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Research article

A neural network-based adaptive fault-tolerant cooperation control for multiple trains with unknown parameters

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Abstract: For the problems of parametric uncertainties and actuator faults encountered during high-speed train operation, this paper proposes a neural network-based adaptive fault-tolerant control strategy for cooperation of multiple trains. First, a multi-train model with state constraints, disturbances, and actuator faults was established, and the radial basis function neural network was utilized to fit the unknown disturbance. Subsequently, the auxiliary control signal was introduced to compensate the impact of actuator faults on train. Then, when designing adaptive laws, the variations of basic resistance parameters were fully considered. By integrating adaptive laws with the adaptive fault-tolerant controller, the effect of disturbances on multi-train systems can be dynamically eliminated. The Lyapunov method was established to prove the stability of multi-train systems. Simulation results show that the proposed adaptive fault-tolerant control strategy can maintain the stability of multi-train systems and achieve cooperation of trains with actuator faults.

Keywords: high-speed trains; neural network; unknown parameters; actuator faults; adaptive fault-tolerant control

1. Introduction

In recent years, with the characteristics of convenience, punctuality, and comfort, high-speed trains have become one of the mainstream long-distance transportation tools for passengers [1]. For enhancing utilization efficiency of high-speed railway infrastructure while ensuring safe operation of trains, it is particularly important to develop automatic train control technology. Meanwhile, with the progress of communication technology for railways, train-to-train communication has become the development trend, which also provides hardware conditions for realizing the cooperative control of trains. In order to avoid the waste of railway resources and improve the utilization rate of railway lines, the application of a multi-train cooperative control strategy has important engineering significance. Through the cooperative control strategy, high-speed trains with different initial positions and speeds can be tracked to the same speed and maintain the desired tracking distance. Especially in the condition of high-density operation, it can greatly improve the operation efficiency of railway systems [2–5].

Many scholars have conducted in-depth research on the problem of cooperative control for high-speed trains. For example, the reference [6] constructed an undirected graph to connect all scattered trains into a whole system and designed an adaptive control strategy to achieve the purpose of consistent speed for all trains. Li et al. [7] utilized the LaSalles invariance principle and integrated it with train state analysis to develop an adaptive control strategy. This approach can ensure that the adjacent trains maintain the desired safe distance. It can be seen that the stabilization process of tracking distance is actually the progressive convergence of both position and speed errors toward zero. To address the above problem, the literature [8] guaranteed the convergence of speed errors and position errors for all trains by introducing a modified coupled sliding mode surface, which ensured the string stability of whole multi-train systems. Similarly, in order to realize the convergence of tracking errors, Liu et al. [9] designed an optimal linear feedback controller, which ensured the local and string stability of multi-train systems.

In real operation scenarios, many factors can adversely affect the normal operation. The safety and reliability of train operation have been increasingly emphasized and attracted extensive attention from researchers and scholars [10]. One of the challenging problems is the parameter uncertainties of trains. The resistance parameters of trains will change with different operation speeds. For example, the problem of cooperative control for high-speed trains with uncertain parameters has been studied in [11,12]. Chen et al. [13] proposed an adaptive iterative learning train control method to solve the nonlinear parameter uncertainty problem. According to references [14–16], it is known that the disturbances affecting the normal operation of trains can be broadly categorized into two types: basic running resistance and external disturbance. In reference [17], by designing a dynamic adaptive controller and an adaptive control law updating mechanism, multi-train systems can maintain stable operation in the presence of multiple disturbances. Considering the actual train operation scenario, the basic running resistance parameters and external disturbance are usually unknown. Therefore, it is essential to deal with uncertain parameters of basic running resistance.

For nonlinear disturbance without fixed expressions, the neural networks can be introduced to fit disturbance. Gao et al. [18] designed an adaptive control strategy by introducing the estimated values of various uncertain basic running resistance parameters into the adaptive control scheme. Combined with the adaptive control laws composed of these parameters, the influence of these unknown parameters on the multi-train systems is dynamically estimated. Due to the excellent nonlinear approximation ability of radial basis function neural networks (RBFNNs), Huang et al. [19] employed RBFNNs to fit uncertain terms in multi-train systems. The results of simulation experiments showed that the designed tracking controller can quickly respond to unknown disturbance and make corresponding adjustments to achieve accurate tracking of the desired speed. Yang et al. [20] combined the advantages of a mathematical parameter estimation method and RBFNNs to dynamically estimate each parameter of the basic running resistance. In general, the varying disturbance will affect the control effect. Hence, in order to ensure the safe and stable operation of trains, the influence of varying disturbance on the train must be fully considered.

In addition to basic running resistance and unknown disturbance, the train controller plays a decisive role in maintaining the stability of multi-train systems, which highlights the particular significance of controller design. The train controller needs to be limited in a reasonable range because of its physical characteristics. The references [21,22] utilized the saturation function to constrain the control input, which ensured that the controller would not be damaged by excessive control input and the train operated safely within the specified control input. Since the hyperbolic tangent function does not have cusps or discontinuous jumps with respect to the saturation function, this makes it smoother on the train control. The reference [23] used the hyperbolic tangent function to approximate the control input, which made the acceleration and deceleration of the train smoother, thus further enhancing the passengers' riding experience. Zhu et al. [24] designed a new auxiliary dynamic system, which solved the controller instability due to input saturation during train coupling and realized cooperative operation of high-speed trains with speed limitation. To solve the problem of calculation resource constraints, the literatures [25–27] designed the train controller as the on-demand triggering method, which significantly reduced the dependence on calculation resource and saved the communication resource.

However, the controllers in the above literatures are based on the normal operating condition of trains and the case of actuator faults is not considered. As a common form of long-distance transportation, the high-speed train needs to run for long periods of time. The actuator of the train may have a temperature rise or other sudden events, which could cause the controller to only exert partial control effectiveness and result in actuator faults. If the train actuator faults, the internal sensors will not be able to obtain accurate control signals in time to drive the motor, and then the actuator will not be able to execute the desired control output accurately. For the problem of actuator faults, the literature [28] utilized the neural network method to compensate for actuator faults, which eliminated the nonlinear influence of traction or braking force through dynamic compensation, and then realized high-precision tracking of speed and position. Mao et al. [29] designed an adaptive fault-tolerant sliding mode control scheme to ensure the tracking error convergence when the train encountered actuator faults. The adaptive fault-tolerant control strategy proposed by Yao et al. [30] ensured that multi-train systems maintained stable speed and tracking distance under actuator faults. Zhu et al. [31] introduced an auxiliary signal-based fault-tolerant control strategy to address the actuator faults of trains. Su et al. [32] designed an adaptive fault-tolerant fixed time cooperative control strategy and used the function approximation method to solve input saturation problems, so as to ensure the system stability of virtual coupled trains with input constraints and actuator faults.

