Distributed Model Predictive Control Based on Multi-agent Model for Electric Multiple Units

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Abstract The distributed-power electric multiple units (EMUs) are widely used in high-speed railway. Due to the structural characteristic of mutual-coupled power units in EMUs, each power unit is set as an agent. Combining with the traction/brake characteristic curve and running data of EMUs, a subtractive clustering method and pattern classification algorithm are adopted to set up a multi-model set for every agent. Then, the multi-agent model is established according to the multi-agent network topology and mutual-coupled constraint relations. Finally, we adopt a smooth start switching control strategy and a multi-agent distributed coordination control algorithm to ensure the synchronous speed tracking control of each agent. Simulation results on the actual CRH380A running data show the effectiveness of the proposed approach.

Key words Electric multiple units (EMUs), multi-agent, nonlinear, multi-models, distributed model predictive control, synchronous tracking

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The electric multiple units (EMUs) consist of several coupled power units. The running process of EMUs is a nonlinear system which could be influenced by the changing complex environment, various working conditions and so on. For the research of the dynamic modeling of the EMUs, the primary state-of-the-art method regards it as a special case of general high speed trains[1−2]. Yet, the nonlinear time-varying air resistance is ignored. Therefore, the basic resistance equation was used to describe the influence of the nonlinear air resistance on the first vehicle in [3], where the authors put forward an adaptive control method of EMUs for speed and position. However, the traction/braking force would change sharply when working condition alters. In addition, to guarantee high-precision position and speed tracking control of each vehicle, a robust adaptive control method which can optimize the control force of each vehicle was presented in [4−5]. Similarly, with the nonlinear feature of EMUs, Yang et al.[6] focused on the multi-model describing EMUs and proposed a multi-model predictive control algorithm. However, a great tracking error exists in the start-up stage of the EMUs.

As a matter of fact, the centralized control method is generally adopted in the EMUs. Specifically, all of the power units′ traction/braking forces are uniformed and given by the central control unit of EMUs. Nevertheless, they can not meet some practical requirements when the train is running on the curvature change points, gradient change points, etc. For example, the traction force of a climbing power unit would be higher than that of a horizontal power unit, and the velocity misalignment would appear among vehicles, which could augment the pressure/tension of the couplers that may threaten the safety of the EMUs.

A multi-input and multi-output complex system such as EMU operation process can be decomposed into multiple mutually coupled subsystems and each subsystem is treated as an agent, which reduces the compliancy and scale of computational problem under distributed coordination control strategy of each agent[7−9]. The coordination among multi-agent controllers has attracted lots of research interests. Du et al.[10] found out the optimal control of each agent based on the idea of Nash optimality. Similarly, when optimizing the local performance index, [11] only considered the influences from other subsystems while ignoring the optimized process impact on others. In addition, Zheng et al.[12−13] utilized the idea of network decentralized predictive control proposed in [14] and adopted neighborhood optimization method to solve the optimal solution for each subsystem. Liu et al.[15] considered the correlation of the input and output of all related subsystems when they established the objective function of the subsystem.

Based on the analysis mentioned above, we regard each power control unit as an agent in this paper. Taking advantage of the agent network topology and mutual coupling constraint relations, we establish a new multi-agent model of EMUs. Subtractive clustering and pattern classification algorithm are used to set up multi-model set according to the traction/brake characteristic curve and the operation process of each agent. For the sake of the synchronous speed tracking control of each agent, a smooth start switching control strategy composed of the proportion integration differentiation (PID) and the generalized predictive controller (GPC) methods and a multi-agent distributed coordination control algorithm are adopted, they can meet actual operation requirements of EMUs.

1 Description of multi-agent model for EMUs

Fig. 1 describes the EMUs composed of the n power units. Each power unit is associated with an adjacent power unit and couples each other. Its dynamic mechanism model is shown as follows:

$$\begin{aligned} m_1 y_{a1} &= u_1 - k(s_1 - s_2) - b(y_1 - y_2) - \\ &\quad \left(c_0 + c_v y_1 + c_a y_1^2\right) m_1 \\ m_i y_{ai} &= u_i - k(s_i - s_{i-1}) - k(s_i - s_{i+1}) - b(y_i - y_{i-1}) - \\ &\quad b(y_i - y_{i+1}) - \left(c_0 + c_v y_i + c_a y_i^2\right) m_i \\ m_n y_{an} &= u_n - k(s_n - s_{n-1}) - b(y_n - y_{n-1}) - \\ &\quad \left(c_0 + c_v y_n + c_a y_n^2\right) m_n \end{aligned} \tag{1}$$

