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Application of multi-machine power system supervised machine-learning in error correction of electromechanical sensors

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Abstract

The shortage of electric energy in the supply process and supply interruption will not only directly affect the production level of all walks of life, but also affect the normal life order, and cause adverse effects on the development of the whole society. In order to ensure the stable operation of the system under the premise of ensuring safety, the actual control system is often affected by constraints. In this paper, the intelligent control strategy based on supervised machine learning is used to restrict the output of the system. The back stepping method and Lyapunov method are used to design the control, and then the supervised machine learning sensor of multi-machine power system under the constraint condition is optimized and improved. By introducing the k-class function adjusted according to the error, the system gain is automatically corrected. The simulation results show that the designed controllers can ensure that the output of the speed difference of the system is in the constrained range. Through comparison, it is concluded that the constrained fuzzy adaptive controller can further improve the rotation speed of the speed difference, reduce the vibration amplitude of the speed difference, and achieve better results.
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Keywords: Power system; Electromechanical sensor; Vibration error; Machine learning; Rotation rate correction

1. Introduction

In order to ensure that the power system can supply power safely and have reliability in the process of power supply, the quality of electric energy is a very important index. In order to ensure industrial production and citizens' daily power consumption, the power system also changes with the current changes. At present, new policies have been issued in terms of power consumption to ensure safety. In this context, it is very important to ensure the smooth operation of power system in a safe environment. Because the single machine power system cannot meet the current demand, many scholars now study the stability of multi machine power system, especially the stability of multi machine power system with flexible AC transmission system.

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Adaptive backstepping method is a kind of nonlinear control method of reverse recursive design. This method is applied more and more in nonlinear power system. The single machine TCSC nonlinear power system is studied, and the TCSC sensor is designed considering the parameter uncertainty. The application method is adaptive backstepping method, which achieves good results.

For the single machine infinite bus system of SVC, considering the uncertainty of damping coefficient to design SVC sensor, the application method is adaptive backstepping method, which improves the stability of power system and has good effect [1]. Nowadays, the power system with supervised machine learning is a strong nonlinear system, so the nonlinear control method in the design process can make the supervised machine learning play a better role. The adaptive backstepping method has been applied in the design of sensor learning supervision [2]. However, for the system with disturbance and uncertain parameters, if the adaptive backstepping method is used alone, there is a certain defect, that is, the perturbation of system parameters is poor. Therefore, the combination of this method and sliding mode control has more advantages, and the designed sensor is better. For the multi machine power system with supervised machine learning, considering the parameter uncertainty, the improved backstepping method, adaptive control and sliding mode control are used to design the sensor learning supervision mode, which improves the stability of the power system [3].

At present, when the single machine infinite bus system with static synchronous compensator is studied in the power system, the Hamiltonian method is used to design the robust controller. When the multi machine power system is designed as the research object in literature [4], the multi machine power system contains excitation control, and the controller achieves good results. When the system is disturbed, The nonlinear large interference suppression controller is designed by backstepping and minimax methods, and the anti-interference effect is very good. In order to solve this problem and maintain the stability of the power system in the mining area, STATCOM is applied to the substation in the mining area to compensate the change of reactive power of the load and maintain stability, so as to achieve the effect of dynamic compensation of reactive power. In order to further improve the performance of the controller, Ref. [5] The particle swarm optimization sliding mode method is used in the design of static synchronous compensator. The effectiveness of the controller is verified by simulation. Considering the problem of reactive power compensation in power system, the genetic algorithm is used to optimize the controller of dynamic reactive power compensation device, so that the voltage can be maintained in a stable state while damping low-frequency oscillation. In Ref. [6], a multi-objective controller is designed to study the dynamic stability of multi generator power system with STATCOM.

This paper mainly considers that the power system is not an ideal state in the actual operation. In the research process, firstly, the multi-machine power system with supervised machine learning is equivalent to a dual machine system. According to the actual operation of the system, considering the system transient stability problem when the damping coefficient cannot be accurately measured, the sensor is designed. It mainly uses supervised machine learning method, adaptive control and sliding mode control to construct Lyapunov function restricted by output constraints to design adaptive sensor and improve the supervision mode of adaptive sensor. This design uses MATLAB software for simulation analysis, through simulation analysis to prove that the method has certain advantages.

