Adaptive Intelligent Super-Twisting Control of Dynamic System

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ABSTRACT This study develops an adaptive Super-Twisting sliding mode control (STSMC) approach using an output feedback fuzzy neural network (OFFNN) for dynamic systems. The OFFNN approximator is designed to approach the model uncertainty, and a signal feedback loop could provide better data learning capabilities and more reasonable learning rate, therefore the proposed controller has full regulation and high approximation accuracy. Real-time experimental studies of an active power filter are accomplished to show the proposed controller has better harmonic suppression and steady-state and dynamic property than existing methods.

INDEX TERMS Output feedback fuzzy neural network control, super-twisting sliding mode control.

I. INTRODUCTION

Most of the systems existing in nature are non-linear, and linear system methods are often used for nonlinear systems for analysis and processing. However, especially in practical applications, for highly nonlinear systems, how to implement control tasks for dynamic systems with uncertain parameters is still a hot research issue. With the study of dynamic systems, the designed model becomes more accurate and more realistic. However, there are still a lot of objects which are still not modeled accurately. Another problem is that the parameters of the system and even the model itself will change due to external environmental influences or internal aging or minor failures. For this issue, control methods with low reliance on system accuracy are needed to make up for the lack of modeling. In recent years, multiple advanced control strategies are developed for nonlinear systems.

Sliding mode controller (SMC) is insensitivity to system disturbances, beneficially for nonlinear controllers. A super-twisting sliding mode control (STSMC) is a high-level SMC algorithm which could effectively decrease the chattering and smooth the control input [1]–[7]. The analytical form of the finite arriving time using a STSMC strategy without system uncertainties and disturbances was solved in [1], proving the validity of the STSMC. A STSMC method to solve a wind energy conversion optimization problem was given in [2]. A STSMC method was designed for the output feedback stabilization of perturbed double-integrator systems in [3]. A direct STSMC power control method was investigated to control a brushless doubly-fed induction generator in [4]. A hybrid STSMC with nonsingular terminal SMC algorithm was studied for second-order uncertain nonlinear systems in [5]. An improved robust STSMC observer was investigated for the finite-time tracking control of a Stewart platform in [6]. A composite STSMC using a novel disturbance observer was discussed for a PMSM speed regulation system in [7].

Neural network method is an effective way to deal with the model uncertainty [8]–[14]. A STSMC with a novel fuzzy neural network was proposed improve the control accuracy of a micro gyroscope in [8]. An adaptive dynamic SMC system using output feedback neural network structure was developed for an induction motor drive in [9]. A composite neural network control using a Based nonsingular terminal SMC was introduced for a MEMS gyroscope in [10]. A novel neural controller using a fractional order SMC was proposed for a micro gyroscope in [11]. A discrete-time neural structure using a triangular feedback weight matrix was explored to solve the time series prediction problem in [12]. New fuzzy neural network strategies were investigated to solve the issue of data uncertainty in [13] and duty cycle of the power switch in a single-stage boost inverter in [14]. A finite-time prescribed performance controller with fuzzy-neural framework was derived ad applied to a waverider aircraft in [15].
optimal tracking control combined with network shows the excellent control effect in [16]. A sliding mode controller for network control systems was proposed to show the feasibility and advantages of combining neural networks and sliding mode control in [17]. A fuzzy neural control protocols was presented to show the ability to deal with actuator saturation in [18]. Neural controller and fuzzy neural controller have been widely used in identification and control for dynamic systems [19]–[21]. A novel recurrent neural network controller has the adaptive ability to update the parameters with higher efficiency in [22].

The OFFNN includes the feedback loop to obtain more dynamic information. Motivated by the above-mentioned works, this paper proposes an adaptive super-twisting sliding mode (STSMC) control method based on an output feedback fuzzy neural network (OFFNN). Compared with the existing literature, the major contributions can be briefly summarized in the following outlines:

1. Adaptive STSMC is employed to decrease the chattering ensuring strong robustness and possessing good smoothness. The OFFNN can set the initial values of center vectors and the base widths arbitrarily and adaptively adjust them to the optimal values according to the adaptive algorithm.

2. An output feedback fuzzy neural network is used to estimate uncertainty including both unknown system characteristics and external disturbance. Internal and external feedbacks are attached to the neural network to improve learning performance. To deal with unknown system which is hard to evaluate through model parameters, the external feedback is added to evaluate performance with system output.

