Adaptive Backstepping Fuzzy Neural Controller Based on Fuzzy Sliding Mode of Active Power Filter

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This work was supported in part by the National Science Foundation of China under Grant 61873085.

ABSTRACT An adaptive backstepping fuzzy neural network (FNN) controller using a fuzzy sliding mode controller is designed to suppress the harmonics and improve the performance of a shunt active power filter (APF). A backstepping method transforms the APF system into a series of subsystems and uses the virtual control to simplify the controller design. A FNN controller is utilized to approach the nonlinear APF system. An adaptive fuzzy system is employed to adjust the sliding gain to compensate the approximation error of neural network and diminish the chattering. The weights of the fuzzy neural network and fuzzy system parameters are adjusted in real-time to guarantee the asymptotic stability of the designed control system. Simulation and experimental studies indicate the validity of the proposed control method, demonstrating the good compensation performance and strong robustness.

INDEX TERMS Fuzzy neural network, adaptive fuzzy control, backstepping control, active power filter.

I. INTRODUCTION Nonlinear electronic devices in power grid often produce a large number of harmonic voltages or harmonic currents, which affect the power quality seriously and increase additional loss of power system equipment. Different from the passive power filter, active power filter (APF) could compensate the harmonic rapidly and eliminate current distortion efficiently. According to the principles of APF, the most critical part for eliminating harmonics is the current operation circuit and current tracking control circuit. With the combination of current control technology and command current signal, corresponding control signal is obtained to drive the Pulse Width Modulation (PWM) converter to eliminate the harmonics by outputting compensation current into the power grid.

The compensation performance of APF depends largely on the current control technology \cite{1}, \cite{2}. Conventional and new current control methods such as hysteresis control and single cycle control \cite{3}, deadbeat control \cite{4}, predictive control \cite{5} sliding mode control \cite{6}, backstepping control \cite{7}, fuzzy and neural network control \cite{8}, \cite{9} have been developed to improve the harmonic performance and power quality of APF. Dey \textit{et al}. \cite{10} presented a synchronous reference frame method based on a modified phase lock loop circuit for an active power filter. Mohapatra \textit{et al}. \cite{11} exploited a partial feedback linearization technique to control an active power filter.

Sliding mode control (SMC) is a variable structure control with property that is insensitive to parameter variations and external disturbances. It has been well applied in the control strategy of chaotic systems, linear systems, nonlinear systems \cite{12}, \cite{13}. Composite super-twisting sliding mode control and second-order sliding mode controller design with output constraint are investigated in \cite{14}, \cite{15}. Fractional-order finite-time super-twisting sliding mode controller is derived in \cite{16}.

The backstepping controller could transforms the nonlinear system into subsystems and uses the virtual controller to make the controller design easily steps \cite{17}–\cite{20}. An adaptive fuzzy backstepping tracking controller for nonlinear strict-feedback systems with unmodeled dynamics is developed in \cite{17}. An adaptive backstepping neural controller for MIMO nonlinear switched systems is discussed in \cite{18}. A command filter-based adaptive fuzzy backstepping controller is designed for a class of switched nonlinear
systems in [19]. A robust backstepping high-order sliding mode control strategy is proposed for grid-connected dg units with harmonic current compensation capability in [20].

The universal approximation theorem indicates that the fuzzy system is a new universal approximator in addition to polynomial function approximators and neural network approximators. The integration of fuzzy neural network system has catch attentions for its combination of advantages of fuzzy control and neural network [21]–[27]. An adaptive fuzzy neural network control is designed for a constrained robot using impedance learning in [21] An compensatory fuzzy neural network control is derived with dynamic parameters estimation for a linear voice coil actuator [22]. Adaptive intelligent control methods such as fuzzy control and neural control have been investigated to improve the power dynamic performance of shunt active power filter in [23]–[27].