Therefore, for the cooperation of trains, except for general state and input constraints, it is essential to consider actuator faults and uncertain parameters to satisfy the requirement of practical operation. In this paper, the actuator faults and uncertainty of resistance parameters are comprehensively considered, and an adaptive fault-tolerant control mechanism is investigated to realize the cooperative control of trains under the condition of state constraints and control input saturation. Overall, the main contributions can be summarized as follows:

1) With state constraints, input saturation, uncertain parameters, unknown disturbance, and actuator faults, the dynamic model of multi-train systems is established. Then the RBFNN is utilized to fit the unknown disturbance.

2) The auxiliary control signal is designed to compensate for the impact of actuator faults and the adaptive laws are designed to eliminate the impact of changing basic resistance parameters.

3) For the proposed adaptive fault-tolerant control scheme, the Lyapunov method is utilized to prove

the stability of multi-train systems, which means the cooperation of multiple trains can be realized.

2. Problem formulation

In complex and varying operating environments, it is not only necessary to overcome the interference of the basic operating resistance, but also one needs to make timely adjustments to cope with the unknown resistance to maintain the stability of multi-train systems. In order to describe the train operation states, in this section, a multi-train model with unknown parameters, state constraints, and actuator faults is first established.

The leader train is usually seen as a virtual reference train. Hence, the dynamics of the leader train are

$$\dot{p}_0(t) = v_0(t) \tag{2.1}$$

where $p_0(t)$ and $v_0(t)$ denote the position and speed of the leader train.

During the normal operation of trains, the actuator may suddenly fail, resulting in a sharp drop in the output value of the controller. For multi-train systems, this unexpected situation will cause the failure of control. Then, with actuator faults, the dynamic model of the following train is established as

$$\begin{cases} \dot{p}_i(t) = v_i(t) \\ M_i\dot{v}_i(t) = k_c sat(\breve{u}_i(t)) - f_{ai}(t) - w_i(t) \end{cases} \tag{2.2}$$

where $v_i(t)$ and $p_i(t)$ denote the speed and position of train i, respectively; M_i means the total weight of train i; and $k_c(t)$ represents the effective factor of the control input, which is affected by actuator faults and satisfies $0 < k_a \le k_c(t) \le 1$, where k_a indicates the known constant. When $k_c(t) = 1$, it means that there are no faults of the train's actuator. $\breve{u}_i(t)$ expresses the control input. $f_{ai}(t)$ represents the basic resistance encountered during train operation. $w_i(t)$ stands for the total unknown disturbance. The expression for the basic resistance is given as [25]

$$f_{ai}(t) = a_i + b_i v_i(t) + c_i v_i^2(t) \tag{2.3}$$

where a_i, b_i, and c_i denote the basic resistance parameters.

To facilitate the design of the control mechanism, the control input is redefined as

$$u_i(t) = \frac{\breve{u}_i(t)}{M_i} \tag{2.4}$$

For the input saturation, we have

$$sat(u_i(t)) = \begin{cases} u_m & u_i(t) > u_m \\ u_i(t) & |u_i(t)| \le u_m \\ -u_m & u_i(t) < -u_m \end{cases} \tag{2.5}$$

where u_m represents the maximum value of the control input.

Combining Eqs (2.2)–(2.5), the simplified model for the following train is

$$\begin{cases} \dot{p}_i(t) = v_i(t) \\ \dot{v}_i(t) = \left(1 - \tau_f\right) sat\left(u_i(t)\right) - \frac{f_{ai}(t)}{M_i} - f_{bi}(x) \end{cases} \tag{2.6}$$

where $\tau_f = 1 - k_c(t)$, $\tau_f \in [0, 1 - k_a]$. The unknown resistance is transformed as $f_{bi}(x) = \frac{w_i(t)}{M_i}$.

Remark 1: Indeed, the unknown resistance of the train is related to its operating environment. For instance, the operation resistance will change when a train passes through grades, curves, or tunnels. In addition, the external weather conditions such as strong wind, rain, and snow can also affect train operation resistance. This type of resistance caused by the external environment is referred to as unknown resistance. Compared to the basic running resistance, the unknown resistance is typically smaller and fluctuates within a certain range. Therefore, the unknown resistance remains bounded during train operation.

Due to the ever-changing environment of train operation, the bounded unknown disturbance encountered by the train can be described as a smooth nonlinear function and it is difficult to model the exact dynamics directly. According to reference [20], it is known that by setting appropriate parameters, the RBFNN can fit the nonlinear function with desired accuracy. Therefore, the RBFNN is utilized in this paper to approximate the bounded unknown disturbance $f_{bi}(x)$. The expression is given as

$$f_{bi}(x) = w_i^{*T} h(x) + \varepsilon(x) \tag{2.7}$$

where $x = [x_1, x_1, ..., x_n]^T$ is the input of the neural network; $\varepsilon(x)$ is the neural network approximation error that satisfies $|\varepsilon(x)| \le \theta_i$; θ_i denotes a constant and $\theta_i > 0$; $h(x) = [h_1(x), h_2(x), ..., h_m(x)]^T$ stands for the Gaussian function of a hidden layer; and $h_i(x)$ denotes the i-th neuron with $i \in [1, m]$ and the expression is established as [28]

$$h_i(x) = exp\left(-\frac{\|x - p_i\|^2}{2q_i^2}\right) \tag{2.8}$$

where p_i and q_i denote the center parameter and width of the basis function, respectively. By choosing appropriate neurons, center parameters, and widths, the RNFNN can approximate the nonlinear function with desired accuracy. In addition, w_i^* represents a vector of ideal weight parameters and

$$w_i^* = arg \min_{\hat{w} \in R^N} \left\{ \sup_{x \in \Omega} |f_{bi}(x) - \hat{w}^T h(x)| \right\} \tag{2.9}$$

where $\Omega \in R^N$ and Ω denotes the set containing x. $\hat{w}$ is the estimate of w_i. The output of the RBFNN is

$$\hat{f}_{bi}(x) = \hat{w}^T h(x) \tag{2.10}$$

where $\hat{f}_{bi}(x)$ denotes the estimate of $f_{bi}(x)$.

For the unknown disturbance, the output of RBFNN Eq (2.10) is utilized to approximate the unknown disturbance. Subsequently, the fitting of the unknown disturbance will be realized by obtaining the ideal weight parameters through the dynamic updating of the adaptive controller and adaptive laws.

In order to analyze the stability of multi-train systems, the train error equation is established as

$$e_{pi}(t) = p_i(t) - p_0(t) + i \times D \tag{2.11}$$

$$e_{vi}(t) = v_i(t) - v_0(t) \tag{2.12}$$

$$e_i(t) = \partial_1 e_{pi}(t) + \partial_2 e_{vi}(t) \tag{2.13}$$

where $e_{pi}(t)$ denotes the position error between train i and the leader train, i indicates the number of following train i, and D represents the desired tracking distance between adjacent trains. $e_{vi}(t)$ shows the speed error between train i and the leader train. In addition, $e_i(t)$ expresses the hybrid tracking error of train i, where ∂_1 and ∂_2 denote constants greater than zero.

