Predictive Control Algorithm for Urban Rail Train Brake Control System Based on T-S Fuzzy Model

Xiaokan Wang[1, 2, *], Qiong Wang[2] and Shuang Liang[3]

Abstract: Urban rail transit has the advantages of large traffic capacity, high punctuality and zero congestion, and it plays an increasingly important role in modern urban life. Braking system is an important system of urban rail train, which directly affects the performance and safety of train operation and impacts passenger comfort. The braking performance of urban rail trains is directly related to the improvement of train speed and transportation capacity. Also, urban rail transit has the characteristics of high speed, short station distance, frequent starting, and frequent braking. This makes the braking control system constitute a time-varying, time-delaying and nonlinear control system, especially the braking force changes directly disturb the parking accuracy and comfort. To solve these issues, a predictive control algorithm based on T-S fuzzy model was proposed and applied to the train braking control system. Compared with the traditional PID control algorithm and self-adaptive fuzzy PID control algorithm, the braking capacity of urban rail train was improved by 8%. The algorithm can achieve fast and accurate synchronous braking, thereby overcoming the dynamic influence of the uncertainty, hysteresis and time-varying factors of the controlled object. Finally, the desired control objectives can be achieved, the system will have superior robustness, stability and comfort.

Keywords: Predictive control, T-S fuzzy model, urban rail train, algorithm.

1 Introduction

With the acceleration of urbanization process in China, the urban traffic pressure is increasing. In order to establish a convenient and fast urban traffic network, more and more cities have incorporated urban rail transit construction into their plans. The metro is the main force of urban rail transit, and the technical performance of metro directly affects its carrying capacity. Brake control technology is one of the key technologies to ensure train operation that attracts much attention today. The braking system is part of the train control system. It is used to adjust the speed and stop, which is the basis for the safe and reliable operation of the train. Hybrid electro-pneumatic braking systems are

[1] School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, 100044, China.

[2] Henan Mechanical and Electrical Vocational College, Xinzheng, 451191, China.

[3] University of Florence,Via Sandro Pertini, Firenze, 50041, Italy.

[*] Corresponding Author: Xiaokan Wang. Email: wxkbbg@163.com.

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commonly used on modern urban rail trains. It uses a brake controller to coordinate the ratio of the electric brakes to air brakes, thereby basically ensuring consistent braking performance in the event of a change in vehicle speed.

Liu et al. [Liu and Xu (2018)] proposed a fuzzy predictive control method. The algorithm determined corresponding evaluation function according to multiple optimization control objectives in train operation, established a multi-step predictive control model, and used multi-objective satisfaction optimization model for rolling optimization. He et al. [He, Xiao, Zhu et al. (2018)] designed a PID speed controller for urban rail train based on the fuzzy predictive control, which can improve the train tracking and comfort. Dai [Dai (2017)] proposed a fuzzy predictive control algorithm, in which the corresponding fuzzy membership function was established as the driving performance index of automatic train, and the corresponding fuzzy control rule was established based on the manual driving strategy, and the curve of energy-saving optimization in inertia was conducted. The fuzzy control algorithm based on the fuzzy predictive control was proposed in Chen et al. [Chen and Sun (2017)] that used the fuzzy genetic algorithm for rolling optimization to obtain the global optimal solution as the output of the predictive control controller, thus improving the system control speed and stability. In the paper Shi et al. [Shi and Wang (2018)], a fuzzy predictive-PID compound control method with comfort constraints was established to optimize the braking distance in the different circumstances. Due to the time lag of the braking system, the stability of the closed-loop system will be destroyed, so the braking system usually adopts an open-loop control strategy. However, the uncertainty of the line resistance, the non-linearity of the friction coefficient of the braking shoes, and the random disturbance of the braking system will all have adverse effects on the braking system. The open-loop control method cannot eliminate the influence of these factors, thus reducing the performance of the braking system to a certain extent [Cao, Su, Wang et al. (2018); Dong, Zhang, Zhang et al. (2018); Ma, Guan, Liu et al. (2019)].