Motivated from the researches above, an adaptive backstepping fuzzy neural network control of APF using a fuzzy sliding scheme is proposed for harmonic compensation. The adaptive backstepping fuzzy neural network control is developed to avoid establishing accurate mathematical model of APF and make controller design simpler and easier. The specific contributions compared to existing works are summarized as:

1. The fuzzy neural network that combines fuzzy logic system and fast nonlinear learning ability of neural network, can approach nonlinear smooth system with unknown parameters fastly. Fuzzy neural network (FNN) is a popular technology combining the knowledge expression ability of fuzzy logic system with the powerful self-learning ability of neural network, and it avoids fuzzy rule design that requires expert prior knowledge.

2. The backstepping method transforms the APF system into a series of subsystems and design the virtual control to facilitate the controller design. Fuzzy neural network controller is employed for approximating nonlinearity in APF model. The sliding gain is adjusted by fuzzy system to compensate the network approximation error and reduce the chattering. Therefore the proposed control system can suppress harmonic and strengthen the quality of power supply.

3. The weights of the fuzzy neural network controller and adaptive fuzzy parameters are adjusted online based on adaptive laws, to guarantee the asymptotic stability. The proposed adaptive backstepping neural controller is implemented based on Digital signal Processing (DSP), processor TMS320F28335 with PSIM tools. The simulation and experimental results indicate the effectiveness of the proposed method under both dynamic and steady state operations, showing the good performance in harmonic suppression.

II. DYNAMIC MODEL OF ACTIVE POWER FILTER

The shunt APF, especially parallel-voltage type of APF shown as in Fig. 1 is the most basic structure of APF. The working principle can be described in two steps. Firstly it acquires the real-time voltage and current in the grid and transmit them respectively to the current control loop and voltage control loop. Then it transits the proposed control signal to the main circuit and obtains the compensation current. The circuit relationships are obtained by Kirchhoff rules as.

\[
\begin{align*}
    v_1 &= L_c \frac{di_1}{dt} + R_c i_1 + v_{1M} + v_{MN} \\
    v_2 &= L_c \frac{di_2}{dt} + R_c i_2 + v_{2M} + v_{MN} \\
    v_3 &= L_c \frac{di_3}{dt} + R_c i_3 + v_{3M} + v_{MN}
\end{align*}
\]

where \(v_{MN}\) is the voltage between \(M\) and \(N\).

Assuming the balanced AC supply voltage, and summing equations in (1), considering the absence of the zero-sequence, yield:

\[
v_{MN} = -\frac{1}{3} \sum_{m=1}^{3} v_{mM}
\]

In order to show the IGBT working status, switch function \(c_k\) is defined as:

\[
c_k = \begin{cases} 
1 & \text{if } S_k \text{ is On and } S_{k+3} \text{ is Off} \\
0 & \text{if } S_k \text{ is Off and } S_{k+3} \text{ is On}
\end{cases}
\]

where \(k = 1, 2, 3\).

In the meantime, considering \(v_{km} = c_k v_{dc}\), thus Eq. (1) is expressed as

\[
\begin{align*}
    \frac{di_1}{dt} &= -\frac{R_c}{L_c} i_1 + \frac{v_1}{L_c} \left( c_1 - \frac{1}{3} \sum_{m=1}^{3} c_m \right) \\
    \frac{di_2}{dt} &= -\frac{R_c}{L_c} i_2 + \frac{v_2}{L_c} \left( c_2 - \frac{1}{3} \sum_{m=1}^{3} c_m \right) \\
    \frac{di_3}{dt} &= -\frac{R_c}{L_c} i_3 + \frac{v_3}{L_c} \left( c_3 - \frac{1}{3} \sum_{m=1}^{3} c_m \right)
\end{align*}
\]

Denote the switching state as

\[
d_{ek} = \left( c_k - \frac{1}{3} \sum_{m=1}^{3} c_m \right)_n
\]
Eq. (5) shows the relation between \( d_{nk} \) and \( c_k \), then Eq. (5) with eight permissible IGBT switching states is expressed as
\[
\begin{bmatrix}
  d_{n1} \\
  d_{n2} \\
  d_{n3}
\end{bmatrix} = \frac{1}{3} \begin{bmatrix}
  2 & -1 & -1 \\
  -1 & 2 & -1 \\
  -1 & -1 & 2
\end{bmatrix} \begin{bmatrix}
  c_1 \\
  c_2 \\
  c_3
\end{bmatrix}
\]
(6)