3. In this way, even the system has fast-changing signals, the neural networks can extend the learning range to the signal range of the system. Internal feedbacks can increase the amount of information in the neural network, thereby providing better data learning capabilities and more reasonable learning rate.

II. PROBLEM STATEMENT
For a class of universal multi-input nonlinear systems:

\[ \dot{X} = (f(X) + \Delta f(X)) + (B + \Delta B)u + g(t) \]  

where \( X = [x_1 \ x_2 \ x_3 \ \cdots \ x_n] \) is a state, \( f(X) \) and \( B \) are nominal coefficients, \( u = [u_1 \ u_2 \ u_3 \ \cdots \ u_n] \) is a control input, \( \Delta f(X) \) and \( \Delta B \) are the uncertainties in \( f(X) \) and \( B \), \( g(t) \) is an unknown disturbance. The lumped uncertainty is expressed as

\[ F = \Delta f(X) + \Delta Bu + g(t) \]  

Assumption: \( |\dot{\bar{F}}(t)| \) is supposed be bounded by \( |\dot{\bar{F}}(t)| \leq \delta \), \( \delta \) is a positive constant, \( C \) is a nonsingular matrix.

Then Eq. (1) becomes

\[ \dot{X} = f(X) + Bu + F \]  

The control target is to design a controller to make \( X \) tracks the reference signal \( X_d \).

A tracking error is given as:

\[ e = X - X_d \]  

Then the derivative of Eq. (4) is:

\[ \dot{e} = \dot{X} - \dot{X}_d \]  

A standard sliding surface is proposed as:

\[ s = Ce \]  

where \( C \) is a designed gain matrix of sliding surface.

Substituting Eq. (3) into derivative of Eq. (6) yields \( \dot{e} = f(X) + Bu + F - \dot{X}_d \), then \( \dot{s} \) becomes:

\[ \dot{s} = C(f(X) + Bu + F - \dot{X}_d) \]  

Making \( \dot{s} = 0 \) to solve the equivalent controller as

\[ u_{eq} = (CB)^{-1}[-CF + CX_d] \]  

In order to ensure the tracking error goes to zero in a finite time to achieve satisfactory control performance, a super-twisting sliding surface is used instead. The switch control law based on STSMC algorithm is designed as:

\[ u_{sw} = -k_1 \sqrt{|s|} \text{sgn}(s) - \int k_2 \text{sgn}(s) dt \]  

where \( k_1 > 0, k_2 \geq |C \dot{\bar{F}}(t)| \).

From Eq. (8) and Eq. (9), a new controller is given as

\[ u = (CB)^{-1}[-CF + CX_d + k_1 \sqrt{|s|} \text{sgn}(s) - \int k_2 \text{sgn}(s) dt] \]  

III. OUTPUT FEEDBACK FUZZY NEURAL NETWORK STRUCTURE
The structure of the proposed new OFFNN is a four-layer neural network with two feedback loop as in Fig.1, where the function of each layer is given as:
1) Input layer. It can accept the input $X = [x_1, x_2, \ldots, x_m]^T$ and the output $exY$ in the previous loop then transfer them to the next layer. The output in the input layer is denoted as $\theta = [\theta_1, \theta_2, \ldots, \theta_m]^T$, where $\theta_m$ is given as

$$\theta_m = x_m \cdot w_{rom} \cdot exY$$  \hspace{1cm} (11)

2) Fuzzy layer. It can calculate the membership function. The output of this layer is denoted as $\mu_{11}, \mu_{22}, \ldots (i = 1 \sim 3, j = 1 \sim 3)$, written by:

$$\begin{align*}
\mu_{1i} &= \exp\left[-\frac{\|\theta_i + w_{ri} \cdot ex\mu_{1i} - c_{\mu_{1i}}\|^2}{b_{1i}^2}\right] \hspace{1cm} (12) \\
\mu_{2j} &= \exp\left[-\frac{\|\theta_2 + w_{rj} \cdot ex\mu_{2j} - c_{\mu_{2j}}\|^2}{b_{2j}^2}\right] \hspace{1cm} (13)
\end{align*}$$

where $w_{ri}, w_{rj}$ are internal feedback gains, $c = [c_{11} \ldots c_{13}, c_{21} \ldots c_{23}]^T$ is the center $b = [b_{11} \ldots b_{13}, b_{21} \ldots b_{23}]^T$ is the base width.