The purpose of this paper is to investigate the nonlinear, time-varying and hysteresis characteristics of urban rail train brake control. By analyzing its dynamic process and the influence of related factors on control, a fuzzy predictive control based on T-S was proposed. The braking control method of the model was simulated and optimized to achieve fast and precise braking of the brake control system.

2 Generalized predictive control algorithm based on T-S fuzzy model

The generalized predictive control algorithm (GPC) was originally proposed by Clarke and his collaborators in 1987. Based on the generalized minimum variance control, the traditional parametric model is used to introduce unequal prediction levels and control levels, with a predictive model and rolling. The three basic features of optimization and feedback correction can be referred in Shi et al. [Shi and Wang (2018); Cao, Ma and Zhang (2018); Xing and Li (2019)]. This algorithm introduces the idea of multi-step prediction in the optimization to slowly and time-varyingly optimize the process parameters. Based on the analysis of the braking system of the urban rail train, the block diagram of the control system shown is established in Fig. 1.

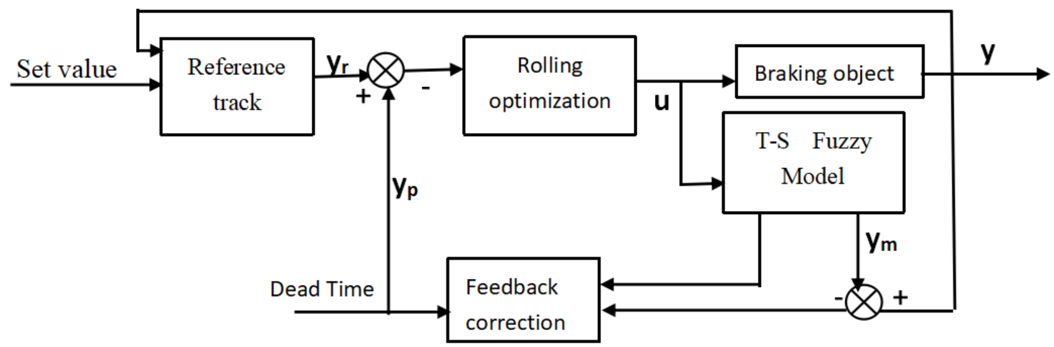

Figure 1: Structure diagram of train predictive control system based on T-S fuzzy model

2.1 T-S fuzzy model

As a nonlinear model, the fuzzy model can easily express the dynamic characteristics of nonlinear systems and can approximate any nonlinear system with arbitrary precision [Su, Sheng, Liu et al. (2020); Teng, Wang, Cai et al. (2017); Liu, Huang, Liu et al. (2008); Wang, Chen and Su (2012)]. The T-S fuzzy model consists of a rule statement and a polynomial linear equation. The rule statement is a condition and the polynomial equation is a conclusion. The T-S model is more proper for representing the output of a nonlinear system. The fuzzy variation is used as the rule input, and the conclusion is the linearization result. Also, fuzzy modeling can realize the global linearization and overcome the high-dimensional problem of the real control system [Sun, Xue and Cheng (2019); Su, Sheng, Leung et al. (2019); Xia, Hu and Luo (2017); Cao and Ishikawa (2016)]. Therefore, the T-S fuzzy model is suitable for modeling nonlinear complex system.

The multi-input single-output T-S model can be as follows:

$$R_i : If\ x_1\ is\ f_1^t \text{ and } x_2\ is\ f_2^t \text{ and} \cdots \text{and } x_m\ is\ f_m^t \tag{1}$$

$$\text{Then: } \dot{x} = A_i x + B_i u \tag{2}$$

In the formula, R_i denotes the rule i; A_j^i represents the fuzzy subset space; y_i represents the output of the i fuzzy rules; c_j^i represents the conclusion parameter. $x = [x_1, x_2, \cdots, x_n]^T$ is the state vector of a fuzzy system. $i = 1,2,\cdots,l$, $m = 1,2,\cdots,n$.