Then Eq. (4) can be written in simplified form as
\[
\begin{align*}
\frac{di_1}{dt} &= -\frac{R_c}{L_c} i_1 + \frac{v_k}{L_c} - \frac{v_{dc}}{L_c} d_{n1} \\
\frac{di_2}{dt} &= -\frac{R_c}{L_c} i_2 + \frac{v_k}{L_c} - \frac{v_{dc}}{L_c} d_{n2} \\
\frac{di_3}{dt} &= -\frac{R_c}{L_c} i_3 + \frac{v_k}{L_c} - \frac{v_{dc}}{L_c} d_{n3}
\end{align*}
\]
(7)

Define two state variables as
\[
\begin{cases}
  x_1 = i_k \\
  x_2 = \dot{x}_1
\end{cases}
\]
(8)

Differentiating \( x_1 \) and \( x_2 \) yields
\[
\dot{x}_1 = i_k = -\frac{R_c}{L_c} i_k + \frac{v_k}{L_c} - \frac{v_{dc}}{L_c} d_{nk}
\]
(9)

\[
\dot{x}_2 = \frac{R_c^2}{L_c^2} i_k - \frac{R_c}{L_c} v_k + \frac{1}{L_c} \frac{dv_k}{dt} + u \left( \frac{R_c}{L_c} v_{dc} - \frac{1}{L_c} \frac{dv_{dc}}{dt} \right) = f(x) + bu
\]
(10)

Considering the external disturbances, the APF model is expressed as
\[
\dot{x}_2 = \frac{R_c^2}{L_c^2} i_k - \frac{R_c}{L_c} v_k + \frac{1}{L_c} \frac{dv_k}{dt} + u \left( \frac{R_c}{L_c} v_{dc} - \frac{1}{L_c} \frac{dv_{dc}}{dt} \right) + f_d
\]
(11)

where
\[
f(x) = \frac{R_c^2}{L_c^2} i_k - \frac{R_c}{L_c} v_k + \frac{1}{L_c} \frac{dv_k}{dt}, \quad b = \frac{R_c}{L_c} v_{dc} - \frac{1}{L_c} \frac{dv_{dc}}{dt}, \quad u = d_{nk}
\]

\( f_d \) is an unknown bounded disturbance satisfying \( |f_d| < D, D > 0 \).

III. BACKSTEPPING FUZZY NEURAL NETWORK CONTROLLER

In this section, a backstepping method is designed in two steps. Firstly, a virtual control function is designed and a real control law is proposed secondly.

Step 1: Define the tracking error as:
\[
z_1 = x_1 - z_d
\]
(12)

where, \( z_d \) is a reference current.

Then
\[
z_1 = x_2 - z_d
\]
(13)

Design a virtual control function as
\[
\alpha_1 = -c_1 z_1 + \dot{z}_d
\]
(14)

where, \( c_1 \) is a positive constant.

Define the first Lyapunov function as
\[
V_1 = \frac{1}{2} z_1^2
\]
(15)

Then the derivative of \( V_1 \) becomes
\[
\dot{V}_1 = z_1 (x_2 - \dot{z}_d)
\]
(16)

Define the error as
\[
z_2 = x_2 - \alpha_1
\]
(17)

Then
\[
\dot{V}_1 = z_1(z_2 + \alpha_1 - \dot{z}_d) = z_1(z_2 - c_1 z_1) = -c_1 z_1^2 + z_1 z_2
\]
(18)

If \( z_2 = 0 \), then \( \dot{V}_1 = -c_1 z_1^2 \leq 0 \).

