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Double Tank Liquid Level Control System Finite Time Sliding Mode Based on Super-Twisting Algorithm

Wenbo Fei[a,*], Xueli Wu[a,b], Dongxu Lin[a]

[a] *Hebei University of Science and Technology, Shijiazhuang, Hebei, 050018,China*

[b] *Hebei Provincial Research Center for Technologies in Process Engineering Automation, Shijiazhuang, Hebei, 050018, China*

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ABSTRACT

In order to realize the intelligent control of the dual-tank liquid level system, this paper proposes a finite time sliding mode control based on the Super-Twisting algorithm. This algorithm can ensure that the control system can converge in a finite time, and can eliminate the chattering phenomenon in traditional sliding mode control. Finally, a numerical example is used to verify the effectiveness of the algorithm.

1. Introduction

In the field of industrial production, dual-capacity reservoirs have a wide range of applications, such as chemical production, beverage production, sewage treatment, etc., but due to the complexity of their working environment and the purpose of saving labor, they need to apply intelligent control to achieve stable and reliable work. Thus it has received extensive attention from the academic engineering community and verified the feasibility of numerous control strategies.

Regardless of whether it is a two-tank level system or a three-tank level system, there is a connection between each container, which makes the system more complicated, and the uncertainty of the system operating environment is difficult to avoid interference. For example, in a beverage production plant or a pharmaceutical company, the accuracy of the liquid level control error will be very important. Therefore, it is essential to apply a robust and highly reliable control algorithm.

Since the dual-capacity liquid level system is a nonlinear time-delay system, the control accuracy of the system is affected by its state, and it is difficult for traditional PID control to achieve good control results (Yu et al., 2014). In (Patel and Patil, 2019), the non-linear tank level control of fractional PI. In (Khadija et al., Wei, 2018), scholars applied PID algorithm, but approximated the nonlinear part through neural network. In (Srivastava et al., 2016), scholars used Luus-Jaakola's PID for the PID controller tuning of the dual tank system In order to achieve a more precise control strategy, hybrid control (Malmborg and Eker, 1997), genetic algorithm (Zhou et al., 2012), S7-200 control (Hong and Deng, 2016) and so on. Some scholars have conducted comparative studies on the prediction and post-control of the double tank process (Gouta et al., 2016). In order to better realize liquid level control, some scholars have proposed a nonlinear feedback control of arctangent function (2020). Under the complex environmental conditions in liquid level control, scholars proposed two-tank non-interaction liquid level fault-tolerant control (2019). In 2, scholars use a fractional-order controller to control the level of the cone tank (Vavilala et al., 2020). In (Paz et al., 2016), scholars solve the problem of liquid level control through sliding mode control. Some scholars use high-order sliding mode to optimize on the basis of traditional sliding mode (Narwekar and Shah, 2017).In recent years, when solving very complex nonlinear problems, the sliding mode of variable structure sliding mode control has excellent robustness to system perturbation and external interference. Therefore, sliding mode variable structure control has received extensive attention from the academic community. In order to achieve precise control, this paper proposes a sliding mode control based on Super-Twisting algorithm. The control law is calculated based on the RBF neural network to approximate and fit the nonlinear part, but it has not been verified by simulation.

* Corresponding author.
E-mail addresses: wenbofei163@163.com (W. Fei)

The problems addressed in this article are as follows:

(1) Design of Super-Twisting sliding mode controller. Due to the particularity of the algorithm, the system can converge in a finite time and solve the chattering of traditional sliding mode.

(2) Solve the nonlinear part of the system based on RBF neural network, but there is no simulation verification.

(3) Compare traditional sliding mode control with super-twisting sliding mode control.

2. Model of Double Tank Liquid Level System

This article adopts mechanism deductive method to model. The double-capacity water tank is the most common control model in the liquid level system, and the liquid level does not change when the inflow and outflow are equal. After the liquid level is balanced, when the inflow side valve is opened, the inflow is greater than the outflow, and the liquid level rises, but the water level rises and the outlet pressure becomes larger. The inflow and outflow will eventually reach equilibrium, making the liquid level finally stabilize at a certain One height. Otherwise, the liquid level will drop and eventually stabilize at another height. Since the inflow of the water tank can be adjusted, and the outflow changes with the height of the liquid level, the mathematical model of the water tank can be established only by establishing the mathematical relationship between the inflow and the height of the liquid level.