$$\dot{x} = \sum_{i=1}^{l} \omega_i (A_i x + B_i u) / \sum_{i=1}^{l} \omega_i \tag{3}$$

In which, $\omega_i = \prod_{k=1}^{n} f_k^t(x)$ denotes the activation of the rule i. If $h_i = \omega_i / \sum_{i=1}^{l} \omega_i$ is substituted into Eq. 3, the following formula can be attained:

$$\dot{x} = \sum_{i=1}^{l} h_i (A_i x + B_i u) \tag{4}$$

T-S fuzzy model is mainly divided into structural identification and parameter identification [Branco and Dente (2010); Cheng, Xu, Tang et al. (2018); Wu, Liu, Zhu et al. (2018)]. Compared with the structural identification, the parameter identification of fuzzy model is relatively simple and mature. It can be divided into two categories: one is based on gradient learning and least square method, and the other is based on fuzzy neural networks. For the initial fuzzy model, the gradient descent method can be used to adjust all the parameters of the former and the latter. For the input variables of the former, the membership functions such as triangle, trapezoid and Gaussian can be used. For triangular and trapezoidal membership function, because the function is not differentiable at its specific inflection point, some constraints need to be added. To avoid this situation, the Gaussian membership function is generally applied.

2.2 Establishment of the T-S fuzzy prediction model and algorithm analysis

The predictive control of the T-S fuzzy model can perform multi-step linearized predictive control, and it has better control effect on nonlinear systems with relatively slow changes [Sun (2007); Su, Sheng, Xie et al. (2019); Hannan, Azidin and Mohamed (2012)]. The steps of predictive control algorithm based on the T-S fuzzy model are as follows:

(1) Firstly, the model $M(k)$ corresponding to the premise variable at time k can be defined, and the predictive control law $u(k)$ is designed using an approximate linearized system.

(2) The output $\hat{y}(k+i)$ of the system can be obtained by using the predictive control law $u(k)$ and the system model $M_i(k)$.

(3) According to the designed fuzzy rules, a new model $M(k+1)$ can be attained with the combination of $\{\hat{y}(k+i), u(k)\}$,.

(4) With the new model $M(k+1)$, the control law $u(k+1)$ at time $k+1$ can be acquired, and then $M(k+2)$ can also be gotten from $\{\hat{y}(k+i), u(k), \ u(k+1)\}$.

In the braking control system of urban rail train, the reference sequence $y_r(k+j)$ can be obtained, and the control values of each stage are constant values. Here, we can use $y_r(k+j)=y_r$ to solve the set value y_r.

$$y_r(k)=y(k)y_r(k+j)=\alpha y_r(k+j-1)+(1-\alpha)y_r, \ j=1,2,\ldots,+\infty \tag{5}$$

In which, $0 \le \alpha < 1$.

The purpose of the fuzzy prediction control is to let the output $y(k+j)$ of the control object as close as possible to $y_r(k+j)$. The performance indicator functions selected in this paper are as follows:

$$J(k)=E\left\{\sum_{j=1}^{N} q(j)(y(k+j)-y(k+j))^2+\sum_{j=1}^{M}\lambda(\Delta u(k+j-1))^2\right\} \tag{6}$$

In which, N is the maximum predictive time domain and M is the control time domain; $q(j)$ is the weighted control coefficient; λ is the control weighted sequence; $\Delta u(k+j)$

is the amount of change in the step j of the system. When $j = M,...,N(M < N)$, $\Delta u(k + j) = 0$.