Step 2: Define a sliding surface as
\[
s = z_2
\]
(19)

From Eq. (17), we can get
\[
\dot{z}_2 = f(x) + bu - \dot{\alpha}_1 = f(x) + bu - \dot{z}_d + c_1 \dot{z}_1
\]
(20)

Define the second Lyapunov function as
\[
V_2 = V_1 + \frac{1}{2} z_2^2
\]
(21)

Then the derivative of \( V_2 \) is
\[
\dot{V}_2 = -c_1 z_1^2 + z_1 z_2 + z_2[f(x) + bu - \dot{z}_d + c_1 \dot{z}_1]
\]
(22)

The backstepping control law is designed as
\[
u = \frac{1}{b} \left[ -f(x) + \dot{z}_d - c_1 \dot{z}_1 - c_2 z_2 - z_1 - \eta \text{sgn}(s) \right]
\]
(23)

where, \( \eta, c_2 \) are positive constants.

Substituting (23) into (22) yields:
\[
\dot{V}_2 = -c_1 z_1^2 - c_2 z_2^2 - \eta |z_2| \leq 0.
\]
(24)

However, the control law (23) cannot be realized directly because \( f(x) \) is unknown in practical situation. In the next step we will design a fuzzy neural network controller to estimate the unknown function \( f(x) \). The fuzzy neural structure is described in Fig. 2.

The neuron function spreading out in successive layers are described as:

1) Input layer: input variable spread to the next level.

2) The membership layer: represent the input values with the Gaussian membership functions as
\[
\mu_{ij} = \exp \left( -\frac{(z_1 - c_{ij})^2}{b_{ij}^2} \right)
\]
(25)

where, \( c_{ij} \) and \( b_{ij} \) are the mean and standard deviation of the Gaussian function on the \( j \)th term of the \( i \)th input linguistic variable to the node of the layer.
The structure of a four-layer FNN.

3) The rule layer: implements the fuzzy inference mechanism, given as

\[ \phi_i(x) = \prod_{j=1}^{N} \mu_j \psi_j \]  \hspace{1cm} (26)

where, \( N = \sum_{i=1}^{n} N_i \), \( N_i \) is the \( i \)th input membership layer nodes. \( \psi_j \) is the weights between the membership layer and the rule layer.

4) The output layer:

\[ f_i = \frac{\sum_{j=1}^{N} \psi_j \phi_i(x)}{\sum_{j=1}^{N} \phi_j(x)} = \sum_{j=1}^{N} \psi_j \phi_j(x), \hspace{1cm} l = 1, 2, \ldots, m \]  \hspace{1cm} (27)

For the sake of convenience in presentation, the outputs of the FNN are denoted as:

\[ \hat{f} = \psi^T \phi(x) \]  \hspace{1cm} (28)

Then a fuzzy-neural-network controller \( \hat{f} \) is used to approximate \( f(x) \) in the APF system. The approximation is described as

\[ f = \psi^* T \phi(x) + \epsilon \]  \hspace{1cm} (29)

where, \( \psi^* \) is the optimal weight, \( \epsilon \) is the approximation error, \( |\epsilon| \leq \bar{\epsilon} \), \( \bar{\epsilon} \) is a small positive constant.

The third Lyapunov function candidate is selected as

\[ V_3 = V_2 + \frac{1}{2n} (\psi - \psi^*)^T (\psi - \psi^*) \]  \hspace{1cm} (30)

where, \( \eta \) is a positive constant.

The derivative of \( V_3 \) is

\[ \dot{V}_3 = \dot{V}_2 + \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} \]

\[ = -c_1 z_1^2 - c_1 z_2^2 + z_2 (f + bu + c_1 \dot{z}_d) + \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} \]  \hspace{1cm} (31)

The new control law now is proposed as

\[ u = \frac{1}{b} \left[-\hat{f} + \dot{z}_d - c_1 \dot{z}_1 - c_2 z_2 - z_1 - \eta \text{sgn}(s)\right]. \]  \hspace{1cm} (32)

Substituting (32) into (31) yields

\[ \dot{V}_3 = -c_1 z_1^2 - c_2 z_2^2 - \eta |z_2| + z_2 \epsilon + \psi^* T \phi(x) - \psi^T \phi(x) \]

\[ + \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} \]

\[ = -c_1 z_1^2 - c_2 z_2^2 - \eta |z_2| + z_2 \epsilon - z_2 (\psi - \psi^*)^T \phi(x) \]

\[ + \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} \]  \hspace{1cm} (33)

