{D}_{i4} \} : V \leq \frac{C^*}{2r}$. This means that compact set $\Phi$ can be arbitrarily small by adjusting the parameters $k_{i1}, k_{i2}, k_{i3}, k_{i4}, \eta_{i2}, \eta_{i3}, \eta_{i4}, \gamma_{i2}, \gamma_{i3}, \gamma_{i4}, c_{i2}, c_{i3}, c_{i4}, K_{i2}, K_{i3}, K_{i4}$. In other words, tracking error $e_{i1}, e_{i4}$ and prediction error $e_{i2p}, e_{i3p}, e_{i4p}$ can be arbitrarily small. So we’re done with Theorem 1.
REFERENCES

[1] Y. Wang, D. J. Hill, R. H. Middleton, and L. Gao, “Transient stability enhancement and voltage regulation of power systems,” *IEEE Trans. Power Syst.*, vol. 8, no. 2, pp. 620–627, May 1993.

[2] C. H. Dharmakeerthi, N. Mithulananthan, and T. K. Saha, “Impact of electric vehicle fast charging on power system voltage stability,” *Int. J. Electr. Power Energy Syst.*, vol. 57, pp. 241–249, May 2014.

[3] Q. Lu, S. Mei, W. Hu, F. F. Wu, Y. Ni, and T. Shen, “Nonlinear decentralized disturbance attenuation excitation control via new recursive design for multi-machine power systems,” *IEEE Trans. Power Syst.*, vol. 16, no. 4, pp. 729–736, Nov. 2001.

[4] F. Hughes, “Power system control and stability,” *Electron. Power, vol. 23*, no. 9, p. 739, 1977.

[5] Y. Wang and J. Zhao, “Extended backstepping method for single-machine infinite-bus power systems with SMES,” *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 3, pp. 915–923, May 2013.

[6] S. Hou and J. Fei, “Adaptive fuzzy backstepping control of three-phase active power filter,” *Control Eng. Pract.*, vol. 45, pp. 12–21, Dec. 2015.

[7] S. Gao, B. Ning, and H. Dong, “Fuzzy dynamic surface control for uncertain nonlinear systems under input saturation via truncated adaptation approach,” *Fuzzy Sets Syst.*, vol. 290, pp. 100–117, May 2016.

[8] X. Tang, “Adaptive neural network dynamic surface control for a class of unknown time-delay nonlinear hysteretic systems,” *J. Northeast Electr. Power Univ.*, vol. 38, no. 3, pp. 52–60, 2018.

[9] Z. Tang and Z. Zhang, “The multi-objective optimization of combustion efficiency,” *IEEE Trans. Power Syst., Man., Cybern.*, vol. 49, no. 12, pp. 2424–2437, Dec. 2019.

[10] S. Xi-yu, L. Cui-ping, W. Jain-guo, and L. Yan, “Adaptive dynamic surface control for generator excitation control system,” *Math. Problems Eng.*, vol. 2014, pp. 1–11, Jan. 2014.

[11] Z. Xiang, Z. Li, C.-Y. Su, Y. Lin, and Y. Fu, “Implementable adaptive inverse control of hysteretic systems via output feedback with application to piezoelectric positioning stages,” *IEEE Trans. Ind. Electron.*, vol. 63, no. 9, pp. 5733–5743, Sep. 2016.

[12] H. Li, L. Bai, L. Wang, Q. Zhou, and H. Wang, “Adaptive neural control of uncertain nonstrict-feedback stochastic nonlinear systems with output constraint and unknown dead zone,” *IEEE Trans. Syst., Man, Cybern.*, vol. 47, no. 8, pp. 2048–2059, Aug. 2017.

[13] G. Zhu, S. Wang, L. Sun, W. Ge, and X. Zhang, “Output feedback adaptive dynamic surface sliding mode control for quadrotor UAVs with tracking error constraints,” *Complexity*, vol. 2020, pp. 1–15, May 2020.

[14] X. Zhang, C. Chen, G. Zhu, and Z.-Y. Su, “Output feedback adaptive motion control and its experimental verification for time-delay nonlinear systems with asymmetric hysteresis,” *IEEE Trans. Ind. Electron.*, vol. 67, no. 8, pp. 6824–6834, Aug. 2020.

[15] S. He, W. Lyu, and F. Liu, “Robust $H_\infty$ sliding mode controller design of a class of time-delayed discrete conic-type nonlinear systems,” *IEEE Trans. Syst., Man, Cybern., Syst.*, early access, Dec. 24, 2018, doi: 10.1109/TSMC.2018.288491.