For safe operation, the hybrid tracking error $e_i(t)$ needs to be limited as

$$|e_i(t)| < \sigma_i \tag{2.14}$$

where σ_i is a positive constant. Then we define

$$\beta_i(t) = \frac{e_i(t)}{\sigma_i} \tag{2.15}$$

and it is obvious that

$$-1 \leq \beta_i(t) \leq 1 \tag{2.16}$$

Then we define the hybrid tracking error function as

$$X_i(t) = arctanh\left(\beta_i(t)\right) \tag{2.17}$$

Remark 2: The hybrid tracking error defined in this paper integrates both position error and speed error. Indeed, this error imposes specific requirements on the initial position error and speed error. The initial hybrid tracking error should satisfy the prescribed constraints, which is a relatively strict constraint. However, by adjusting the relevant parameters, the hybrid tracking error constraint can be satisfied when the initial error is relatively large. Furthermore, during the operation of trains, the distance between trains can be maintained within a safe range by setting this constraint. When the multi-train systems are stable, the hybrid tracking errors for trains approach zero. Meanwhile, the designed hybrid tracking error also meets the reliability requirements in the actual operation of trains.

By establishing the error function, the control effect of the control strategy on multi-train systems can be reflected in real time. When the actuator faults, the fluctuations of the error function can reflect the severity of the faults' impact on train systems. To compensate for the effects of faults, the fault-tolerant controller should be designed to maintain the stability of multi-train systems.

The control objective of this paper is to make following trains with different initial positions and speeds dynamically adjust the tracking distance with adjacent trains, which can finally stabilize at the desired tracking distance and reach the speed of the leader train. At the same time, the speed errors, position errors, and hybrid tracking errors of all following trains converge to zero. Next, the adaptive fault-tolerant control strategy will be designed and the stability of multi-train systems will be analyzed.

3. Main results

To minimize the impact of actuator faults on multi-train systems, the auxiliary control signal is introduced to compensate for the faults when designing the adaptive fault-tolerant control strategy. First, define the auxiliary control signal as

$$\dot{\bar{\chi}}_i(t) = -\alpha\bar{\chi}_i(t) + \partial_2\mathcal{D}(t)\Delta u(t) \tag{3.1}$$

where $\mathcal{D}(t) = \frac{\sigma_i}{\sigma_i^2 - e_i^2(t)}$, $\Delta u(t) = sat(u_i(t)) - u_i(t)$, α denotes a constant, and $\alpha > 0$.

Remark 3: The magnitude of the auxiliary control signal is dynamically adjusted according to the current error. When the error is large, the auxiliary control signal increases to enhance the compensation effect. If the error is small, the auxiliary control signal decreases to avoid over-adjustment. In Eq (3.1), α is a parameter that is used to adjust the strength of the auxiliary control signal. By selecting an appropriate α, it can be ensured that the auxiliary control signal will not over-adjust when compensating for actuator faults, thereby avoiding system oscillation or instability.

Then, the new error equation is

$$S_i(t) = X_i(t) - \bar{\chi}_i(t) \tag{3.2}$$

The adaptive fault tolerant controller is designed as

$$u_i(t) = \bar{u}_i(t) - u_m sign\,(S_i(t)D(t)) \tag{3.3}$$

where $sign\,(S_i(t)D(t))$ denotes a sign function and

$$\begin{aligned}\bar{u}_i(t) = &-\frac{\partial_1}{\partial_2}\frac{e_{vi}^2(t)S_i(t)}{|e_{vi}(t)S_i(t)| + \delta_i} - \frac{k_i}{\partial_2}\frac{\sigma_i^2 - e_i^2(t)}{\sigma_i}S_i(t) - \hat{\theta}_i - \frac{\alpha}{\partial_2}\frac{\sigma_i^2 - e_i^2(t)}{\sigma_i}\bar{\chi}_i(t) \\ &+ |\sin(S_i(t))|\left(\frac{1}{M_i}\left(\hat{a}_i + \hat{b}_i v_i(t) + \hat{c}_i v_i^2(t)\right) + \hat{w}_i^T h(x)\right)\end{aligned} \tag{3.4}$$

δ_i is a small value greater than 0 and k_i represents the controller gain. $\hat{a}_i$, $\hat{b}_i$, $\hat{c}_i$ are estimation values of a_i, b_i, c_i.

In order to eliminate the effects of basic running resistance and unknown disturbance, the adaptive laws are designed as

$$\dot{\hat{a}}_i = -\varsigma_i\left[\frac{\partial_2 S_i(t)\mathcal{D}(t)}{M_i} + \hat{a}_i\right] \tag{3.5}$$

$$\dot{\hat{b}}_i = -\zeta_i\left[\frac{\partial_2 S_i(t)\mathcal{D}(t)v_i(t)}{M_i} + \hat{b}_i\right] \tag{3.6}$$

$$\dot{\hat{c}}_i = -\xi_i\left[\frac{\partial_2 S_i(t)\mathcal{D}(t)v_i^2(t)}{M_i} + \hat{c}_i\right] \tag{3.7}$$

$$\dot{\hat{\theta}}_i = \vartheta_i[\partial_2 D(t)S_i(t) - \hat{\theta}_i] \tag{3.8}$$

$$\dot{\hat{w}}_i = -\mu_i[\partial_2 S_i(t)\mathcal{D}(t)h(x) + \hat{w}_i] \tag{3.9}$$

where ς_i, ζ_i, ξ_i, ϑ_i, and μ_i represent positive constants. Then, the stability of multi-train systems will be analyzed with the presented fault-tolerant strategy.

Remark 4: In the control scheme, k_i represents the controller gain, which affects the amplitude of the control input. Generally, the selection of k_i needs to consider the initial tracking error of the train. For example, if the train has a relatively large initial tracking error, a larger controller gain can be selected. By designing appropriate ς_i, ζ_i, ξ_i, ϑ_i, and μ_i, the estimated parameters in adaptive laws can be ensured to converge to the true value at a suitable rate, which means that, for ς_i, ζ_i, ξ_i, ϑ_i, and μ_i, we usually choose small positive values.

Theorem 1. For multi-train systems with actuator faults, input saturation, and unknown resistance parameters, the adaptive fault-tolerant control strategy Eqs (3.3)–(3.9) can realize the cooperative operation of trains. In addition, the proposed strategy can meet the safe operation requirement and maintain the stability of multi-train systems.