2. Design of supervised machine learning adaptive control considering output constraints

In this chapter, based on the design of the controller, the improved design is carried out, and the function and supervised machine learning control are introduced to design the constrained sliding mode nonlinear controller.

2.1. *Measurement accuracy coefficient of sensor in electromechanical system*

The system model in this paper mainly considers that the damping coefficient cannot be accurately measured, and the damping coefficients are expressed by D1 and D2 respectively, $\theta = \frac{Q}{H_1} = \frac{D_2}{H_2}$ Then the system can be transformed into:

$$\begin{cases} x_1 = x_2 \\ x_2 = x_3 \\ x_3 = \theta x_3 + b_1 x + b_2 \\ y = x_2 + v_0 \end{cases} \tag{1}$$

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2.2. Design of learning supervision method for constraint adaptive sensor

In this section, we design the learning supervision method of constraint adaptive sensor, mainly adopting Lyapunov and backstepping method, and the adaptive method is designed when the damping coefficient cannot be measured accurately.

Firstly, defining $E_1 = x_1$, $E_2 = x_2 - x_{2d}$, X2 is defined as a virtual control, and the stabilization function is taken as follows:

$$x_{2d} = -k_1(k_b^2 - z_1^2)z_1 \tag{2}$$

In the 2nd formula, K1, KB are the normal numbers in the design, and $|z_1|\, k_b$. The results are as follows:

$$z_1 = z_2 - k_1(k_0^2 - z_1^2)z_1 \tag{3}$$

Let the Lyapunov function of the first order subsystem be:

$$V_1 = \frac{1}{2}\log\frac{k_5^2}{k_0^2 - z_1^2} \tag{4}$$

Therefore, the derivative of V1 in Eq. (4) is:

$$V_1 = \frac{-\frac{2}{z_1 - 1}}{k_3^2 - z_1^2} = -k_1^2 + \frac{z_{12}}{k_0^2 - z_1^2} \tag{5}$$

The coupling term $\frac{\sum_2^{i-2} - z}{k_i^2 - z_i^2}$ in Eq. (5) is eliminated in the second step.

(1) Define $E_3 = x_3 - x_{3d}$, X3 is virtual control, and the stabilization function is chosen as:

$$x_{3d} = -k_2 z_2 - \frac{k_1}{k_6^2 - z_1^2} + x_{2d} \tag{6}$$

In Eq. (6), K2 and KB are the normal numbers of the design. Let the Lyapunov function of the second order subsystem be:

$$V_2 = V_1 + \frac{1}{2} = z^2 \tag{7}$$

Then the derivative of 2 V in Eq. (7) is:

$$\begin{aligned} V_2 &= -k_1 = 1^2 + \frac{z_1 = 2}{k_3^2 - z_1^2} + z_2^2 \\ &= 2 - k_1 = 1^2 - k_2 z_2 + z_2 = z_3 \end{aligned} \tag{8}$$

The coupling term $z_2 z_3$ in Eq. (8) is eliminated in the third step.

The derivative of x_{3d} is:

$$k_{34} = -k_{23}x_3 - (1 + k_2)k_1^2 k_3 + 3k_4(1 + k_2) - \frac{x_2(k_b^2 - x_1^2) + 2x_1^2 x_2}{(k_b^2 - x_1^2)^2} \tag{9}$$

(2) Take the global Lyapunov function as:

$$V_3 = V_2 + \frac{1}{2} = \frac{1}{3} + \frac{1}{2p} + \theta^2 \tag{10}$$

In Eq. (10): $p > 0$ is the adaptive gain coefficient, $\overline{\theta}$ is the error value, $\widetilde{\theta}$ is the estimated value. $\widetilde{\theta} = \theta - \overline{\theta}$The global Lyapunov function is derived.

$$\begin{aligned} V_3 = V_2 + z_3^2 Z_3 - \frac{1}{0}\theta d &= -k_1 z_1^2 - k_2 z_2^2 + z_3(\theta x_3 + b_2 \\ &+ b_1 u + z_2 - x_{3d}) + \theta(z_3 x_3 - \frac{1}{p}s) \end{aligned} \tag{11}$$