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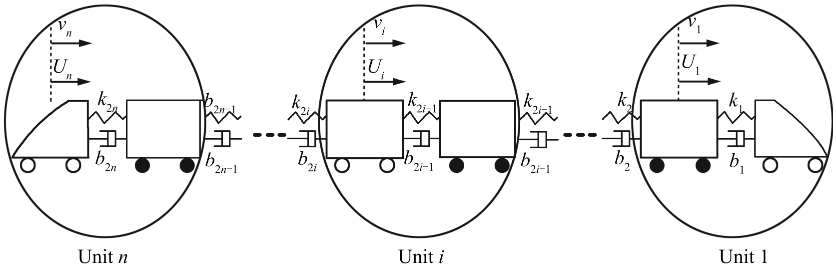


Fig. 1 Analysis of the high speed EMU longitudinal dynamics

where $i = 2, \cdots, n-1$, n is the number of power units, $c_a y_i^2$ is the air resistance on the EMUs, $c_0 + c_v y_i$ is the mechanical resistance, u_i represents the traction/braking force of each vehicle, s_i, y_i and y_{ai} respectively represent the displacement of each vehicle, running speed and operation acceleration, m_i is the quality of each control unit, k is the spring coefficient between adjacent control units, b is the damping coefficient of adjacent vehicle. c_0, c_v, c_a are resistance coefficients. With the increase of the EMUs speed, the value of $c_a y_i^2$ becomes larger, and consequently the system tends to be more nonlinear.

Each power unit in Fig. 1 is viewed as an agent. The coupling forces of each agent change essentially along with the changing of traction/braking. So we adopt traction/braking force coupling relationship instead of coupler force coupling relationship to describe the mathematical model of EMU operation process. The discrete mathematical model can be expressed as

$$\begin{aligned} y_i(k) = f\{&y_i(k-1), u_1(k-1), \cdots, \\ &u_j(k-1), \cdots, u_n(k-1)\} \end{aligned} \tag{2}$$

where $i, j = 1, \cdots, n$, $y_i(k)$ is the speed of the ith agent, $u_j(k)$ denotes the traction/braking force of the jth agent and f is the nonlinear function.

Fig. 2 shows the description of EMUs distributed multi-agent model based on graph theory, which reveals a serial structure of the distributed multi-agent model. $V_{\rm in}$ and $V_{\rm out}$ respectively represent the input and output adjacent set of the agent[16], and can be expressed as

$$\begin{cases} \boldsymbol{V}_G^+(\text{agent}_1) = \{\text{agent}_2\}: & \text{input adjacent set} \\ \boldsymbol{V}_G^-(\text{agent}_1) = \{\text{agent}_2\}: & \text{output adjacent set} \\ \boldsymbol{V}_G^+(\text{agent}_i) = \{\text{agent}_{i-1}, \text{agent}_{i+1}\}: & \text{input adjacent set} \\ \boldsymbol{V}_G^-(\text{agent}_i) = \{\text{agent}_{i-1}, \text{agent}_{i+1}\}: & \text{output adjacent set} \\ \boldsymbol{V}_G^+(\text{agent}_n) = \{\text{agent}_{n-1}, \}: & \text{input adjacent set} \\ \boldsymbol{V}_G^-(\text{agent}_n) = \{\text{agent}_{n-1}, \}: & \text{output adjacent set} \end{cases}$$

Fig. 2 The description of EMU distributed multi-agent model based on graph theory

2 Multi-agent modeling

In order to describe the non-linear characteristics of each agent effectively, a multi-modeling theory is adopted to model each agent. The basic idea of multi-modeling theory divides the entire work area into several subintervals according to certain criteria. It establishes the corresponding sub-model in each subinterval and then uses the optimal sub-model to substitute the global model[17−19]. Spreading each agent of the EMUs in multiple operating points respectively, m models $R_{i1}, R_{i2}, \cdots, R_{im}$ of the ith agent are as follows:

$$\begin{aligned} R_{il}: \ A_{il}(z^{-1})y_i(k) = B_{ijl}(z^{-1})u_j(k-d) + \xi_{il}(k), \\ i, j = 1, 2, \cdots, n; \ \ l = 1, 2, \cdots, m \end{aligned} \tag{3}$$

Equation (3) could be expressed as least squares:

$$y_{i_l}(k) = \boldsymbol{\phi}_{il}^{\rm T}\boldsymbol{\theta}_{il} + \xi_{il}(k) \tag{4}$$

In order to obtain multi-model (4), the model structure m and parameter $\boldsymbol{\theta}_{il}$ need to be determined. This paper uses the subtractive clustering algorithm to determine m and uses least square method to estimate parameter $\boldsymbol{\theta}_{il}$.