Proof:

Design the Lyapunov equation as follows:

$$V_i(t) = \frac{1}{2}S_i^2(t) + \frac{1}{2\varsigma_i}\tilde{a}_i^2 + \frac{1}{2\zeta_i}\tilde{b}_i^2 + \frac{1}{2\xi_i}\tilde{c}_i^2 + \frac{1}{2\vartheta_i}\tilde{\theta}_i^2 + \frac{1}{2\mu_i}\tilde{w}_i^T\tilde{w}_i \tag{3.10}$$

Taking the derivative of Eq (3.10), we can obtain

$$\dot{V}_i(t) = S_i(t)\dot{S}_i(t) + \frac{1}{\varsigma_i}\tilde{a}_i\dot{\tilde{a}}_i + \frac{1}{\zeta_i}\tilde{b}_i\dot{\tilde{b}}_i + \frac{1}{\xi_i}\tilde{c}_i\dot{\tilde{c}}_i + \frac{1}{\vartheta_i}\tilde{\theta}_i\dot{\tilde{\theta}}_i + \frac{1}{\mu_i}\tilde{w}_i^T\dot{\tilde{w}}_i \tag{3.11}$$

Setting $\tilde{a}_i = a_i - \hat{a}_i$, $\tilde{b}_i = b_i - \hat{b}_i$, $\tilde{c}_i = c_i - \hat{c}_i$, $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$, $\tilde{w}_i = w_i^* - \hat{w}_i$, it is possible to show that $\dot{\tilde{a}}_i = -\dot{\hat{a}}_i$, $\dot{\tilde{b}}_i = -\dot{\hat{b}}_i$, $\dot{\tilde{c}}_i = -\dot{\hat{c}}_i$, $\dot{\tilde{\theta}}_i = -\dot{\hat{\theta}}_i$, $\dot{\tilde{w}}_i = -\dot{\hat{w}}_i$. Combining Eqs (3.2) and (3.11), we can get

$$\dot{V}_i(t) = S_i(t)\left(\dot{X}_i(t) - \dot{\bar{\chi}}_i(t)\right) - \frac{1}{\varsigma_i}\tilde{a}_i\dot{\hat{a}}_i - \frac{1}{\zeta_i}\tilde{b}_i\dot{\hat{b}}_i - \frac{1}{\xi_i}\tilde{c}_i\dot{\hat{c}}_i - \frac{1}{\vartheta_i}\tilde{\theta}_i\dot{\hat{\theta}}_i - \frac{1}{\mu_i}\tilde{w}_i^T\dot{\hat{w}}_i \tag{3.12}$$

From Eqs (2.17), (3.1), and (3.12), we have

$$\begin{aligned}\dot{V}_i(t) = {} & \partial_1 S_i(t)\mathcal{D}(t)e_{vi}(t) + \partial_2 S_i(t)\mathcal{D}(t)\left(1 - \tau_f\right) sat\left(u_i(t)\right) - \partial_2 S_i(t)\mathcal{D}(t)\frac{f_{ai}(t)}{M_i} \\ & - \partial_2 S_i(t)\mathcal{D}(t)w_i^{*T}h(x) - \partial_2 S_i(t)\mathcal{D}(t)\varepsilon(x) + \alpha S_i(t)\bar{\chi}_i(t) - \partial_2 S_i(t)\mathcal{D}(t)\Delta u(t) \\ & - \frac{1}{\varsigma_i}\tilde{a}_i\dot{\hat{a}}_i - \frac{1}{\zeta_i}\tilde{b}_i\dot{\hat{b}}_i - \frac{1}{\xi_i}\tilde{c}_i\dot{\hat{c}}_i - \frac{1}{\vartheta_i}\tilde{\theta}_i\dot{\hat{\theta}}_i - \frac{1}{\mu_i}\tilde{w}_i^T\dot{\hat{w}}_i\end{aligned} \tag{3.13}$$

Since $\Delta u(t) = sat\left(u_i(t)\right) - u_i(t)$, $|\varepsilon(x)| \le \theta_i$, taking into account the simplification of Eq (3.13), it gives

$$\begin{aligned}\dot{V}_i(t) \le {} & \partial_1 S_i(t)\mathcal{D}(t)e_{vi}(t) + \partial_2 S_i(t)\mathcal{D}(t)u_i(t) - \partial_2 S_i(t)\mathcal{D}(t)\tau_f sat\left(u_i(t)\right) \\ & - \partial_2 S_i(t)\mathcal{D}(t)\frac{f_{ai}(t)}{M_i} - \partial_2 S_i(t)\mathcal{D}(t)w_i^{*T}h(x) + \partial_2 S_i(t)\mathcal{D}(t)\theta_i + \alpha S_i(t)\bar{\chi}_i(t) \\ & - \frac{1}{\varsigma_i}\tilde{a}_i\dot{\hat{a}}_i - \frac{1}{\zeta_i}\tilde{b}_i\dot{\hat{b}}_i - \frac{1}{\xi_i}\tilde{c}_i\dot{\hat{c}}_i - \frac{1}{\vartheta_i}\tilde{\theta}_i\dot{\hat{\theta}}_i - \frac{1}{\mu_i}\tilde{w}_i^T\dot{\hat{w}}_i\end{aligned} \tag{3.14}$$

Then combining Eqs (3.3) and (3.4) into (3.14), we have

$$\dot{V}_i(t) \le \partial_1 S_i(t)\mathcal{D}(t)e_{vi}(t) - \partial_1 S_i(t)\mathcal{D}(t)\frac{e_{vi}^2(t)S_i(t)}{|e_{vi}(t)S_i(t)| + \delta_i} - k_i\mathcal{D}(t)\frac{\sigma_i^2 - e_i^2(t)}{\sigma_i}S_i^2(t)$$

$$
\begin{aligned}
&+ \partial_2 S_i(t)\mathcal{D}(t)|sin\left(S_i(t)\right)|\left(\frac{1}{M_i}\left(\hat{a}_i + \hat{b}_i v_i(t) + \hat{c}_i v_i^2(t)\right) + \hat{w}_i^T h(x)\right) - \partial_2 S_i(t)\mathcal{D}(t)\hat{\theta}_i \\
&- \alpha S_i(t)\mathcal{D}(t)\frac{\sigma_i^2 - e_i^2(t)}{\sigma_i}\bar{\chi}_i(t) - \partial_2 u_m|S_i(t)\mathcal{D}(t)| - \partial_2 S_i(t)\mathcal{D}(t)\tau_f sat\left(u_i(t)\right) \\
&- \partial_2 S_i(t)\mathcal{D}(t)\frac{f_{ai}(t)}{M_i} - \partial_2 S_i(t)\mathcal{D}(t)w_i^{*T} h(x) + \partial_2 S_i(t)\mathcal{D}(t)\theta_i + \alpha S_i(t)\bar{\chi}_i(t) \\
&- \frac{1}{\varsigma_i}\tilde{a}_i\dot{\hat{a}}_i - \frac{1}{\zeta_i}\tilde{b}_i\dot{\hat{b}}_i - \frac{1}{\xi_i}\tilde{c}_i\dot{\hat{c}}_i - \frac{1}{\vartheta_i}\tilde{\theta}_i\dot{\hat{\theta}}_i - \frac{1}{\mu_i}\tilde{w}_i^T\dot{\hat{w}}_i
\end{aligned} \tag{3.15}
$$