The dual tank liquid level system has a nonlinear system with two inputs and two outputs. The system structure diagram is as follows:

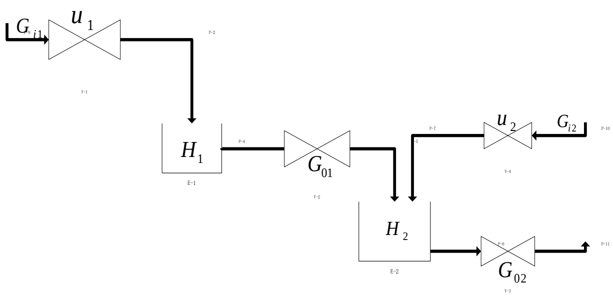

Fig. 1. Double tank liquid level control system.

For the above-mentioned dual-capacity liquid level system, the change of the upper water tank liquid level will satisfy the following equation:

$$\dot{H}_1 = \frac{1}{F_1}(G_{i1} - G_{01}) = \frac{1}{F_1}(k_{u1}u_1 - \lambda_1\sqrt{H_1}) \qquad (1)$$

Where H_1 - upper water tank level, F_1 - Bottom area of upper water tank, $G_{i1} = k_{u1}u_1$ - Inflow, $G_{01} = \lambda_1\sqrt{H_1}$ - outflow, k_{u1} - control valve opening coefficient, λ_1 - load valve flow characteristic parameters.

Similarly, the level equation of the water tank is

$$\begin{aligned}\dot{H}_2 &= \frac{1}{F_2}(G_{i2} + G_{01} - G_{02}) \\ &= \frac{1}{F_2}(k_{u2}u_2 - \lambda_1\sqrt{H_1} - \lambda_2\sqrt{H_2})\end{aligned} \qquad (2)$$

where H_2 - lower water tank level, F_2 - Bottom area of lower water tank, $G_{i2} = k_{u2}u_2$ -Inflow, $G_{02} = \lambda_2\sqrt{H_2}$ - outflow, k_{u2} - control valve opening coefficient, λ_2 - load valve flow characteristic parameters.

In summary, the dual-capacity liquid level control system is

$$\begin{bmatrix}\dot{H}_1 \\ \dot{H}_2\end{bmatrix} = \begin{bmatrix}a_1 & 0 \\ a_2 & a_3\end{bmatrix}\begin{bmatrix}\sqrt{H_1} \\ \sqrt{H_2}\end{bmatrix} + \begin{bmatrix}b_1 & 0 \\ 0 & b_2\end{bmatrix}\begin{bmatrix}u_1 \\ u_2\end{bmatrix} \qquad (3)$$

where

$$a_1 = -\frac{\lambda_1}{F_1}, a_2 = \frac{\lambda_1}{F_2}, a_3 = -\frac{\lambda_2}{F_2}, b_1 = \frac{k_{u1}}{F_1}, b_2 = \frac{k_{u2}}{F_1}.$$

3. Algorithm analysis

3.1 Super-Twisting algorithm analysis

Due to the discontinuous function of the high-frequency switch under the traditional sliding mode control rate, resulting in jitter, the super-twisted sliding mode control can transfer the discrete control rate to the higher-order sliding mode surface to solve this problem (Lo and Bassu). And a large number of articles have proved that the algorithm can guarantee the finite time convergence (Fei and Feng, 2020). The super-twist sliding mode control algorithm is composed of a continuous function of sliding mode variables and a discontinuous time difference. The algorithm is as follows:

$$\begin{cases}\dot{x}_1 = -k\left|x_1\right|^{\frac{1}{2}} sign(x_1) + x_2 \\ \dot{x}_2 = -k_1 sign(x_1) + \dot{d}_t\end{cases} \qquad (4)$$

In the formula, $x_i(i = 1, 2)$ represents the state variable, and k_1, k_2 represents the set gain, $\dot{d}_t$ is external interference. When ignoring external interference, $\vartheta^T = \begin{bmatrix}x_1 & x_2\end{bmatrix} = \begin{bmatrix}\left|x_1\right|^{\frac{1}{2}}\mathrm{sgn}(x_1) & x_2\end{bmatrix}$,get

$$\dot{\vartheta} = \frac{1}{\left|\vartheta_1\right|}B\vartheta, B = \begin{bmatrix}-\frac{1}{2}k & \frac{1}{2} \\ -k_1 & 0\end{bmatrix} \qquad (5)$$

Among them, B satisfies $Hurwitz$ and the real parts of the characteristic roots are all on the left half.