Assuming $y_r^T = [y_r(k+1),...,y_r(k+N)]$, the performance indicator function can be simplified to:

$$J = E\{(y - y_r)^T (y - y_r) + \lambda^T uu\} \tag{7}$$

The control law that minimizes P can be obtained as follows:

$$G^T[Gu + Fy(k) + H\Delta u(k-1) - y_r] + \lambda u = 0 \tag{8}$$

$$u = (GG^T + \lambda I)^{-1} G^T [y_r - Fy(k) - H\Delta u(k-1)] \tag{9}$$

Suppose that the first row of the P matrix is defined as:

$$p^T = [p_1, p_2,..., p_N] \text{ and } p(z^{-1}) = p_N + p_{N-1}z^{-1} + \cdots + p_1 z^{-N+1} \tag{10}$$

Next, the base T-S fuzzy prediction model can be expressed as:

$$\begin{aligned}\Delta u(k) &= p^T[y_r - Fy(k) - H\Delta u(k-1) \\ &= p(z^{-1})y_r(k+N) - \alpha(z^{-1})y(k) - \beta(z^{-1})\Delta u(k-1)\end{aligned} \tag{11}$$

$$u(k) = u(k-1) + \Delta u(k) \tag{12}$$

In this way, we can get the control law of the braking fuzzy prediction control model as:

$$\alpha(z^{-1}) = \sum_{j=1}^{N} p_j F_j(z^{-1}) = \alpha_0 + \alpha_1 z^{-1} + \cdots + \alpha_k z^{-k} \tag{13}$$

$$\beta(z^{-1}) = \sum_{j=1}^{N} p_j F_j(z^{-1}) = \beta_0 + \beta_1 z^{-1} + \cdots + \beta_k z^{-k} \tag{14}$$

3 Algorithm simulation analysis based on the T-S fuzzy model

Based on the above analysis, the train brake control system was simulated by data acquisition of electro-pneumatic braking trains and GPC algorithm based on T-S fuzzy model [Abonyi, Nagy and Szeifert (2014); Senouci and Boukabou (2009)], and the simulation curve of the braking system can be obtained as shown in Fig. 2.

It can be seen from Figs. 2 and 3 that after the braking system received the braking command, the fuzzy predictive control can stabilize in the shortest 400 ms, and the braking control pressure can basically be at 260 kPa, without fluctuation. The braking curve is closer to the target value, and the braking is more accurate. In emergency braking (550 ms), the fuzzy predictive control algorithm restores to a stable state before other algorithms. It can be found that the GPC algorithm based on the T-S fuzzy model had better control accuracy than fuzzy adaptive PID control. But in the process of rising, there existed the fluctuations before 100ms. After analysis Núñez et al. [Núñez, Sáez, Oblak et al. (2009); Aleksander, Jakob, Daniel et al. (2014)], the main reasons for the above issues are as follows:

(1) During train braking, the rolling optimization was performed. In different static experiments, there may be random disturbances, such as harsh natural environment, the total aerodynamic wind in the train body that is a variable in the actual train running process, the real-time fluctuation, and the increment of braking control may be affected by prediction error, etc.

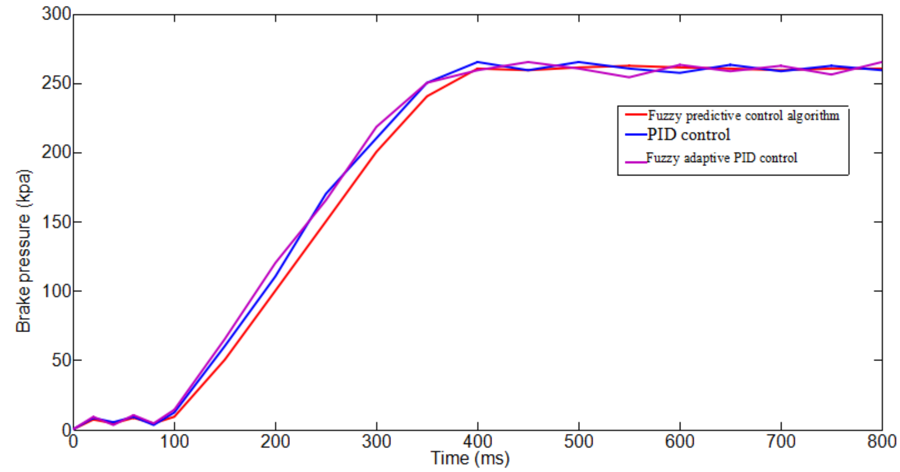

Figure 2: Relationship between the braking pressure and time under the different algorithms (Normal braking)