3) Rule layer. The output of the rule layer is expressed by multiplying the membership weights by the input and then sending to the output layer:

$$h_k = \mu_{1i} \cdot \mu_{2j}$$  \hspace{1cm} (14)

where, $k = 3 \times (i-1) + j, i = 1 \sim 3, j = 1 \sim 3, k = 1 \sim 9$.

4) Output layer. Its neuron is connected with the rule layer by the weight $w = [w_1, w_2, \ldots, w_k]$, given as:

$$Y = \sum_{k=1}^{9} w_k h_k = w_1 h_1 + w_2 h_2 + \ldots + w_k h_k = W^T h$$  \hspace{1cm} (15)

where $W = [w_1 w_2 \ldots w_k]^T$, $h = [h_1, h_2 \ldots, h_k]^T$.

IV. STSMC-OFFNN CONTROLLER

The block diagram of the STSMC-OFFNN system is described in Fig.2. However, since $f(X)$ in Eq. (3) is unknown, the controller in Eq. (10) cannot be directly accomplished. Consequently, the OFFNN approximator is used instead to approach $f(X)$ as $\hat{f}(X)$, then the controller as in Eq. (10) becomes:

$$u = (CB)^{-1}[-C\hat{f}(X) + CX_d - k_1 \sqrt{|s|}sgn(s)$$

$$- \int k_2 sgn(s)ds] \hspace{1cm} (16)$$

where $\hat{f} = \tilde{u}^T \hat{h}(x, \hat{c}, \hat{b}, \hat{w}_r, \hat{w}_o)$.

Assuming there are best weight $w^*$, base width $b^*$, center $c^*$, inner and out feedback gains $w^*_r$ and $w^*_o$ to estimate $f$, then

$$f = w^T h^* + \xi$$  \hspace{1cm} (17)

where $h^* = h^*(x, c^*, b^*, w^*_r, w^*_o)$, $\xi$ is mapping errors.

The STSMC using in (16) has adaptive characterist. When the error of the state $X$ approaches error, $S$ also converges to 0, then the absolute value of the switching control law could drop. Therefore the chattering problem is alleviated in this way.

Define the parameter errors in the approximation as:

$$\begin{align*}
\hat{h} &= h^* - \hat{h} \\
\hat{w} &= w^* - \hat{w} \\
\hat{b} &= b^* - \hat{b} \\
\hat{c} &= c^* - \hat{c} \\
\hat{w}_r &= w^*_r - \hat{w}_r \\
\hat{w}_o &= w^*_o - \hat{w}_o
\end{align*}$$  \hspace{1cm} (18)

Then, the approximation error is calculated as:

$$f - \hat{f} = w^T h^* + \xi - \hat{w}^T \hat{h}$$

$$= w^T h^* + w^T \hat{h} - \hat{w}^T \hat{h} + \xi$$

$$= (w^T - \hat{w}^T) \hat{h} + w^T \hat{h} + \xi$$

$$= \hat{w}^T \hat{h} + (w^T - \hat{w}^T) \hat{h} + \xi$$

$$= \hat{w}^T \hat{h} + \hat{w}^T \hat{h} + \hat{w}^T \hat{h} + \xi$$  \hspace{1cm} (19)

Define the total approximation error as:

$$\xi_0 = \hat{w}^T \hat{h} + \xi$$  \hspace{1cm} (20)

Substituting Eq. (20) in Eq.(19) gets

$$f - \hat{f} = \hat{w}^T \hat{h} + \hat{w}^T \hat{h} + \xi_0$$  \hspace{1cm} (21)