Take the Lyapunov function

$$V = \vartheta^T P \vartheta \tag{6}$$

So there is

$$\dot{V} = -|x_1|^{\frac{1}{2}} \vartheta^T Q \vartheta \tag{7}$$

Satisfy the Lyapunov theorem

$$B^T P + PB = -Q \tag{8}$$

The system reaches the equilibrium point $x=0$ and is stable in finite time, any positive definite symmetric matrix $Q = Q^T > 0$, and equation (7)has a positive definite symmetric solution. The trajectory of the solution $t=0$ has $x(0)=x_0$, and it will reach the origin in a finite time $T(x_0)$.

$$T(x_0) = \frac{2}{\partial} V^{\frac{1}{2}}(x_0), \partial = \frac{\lambda_{\min}^{\frac{1}{2}}(P)\lambda_{\min}(Q)}{\lambda_{\max}(P)} \tag{9}$$

The research results show that the system converges in a finite time and has good robust performance (Polyakov and Poznyak, 2008).

3.2 RBF neural network algorithm analysis

The RBF neural network is a three-layer neural network, which includes an input layer, a hidden layer, and an output layer. The transformation from the input space to the hidden layer space is nonlinear, and the transformation from the hidden layer space to the output layer space is linear. The flow diagram is as follows:

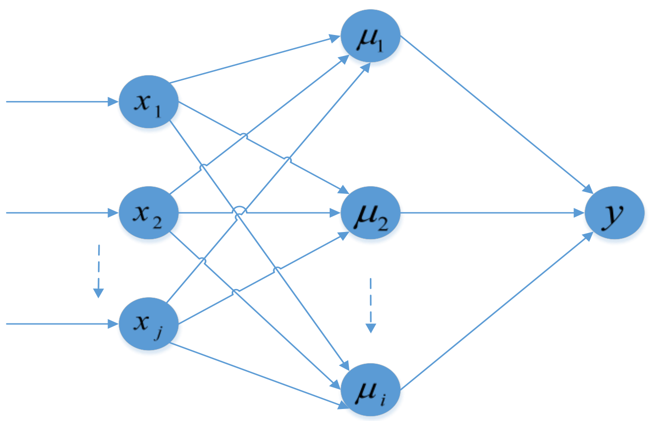

Fig. 2. RBF neural network flow diagram

The basic idea of the RBF network is: use RBF as the "base" of the hidden unit to form the hidden layer space, so that the input vector can be directly mapped to the hidden space without the need for weight connection. When the central point of the RBF is determined, this mapping relationship is also determined. The mapping from the hidden layer space to the output space is linear, that is, the output of the network is the linear weighted sum of the hidden unit output, and the weight here is the network adjustable parameter. Among them, the function of the hidden layer is to map the vector from the low-dimensional p to the high-dimensional h, so that the low-dimensional linear inseparability can become linearly separable to the high-dimensional, mainly the kernel function idea.

To design the neural networks control, radial basis function (RBF) NN is adopted in order to approximate the continuous function $F(x): \Re^n \to \Re$ over a compact set

$$F_{NN}(x, W) = W^T \Psi(x) \tag{10}$$

where $x \in \Omega \subset \Re^n$ is neural networks input, $W = [w_1 \ \cdots \ w_l]^T \in \Re^l$ is weight vector, $\Psi(x) = [\psi_1(x) \ \cdots \ \psi_l(x)]^T$ is node vector, and element $\psi_i(x)$ is Gaussian function in form of

$$\psi_i(x) = \exp\left[\frac{-(x-\mu_i)^T(x-\mu_i)}{\eta_i^2}\right], i = 1, 2, \cdots l. \tag{11}$$

where $\mu_i = [\mu_{i1} \ \cdots \ \mu_{in}]^T$ is the center of the basis function and η_i is the scalar width of the Gaussian function.

The RBF NNs can be used to approximate any continuous function over a compact set $\Omega_x \subset \Re^n$ as

$$F(x) = W^{*T}\Psi(x) + \varepsilon(x) \tag{12}$$

where $\varepsilon(x)$ is the NN approximation error, W^* is the ideal NN weight as

$$W^* = \arg\min_{W \in \Re^l}\left\{\sup\left|F(x) - W^T\Psi(x)\right|\right\} \tag{13}$$

$\hat{W}$ is estimated weight and $\tilde{W} = \hat{W} - W^*$.

4. Super-Twisting sliding mode control

Dynamic model

$$\begin{cases} \dot{H}_1 = a_1\sqrt{H_1} + b_1 u_1 + d_1 \\ \dot{H}_2 = (a_2 + a_3)\sqrt{H_2} + b_2 u_2 + d_2 \end{cases} \tag{14}$$

where $d_i (i = 1, 2)$ is external interference.