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The replacement rate of the selected parameter is: $\widetilde{\theta} = pz_5x_3$. The optimal control law is as follows:

$$u = \frac{1}{b_1}(-k_3 = z_3 + x_{34} - b_3 - b_2 - z_2) \tag{12}$$

In Eq. (12), where K3 is the designed normal number. So for the whole system:

$$V_3 = -k_1z_1^2 - k_2^2z_2^2 - k_3z_3^2 \leq 0 \tag{13}$$

By selecting the appropriate parameters, make $V_3 < 0$ achieved.
It is concluded that the error dynamic system under the control law u is as follows:

$$\begin{cases} z_1 = -k_1(k_0^2 - z_1^2)z_1 + z_2 \\ z_2 = -k_2z_2 - \dfrac{z_1}{k_0^2 - z_1^2} + z_3 \\ z_3 = -k_3z_3 - z_2 + \theta_3 \end{cases} \tag{14}$$

Because z_3 is negative definite, if $|Z_1(t)| < k_0$ is made ture, then make the initial condition $|z(0)| < k_0$, Under the control law u, the error system is asymptotically stable.

3. Learning supervision design of improved constrained sliding mode adaptive sensor

The learning supervision method of the improved constraint adaptive sensor is designed. The k-class function is mainly introduced, and the Lyapunov and backstepping method, adaptive method and sliding mode method are used for the design

(1) The error sliding surface is defined, where x_{2d} and x_{3d} are virtual control variables

$$\begin{cases} s_1 = x_1 \\ s_2 = x_1 - x_2 \\ s_3 = x_3 - x_3 \end{cases} \tag{15}$$

The derivative of s1 is as follows:

$$s_1 = x_2 = x_2 = s_2 + x_{2d} \tag{16}$$

Take the s_2 in the formula above as an indefinite term, In the following design, we get the following results. Suppose that: $\|s_2\| \leq a_1$ is an unknown bounded normal number. Therefore, the virtual control quantity x_{2d} is:

$$x_2 = \{-[a_1 + q_1(s_1)]\}_1 - \frac{a_1, y_1}{(s_1^2 + e_1)^2}(k_0^2 - s_1^2) \tag{17}$$

In Eq. (17), $q_1(s_1)$ is K-class function which is designed

Eq. (18) is an adaptive estimation rate, among them, $ei > 0$ is the parameter to be designed

$$\widetilde{a_1} = n_1\frac{c_1s_1^2}{(n_1^2 + ei)^{\frac{3}{1}}} \tag{18}$$

Let the Lyapunov function of the first order subsystem be:

$$V_i = \frac{1}{2}\log\frac{k_{ij}^2}{k_{ij} - e_i^2} + \frac{1}{2p_{ij}^2} \tag{19}$$

Therefore, the derivative of V_1 in Eq. (19) is:

$$V_1 = s_1';_1 - \frac{a_1a_1^2}{p_1} = -(a_1 + \phi_1(s_1)|)s_1^2 + s_1s_2 \leq -(a_1 + q_1)(s_1)s_1^2 + a_1|s_1| \tag{20}$$

When the Sliding surface meets the condition of $|s_1 \| > (k_0^2 - s_1^2)\frac{k_1}{(c_1-1)^{\frac{1}{2}}}$ then $V_1' \leq -(a_1 + q_1(s_1))s_1^2 \leq 0$.

(1) The derivative of s_2 is:

$$s_2 = x_2 = x_3 = s_3 + x_{3d} \tag{21}$$

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Suppose that : $\|s_3\| \leq a_2$, a_1 is an unknown bounded normal numbers.

$$x_{34} = -\{[a_1 + q_2(x_2)]\}_2 - \frac{dye^2xe^3}{(s_2^2 + e_2^2)^{\frac{1}{2}}} \tag{22}$$

In the formula (22), $e_2 > 0, k_2 > 0, c_2 > 0$, $q_2(.)$ is designed k-class function. The Valuation of a_2 is a_2', using adaptive estimation rate formula (23):

$$d_2 = p_1 \frac{\cos^2}{(s_2^2 + e_2^2)^{\frac{1}{2}}} \tag{23}$$

$p_1 > 0$ is a parameter going to be designed.