In order to adaptively adjust the parameters of OFFNN approximator, the Taylor expansion is calculated on $h$, generating the expressions as:

$$\begin{align*}
\hat{h} &= \left. \frac{\partial \hat{h}}{\partial c} \right|_{c=c^*} (c^* - \hat{c}) + \left. \frac{\partial \hat{h}}{\partial b} \right|_{b=b^*} (b^* - \hat{b}) \\
+ \left. \frac{\partial \hat{h}}{\partial w_r} \right|_{w_r = \hat{w}_r} (w^*_r - \hat{w}_r) \\
+ \left. \frac{\partial \hat{h}}{\partial w_o} \right|_{w_o = \hat{w}_o} (w^*_o - \hat{w}_o) + O_h
\end{align*}$$

$$= dh_c \cdot \hat{c} + dh_b \cdot \hat{b} + dh_{w_r} \cdot \hat{w}_r + dh_{w_o} \cdot \hat{w}_o + O_h$$  \hspace{1cm} (22)
where \( O_h \) is high-order terms. Coefficient matrix \( dh_c, dh_b, dh_{wr}, dh_{wro} \) are denoted as

\[
\begin{align*}
\frac{dh_c}{dc} &= \begin{bmatrix} \frac{\partial h_1}{dc} \frac{\partial h_2}{dc} \cdots \frac{\partial h_k}{dc} \end{bmatrix}^T |_{c=c} \\
\frac{dh_b}{db} &= \begin{bmatrix} \frac{\partial h_1}{db} \frac{\partial h_2}{db} \cdots \frac{\partial h_k}{db} \end{bmatrix}^T |_{b=b} \\
\frac{dh_{wr}}{dw_{wr}} &= \begin{bmatrix} \frac{\partial h_1}{dw_{wr}} \frac{\partial h_2}{dw_{wr}} \cdots \frac{\partial h_k}{dw_{wr}} \end{bmatrix}^T |_{w_{wr}=w_{wr}} \\
\frac{dh_{wro}}{dw_{wro}} &= \begin{bmatrix} \frac{\partial h_1}{dw_{wro}} \frac{\partial h_2}{dw_{wro}} \cdots \frac{\partial h_k}{dw_{wro}} \end{bmatrix}^T |_{w_{wro}=w_{wro}}
\end{align*}
\]

e.g. \( \frac{\partial h_1}{dc} = \begin{bmatrix} \frac{\partial h_1}{dc_1} \frac{\partial h_1}{dc_2} \cdots \frac{\partial h_1}{dc_j} \end{bmatrix}^T 
\]

Substituting Eq. (13) into Eq. (21) yields:

\[
f - \hat{f} = \hat{w}^T (dh_c \cdot \hat{c} + dh_b \cdot \hat{b} + dh_{wr} \cdot \hat{w}_r + dh_{wro} \cdot \hat{w}_{wro} + O_h) \\
+ \xi_0 + \hat{w}^T \hat{h} = \hat{w}^T (dh_c \cdot \hat{c} + dh_b \cdot \hat{b} + dh_{wr} \cdot \hat{w}_r + dh_{wro} \cdot \hat{w}_{wro} + \hat{w}^T \hat{h}) \\
+ \xi_0 + \hat{w}^T \hat{h}
\]

Define the summation of approximation errors as: \( O_h = \hat{w}^T \hat{h} + \xi_0 \). Suppose it and its derivative are bounded signals, satisfying \( |O_h| \leq O_d \), where \( O_d \) is a positive value.

**Remark 1:** In mathematical model the correction of the constraint can be discussed, but in the actual system, energy is difficult to mutate, so the variation degree in actual system has a limit. It is also hard to get a specific limit value, but here it is enough to know that there exists a limit.

The adaptive laws are designed as:

\[
\begin{align*}
\dot{\hat{w}} &= -\eta_1 \hat{s} \hat{h} \\
\dot{\hat{c}} &= -\eta_2 \hat{s} \hat{w}^T dh_c \\
\hat{\hat{b}} &= -\eta_3 \hat{s} \hat{w}^T dh_b \\
\dot{\hat{w}}_r &= -\eta_4 \hat{s} \hat{w}^T dh_{wr} \\
\dot{\hat{w}}_{wro} &= -\eta_5 \hat{s} \hat{w}^T dh_{wro}
\end{align*}
\]

where \( \eta_1, \eta_2, \eta_3, \eta_4, \eta_5 \) are positive constants.