Expect the system attitude output H_1 to be able to track H_{d1}, so there is

$$z_1 = H_1 - H_{d1} \tag{15}$$

According to formula (4) Super-Twisting algorithm can be obtained

$$z_2 = H_1 - H_{d1} + k\left|z_1\right|^{\frac{1}{2}}\operatorname{sgn}(z_1) \tag{16}$$

so

$$\dot{z}_2 = \dot{H}_1 - \dot{H}_{d1} + \frac{k}{2}\frac{\dot{z}_1}{\left|z_1\right|^{\frac{1}{2}}} \tag{17}$$

Substituting formula into

$$\dot{z}_2 = a_1\sqrt{H_1} + b_1u_1 + d_1 - \dot{H}_{d1} + \frac{k}{2}\frac{\dot{z}_1}{\left|z_1\right|^{\frac{1}{2}}} \tag{18}$$

In summary, the controller

$$u_1 = \frac{1}{b_1}[-k_1\operatorname{sgn}(z_1) - a_1\sqrt{H_1} + \dot{H}_{d1} - \frac{k}{2}\frac{\dot{z}_1}{\left|z_1\right|^{\frac{1}{2}}}] \tag{19}$$

Select the Lyapunov function

$$V = \frac{1}{2}z_2^2 \tag{20}$$

$$\begin{aligned}\dot{V} &= z_2\dot{z}_2 = z_2(\dot{H}_1 - \dot{H}_{d1} + \frac{k}{2}\frac{\dot{z}_1}{\left|z_1\right|^{\frac{1}{2}}})\\ \dot{V} &= z_2(a_1\sqrt{H_1} + b_1u_1 - \dot{H}_{d1} + \frac{k}{2}\frac{\dot{z}_1}{\left|z_1\right|^{\frac{1}{2}}})\end{aligned} \tag{21}$$

$$\dot{V} = (z_1 + k\left|z_1\right|^{\frac{1}{2}}\operatorname{sgn}(z_1))(-k_1\operatorname{sgn}(z_1)) \tag{22}$$

when $z_1 > 0$, $\dot{V}(t) < 0$ is stable, and $k, k_1 > 0$, when $z_1 < 0$, $\dot{V}(t) < 0$ is stable, $k, k_1 > 0$, when $z_1 \neq 0$ is stable, where $\operatorname{sgn}(z_1) = \begin{cases} 1 & z_1 > 0 \\ -1 & z_1 < 0 \end{cases}$.

Expect the system attitude output H_2 to be able to track H_{d2}, so there is

$$z_3 = H_2 - H_{d2} \tag{23}$$

According to formula(4) Super-Twisting algorithm can be obtained

$$z_4 = H_2 - H_{d2} + k\left|z_3\right|^{\frac{1}{2}}\operatorname{sgn}(z_3) \tag{24}$$

So

$$\dot{z}_4 = \dot{H}_2 - \dot{H}_{d2} + \frac{k}{2}\frac{\dot{z}_3}{\left|z_3\right|^{\frac{1}{2}}} \tag{25}$$

Substituting formula into

$$\dot{z}_4 = (a_2 + a_3)\sqrt{H_2} + b_2u_2 + d_2 - \dot{H}_{d2} + \frac{k}{2}\frac{\dot{z}_3}{\left|z_3\right|^{\frac{1}{2}}} \tag{26}$$

In summary, the controller

$$u_2 = \frac{1}{b_2}[-k_1\operatorname{sgn}(z_3) - (a_2 + a_3)\sqrt{H_2} + \dot{H}_{d2} - \frac{k}{2}\frac{\dot{z}_3}{\left|z_3\right|^{\frac{1}{2}}}] \tag{27}$$

Select the Lyapunov function

$$V = \frac{1}{2}z_4^2 \tag{28}$$

$$\begin{aligned}\dot{V} &= z_4\dot{z}_4 = z_4(\dot{H}_2 - \dot{H}_{d2} + \frac{k}{2}\frac{\dot{z}_3}{\left|z_3\right|^{\frac{1}{2}}})\\ \dot{V} &= z_4((a_2 + a_3)\sqrt{H_2} + b_2u_2 - \dot{H}_{d2} + \frac{k}{2}\frac{\dot{z}_3}{\left|z_3\right|^{\frac{1}{2}}})\end{aligned} \tag{29}$$

$$\dot{V} = (z_3 + k\left|z_3\right|^{\frac{1}{2}}\operatorname{sgn}(z_3))(-k_3\operatorname{sgn}(z_3)) \tag{30}$$

when $z_3 > 0$, $\dot{V}(t) < 0$ is stable, and $k, k_3 > 0$, when $z_3 < 0$, $\dot{V}(t) < 0$ is stable, $k, k_3 > 0$, when $z_3 \neq 0$ is stable, where $\operatorname{sgn}(z_3) = \begin{cases} 1 & z_3 > 0 \\ -1 & z_3 < 0 \end{cases}$.