Let the Lyapunov function of the second order subsystem be:

$$V_2 = V_1 + \frac{1}{2}s_2^2 + \frac{1}{2p_2}a_2^2 \tag{24}$$

The derivatives of V_2 in the formula (24) is:

$$\begin{aligned} V_2 = V_1^{\phi} + s_2 s_2 - \frac{a_2 a_2^2}{p_2} &= -[a_1 + \phi(s_1)|]s_1^2 \\ - \left[a_2 + q_2[|s_2|]s_2^2 + s_2 s_3 \leq -[a_1 + \phi(s_1)]\right] s_1^2 \\ - \left[a_2 + \phi_2[S_2]|\right]s_2^2 + a_2\|s_2\| \end{aligned} \tag{25}$$

According to the formula (25), when the Sliding surface meets the condition of $\|s_2\| > \frac{e_2}{\sqrt{(c_2-1)}}$, the result can be achieved as following:

$$v_2' \leq -(a_1 + q_1(s_1))x_1^2 - (a_2 + q_2(s_2))s_2^2 \leq 0 \tag{26}$$

(2) The derivative of s_3 is:

$$s_3 = x_3 - x_3 u = \beta x_3 + b_2 + b_1 u - x_{3a} \tag{27}$$

In the formula (27), take the x_{3d} as an uncertain items, and suppose that $\|x_{3a}\| \leq a_3$, a_3 is an Unknown normal numbers with upper and lower bounds. Next, take the feedback control quantity u, and consider the uncertainty of x_{3d} when selecting the control quantity U. So select $u = -\frac{1}{b_1}\{[q_3(x_3) + a_3]\}_3 + b_3 + b_2 + \frac{a_5 s_3}{(s_3^2 + z_3)^{\frac{1}{2}}}$, using adaptive rate of parameter a_3:

$$a_3 = q_3 - \frac{C_3 S_3}{p_3 - s_3^2} \tag{28}$$

At the same time, using adaptive rate of parameter β: $\beta = y_1 s_3 x_3$, $y_1 > 0$ is the parameter to be designed [7–9]. The global Lyapunov function is as follows:

$$V_3 = V_2 + \frac{1}{2}s^2 + \frac{1}{2p_3}a_3^2 + \frac{1}{2y_1}\beta^2 \tag{29}$$

The global Lyapunov function is derived.

$$\begin{aligned} V_3' &= V_2^1 + qs^2 3^2 - \frac{Q_3^2 s_3^4}{P_3} - \frac{\theta_1^2}{R_1} \\ &= -(a_1 + q_1(s_1))s_1^2 - (a_2 + \phi(s_2))s_2^2 - (a_3 + \phi_3(s_3))s_3^2 \end{aligned} \tag{30}$$

when the Sliding surface s_3 meets the condition of $\|s_3\| > \frac{e3}{(e_3-1)^{\frac{1}{2}}}$, the result can be achieved as following:

$$V_3 \leq -(a_1 + q_1(s_1)s_1^2) - (a_2 + \phi_2(|s_2))s_2^2 - (a_3 + q_3(s_3))s_3^2 \tag{31}$$

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Under the control law u, the error dynamic system is as follows:

$$\begin{cases} s_1 = s_2 - (a_1 + q_1(s_1))s_1 - \dfrac{a_1(c_1 s_1^{s_1})}{(s_1^2 + g_1)^2} \\ s_2 = s_3 - (a_2 + q_2(s_2))s_2 - \dfrac{Q_2 c_3^3}{(s_2^2 + g_2)^{\frac{1}{2}}} \\ s_3 = \beta x_3 - (a_3 + \phi_3(s_3))s_3 - \dfrac{d_3 c_3^c s_3}{(s_3^2 + e_3^2)^{\frac{1}{2}}} - a_3 \end{cases} \tag{32}$$

Because V_3 is negative, if make the formula $|z_1(t)| < k_b$ to set up at any time, then let the Initial condition $|z_{-1}(0)| < k_0$ that can meet $V_3 \leq 0$, Under the action of control law u, the error system is gradually stable [10–12] when $t \to \infty$, $z_1 \to 0$, $z_2 \to 0$, $x_1 \to 0$, $x_2 \to 0$, according to the definition of $x_1, x_2, x_3, x_{2d}, x_{3d}$ can get the result that $z_3 \to x_0$, is bounded.

There are many forms of K-type function selection in the system. The K-type function selected in this design is $q_i(s_i) = \tau_i s_i^2$, $s_i = 1, 2, 3$. $\tau_i > 0$ is a constant to be designed [13–15].

4. The analysis of simulation experiment

This paper mainly studies the output constraint control performance of multi machine power system. For the stable operation of multi machine power system, a simulation experiment platform is built to verify the research results.