Choose an adaptive law:

\[ \dot{\psi} = \eta z_2 \phi(x) \]  \hspace{1cm} (34)

Substituting (34) into (33) yields

\[ \dot{V}_3 = -c_1 z_1^2 - c_2 z_2^2 - \eta |z_2| + z_2 \epsilon \]

\[ \leq -c_1 z_1^2 - c_2 z_2^2 - |z_2| (\eta - \bar{\epsilon}) \]  \hspace{1cm} (35)

If we choose \( \eta \geq \bar{\epsilon} \), then Eq. (35) becomes

\[ \dot{V}_3 \leq -c_1 z_1^2 - c_2 z_2^2 \leq 0 \]  \hspace{1cm} (36)

Since \( \dot{V}_3 \leq 0 \), \( \dot{V}_3 \) is negative semidefinite, ensuring \( z_1 \) and \( z_2 \) are bounded. We can get:

\[ W(t) = c_1 z_1^2 + c_2 z_2^2 \leq -\dot{V}_3 \]  \hspace{1cm} (37)

Then

\[ \int_{0}^{t} W(t) d\tau \leq V_3(0) - V_3 \]  \hspace{1cm} (38)

Since \( V_3(0) \) is bounded and \( V_3 \) is nonincreasing and bounded, we get \( \lim_{t \to \infty} \int_{0}^{t} W(t) d\tau < \infty \). Moreover, \( W(t) \) is also bounded. \( W(t) \) is continuous. According to Barbalat’s lemma, \( \lim_{t \to \infty} W(t) = 0 \), implying that \( z_1 \) and \( z_2 \) converge to zero, and the asymptotic stability of the close-loop system is guaranteed.

IV. ADAPTIVE BACKSTEPPING FUZZY NEURAL NETWORK CONTROLLER USING FUZZY SLIDING MODE CONTROLLER

From (32), the chattering is generated by the constant value of \( \bar{\epsilon} \) and the discontinuous function \( \text{sgn}(s) \). In this section, we use a fuzzy controller to update the gain in sliding controller to decrease the chattering. Let the control gain \( \text{sgn}(s) \) be replaced by a fuzzy gain \( \tilde{y}(s) \). The block diagram of the proposed is shown in Fig.3.

Then the output of the fuzzy system is expressed as

\[ y(s) = \tilde{y}^T \phi(s) \]  \hspace{1cm} (39)
where, $\theta = [\theta_1, \theta_2, \ldots, \theta_m]^T$ are adjustable parameters, 
$\varphi(s) = [\varphi_1, \varphi_2, \ldots, \varphi_m]^T$ are fuzzy vectors.

The actual output of the fuzzy system is expressed as

$$\hat{y}(s) = \theta^* \varphi(s) + e \quad (40)$$

where, $e$ is an approximation error of the fuzzy system and $|e| \leq e_N$, $e_N$ is a small positive constant, $\hat{y}(s)$ is the estimated value of $y(s)$, $\theta^*$ is the actual adjustable parameters.

We use an adaptive fuzzy controller $\hat{y}(s)$ to approximate $\text{sgn}(s)$ in (32). Then, the new control law is designed as:

$$u = \frac{1}{b} [-\hat{f} + \hat{z}_d - c_1 \hat{z}_1 - c_2 \hat{z}_2 - \hat{y}]. \quad (41)$$

Define a new Lyapunov function candidate as

$$V_4 = V_3 + \frac{1}{2} \theta^T \hat{\theta} \quad (42)$$

where, $\hat{\theta} = \theta^* - \hat{\theta}$ is a parameter estimation.