[16] M. S. Rafaq, A. T. Nguyen, H. H. Choi, and J.-W. Jung, “A robust high-order disturbance observer design for SDRE-based suboptimal speed controller of interior PMSM drives,” *IEEE Access*, vol. 7, pp. 165671–165683, 2019.

[17] C. Jia, X. Wang, Y. Liang, and K. Zhou, “Robust current controller for IPMSM drives based on explicit model predictive control with online disturbance observer,” *IEEE Access*, vol. 7, pp. 45898–45910, 2019.

[18] S. He, H. Fang, M. Zhang, F. Liu, X. Luan, and Z. Ding, “Online policy iterative-based $H_\infty$ optimization algorithm for a class of nonlinear systems,” *IEEE Trans. Automat. Sci. Eng.*, vol. 16, no. 4, pp. 1495–1509, Apr. 2019.

[19] Z. Li and J. Shan, “Inverse compensation based synchronization control of the piezo-actuated Fabry–Pérot spectrometer,” *IEEE Trans. Ind. Electron.*, vol. 64, no. 11, pp. 8588–8597, Nov. 2017.

[20] D.-K. Gu and D.-W. Zhang, “A parametric method to design dynamic compensator for high-order quasi-linear systems,” *Nonlinear Dyn.*, vol. 100, no. 2, pp. 1379–1400, Apr. 2020.

[21] Z. Li, J. Shan, and U. Gabbert, “Dynamics modeling and inversion-based synchronized model predictive control for a Fabry–Perot spectrometer,” *IEEE/ASME Trans. Mechatronics*, vol. 24, no. 4, pp. 1818–1828, Aug. 2019.

[22] Y. Li and S. Tong, “Adaptive fuzzy control with prescribed performance for block-triangular-structured nonlinear systems,” *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 3, pp. 1153–1163, Jun. 2018.

[23] X. Zhang, Y. Wang, C. Wang, C.-Y. Su, Z. Li, and X. Chen, “Adaptive estimated inverse output-feedback quantized control for piezoelectric positioning stage,” *IEEE Trans. Cybern.*, vol. 49, no. 6, pp. 2106–2118, Jun. 2019.

[24] Z. Zhang and Z. Zhang, “The multi-objective optimization of combustion system operation based on deep data-driven models,” *Energy*, vol. 182, pp. 37–47, Sep. 2019.

[25] C. Zhang, Y. Yu, Y. Wang, and M. Zhou, “Takagi-Sugeno fuzzy neural network hysteresis modeling for magnetic shape memory alloy actuator based on modified bacteria foraging algorithm,” *Int. J. Fuzzy Syst.*, vol. 22, no. 4, pp. 1314–1329, Jun. 2020.

[26] Y. Yu, C. Zhang, and M. Zhou, “NARMAX model-based hysteresis modeling of magnetic shape memory alloy actuators,” *IEEE Trans. Nanotechnol.*, vol. 19, pp. 1–4, 2020.

[27] X. Zhang, Y. Wang, G. Zhu, X. Chen, Z. Li, C. Wang, and C.-Y. Su, “Compound adaptive fuzzy quantized control for quadrotor and its experimental verification,” *IEEE Trans. Cybern.*, early access, May 14, 2020, doi: 10.1109/TCYB.2020.2987811.

[28] S. Hou and J. Fei, “Adaptive fuzzy backstepping control of three-phase active power filter,” *Control Eng. Pract.*, vol. 45, pp. 12–21, Dec. 2015.
[44] W.-H. Chen, J. Yang, L. Guo, and S. Li, “Disturbance-observer-based control and related methods—An overview,” *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1083–1095, Feb. 2016.

[45] X. Liu, H. Yu, J. Yu, and L. Zhao, “Combined speed and current terminal sliding mode control with nonlinear disturbance observer for PMSM drive,” *IEEE Access*, vol. 6, pp. 29594–29601, 2018.

[46] Y. Li, L. Liu, and G. Feng, “Robust adaptive output feedback control to a class of non-triangular stochastic nonlinear systems,” *Automatica*, vol. 89, pp. 325–332, Mar. 2018.