4.1. Setting of simulation experiment environment

In this design, MATLAB software is used to simulate and analyze it. In the simulation process, the parameters are selected as follows: w_{1n}, w_{2n} are the rated rotor angular velocity of the generator, H_1 and H_2 are the moment of inertia of the generator, D_1 and D_2 are the damping coefficient of the generator [16]. The values of other parameters are shown in Table 1.

Table 1. Parameter selection of simulation environment.

Index	Parameter
δ_{10}	45°
e_{10}	314.159 rad/s
H_1	6.4
H_2	6.147
D_1	1
E_1	1
X_1	0.5
X_2	0.7
I_q	0.1
T_q	0.07
K_q	4
K_1	2
K_2	3
K_3	7
K_b	1

In the analysis of the simulation results, there are two control methods: constraint method and traditional method. The traditional method has no constraint. By comparing the response changes of the two methods in the simulation results, it shows that this method has good accuracy and effect, and proves the advantages of the constraint method [17].

The output y of the speed difference of the equivalent two machine system changes in the range of $(a_n - k_n)(a_n + k_n)$, from which it can be concluded that $a_n - k_n < a_1 - a_2 < a_n + k_n$, the speed difference changes between ± 1 Hz, the frequency is 50 Hz in the stable operation of the actual power system, it can change between ± 0.2 Hz and ± 0.5 Hz in the allowable error range, and the speed difference range is ± 0.4 Hz to ± 1 Hz, The variation range of speed difference is ± 0.4hz to ± 1 Hz [18–20].

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4.2. The process of simulation experiment

(1) In the actual power system operation process, the system is in normal and stable operation state. When t = 0.1s, the relative speed of the generator changes, that is $\Delta a = 1$ rad/s[[21]. The simulation results are shown in Figs. 1 and 2.

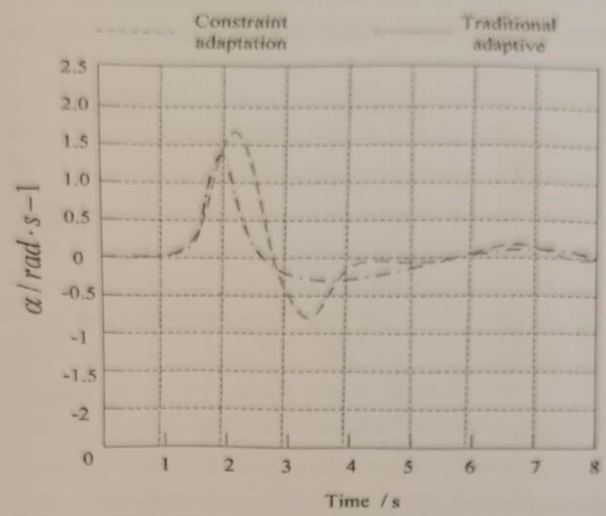

Fig. 1. Transient response curve of rotational speed difference.

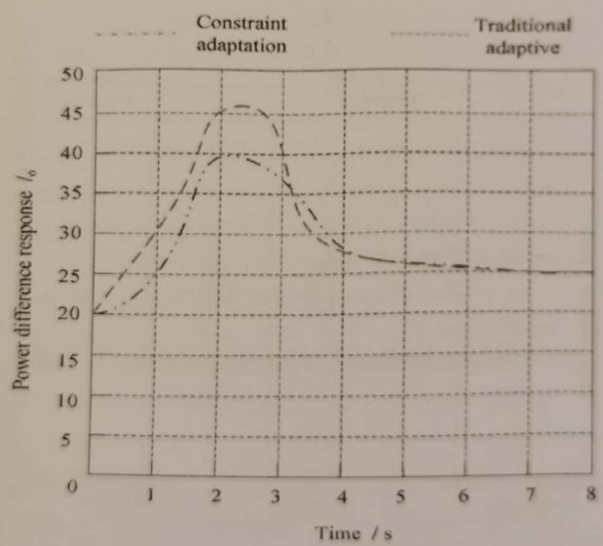

Fig. 2. Transient response curve of power angle difference.