Even if the above-mentioned control algorithm can meet the basic control requirements, and achieve finite time convergence and eliminate chattering, it can ensure better robustness for such nonlinear systems by approximating the nonlinear part through neural networks. The following will apply the RBF neural network for the approximation calculation of the nonlinear part of the above system, but it has not been verified by simulation.

The dual tank level control system can be written as:

$$\begin{cases} \dot{H}_1 = f_1 + b_1u_1 + d_1 \\ \dot{H}_2 = f_2 + b_2u_2 + d_2 \end{cases} \tag{31}$$

where $f_1 = a_1\sqrt{H_1}$, $f_2 = (a_2 + a_3)\sqrt{H_2}$.

Using RBF NN to approximate the nonlinear part $f_i (i = 1, 2)$, the output of RBF neural network is

$$h_j = \exp\left(\frac{\|x - c_i\|^2}{2b_i^2}\right) \tag{32}$$

$$f = W^{*T} h(x) + \varepsilon \tag{33}$$

where x - Network input, i - The i -th input of the network input layer, j - The j -th network input of the hidden network layer, $h = \left[h_j\right]^T$ - Gaussian function output, W^* - Ideal weight, ε - The error of the ideal network approximating f , $\hat{f}$ - Network output, $\hat{W}$ - The estimated weight of the neural network.

So

$$\hat{f}(\cdot) = \hat{W}^T h(x) \tag{34}$$

Get

$$u_1 = \frac{1}{b_1}[-k_1 \operatorname{sgn}(z_1) - \hat{f}_1 + \dot{H}_{d1} - \frac{k}{2}\frac{\dot{z}_1}{|z_1|^{\frac{1}{2}}}] \tag{35}$$

$$\delta_2 = H_1 - H_{d1} + k|z_1|^{\frac{1}{2}} \operatorname{sgn}(z_1) \tag{36}$$

$$\dot{\delta}_2 = f_1 - \hat{f}_1 + k|z_1|^{\frac{1}{2}} \operatorname{sgn}(z_1) \tag{37}$$

Neural networks approximate the nonlinear system as

$$f_1 = W_1^{*T} h(x) + \varepsilon_1 \tag{38}$$

$$\dot{\delta}_2 = W_1^{*T} h(x) + \varepsilon_1 - \hat{f}_1 + k|z_1|^{\frac{1}{2}} \operatorname{sgn}(z_1) \tag{39}$$

$$\begin{aligned} \tilde{f}_1 &= W_1^{*T} h(x) + \varepsilon_1 - \hat{W}_1^T h(x) \\ &= \tilde{W}_1^T h(x) + \varepsilon_1 \\ \tilde{W} &= W^* - \hat{W} \end{aligned} \tag{40}$$

Select the Lyapunov function

$$V = \frac{1}{2}\delta_2{}^2 + \frac{1}{2}\xi_1 \tilde{W}_1 \tilde{W}_1, \xi_1 > 0 \tag{41}$$

$$\begin{aligned} \dot{V} &= \delta_2 \dot{\delta}_2 - \xi_1 \tilde{W}_1 \dot{\hat{W}}_1 \\ &= \delta_1(\tilde{W}_2{}^T h(x) + \varepsilon_1 - k_1 \operatorname{sgn}(z_1)) - \xi_1 \tilde{W}_1 \dot{\hat{W}}_1 \\ &= \tilde{W}_1(\delta_2 h(x) - \xi_1 \dot{\hat{W}}_1) + \delta_2(\varepsilon_1 - k_1 \operatorname{sgn}(z_1)) \end{aligned} \tag{42}$$

Available control law

$$\dot{\hat{W}}_1 = \frac{1}{\xi_1}\delta_2 h(x) \tag{43}$$

In the same way, an approximation control law of f_2 .