[47] H.-N. Wu, S. Feng, Z.-Y. Liu, and L. Guo, “Disturbance observer based robust mixed H\(_2\)/H\(_\infty\) fuzzy tracking control for hypersonic vehicles,” *Fuzzy Sets Syst.*, vol. 306, pp. 118–136, Jan. 2017.

[48] B. Xu, Z. Shi, and C. Yang, “Composite fuzzy control of a class of uncertain nonlinear systems with disturbance observer,” *Nonlinear Dyn.*, vol. 80, nos. 1–2, pp. 341–351, Apr. 2015.

[49] X. Zhang, L. Sun, K. Zhao, and L. Sun, “Nonlinear speed control for PMSM system using sliding-mode control and disturbance compensation techniques,” *IEEE Trans. Power Electron.*, vol. 28, no. 3, pp. 1358–1365, Mar. 2013.

[50] S. K. Patel, S. R. Arya, R. Maurya, and B. C. Babu, “Control scheme for DSTATCOM based on frequency-adaptive disturbance observer,” *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 6, no. 3, pp. 1345–1354, Sep. 2018.

[51] Y. Guo, D. J. Hill, and Y. Wang, “Nonlinear decentralized control of large-scale power systems,” *Automatica*, vol. 36, no. 9, pp. 1275–1289, Sep. 2000.

[52] L.-X. Wang and J. M. Mendel, “Fuzzy basis functions, universal approximation, and orthogonal least-squares learning,” *IEEE Trans. Neural Netw.*, vol. 3, no. 5, pp. 807–814, Sep. 1992.

[53] L. X. Wang, *Adaptive Fuzzy Systems and Control: Design and Stability Analysis*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1994.

**GUOQIANG ZHU** was born in Heze, China. He received the B.S. and M.S. degrees from Northeast Electric Power University, Jilin, China, in 2003 and 2007, respectively, and the Ph.D. degree from the Beijing University of Aeronautics and Astronautics (BUAA), Beijing, China, in 2015. He is currently an Associate Professor with the School of Automation Engineering, Northeast Electric Power University. His research interest includes robust and adaptive control for nonlinear systems.

**LINGFANG SUN** was born in Heze, China. He received the B.S. and M.S. degrees from Northeast Electric Power University, Jilin, China, in 2003 and 2006, respectively, and the Ph.D. degree in control theory and control engineering from Jilin University, China, in 2009. He is currently a Professor with the School of Automation Engineering, Northeast Electric Power University. His research interest includes advanced control of thermal process and fouling monitoring of heat exchange equipment.

**XIUYU ZHANG** (Member, IEEE) was born in Jinl City, China. He received the B.S. and M.S. degrees from Northeast Electric Power University, Jilin, China, in 2003 and 2006, respectively, and the Ph.D. degree from the Beijing University of Aeronautics and Astronautics (BUAA), Beijing, China, in 2012. He is currently a Professor with the School of Automation Engineering, Northeast Electric Power University. His research interest includes robust and adaptive control for nonlinear systems with smart-material-based actuators.

**CHENG ZHONG** was born in Changchun, China. He received the B.S. and M.S. degrees from Northeast Electric Power University, Jilin, China, in 2003 and 2006, respectively. He is currently a Senior Engineer with Tangshan Power Supply Company, State Grid Jibei Electric Power Company, Tangshan, China. His research interests include power system stability analysis and power supply management.

**MIAOLEI ZHOU** (Member, IEEE) was born in 1976. He received the B.S. and M.S. degrees in industrial electric automation from the Jilin Institute of Technology, China, in 1997 and 2000, respectively, and the Ph.D. degree in control theory and control engineering from Jilin University, China, in 2004. From 2006 to 2008, he was a Postdoctoral Researcher with Tokyo University, Japan. In 2000, he joined the Department of Control Science and Engineering, Jilin University, where he became an Associate Professor in 2009 and a Professor in 2014. He has supervised over 20 research projects, including the National Natural Science Funds of China and the National High Technology Research and Development Program. He has authored over 70 articles. His research interests include micro-/nano-drive and control technology, nonlinear control theory, and navigation and control of robot. He is an Editorial Board Member of the scientific *Journal of Control Engineering*.

**LINLIN NIE** was born in China, in 1994. She received the B.S. degree from the Henan University of Science and Technology, Luoyang, China, in 2017, and the M.S. degree from Northeast Electric Power University, Jilin City, China, in 2020. She is currently pursuing the Ph.D. degree with Jilin University, Changchun, China. Her research interest includes robust and adaptive control for multi-machine power systems.