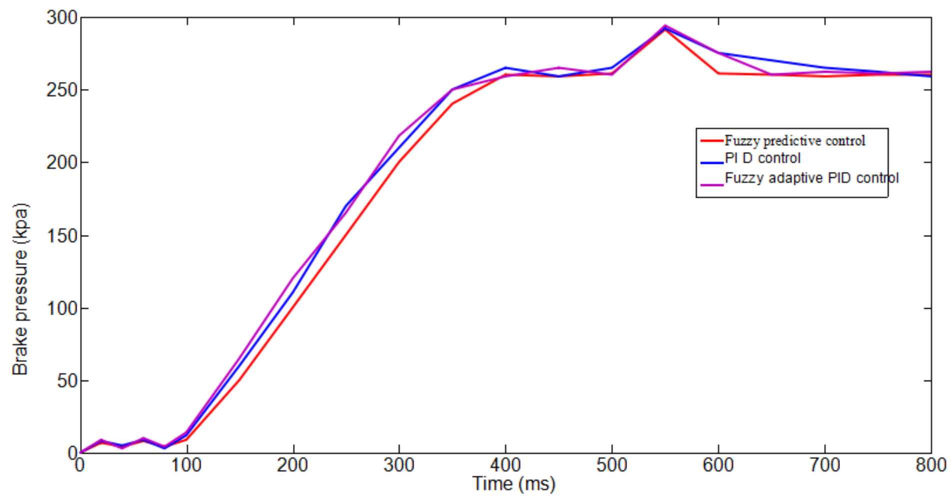

Figure 3: Relationship between the braking pressure and time under the different algorithms (Emergency braking)

(2) The train brake control system itself has many characteristic errors. In the braking control, whenever the air pressure rises or falls to the vicinity of the target value, an inverse descent process will occur, which will cause the system to slow convergence and low accuracy. In the extreme case, it will even lead the system to fail to brake relief; The characteristics of the high-speed electro-pneumatic switch valve used to control braking will

also affect the control accuracy of the system; other random interferences and modeling errors cannot be effectively eliminated by conventional feedback correction methods.

4 Conclusion

The braking system of urban rail trains is limited by the ground, the environment, the weather and people, with features of complexity, non-linearity, large hysteresis and uncertainty. Therefore, it is difficult to obtain an accurate mathematical model. In this study, the fuzzy predictive control algorithm proposed can fully exhibit its advantages. According to the emergency situation of train braking, classification and fuzzy processing can be implemented to adjust the braking force, implement the rolling optimization of braking force, and accurately predict the future trend of trains. According to simulation results, it was difficult to measure pressure feedback when emergency braking was required. Fuzzy predictive control can better avoid the real-time problem of pressure feedback and give the next trend of trains. Simulation results indicated that the algorithm performed well in the dynamic control, which can largely reduce the influence of non-linear factors, with the enhancement of the response controllability of pressure control. Thus, the braking synchronization of urban rail train can be improved, the longitudinal force of trains can be lowered, and the safe operation of trains can be guaranteed.

The proposed algorithm used real-time information and model information to continuously optimize the objective function, and revised or compensated the prediction model according to the actual output of the object. Consequently, the algorithm is suitable for complex industrial processes and can be widely used in complex industrial process control. However, the original rolling optimization method and feedback correction method cannot effectively overcome the dynamic impact of uncertainties, hysteresis and time-varying factors of the controlled object, so as to achieve the desired control objectives, and make the system have good robustness and stability. Therefore, it is necessary to combine other intelligent control methods to further realize accurate, fast and stable control of the braking volume of the train brake system, in order to better realize the train safe operation with high-quality services.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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