$$u_2 = \frac{1}{b_2}[-k_1 \operatorname{sgn}(z_3) - \hat{f}_2 + \dot{H}_{d2} - \frac{k}{2}\frac{\dot{z}_3}{|z_3|^{\frac{1}{2}}}]$$

$$\delta_3 = H_2 - H_{d2} + k|z_3|^{\frac{1}{2}} \operatorname{sgn}(z_3)$$

Get

$$\dot{\delta}_3 = f_2 - \hat{f}_2 + k|z_3|^{\frac{1}{2}} \operatorname{sgn}(z_3)$$

neural networks approximate the nonlinear system as

$$f_2 = W_2^{*T} h(x) + \varepsilon_2$$

Get

$$\dot{\delta}_3 = W_2^{*T} h(x) + \varepsilon_2 - \hat{f}_2 + k|z_3|^{\frac{1}{2}} \operatorname{sgn}(z_3)$$

$$\begin{aligned} \tilde{f}_2 &= W_2^{*T} h(x) + \varepsilon_2 - \hat{W}_2{}^T h(x) \\ &= \tilde{W}_2{}^T h(x) + \varepsilon_2 \\ \tilde{W} &= W^* - \hat{W} \end{aligned}$$

Select the Lyapunov function

$$V = \frac{1}{2}\delta_3{}^2 + \frac{1}{2}\xi_2 \tilde{W}_2 \tilde{W}_2, \xi_2 > 0$$

$$\begin{aligned} \dot{V} &= \delta_3 \dot{\delta}_3 - \xi_2 \tilde{W}_2 \dot{\hat{W}}_2 \\ &= \delta_3(\tilde{W}_2{}^T h(x) + \varepsilon_2 - k_1 \operatorname{sgn}(z_3)) - \xi_2 \tilde{W}_2 \dot{\hat{W}}_2 \\ &= \tilde{W}_2(\delta_3 h(x) - \xi_2 \dot{\hat{W}}_2) + \delta_3(\varepsilon_2 - k_1 \operatorname{sgn}(z_3)) \end{aligned}$$

Available control law

$$\dot{\hat{W}}_2 = \frac{1}{\xi_2}\delta_3 h(x)$$

Finally, the control rate $\dot{\hat{W}}_1, \dot{\hat{W}}_2$ is obtained to approximate the nonlinear part of the system.

5. Result

In this section, Matlab simulation is used to verify the effectiveness of the finite-time sliding mode control dual-volume level system based on the Super-Twisting algorithm. Since the selection of the control law of the traditional sliding mode control system is related to the first derivative of the sliding mode surface, in order to meet the requirements of the approach rate, the control rate naturally contains a sign function, resulting in chattering. In order to solve the chattering phenomenon, high-order sliding mode control can be used. The n-1 order derivative of the system control rate is related to the n-order derivative of its sliding mode surface, so that the discrete control rate is transferred to a higher order sliding mode surface. The super-twisting sliding mode control used in this article is a typical second-order sliding mode control algorithm, which can effectively eliminate chattering. It was verified by simulation.

The controller for the upper water tank is

$$u_1 = \frac{1}{b_1}[-k_1 \operatorname{sgn}(z_1) - a_1\sqrt{H_1} + \dot{H}_{d1} - \frac{k}{2}\frac{\dot{z}_1}{|z_1|^{\frac{1}{2}}}]$$

$$b_1 = 0.003, a_1 = -0.5$$

$$k_1 = 32, k = 0.02$$

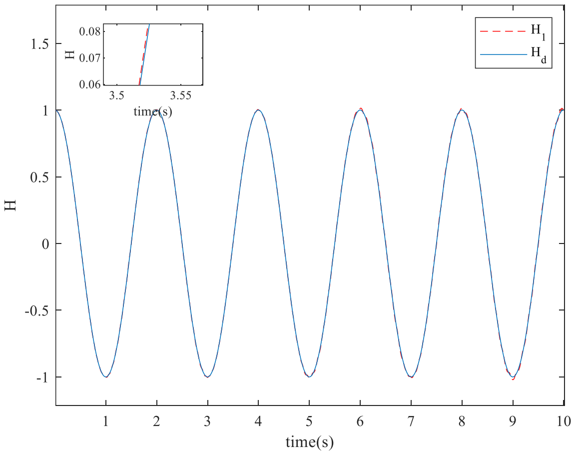

Fig.3. Trajectories of liquid level H_1, ideal position H_d.