Equation (3.15) can be simplified as

$$
\begin{aligned}
\dot{V}_i(t) \leq\ & -k_i S_i^2(t) + \partial_2 S_i(t)\mathcal{D}(t)\left(\frac{1}{M_i}\left(\hat{a}_i + \hat{b}_i v_i(t) + \hat{c}_i v_i^2(t)\right) + \hat{w}_i^T h(x)\right) - \partial_2 S_i(t)\mathcal{D}(t)\hat{\theta}_i \\
&- \partial_2 u_m|S_i(t)\mathcal{D}(t)| - \partial_2 S_i(t)\mathcal{D}(t)\tau_f sat\left(u_i(t)\right) - \partial_2 S_i(t)\mathcal{D}(t)\frac{f_{ai}(t)}{M_i} - \partial_2 S_i(t)\mathcal{D}(t)w_i^{*T} h(x) \\
&+ \partial_2 S_i(t)\mathcal{D}(t)\theta_i - \frac{1}{\varsigma_i}\tilde{a}_i\dot{\hat{a}}_i - \frac{1}{\zeta_i}\tilde{b}_i\dot{\hat{b}}_i - \frac{1}{\xi_i}\tilde{c}_i\dot{\hat{c}}_i - \frac{1}{\vartheta_i}\tilde{\theta}_i\dot{\hat{\theta}}_i - \frac{1}{\mu_i}\tilde{w}_i^T\dot{\hat{w}}_i
\end{aligned} \tag{3.16}
$$

Placing adaptive laws Eqs (3.5)–(3.9) into (3.16), one has

$$
\begin{aligned}
\dot{V}_i(t) \leq\ & -k_i S_i^2(t) + \partial_2 S_i(t)\mathcal{D}(t)\left(\frac{1}{M_i}\left(\hat{a}_i + \hat{b}_i v_i(t) + \hat{c}_i v_i^2(t)\right) + \hat{w}_i^T h(x)\right) - \partial_2 S_i(t)\mathcal{D}(t)\hat{\theta}_i \\
&- \partial_2 u_m|S_i(t)\mathcal{D}(t)| - \partial_2 S_i(t)\mathcal{D}(t)\tau_f sat\left(u_i(t)\right) - \partial_2 S_i(t)\mathcal{D}(t)\frac{f_{ai}(t)}{M_i} - \partial_2 S_i(t)\mathcal{D}(t)w_i^{*T} h(x) \\
&+ \partial_2 S_i(t)\mathcal{D}(t)\theta_i + \frac{\tilde{a}_i\partial_2 S_i(t)\mathcal{D}(t)}{M_i} + \tilde{a}_i\hat{a}_i + \frac{\tilde{b}_i\partial_2 S_i(t)\mathcal{D}(t)v_i(t)}{M_i} + \tilde{b}_i\hat{b}_i + \frac{\tilde{c}_i\partial_2 S_i(t)\mathcal{D}(t)v_i^2(t)}{M_i} \\
&+ \tilde{c}_i\hat{c}_i - \tilde{\theta}_i\partial_2\mathcal{D}(t)S_i(t) + \tilde{\theta}_i\hat{\theta}_i + \tilde{w}_i^T\hat{w}_i + \partial_2 S_i(t)\mathcal{D}(t)\tilde{w}_i^T h(x)
\end{aligned} \tag{3.17}
$$

Then, a simplification of Eq (3.17) yields

$$
\begin{aligned}
\dot{V}_i(t) \leq\ & -k_i S_i^2(t) - \partial_2 u_m|S_i(t)\mathcal{D}(t)| - \partial_2\tau_f sat\left(u_i(t)\right)S_i(t)\mathcal{D}(t) + \tilde{a}_i\hat{a}_i + \tilde{b}_i\hat{b}_i + \tilde{c}_i\hat{c}_i \\
&+ \tilde{\theta}_i\hat{\theta}_i + \tilde{w}_i^T\hat{w}_i
\end{aligned} \tag{3.18}
$$

It is known that $\partial_2 > 0$, $u_m > 0$, and $0 < \tau_f < 1$. There exist $\partial_2 u_m \geq \partial_2\tau_f sat\left(u_i(t)\right)$ and $|S_i(t)\mathcal{D}(t)| \geq S_i(t)\mathcal{D}(t)$. Therefore, the following inequality holds:

$$
\partial_2 u_m|S_i(t)\mathcal{D}(t)| + \partial_2\tau_f sat\left(u_i(t)\right)S_i(t)\mathcal{D}(t) \geq 0 \tag{3.19}
$$

Hence, with Eqs (3.18) and (3.19), one has

$$
\dot{V}_i(t) \leq -k_i S_i^2(t) + \tilde{a}_i\hat{a}_i + \tilde{b}_i\hat{b}_i + \tilde{c}_i\hat{c}_i + \tilde{\theta}_i\hat{\theta}_i + \tilde{w}_i^T\hat{w}_i \tag{3.20}
$$

By Young's inequality, we can get

$$
\tilde{a}_i\hat{a}_i \leq \frac{1}{2}a_i^2 - \frac{1}{2}\tilde{a}_i^2 \tag{3.21}
$$

$$\tilde{b}_i\hat{b}_i \leq \frac{1}{2}b_i^2 - \frac{1}{2}\tilde{b}_i^2 \tag{3.22}$$

$$\tilde{c}_i\hat{c}_i \leq \frac{1}{2}c_i^2 - \frac{1}{2}\tilde{c}_i^2 \tag{3.23}$$

$$\tilde{\theta}_i\hat{\theta}_i \leq \frac{1}{2}\theta_i^2 - \frac{1}{2}\tilde{\theta}_i^2 \tag{3.24}$$

$$\tilde{w}_i^T\hat{w}_i \leq \frac{1}{2}w_i^{*2} - \frac{1}{2}\tilde{w}_i^T\tilde{w}_i \tag{3.25}$$

By substituting Eqs (3.21)–(3.25) into (3.20), we can obtain

$$\begin{aligned}\dot{V}_i(t) \leq& -k_iS_i^2(t) + \frac{1}{2}a_i^2 - \frac{1}{2}\tilde{a}_i^2 + \frac{1}{2}b_i^2 - \frac{1}{2}\tilde{b}_i^2 + \frac{1}{2}c_i^2 - \frac{1}{2}\tilde{c}_i^2 \\ &+ \frac{1}{2}\theta_i^2 - \frac{1}{2}\tilde{\theta}_i^2 + \frac{1}{2}w_i^{*2} - \frac{1}{2}\tilde{w}_i^T\tilde{w}_i\end{aligned} \tag{3.26}$$

Simplifying Eq (3.26), we have

$$\dot{V}_i(t) \leq -Q_{1i}V_i(t) + Q_{2i} \tag{3.27}$$

where $Q_{1i} = \min\{2k_i, \varsigma_i, \zeta_i, \xi_i, \vartheta_i, \mu_i\}$, $Q_{2i} = \frac{1}{2}\left(a_i^2 + b_i^2 + c_i^2 + \theta_i^2 + w_i^{*2}\right)$.

