Research Article

Adaptive Backstepping Current Control of Active Power Filter Using Neural Compensator

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A backstepping-based adaptive controller with neural compensator is designed for harmonic suppression in a three-phase active power filter (APF). The fundamental rule of backstepping method is to take some state variables as “virtual controls” and then design intermediate controller. An adaptive neural controller using radial basis function (RBF) is derived to estimate the APF system nonlinearity and strengthen the current’s tracking property and power grid quality. Simulations studies indicate the proposed backstepping-based adaptive neural controller has good current tracking behavior and increased power quality.

1. Introduction

The harmonic distortion of power grid quality is becoming a serious issue with the increasing nonlinear loads in electrical equipment and power systems. Shunt active power filters (SAPF) become the main harmonic treatment way because they can effectively reduce current harmonic distortion and reactive power.

The active power filter (APF) is an intelligent harmonic control device, which detects harmonics and injects compensation current into the grid to improve power quality. There are some current controllers, i.e., hysteresis current control, triangular wave modulation control, and space vector modulation control. With the introduction of the smart grid concept, the control algorithms can achieve more accurate harmonic current tracking control effects. Yue et al. [1] designed a predictive double loop controller in order to increase the robustness and adaptive property of an active filter. Swain et al. [2] improved the robustness and stability of APF with a novel sliding controller. Intelligent control methods were developed in [3–5] to remove the current with harmonics and increase the power grid quality. Carpinelli et al. [6] adopted a multiobjective method in a multiconverter distribution system. Tareen et al. [7] decreased the power switches and improved the properties of grid-connected inverters by reducing the cost, weight, and size.

In the nonlinear systems, unknown nonlinearities can be approximated by intelligent methods such as neural networks [8] and fuzzy systems [9]. Liu et al. [10] derived an adaptive fuzzy controller with output feedback for full state constrained nonlinear systems. Wu et al. [11] proposed mixed fuzzy/boundary schemes for nonlinear parabolic PDE systems. Li et al. [12] developed a novel adaptive neural strategy with prescribed property for nonlinear systems with switched and interconnected uncertainties. Peng et al. [13] designed a novel dynamic surface controller with neural network based on a predictor for nonlinear system with uncertainty. Wang et al. [14–16] developed neural and fuzzy controllers for nonlinear systems with unknown nonlinearities. Xu et al. [17] derived and applied composite neural control strategy to hypersonic flight dynamics. Chen et al. [18] designed a novel intelligent sliding controller with dynamic structure using fuzzy neural controller. Wai et al. [19] designed a fuzzy-neural sliding controller to deal with the chattering.

Backstepping controller can obtain the targets of tracking and stabilization because it is a controller with recursive property, dividing a full system into lower order systems. It can relax the matching condition in the strict feedback system and avoid cancelling the useful existing nonlinearities. The fundamental idea of backstepping is to recursively derive a controller and step back from the subsystem progressively, ensuring stability for each step, until getting to the final step.

FIGURE 1: Block diagram of APF.

Thus, adaptive control is combined with neural control and backstepping approach for dynamic systems [20, 21].

Adaptive neural controller was put forward to treat the harmonics in APF and improve the power grid quality in [22–24]. In this work, an adaptive neural backstepping scheme is designed to guarantee the current tracking and improve the system robustness. The innovative points can be listed as follows:

(1) A backstepping method is incorporated with the adaptive neural control to obtain the desired harmonic suppression related to the current in power grid system. The adaptive neural backstepping controller is used to compensate the nonlinear loads and increase the current tracking property and total harmonic distortion (THD) index.

(2) This control method is realized by neural controller without known accurate model of APF, making the controller simpler and easier to be achieved, strengthening the power supply quality. A robust current compensation controller is added to solve the nonzero issue with respect to the approximation errors existing in the neural system.