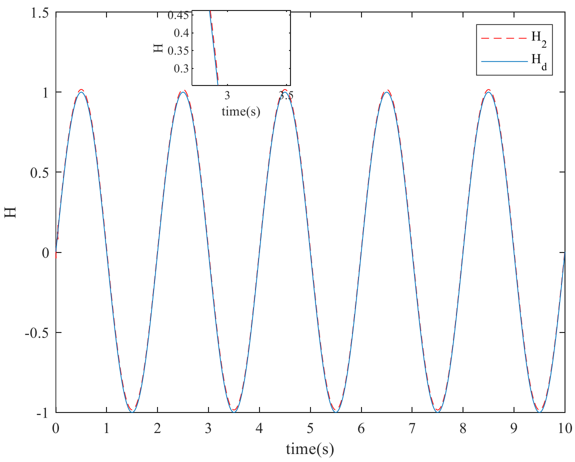

Fig.4. Trajectories of liquid level H_2, ideal position H_d.

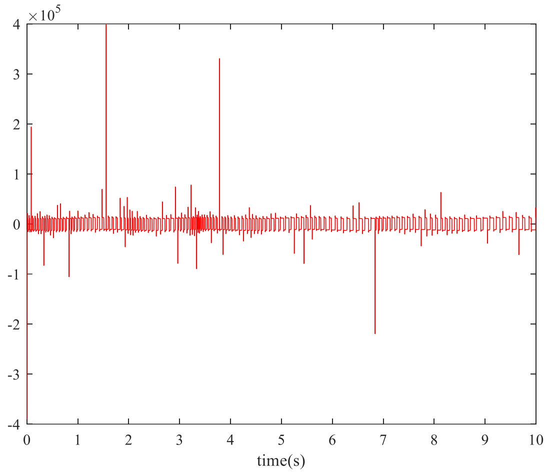

Fig.5. Trajectories of controller u_1

The controller for the lower water tank is

$$u_2 = \frac{1}{b_2}[-k_2 \operatorname{sgn}(z_3) - (a_2 + a_3)\sqrt{H_2} + \dot{H}_{d2} - \frac{k_3}{2}\frac{\dot{z}_3}{|z_3|^{\frac{1}{2}}}]$$

where

$$a_2 = 0.4, a_3 = -0.2, b_2 = 0.003$$
$$k_2 = 0.0047, k_3 = 100$$

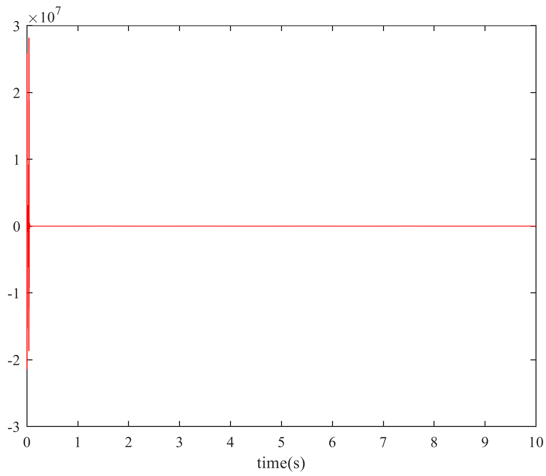

Fig.6. Trajectories of controller u_2

System initial conditions

$$H_1 = 1, H_2 = 0$$

$$H_{d1} = \cos(\pi t), \quad H_{d2} = \sin(\pi t)$$

Fig.3.- Fig.6. shows the effectiveness of Super-Twisting sliding mode control, which can almost perfectly realize the control of the dual-capacity liquid level system and is robust.

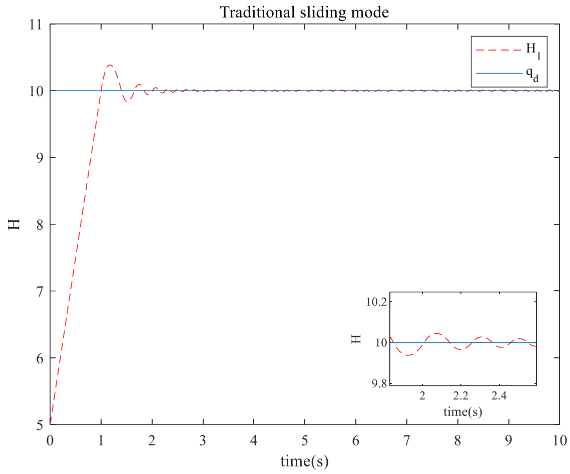

Fig.7. Trajectories of liquid level H_2, ideal position q_d.