The Lyapunov function candidate is set as:

\[
V = \frac{1}{2} \hat{s}^T \hat{s} + \frac{1}{2 \eta_1} \hat{w}^T \hat{w} + \frac{1}{2 \eta_2} \hat{c}^T \hat{c} + \frac{1}{2 \eta_3} \hat{b}^T \hat{b} \\
+ \frac{1}{2 \eta_4} \hat{w}_r^T \hat{w}_r + \frac{1}{2 \eta_5} \hat{w}_{wro}^T \hat{w}_{wro}
\]

Define

\[
T = \begin{bmatrix} \frac{1}{2 \eta_1} \hat{w}^T \hat{w} + \frac{1}{2 \eta_2} \hat{c}^T \hat{c} + \frac{1}{2 \eta_3} \hat{b}^T \hat{b} \\
+ \frac{1}{2 \eta_4} \hat{w}_r^T \hat{w}_r + \frac{1}{2 \eta_5} \hat{w}_{wro}^T \hat{w}_{wro} \end{bmatrix} 
\]

Then the derivative of Eq. (26) becomes:

\[
\dot{V} = s^T \hat{s} + \hat{T}
\]

Substituting Eq. (16) and Eq. (27) into Eq. (28) generates:

\[
\dot{V} = s^T C (f - k_1 \| \hat{s} \| sgn(s) - k_2 \int sgn(s) dt + F) + \hat{T}
\]

Then substituting Eq. (24) into Eq. (29) yields:

\[
\dot{V} = s^T (\hat{w}^T \hat{h} + \hat{w}^T dh_c \cdot \hat{c} + \hat{w}^T dh_b \cdot \hat{b} + \hat{w}^T dh_{wr} \cdot \hat{w}_r + \hat{w}^T dh_{wro} \cdot \hat{w}_{wro} + O_h) \\
+ \hat{w}^T dh_{wro} \cdot \hat{w}_{wro} + k_1 \| \hat{s} \| |s| \int sgn(s) dt + F) + \frac{1}{\eta_1} \hat{w}^T \hat{w}
\]

Substituting Eq. (25) into Eq. (30) yields:

\[
\dot{V} = s^T (O_h - k_1 \| \hat{s} \| sgn(s) - k_2 \int sgn(s) dt + CF) \\
= -k_1 \| \hat{s} \| \| s \| \int k_2 dt + s^T CF + \| s \| O_m \\
\leq -k_1 \| \hat{s} \| \| s \| \int k_2 dt + s^T |CF| + \| s \| |O_m| \\
= -k_1 \| \hat{s} \| \| s \| \int (k_2 - |CF| - \| \hat{O}_m \|) dt
\]

Since \( |CF| \leq \delta, |\hat{O}_m| \leq O_d \), Eq. (31) becomes:

\[
\dot{V} \leq -k_1 \| \hat{s} \| \| s \| \int (k_2 - \delta - O_d) dt
\]

Therefore, if \( k_2 \geq (\delta + O_d) \), then

\[
\dot{V} \leq -k_1 \| \hat{s} \| \| s \| \leq 0
\]

From the fact that \( \hat{s} \| s \| \) is bounded and Barbalat’s lemma exists, \( s(t) \) asymptotically converges to zero and the asymptotic stability of the control system is prove.

### V. EXPERIMENTAL VERIFICATION

In order to show the adaptive STSMC–OFFNN, a single-phase APF prototype with dSPACE DS1104 is built, as shown in Fig.3, where a series of hardware experiments are implemented.

Setting grid power and main circuit as a voltage loop, according to Kirchhoff’s voltage theory, it is obtained as:

\[
u_s = L \frac{di_c}{dt} + R i_c + Q u_{dc}
\]

where \( u_s \) is a grid voltage, \( i_c \) is a compensation current, \( u_{dc} \) is a DC side capacitor voltage, and \( L \) and \( R \) are the inductance and resistance of the active filter main circuit respectively. \( Q \) is the switch function. Then define switch function \( Q \) as:

\[
Q = \begin{cases} 
1 VT_1, VT_4 \text{ on}, & \text{VT}_2, VT_3 \text{ off} \\
-1 VT_2, VT_3 \text{ on}, & \text{VT}_1, VT_4 \text{ off}
\end{cases}
\]
The state equation of the compensation current, derived as:

$$
\dot{i}_c = -\frac{R}{L}i_c + \frac{u_s}{L} - \frac{u_{dc}}{L}Q
$$

(36)

Generally, for the needs of higher-order controller design, in power electronics modeling, the active power filter system model is usually considered as a second-order model. Therefore, taking the derivative of Eq. (36) obtains:

$$
\ddot{i}_c = -\frac{R}{L^2}i_c + \frac{\dot{u}_s}{L} - \frac{\dot{u}_{dc}}{L}Q - \frac{u_{dc}}{L} \dot{Q}
$$