2. System Description

The schematic diagram of a three-phase shunt APF discussed in this paper is depicted in Figure 1. The main components are nonlinear loads, source and PWM generator, control system, and harmonic current detector module. The control system aimed to stabilize DC link voltage according to a

basic value and track the instruction current so as to generate the compensating current to decrease the distortion current caused by nonlinear loads. In Figure 1, v_{s1} , v_{s2} , and v_{s3} represent the voltages in the grid, i_{s1} , i_{s2} , and i_{s3} represent the power currents, i_{L1} , i_{L2} , and i_{L3} represent the loading currents, v_1 , v_2 , and v_3 represent the voltages in the public joint points, i_1 , i_2 , and i_3 represent the compensating current, C is the capacitor in the DC side, v_{dc} is the voltage in the capacitance C , i_{dc} is the current in the capacitance C , L_c is the inductance in the AC side, and R_c denotes the equivalent resistance.

The model of an APF system is derived in the next procedure. The circuit relationships

$$\begin{aligned} v_1 &= L_c \frac{di_1}{dt} + R_c i_1 + v_{1M} + v_{MN} \\ v_2 &= L_c \frac{di_2}{dt} + R_c i_2 + v_{2M} + v_{MN} \\ v_3 &= L_c \frac{di_3}{dt} + R_c i_3 + v_{3M} + v_{MN} \end{aligned} \quad (1)$$

are obtained by Kirchhoff rules [3], 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

$$v_{MN} = -\frac{1}{3} \sum_{m=1}^3 v_{mM}. \quad (2)$$

To indicate the IGBT working status, switch function c_k is defined as

$$c_k = \begin{cases} 1, & \text{if } S_k \text{ is On and } S_{k+3} \text{ is Off} \\ 0, & \text{if } S_k \text{ is Off and } S_{k+3} \text{ is On,} \end{cases} \quad (3)$$

where $k = 1, 2, 3$.

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

$$\begin{aligned} \frac{di_1}{dt} &= -\frac{R_c}{L_c} i_1 + \frac{v_1}{L_c} - \frac{v_{dc}}{L_c} \left(c_1 - \frac{1}{3} \sum_{m=1}^3 c_m \right) \\ \frac{di_2}{dt} &= -\frac{R_c}{L_c} i_2 + \frac{v_2}{L_c} - \frac{v_{dc}}{L_c} \left(c_2 - \frac{1}{3} \sum_{m=1}^3 c_m \right) \\ \frac{di_3}{dt} &= -\frac{R_c}{L_c} i_3 + \frac{v_3}{L_c} - \frac{v_{dc}}{L_c} \left(c_3 - \frac{1}{3} \sum_{m=1}^3 c_m \right). \end{aligned} \quad (4)$$

Denote the switching state as

$$d_{nk} = \left(c_k - \frac{1}{3} \sum_{m=1}^3 c_m \right)_n. \quad (5)$$

Equation (5) shows the relation between d_{nk} and c_k ; then, (5) with the consideration of eight permissible IGBT switching states generates

$$\begin{bmatrix} d_{n1} \\ d_{n2} \\ d_{n3} \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}. \quad (6)$$

Then, (4) can be written in simplified form as

$$\begin{aligned} \frac{di_1}{dt} &= -\frac{R_c}{L_c} i_1 + \frac{v_1}{L_c} - \frac{v_{dc}}{L_c} d_{n1} \\ \frac{di_2}{dt} &= -\frac{R_c}{L_c} i_2 + \frac{v_2}{L_c} - \frac{v_{dc}}{L_c} d_{n2} \\ \frac{di_3}{dt} &= -\frac{R_c}{L_c} i_3 + \frac{v_3}{L_c} - \frac{v_{dc}}{L_c} d_{n3}. \end{aligned} \quad (7)$$