According to the simulation results, it can be concluded that when the system is disturbed, the stable operation system will change and cannot maintain normal state. Therefore, the transient response of the system will fluctuate. It can be seen from the simulation diagram that the transient response curve of the rotational speed difference fluctuates after being disturbed in the simulation diagram with constraint method, but the speed difference is kept within ± 1 Hz, It is specified that the frequency of the actual power system is 50 Hz when it is stable. The range of error permission can be between ± 0.2 hz and ± 0.5 Hz, that is, the range of speed difference is ± 0.4 hz–1 hz. Therefore, the simulation results show that the sensor designed by the constraint method can keep the output speed difference within the allowable range, The results show that the output speed difference of the sensor designed by traditional method has exceeded the allowable range of ± 0.4 hz–1 hz in the simulation diagram. By comparing the two design methods, the traditional method cannot guarantee the change of the output speed difference within the allowable range, The sensor designed by traditional method cannot meet the design requirements. The sensor

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designed by the constrained method makes the speed difference change within the allowable range, and meets the design requirements.

(2) During the actual power system operation, the system operates in a stable state under normal conditions. When the operation time is t=0.5 s, the fault of three-phase short circuit occurs on the line. When the operation time is t=0.6 s, the line will return to normal and stable operation state [22], The simulation comparison and analysis of the sensor design method by traditional method and constraint method are carried out. The transient response curve of the system obtained from the simulation results is shown in Figs. 3 and 4.

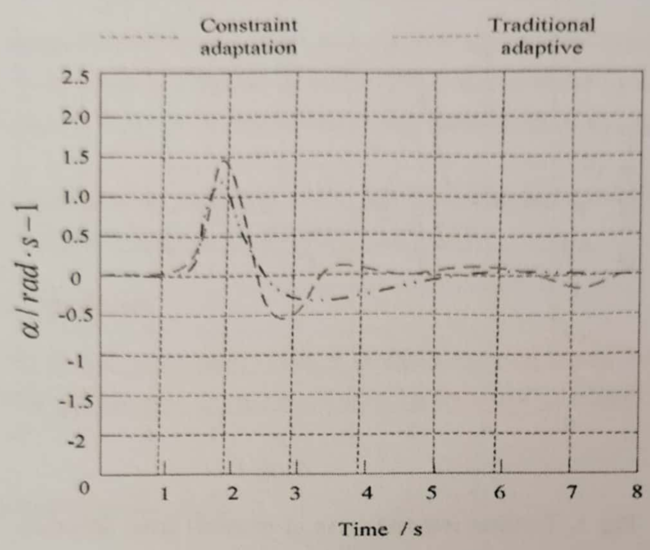

Fig. 3. Transient response curve of rotational speed difference.

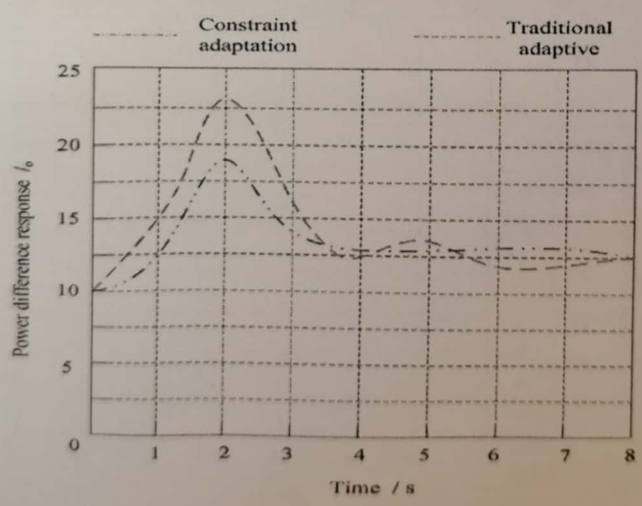

Fig. 4. Transient response curve of power angle difference.

From the simulation results, it can be concluded that when the short circuit fault occurs in the system, the stability of the system will be destroyed and the transient stability response will change. From the simulation results, it can be seen that the speed difference of the constraint method simulation diagram is limited to ± 1 Hz, that is, in the normal allowable range of ± 0.4 Hz to ± 1 Hz, At the same time, it can be concluded that not only the speed difference changes in the normal allowable range, but also the power angle difference is in the limited range [23–25].

(3) Analysis of improved adaptive simulation results

This design mainly compares and analyzes the constraint adaptive method, the constraint sliding mode adaptive method and the improved constraint sliding mode adaptive method, and carries out the transient stability simulation analysis by using MATLAB software. The parameter selection in the simulation process is shown in Table 2.

According to the simulation results, the response curves of the three methods are analyzed and compared, as shown in Figs. 5 and 6.