Then, the derivative of $V_4$ becomes

$$\dot{V}_4 = \dot{V}_3 + \theta^T \ddot{\theta}$$

$$= -c_1 \hat{z}_1^2 + z_1 \dot{z}_2 + z_2 (f - \dot{\hat{f}} - \dot{z}_1 - c_2 \dot{z}_2 - \dot{y})$$

$$+ \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} + \theta^T \ddot{\theta} \quad (43)$$

Substituting (41) into (43) yields

$$\dot{V}_4 = -c_1 \hat{z}_1^2 + z_1 \dot{z}_2 + z_2 (f - \dot{\hat{f}} - \dot{z}_1 - c_2 \dot{z}_2 - y)$$

$$+ \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} + \theta^T \ddot{\theta}$$

$$= -c_1 \hat{z}_1^2 + z_1 \dot{z}_2 + z_2 (f - \dot{\hat{f}}) + \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} + \theta^T \ddot{\theta}$$

$$= -c_1 \hat{z}_1^2 + z_2^2 - c_2 z_2 + z_2 (f - \dot{\hat{f}}) + \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} + \theta^T \ddot{\theta}$$

$$= c_1 \hat{z}_1^2 - c_2 z_2 + z_2 (e - \dot{y}) + z_2 (\psi^* - \psi) \phi(x)$$

$$+ \frac{1}{\eta} (\psi - \psi^*)^T \dot{\psi} + \theta^T \ddot{\theta} \quad (44)$$

Choose adaptive laws as

$$\dot{\hat{\theta}} = s \varphi(s) \quad (45)$$

$$\dot{\psi} = \eta_2 \phi(x) \quad (46)$$

Substituting (45), (46) into (44) yields

$$V_4 = -c_1 \hat{z}_1^2 - c_2 z_2 + z_2 (e - \dot{y}) + \theta^T \dot{\theta}$$

$$= -c_1 \hat{z}_1^2 - c_2 z_2 + z_2 (e - \dot{y}) + \theta^T \dot{z}_2 \varphi(s)$$

$$= -c_1 \hat{z}_1^2 - c_2 z_2 + z_2 (e - \dot{\hat{f}} \dot{\theta})$$

$$+ \theta^T (\varphi(s) + \hat{\theta} \dot{z}_2 \varphi(s))$$

$$= -c_1 \hat{z}_1^2 - c_2 z_2 + z_2 (e - \theta^T \varphi(s)) \quad (47)$$

Assume that

$$|e - \theta^T \varphi(s)| \leq \omega \leq \gamma |s| \quad (48)$$

where, $\omega > 0$, $0 \leq \gamma \leq 1$, then

$$z_2 (e - \theta^T \varphi(s)) \leq \gamma |z_2| |s| = \gamma s^2 \quad (49)$$

Substituting (49) into (47) yields

$$\dot{V} \leq -c_1 \hat{z}_1^2 - c_2 z_2^2 + \gamma s^2$$

$$= -c_1 \hat{z}_1^2 - c_2 z_2^2 + \gamma s^2 - c_1 \hat{z}_1^2 - (c_2 - \gamma) z_2^2$$

$$\leq 0 \quad (50)$$

If $c_2 > \gamma$, $\dot{V}_4 \leq 0$. According to Barbalat lemma, $s(t)$ will asymptotically converge to zero, $\lim_{t \to \infty} s(t) = 0$. Then the asymptotic stability of the close-loop system is guaranteed.

V. SIMULATION AND EXPERIMENT STUDY

A. SIMULATION STUDY

Matlab/Simulink package with SimPower Toolbox is used to validate the effectiveness of the proposed strategy. APF system’s parameters are shown in Table 1.

### TABLE 1. Parameters in APF system.

| Parameter                        | Value                        |
|----------------------------------|------------------------------|
| Supply voltage and frequency      | $V_{s1} = V_{s2} = V_{s3} = 220V$, $f = 50Hz$ |
| Nonlinear load                    | $R = 40\Omega$, $L = 5mH$    |
| Active power filter parameters    | $L_c = 10mH$, $R_c = 0.1\Omega$ |
|                                  | $C = 5000\mu F$, $\gamma_{dref} = 1000V$ |
| Switching frequency              | $f_{sw} = 10KHz$             |