Define two state variables

$$\begin{aligned} x_1 &= i_k \\ x_2 &= \dot{i}_k. \end{aligned} \quad (8)$$

Differentiating x_1 and x_2 with respect to time yields

$$\dot{x}_1 = \dot{i}_k = -\frac{R_c}{L_c} i_k + \frac{v_k}{L_c} - \frac{v_{dc}}{L_c} d_{nk} \quad (9)$$

$$\begin{aligned} \dot{x}_2 = \ddot{i}_k &= \frac{d \left(-\left(R_c/L_c \right) i_k + v_k/L_c - \left(v_{dc}/L_c \right) d_{nk} \right)}{dt} \\ &= -\frac{R_c}{L_c} \dot{i}_k + \frac{1}{L_c} \frac{dv_k}{dt} - \frac{1}{L_c} \frac{dv_{dc}}{dt} d_{nk} \\ &= \frac{R_c^2}{L_c^2} i_k - \frac{R_c}{L_c^2} v_k + \frac{1}{L_c} \frac{dv_k}{dt} \\ &\quad + \left(\frac{R_c}{L_c^2} v_{dc} - \frac{1}{L_c} \frac{dv_{dc}}{dt} \right) d_{nk}. \end{aligned} \quad (10)$$

Considering the external disturbances, the model of the APF system is rewritten as

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{R_c^2}{L_c^2} i_k - \frac{R_c}{L_c^2} v_k + \frac{1}{L_c} \frac{dv_k}{dt} + u \left(\frac{R_c}{L_c^2} v_{dc} - \frac{1}{L_c} \frac{dv_{dc}}{dt} \right) \\ &\quad + f_d = f(x) + bu + f_d, \end{aligned} \quad (11)$$

where $f(x) = (R_c^2/L_c^2)i_k - (R_c/L_c^2)v_k + (1/L_c)(dv_k/dt)$, $b = (R_c/L_c^2)v_{dc} - (1/L_c)(dv_{dc}/dt)$, $u = d_{nk}$, f_d is an unknown, bounded external disturbance satisfying $|f_d| < D$, $D > 0$.

3. Adaptive Backstepping Control

The design of backstepping method consists of two steps. Firstly, a “virtual” controller is designed. Secondly, the real backstepping controller is derived. The detailed procedure with respect to the backstepping method is introduced as follows.

Step 1. The ideal current is denoted as y_d with continuous second-order derivatives. The tracking error is

$$e_1 = x_1 - y_d. \quad (12)$$

Then,

$$\dot{e}_1 = \dot{x}_1 - \dot{y}_d = x_2 - \dot{y}_d. \quad (13)$$

The virtual control is designed as

$$\alpha_1 = -c_1 e_1 + \dot{y}_d, \quad (14)$$

where $c_1 > 0$.

Define current tracking error as

$$e_2 = x_2 - \alpha_1. \quad (15)$$

We choose the first Lyapunov function candidate as

$$V_1 = \frac{1}{2} e_1^2. \quad (16)$$

FIGURE 2: Neural network structure.

Differentiating (16) yields

$$\begin{aligned}\dot{V}_1 &= e_1 (x_2 - \dot{y}_d) = e_1 (e_2 + \alpha_1 - \dot{y}_d) \\ &= e_1 (e_2 - c_1 e_1 + \dot{y}_d - \dot{y}_d) = -c_1 e_1^2 + e_1 e_2.\end{aligned}\quad (17)$$

If $e_2 = 0$, then $\dot{V}_1 = -c_1 e_1^2 \leq 0$. So we need to take the second step.

Step 2. From (15), we can get

$$\begin{aligned}\dot{e}_2 &= \dot{x}_2 - \dot{\alpha}_1 = f(x) + bu - \dot{\alpha}_1 \\ &= f(x) + bu - \ddot{y}_d + c_1 \dot{e}_1.\end{aligned}\quad (18)$$

The second Lyapunov function is selected as

$$V_2 = V_1 + \frac{1}{2} e_2^2 \quad (19)$$

and the derivative of V_2 is

$$\dot{V}_2 = -c_1 e_1^2 + e_1 e_2 + e_2 [f(x) + bu - \ddot{y}_d + c_1 \dot{e}_1]. \quad (20)$$

To make $\dot{V}_2 \leq 0$, backstepping controller is proposed as

$$u = \frac{1}{b} [-f(x) + \ddot{y}_d - c_1 \dot{e}_1 - c_2 e_2 - e_1], \quad (21)$$

where $c_2 > 0$.