With Eq (3.27), we can get

$$\begin{aligned}V_i(t) &\leq \left(V_i(0) - \tfrac{Q_{2i}}{Q_{1i}}\right)e^{-Q_{1i}t} + \frac{Q_{2i}}{Q_{1i}} \\ &\leq V_i(0) + \frac{Q_{2i}}{Q_{1i}}\end{aligned} \tag{3.28}$$

Then, the entire Lyapunov function for multi-train systems is described as

$$V(t) = \sum_{i=1}^{N} V_i(t) \tag{3.29}$$

Taking the derivative of Eq (3.29), one has

$$\dot{V}(t) = \sum_{i=1}^{N}\dot{V}_i(t) \leq -Q_1V(t) + \sum_{i=1}^{N}Q_{2i} \tag{3.30}$$

where $Q_1 = \min(Q_{1i})$.

Integrating Eq (3.30), we have

$$V(t) \leq V(0) + \frac{\Sigma_{i=1}^N Q_{2i}}{Q_1} \tag{3.31}$$

Therefore, $V(t)$ is bounded. From inequation (3.28), one has

$$\lim_{t\to\infty} S_i(t) \le \sqrt{\frac{2Q_{2i}}{Q_{1i}}} \tag{3.32}$$

By reducing Q_{2i} or increasing Q_{1i}, the error equation $S_i(t)$ will gradually tend to zero. Meanwhile, the position errors, speed errors, and hybrid tracking errors will also gradually decrease to zero, thus ensuring the stability of multi-train systems. The cooperative operation of trains can be realized. The proof is complete.

With the above theoretical derivation, it can be concluded that the proposed fault-tolerant control strategy can realize the cooperation of multiple trains with train actuator faults.

4. Simulation examples

In this section, simulation experiments are given to verify the effectiveness of the adaptive fault-tolerant control strategy designed in this paper. We set the initial states of the trains as: $x_0 = [17,990 \ \ 70]^T$, $x_1 = [11,820 \ \ 74]^T$, $x_2 = [6200 \ \ 68]^T$, $x_3 = [0 \ \ 71]^T$. The desired tracking distance between adjacent trains is $D = 6000$ m. The maximum control input of the train controller is $u_m = 0.7$ m/s^2. The relevant parameters of the control scheme are selected as $\delta_i = 0.5$, $\varsigma_i = \zeta_i = \xi_i = \vartheta_i = \mu_i = 0.002$, $k_i = 3$. The initial values of the adaptive parameters are given as $\hat{a}_i = \hat{b}_i = \hat{c}_i = \hat{\theta}_i = \hat{w}_i = 0$.

The parameters related to the hybrid tracking error limitation are set as $\sigma_i = 40$, $\partial_1 = 0.06$, and $\partial_2 = 0.6$. The weight of the train is $M_i = 80 \times 10^4$ kg. In simulation experiments, all of the following trains are able to obtain the information of the leader train. The acceleration of the leader train is

$$u_0(t) = \begin{cases} 0\,\text{m/s}^2 & 0\,\text{s} \le t < 70\,\text{s} \\ 0.25\,\text{m/s}^2 & 70\,\text{s} \le t < 100\,\text{s} \\ 0\,\text{m/s}^2 & 100\,\text{s} \le t < 130\,\text{s} \\ -0.25\,\text{m/s}^2 & 130\,\text{s} \le t < 160\,\text{s} \\ 0\,\text{m/s}^2 & 160\,\text{s} \le t \le 200\,\text{s} \end{cases}$$

The simulation first gives the validation of the designed method without actuator faults. As shown in Figure 1, the trains with different initial positions are able to maintain a safe running distance. The distance between two trains will gradually stabilize at the desired following distance $D = 6000$ m. The specific speeds of trains are shown in Figure 2 and the speeds of all following trains can gradually follow to the speed of the leader train, 70 m/s. When the speed of the leader train changes, the multi-train systems can also respond and adjust in time, so that the following trains closely follow the speed of the leader train. From Figures 3–5, it can be seen that the speed errors, position errors, and hybrid tracking errors eventually converge to zero. As shown in Figure 6, the control inputs of the trains are always constrained within the specified range of ± 0.7 m/s^2.

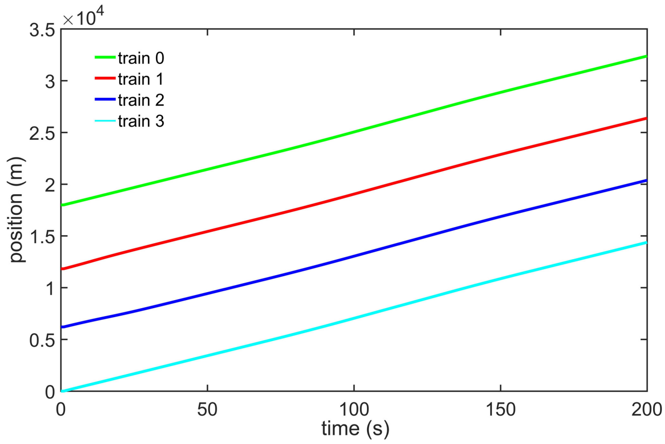

Figure 1. Positions of trains without actuator faults.

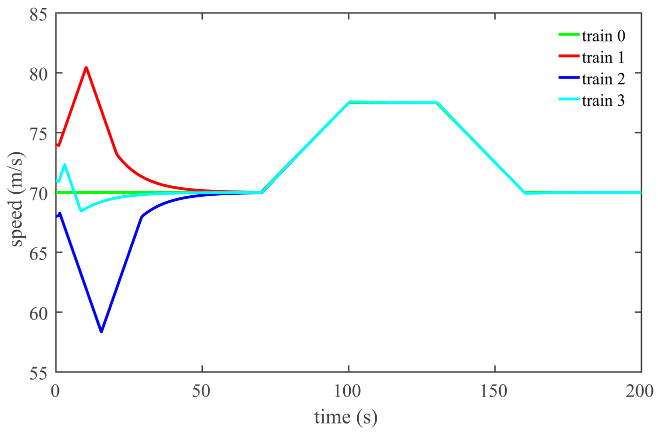

Figure 2. Speeds of trains without actuator faults.