The controller of traditional sliding mode for the upper water tank is

$$u_1 = \frac{1}{b_1}[-\xi_1 \operatorname{sgn}(e_1) - c_1\dot{e}_1 - a_1\sqrt{H_1} + \dot{H}_{d1}]$$

where $\xi_1 = 20, c_1 = 4$

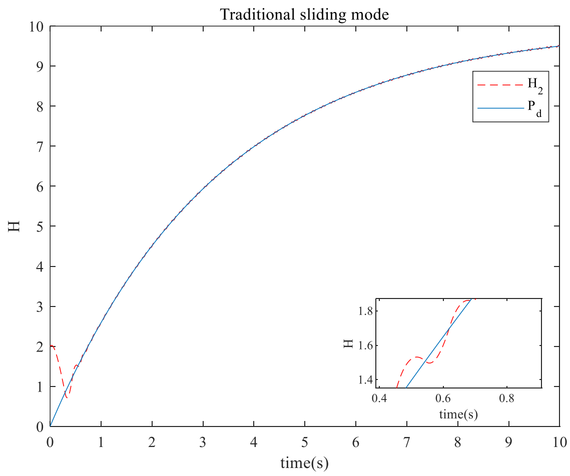

Fig.8. Trajectories of liquid level H_2, ideal position P_d.

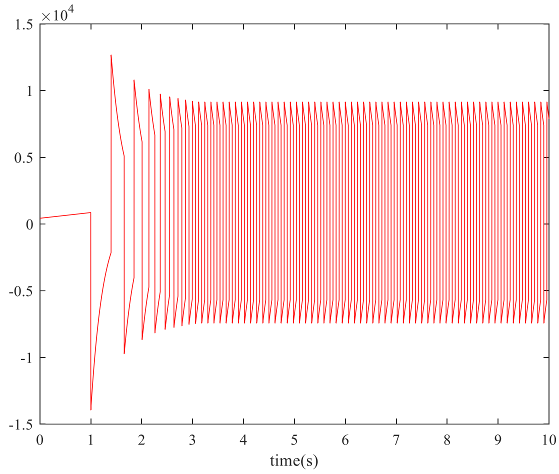

Fig.9. Trajectories of controller u_1

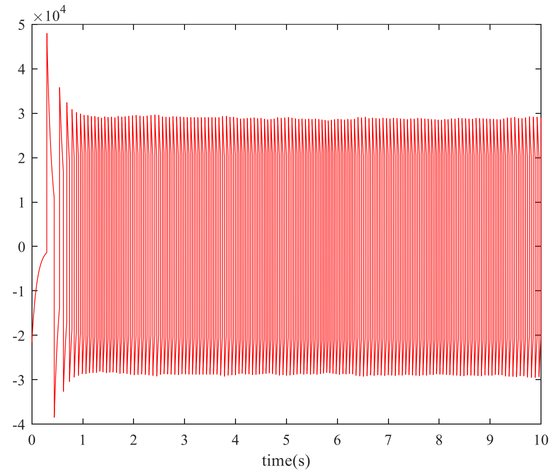

Fig.10. Trajectories of controller u_2

The controller of traditional sliding mode for the lower water tank is

$$u_2 = \frac{1}{b_2}[-\xi_2 \operatorname{sgn}(e_2) - c_2\dot{e}_2 - (a_2 + a_3)\sqrt{H_2} + \dot{H}_{d2}]$$

where $\xi_2 = 100, c_2 = 10$

System initial conditions

$$H_1 = 5, H_2 = 2$$

$$q_d = 10, P_d = 10(1 - \exp(0.3t))$$

Fig.7-Fig.10 are the simulation results of traditional sliding mode control. After comparing with Fig.3.-Fig.6, it can be seen that super-twisting sliding mode control can effectively solve chattering.

6. Conclusion

The simulation results of numerical examples show the effectiveness of Super-Twisting sliding mode control. The control system can converge in a finite time and can obviously eliminate the chattering that exists in the traditional sliding mode. This article also proposes to use RBF neural network to approximate the nonlinear part of the system, but unfortunately it has not been verified by simulation.

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Fei Wenbo is currently studying for a master's degree in the School of Electrical Engineering, Hebei University of Science and Technology, Hebei Province, China. His main research interests are neural network control of nonlinear systems and sliding mode control.

Xueli Wu was born in July 1961, Manchu, Qiqihar, Heilongjiang Province. In October 2005, he graduated from Huazhong University of Science and Technology. He joined the NLD in 1993. Since November 1998, he has been a professor and doctoral tutor at Hebei University of Science and Technology. He is currently the dean of the Science and Technology Development Research Institute of Hebei University of Science and Technology. In 2019, he was awarded as an excellent expert in provincial management in Hebei Province.

Lin Dongxu is currently studying for a master's degree in the School of Electrical Engineering, Hebei University of Science and Technology. His main research interest is the definition of mixed airspace and the establishment of a dynamic operating rule base.