Then,

$$\dot{V}_2 = -c_1 e_1^2 - c_2 e_2^2 \leq 0. \quad (22)$$

Based on Lyapunov stability theory, the asymptotic stability is ensured.

4. Adaptive Neural Backstepping Controller

Figure 2 is a block diagram of a three-layer RBF neural network structure, which mainly includes input layer, hidden layer, and output layer. The hidden layer maps the signal from the input space to a higher-dimensional space, and the output layer performs a weighted summation operation to generate an RBF network output value.

RBF network can approach any nonlinear function over a compact set with arbitrary precision. The block diagram of adaptive neural backstepping system is designed in Figure 3.

Since $f(x)$ in (11) is unknown, a RBF neural estimator is used to approach $f(x)$. Because there is minimum approximation error in the neural network system, in order to guarantee the stability of the closed-loop system, a compensation controller u_s is added to the controller (21). The detailed reason why the compensation controller is incorporated in the control will be discussed in the next derivation steps. As shown in Figure 3, based on (21), the new controller is proposed as

$$u = \frac{1}{b} [-\hat{f}(x) + \ddot{y}_d - c_1 \dot{e}_1 - c_2 e_2 - e_1 - u_s], \quad (23)$$

where

$$\hat{f}(x) = \hat{f}(x\theta_f) = \theta_f^T \varphi(x). \quad (24)$$

In (27), radial basis $\varphi(x) = \exp(-\|x - k_j\|^2/2b_j^2)$, $j = 1, 2, \dots, m$, b_j is the base width of the node j , k_j is the centric vector of the node j , θ_f denotes the weight of the neural structure:

$$\dot{\theta}_f = r e_2 \varphi(x), \quad (25)$$

where r is a positive constant.

Define optimal parameter

$$\theta_f^* = \arg \min_{\theta_f \in \Omega_f} \left[\sup_{x \in R^n} \left| \hat{f}(x\theta_f) - f(x) \right| \right], \quad (26)$$

where Ω_f is an assemble for θ_f .

Define minimum approximation error:

$$\omega = f(x) - \hat{f}(x\theta_f^*), \quad (27)$$

where $|\omega| \leq \omega_{\max}$.

TABLE 1: Simulation Parameters.

neural output nodes, hidden layer neuron, hidden nodes	3, 6, 3
centric vectors k , base width b	$-3 : 1 : 2, 1$
adaptive gain r	1000
parameters of backstepping c_1, c_2, c_3	10000, 10000, 10000
u_s	2.5
PI control parameters K_p, K_i	0.05, 0.01

FIGURE 3: Control structure of adaptive neural backstepping controller.

Define the third Lyapunov function candidate as

$$V_3 = V_2 + \frac{1}{2r} \varphi_f^T \varphi_f, \quad (28)$$

where $\varphi_f = \theta_f^* - \theta_f$.

The derivative of V_3 is calculated as

$$\begin{aligned}
 \dot{V}_3 &= \dot{V}_2 + \frac{1}{r} \varphi_f^T \dot{\varphi}_f \\
 &= -c_1 e_1^2 + e_1 e_2 + e_2 [f(x) + bu - \ddot{y}_d + c_1 \dot{e}_1] \\
 &\quad + \frac{1}{r} \varphi_f^T \dot{\varphi}_f \\
 &= -c_1 e_1^2 - c_2 e_2^2 + e_2 [\hat{f}(x\theta_f^*) - \hat{f}(x) + \omega - u_s] \\
 &\quad + \frac{1}{r} \varphi_f^T \dot{\varphi}_f \\
 &= -c_1 e_1^2 - c_2 e_2^2 + e_2 [\varphi_f^T \varphi(x) + \omega - u_s] + \frac{1}{r} \varphi_f^T \dot{\varphi}_f \\
 &= -c_1 e_1^2 - c_2 e_2^2 + \frac{1}{r} \varphi_f^T (r e_2 \varphi(x) + \dot{\varphi}_f) \\
 &\quad + e_2 (\omega - u_s),
 \end{aligned} \quad (29)$$

where $\dot{\varphi}_f = -\dot{\theta}_f$.