The membership function is chosen as $\mu = \exp[-((x + 15 - (i - 1)7.5)/3.75)^2]$, where, $i = 1, 2, \ldots, 5$. The controller parameters are selected as: Virtual control parameters are designed as $c_1 = 100000$, $c_2 = 100000$. Adaptive parameter is $\eta = 50000000$. The node number in hidden layer is 6, the centric vector $c = [157.5 \ 0 \ -7.5\ -15]$ and base width vector $b = [2.2 \ 2.2 \ 2.2]^T$. Initial network weights are setting to zero. At $t = 0.04s$, the switch of compensation circuit is closed off and then APF begins to operate. Nonlinear loads was subjected to 100% step increase at $t = 0.1s$ and $t = 0.2s$. There is a serious distortion in the grid current waveform because of nonlinear load in Fig. 4. Source current distortion is significantly diminished using the proposed adaptive fuzzy neural controller with a fuzzy sliding controller.
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FIGURE 4. Load current waveform.

FIGURE 5. Source current waveform using the proposed controller.

FIGURE 6. Tracking error between instruction current and compensation current using the proposed controller.

in Fig.5. Fig.6 is the tracking error between instruction current and compensation current using the proposed controller, showing the compensation current can properly track the instruction current. The harmonic spectrum of source current after harmonic compensation using the proposed controller in $t = 0s$, $t = 0.06s$, $t = 0.16s$, $t = 0.26s$ are shown in Fig. 7(a), (b), (c), (d). The comparative results are summarized in Table 2.

From Table 2, with the increase of nonlinear load, the APF system with the proposed controller shows better tracking performance, suitability and robustness at different simulation stages. From Fig. 4 and Table 2, the proposed fuzzy neural network controller has superior learning ability, function fitting ability, and generalization ability.

TABLE 2. THD values at different simulation times.

| Time   | Adaptive fuzzy neural network using fuzzy sliding mode controller | Without control |
|--------|-----------------------------------------------------------------|-----------------|
| 0      | 24.70                                                           | 24.70           |
| 0.06s  | 3.13                                                            | 24.72           |
| 0.16s  | 1.40                                                            | 22.24           |
| 0.26s  | 1.24                                                            | 20.06           |

B. EXPERIMENTAL VERIFICATION

An experimental prototype is designed and built using a TSM320F28335 floating-point DSP. The proposed algorithm
is used in the three-phase active power filter in the simulation. However, the system can be seen as three single phase APFs in Eq.7. As a result, the hardware experiment is simply implemented as a single phase APF shown as in Fig. 8 and Fig 9. The prototype mainly includes: APF main circuit, power supply, nonlinear load, drive circuit, acquisition circuit and control board.

Steady-state experiments are accomplished to testify the performance of the APF system with the proposed control compared with the case without controller. According to the waveform of the oscilloscope, the red wave in Fig.10 is close to sine wave, meaning the proposed controller controller is satisfactory in the aspect of suppressing harmonics. According to Fig.11 and Fig. 12, the current distortion is up to 25.10%, far beyond the defined IEEE limits 5%. However, when the proposed controller is adopted to APF, THD decreases to 4.48%. Hence, the proposed controller can greatly compensate harmonics.

The dynamic experiment is based on a nonlinear load, and then a nonlinear load of the same type is connected to simulate the load change scenario in an actual engineering scenario. As shown in Fig. 13 and Fig. 14, the dynamic experiment has two cases: (1) nonlinear load increases abruptly, that is 100%-150% nonlinear load increases abruptly.
load decreases abruptly, that is 150%-100% nonlinear load changes. After the nonlinear loads change, the proposed control algorithm in this paper can still suppress harmonics. Compared with the steady state, the waveform generally maintains the sine wave, and the fluctuation before and after the load increase is about 1%. Then, the simulation and experiment results both verify the effectiveness of the proposed controller.

VI. CONCLUSION
An adaptive fuzzy neural network controller using a fuzzy sliding mode controller is derived for the harmonic suppression of a shunt APF. A fuzzy neural network controller is used to approximate the nonlinearities in APF model and a sliding controller is designed with adaptive fuzzy systems to compensate the network approximation error and eliminate the chattering. Simulation studies confirm the effectiveness of the proposed controller and an APF prototype based on DSP TMS320F28335 was built to indicate the validity of the proposed control algorithm, illustrating that the APF system with the proposed controller has good compensation performance and strong robustness.

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