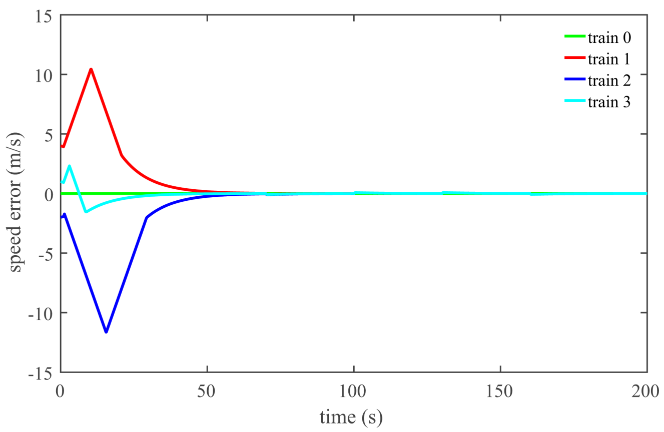

Figure 3. Speed errors of trains without actuator faults.

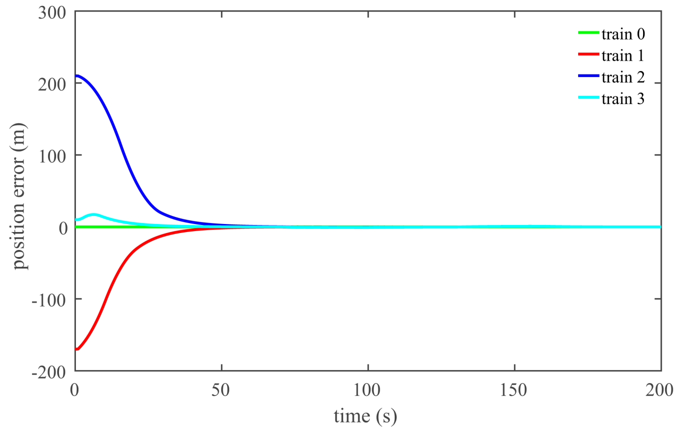

Figure 4. Position errors of trains without actuator faults.

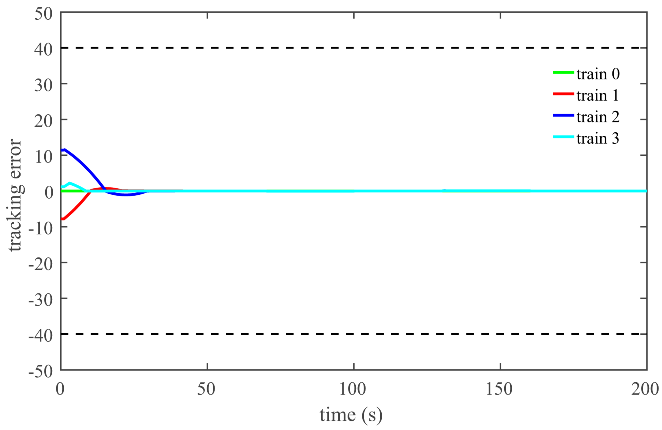

Figure 5. Hybrid tracking errors of trains without actuator faults.

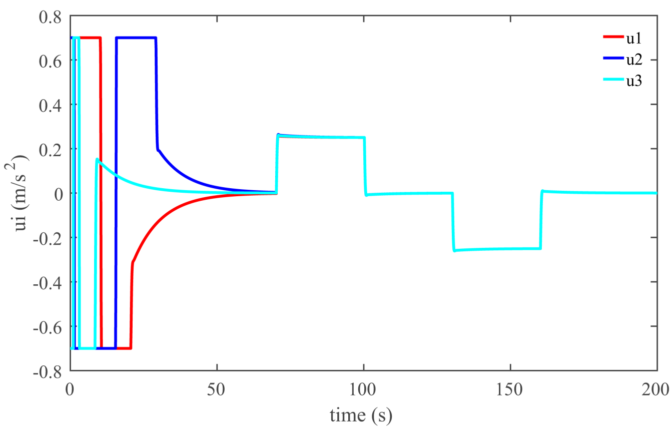

Figure 6. Control inputs of trains without actuator faults.

In order to verify the effectiveness of the adaptive fault-tolerant control strategy designed in this paper with actuator faults, the failures of control inputs for following trains will be simulated in the following simulation experiments. Let the control input values of following trains 1, 2, and 3 be $0.6 * u_1$, $0.3 * u_2$, and $0.4 * u_3$ in $80 \text{ s} \leq t < 85$ s, and set the control input values of following trains 1, 2, and 3 as $0.3 * u_1$, $0.6 * u_2$, and $0.4 * u_3$ in $140 \text{ s} \leq t < 145$ s. In Figures 7 and 8, the desired distance and speed tracking can be achieved. With Figures 9–11, the speed errors, position errors, and hybrid tracking errors of trains are always constrained within the safe range and multi-train systems are stable with existing actuator faults. As can be seen in Figure 12, the control inputs are always constrained within ± 0.7 m/s^2 although there exist actuator faults.

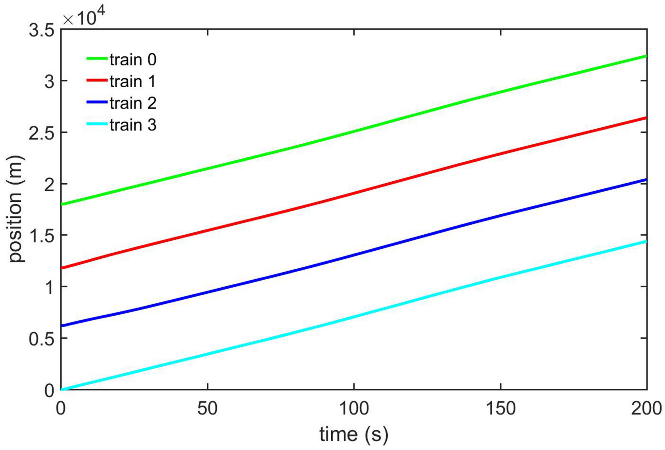

Figure 7. Positions of trains with actuator faults.