Substituting (25) into (29) yields

$$\begin{aligned}
 \dot{V}_3 &= -c_1 e_1^2 - c_2 e_2^2 + e_2 (\omega - u_s) \\
 &\leq -c_1 e_1^2 - c_2 e_2^2 + e_2 \left(\sup_{t \geq 0} |\omega| - u_s \right).
 \end{aligned} \quad (30)$$

If we choose $u_s \geq \sup_{t \geq 0} |\omega|$, then

$$\dot{V}_3 \leq -c_1 e_1^2 - c_2 e_2^2 \leq 0. \quad (31)$$

This implies that $\dot{V}$ is negative semidefinite, and e_1, e_2 , and φ_f are bounded signals. From Barbalat's Lemma [25], that is, if a scalar function $g(t)$ is uniformly continuous such that $\lim_{t \rightarrow \infty} \int_0^t g(\tau) d\tau$ exists and is finite, then $\lim_{t \rightarrow \infty} g(t) = 0$. Then, we can conclude $\lim_{t \rightarrow \infty} e_1(t) = 0$, $\lim_{t \rightarrow \infty} e_2(t) = 0$.

5. Simulation Discussion

Simulation studies using Matlab/Simulink and SimPower Toolbox are conducted to verify the performance of the proposed controller. The APF controller starts to work at 0.05 s, and load shock is introduced at 0.12 s. Table 1 shows the simulation parameters adopted in the APF control system: The parameters of APF: inductance L on the AC side is selected $L = 5\text{mH}$; capacitor voltage v_{dc} on the DC side is $v_{dc} = 100\text{uF}$.

Figures 4 and 5 show the source current and harmonics spectrum, giving that A phase current contains harmonic

FIGURE 4: A phase current using backstepping control.

FIGURE 5: A phase current with the designed method.

FIGURE 6: Source current harmonic graph when $t = 0s$.

whose THD value is 24.71%. Figure 6 is the source current harmonic graph at the beginning. After 0.05 s, APF begins to work to make the current close to sine wave in no more than 0.01 s. The load shock is added at 0.12. Figures 4, 7, and 9 plot the source current and harmonics spectrum using backstepping method, and Figures 5, 8, and 10 show the source current and harmonics spectrum using the proposed method. The source current is close to sine waveform after adaptive neural backstepping compensation even with load shock. The THD values are decreased to 2.96% and 3.81% with the backstepping method, whereas the THD values are

decreased to 1.63% and 2.08% with the proposed method. The proposed method has better compensation property in the presence of the load shock than the backstepping control.

Figure 11 is the current compensation using the designed method where the tracking performance is well in the presence of nonlinear load shock. For the voltage control, we add the loads in a ladder-type increase. Specifically speaking, we add the same loads to the system at the time 0.1s and 0.2s to see the performance of the controlled system. PI controller is used in the voltage control. DC capacitor voltage is shown in Figure 12, indicating that it is in the range of the reference

FIGURE 7: Source current harmonic graph when $t = 0.05s$ with the backstepping controller. FIGURE 8: Source current harmonic analysis when $t = 0.05s$ with the designed controller. FIGURE 9: Source current harmonic when $t = 0.13s$ with the backstepping controller. FIGURE 10: Source current harmonic graph when $t = 0.13s$ with the designed controller.

FIGURE 11: Instruction current and compensation current with the designed controller.

FIGURE 12: DC capacitor voltage with the designed controller.

voltage, and tends to be steady state quickly under the load shock.

6. Conclusion

An adaptive NN backstepping controller is designed for the harmonic suppression of a three-phase APF. A RBF NN controller is used to adaptively estimate and compensate the system nonlinearities, enhancing the robust performance. A compensation control u_s is added to the controller to guarantee the stability. Simulation studies demonstrated that the proposed control strategy can reduce THD values effectively, improving the electric quality.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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