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Table 2. Parameter selection in simulation process.

Index	Parameter
$\delta_{10} = \delta_{30}$	45°
$e_{10} = e_{20}$	302.474 rad/s
H_1	6.2
H_2	6.147
D_1	1
$E_1 = E_3$	1
X_1	0.5
X_2	0.7
I_q	0.1
T_q	0.07
K_b	2
$K_1 = K_2 = K_3$	2
K_b	1
γ_1	1
ρ_1	15
ρ_2	125
ρ_3	45
$d_1 = d_2 = d_3$	2

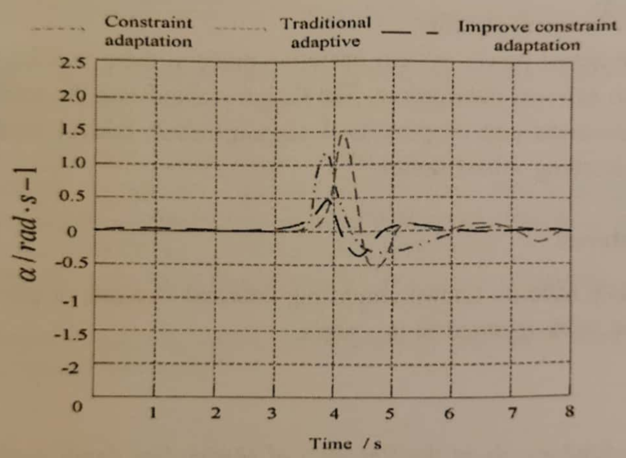

Fig. 5. Transient response curve of rotational speed difference.

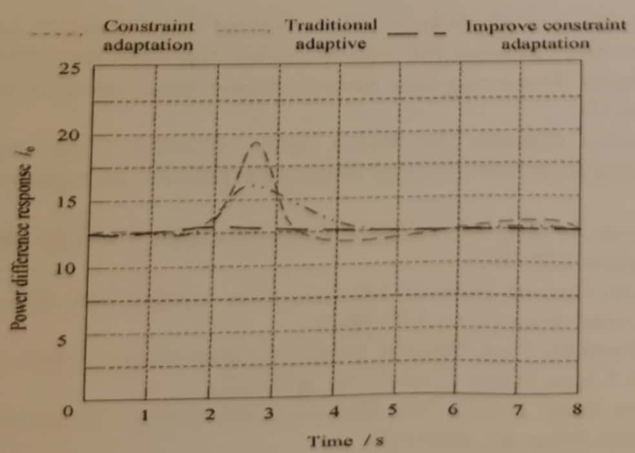

Fig. 6. Transient response curve of power angle difference.

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In the test results, the vibration amplitude of the improved constrained sliding mode adaptive method is the smallest, on the contrary, the vibration amplitude of the constrained adaptive method is the largest, which is beyond the specified range [26–28]. Under the requirement of ensuring the change range, the improved method has fast recovery time. From the above analysis, it can be concluded that the constrained sliding mode adaptive method is better than the constrained adaptive method, And the improved method is better than the other two methods. In order to make the advantages of the system greater, the method of adding K-type function and sliding mode control is used to design the improved constrained sliding mode adaptive sensor. Through the research, it is concluded that the sensor designed by this method makes the vibration amplitude of the speed difference minimum and takes the shortest time to restore stability, which proves that this method has certain benefits and advantages.

5. Conclusion

In this paper, for the design of learning supervision of sensor with uncertain parameters, the constraint adaptive method is adopted. Through the design and simulation analysis, it is concluded that the learning supervision mode of constraint adaptive sensor controls the output of speed difference within the limited range, and the time to recover to stability after interference is shorter, which meets the design requirements. The reactive power of the system is supplemented when necessary, and can make the system more efficient and stable. Comprehensive analysis STATCOM plays a very important role in facts device, and is widely used in power system. STATCOM is mainly composed of power electronic converters. During operation, it mainly inputs the changing reactive power compensation current into the power system, so as to maintain the voltage stability of the bus at the device access point and expand the range of transient stability.

In the future work, for the actual power system operation process, there will be not only the phenomenon of parameter uncertainty, but also external interference. The design methods are the traditional adaptive backstepping robust control method and the constraint adaptive backstepping robust control method to design the constraint adaptive supervised machine learning robust sensor.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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