(37)

Eq. (37) can be rewritten as follows:

$$
\ddot{i}_c = f_0(i_c) + B_0u
$$

(38)
TABLE 2. Comparison of THD in experiment.

| Control method | THD     |
|----------------|---------|
| STSMC-OFFNN    | 4.13%   |
| ABNNCSMC       | 6.05%   |
| ANNSMC         | 6.48%   |
| LCL            | 5.16%   |
| LLCL           | 4.40%   |

where $f_0(i_c)$ represents $\int \frac{R}{L} \dot{i}_c + \frac{\dot{u}}{L} - \frac{R}{L^2} u_s$, $B_0$ represents $\frac{R}{L^2} u_{dc} - \frac{u}{L^2}$, $u$ represents $Q$.

The main parameters in APF system are chosen as in Table 1. The initial values of $b,c,w,w_r$ are all set as 1, $w_{ro}$ is set as 0. $\eta_1$, $\eta_2$, $\eta_3$, $\eta_4$, $\eta_5$ are set as $5 \times 10^8$, $1 \times 10^8$, $1 \times 10^8$, $1 \times 10^9$. $k_1,k_2$ are set as 2 and 3. Fig.4 shows the structure of the single-phase APF hardware platform, which mainly includes the parts shown in Fig. 3 and other parts.

A. STEADY-STATE EXPERIMENT

Fig. 5 shows the output waveform and spectrum analysis of the real oscilloscope. In Fig. 5(a), from above to below is power supply voltage, load current, compensation current, and power supply current. While the load current is severely distorted, showing the characteristics of a nonlinear signal, the power supply current remains a smooth sinusoidal current. In Fig.5 (b), the THD changes to 4.13% after compensation, showing the proposed method has sufficient control performance and harmonic compensation. For comparison, results of ANNSMC, ABNNCSMC, LCL, LLCL, referenced from [23], [24] and [25], are shown in Table 2, proving that under actual conditions, STSMC-OFFNN also has good performance. Among them, LCL and LLCL are traditional resonant methods which are proved to be sufficient on power
generation and adjustment systems like APF. The proposed STSMC-OFFNN method has the same level of control effects as the specialization methods through using a generic model and a universal approach, showing its excellent control effects while being versatile.

Though THD of STSMC-OFFNN is a bit higher than that of ABNNCSMC (1.15%~1.24%, provided in [24]), STSMC-OFFNN has better performance, demonstrating its great stability and robustness.

B. DYNAMIC EXPERIMENT OF LOAD CHANGE

For further discussion of the effectiveness of the proposed method, a nonlinear load is increased and decreased to simulate the load changes. Fig.6 shows the system response when the load suddenly increases and Fig.7 shows the opposite. As is seen, the waveform is out of shape for a just time. Due to quick stabilization, it maintains the sinusoidal wave in no time. THD is 3.88% and 4.45%, close to those of steady state (4.13%), with a change of roughly 0.3%. It shows that the change of load has small effect, demonstrating the robustness of the proposed STSMC-OFFNN method. The experimental results show the STSMC-OFFNN method has good current tracking ability, harmonic compensation performance and robustness.

VI. CONCLUSION

In this paper, an adaptive STSMC method of nonlinear system using a novel fuzzy neural network is proposed. Super-twisting sliding mode controller is used to process high frequency dynamics and reduce chattering. An OFFNN approximator is designed to improve the accuracy and property of the neural system. It has the characteristics of two hidden layer and output feedback, where the feedback loop can increase the neural information, thus making the neural network more powerful to learn complex systems. Hardware experiments of a single-phase APF prototype using dSPACE DS1104 real-time control system prove the designed STSMC-OFFNN could obtain good harmonic compensation regardless the uncertainties and load variations.

Remark 2: The main problem of applying the general model method to APF is that compared with the orthodox continuous control system, the APF system has a certain degree of discrete characteristics because of the IGBT controller. The high-dimensional signals and chattering caused by system characteristics are unavoidable. To deal with the fast-changing signals, the learning rate of OFFNN is set aggressive and high order sliding mode control is chosen as the compensator.

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