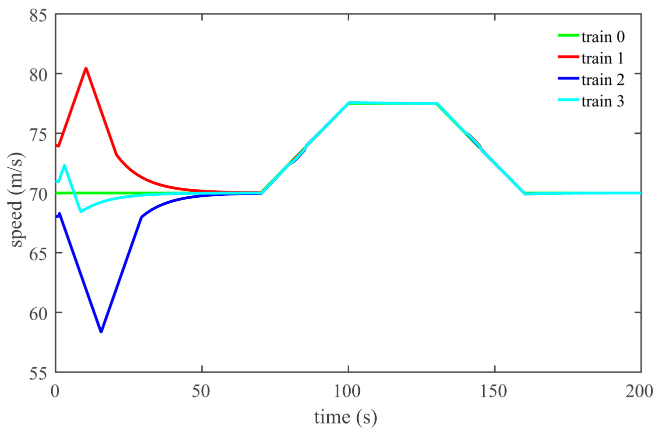

Figure 8. Speeds of trains with actuator faults.

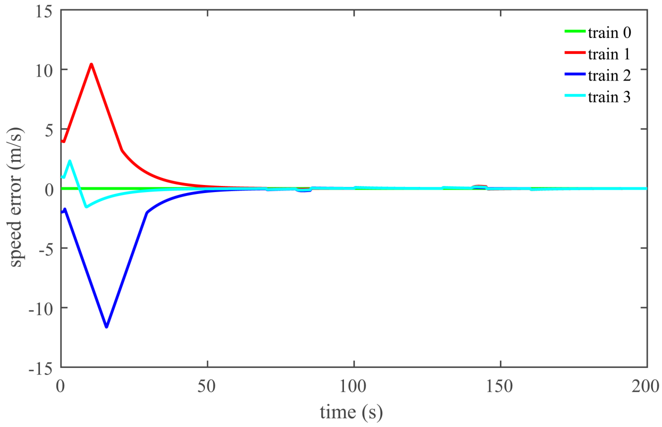

Figure 9. Speed errors of trains with actuator faults.

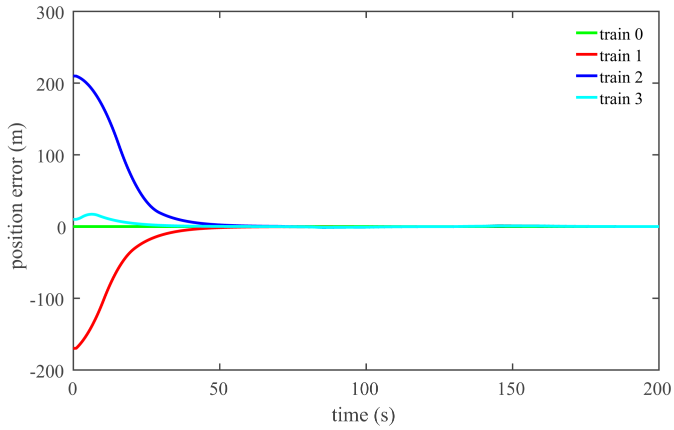

Figure 10. Position errors of trains with actuator faults.

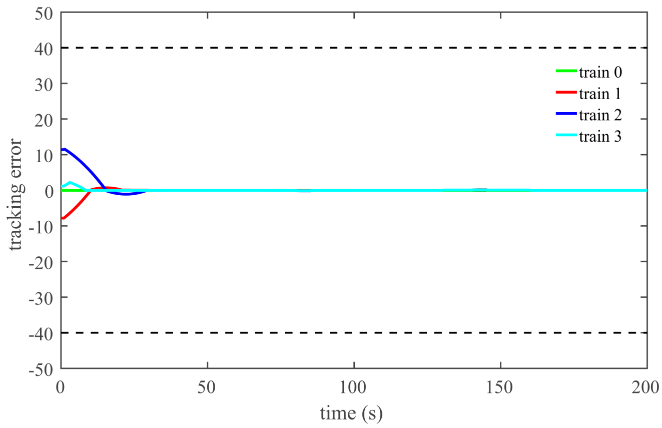

Figure 11. Hybrid tracking errors of trains with actuator faults.

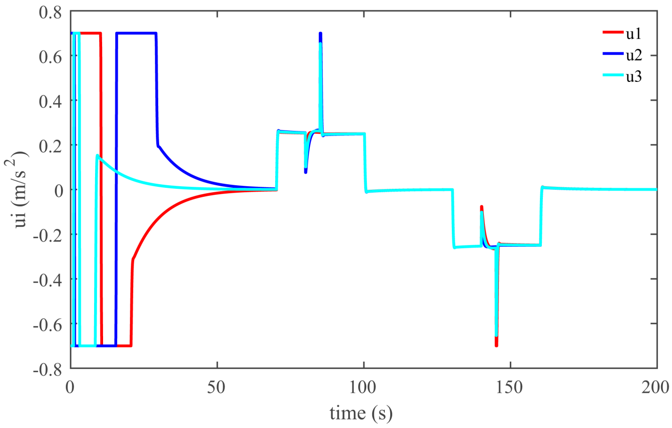

Figure 12. Control inputs of trains with actuator faults.

Then, a comparative analysis is conducted with the fault-tolerant approach presented in reference [33]. Figure 13 illustrates the train speed curves by utilizing the method from [33]. When comparing the speed curves in Figures 8 and 13, it becomes evident that while both control strategies successfully maintain speed tracking for train 0, the proposed control scheme in this paper demonstrates better performance in the dynamic fluctuation process.

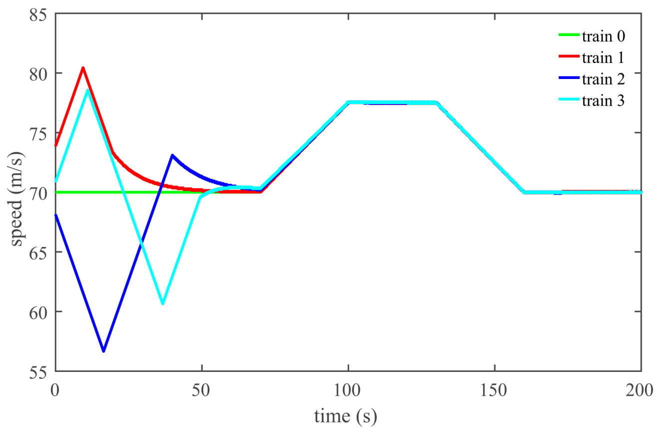

Figure 13. Speeds of trains based on reference [33].

5. Conclusions

In this paper, a neural network-based adaptive fault-tolerant control strategy is proposed for the actuator faults problem during multi-train cooperative operation. When the train actuator faults, the adaptive fault-tolerant controller reacts and compensates quickly to maintain the stability of multi-train systems. Meanwhile, for eliminating the effects of basic resistance parameter uncertainties and unknown disturbance, the adaptive laws are designed. The designed adaptive fault-tolerant control strategy can effectively compensate for the impact caused by the actuator faults and realize cooperation of trains. In this paper, only the fault-tolerant control mechanism under partial controller faults is considered. In future research, the integrated control strategy under the condition of both controller and communication faults will be considered.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there are no conflicts of interest.

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