2.1 Model structure identification

Subtractive clustering is a single fast algorithm used to estimate the number of clusters and the cluster center position of one set of data[20−21]. In the multi-model modeling, as the number of models increases, the influence of nonlinear characteristics becomes weaker, and the control precision gets higher. However, an excessive number of models will lead to a big calculation. So determining the optimal number of dynamic models is necessary. The merits of clustering center′s number could be measured by the effective index. The following index function is used in this paper:

$$Q_m = \sum_{i=1}^{N}\sum_{j=1}^{m}\mu_{ij}^2 \left\|\boldsymbol{X}_i - \boldsymbol{X}_j^c\right\|^2 \tag{5}$$

where N is the number of sample data, m is the number of clusters, namely number of models, $\boldsymbol{X}_i$ denotes the ith sample data, $\boldsymbol{X}_j^c$ is the jth cluster center, μ_{ij} is the membership of the ith sample data in the jth cluster.

2.2 Model parameter estimation

According to (2) we know that the operational process of each agent is a multi-input single-output system. In this paper, each agent can be described as multi-input single-output auto-regressive and moving average (ARMA) models

$$\begin{aligned} A_{il}(z^{-1})y(k) = B_{1jl}(z^{-1})u_1(k-d) + \cdots + \\ B_{ijl}(z^{-1})u_j(k-d) + \cdots + \\ B_{njl}(z^{-1})u_n(k-d) + \xi_{il}(k) \end{aligned} \tag{6}$$

where $i, j = 1, \cdots, n$, $l = 1, \cdots, m$. $\xi_{il}(k)$ is white noise sequence, A_{il} and B_{ijl} are shown as follows:

$$A_{il}(z^{-1}) = 1 + a_{il_1}z^{-1} + a_{il_2}z^{-2} + \cdots + a_{il_{n_a}}z^{-n_a}$$
$$B_{ijl}(z^{-1}) = b_{ijl_0} + b_{ijl_1}z^{-1} + b_{ijl_2}z^{-2} + \cdots + b_{ijl_{n_b}}z^{-n_b} \tag{7}$$

Equation (6) can be transferred into a least squares form:

$$\begin{aligned} y_{i_l}(k) =& - a_{il_1}y_i(k-1) - \cdots - a_{il_{n_a}}y_i(k-n_a) + \\ & b_{i1l_0}u_1(k-d) + \cdots + b_{i1l_{n_b}}u_1(k-d-n_b) + \\ & b_{ijl_0}u_j(k-d) + \cdots + b_{ijl_{n_b}}u_n(k-d-n_b) + \\ & b_{inl_0}u_n(k-d) + \cdots + b_{inl_{n_b}}u_n(k-d-n_b) + \\ & \xi_{il}(k) = \boldsymbol{\phi}_{il}^{\mathrm{T}}\boldsymbol{\theta}_{il} + \xi_{il}(k) \end{aligned} \tag{8}$$

where $\boldsymbol{\phi}_{il}^{\mathrm{T}}$ is the data vector, $\boldsymbol{\theta}_{il}$ is the estimated parameter vector, it is identified by the recursive least square method (RLSM)[22] based on each agent′s input and output data in the course of EMUs running. RLSM is shown as follows:

$$\begin{aligned} &\hat{\boldsymbol{\theta}}(k+1) = \hat{\boldsymbol{\theta}}(k) + \boldsymbol{K}(k+1)\left[y(k+1) - \boldsymbol{\phi}^{\mathrm{T}}(k+1)\hat{\boldsymbol{\theta}}(k)\right] \\ &\boldsymbol{K}(k+1) = \frac{\boldsymbol{P}(k)\boldsymbol{\phi}(k+1)}{\lambda + \boldsymbol{\phi}^{\mathrm{T}}(k+1)\boldsymbol{P}(k)\boldsymbol{\phi}(k+1)} \\ &\boldsymbol{P}(k+1) = \frac{1}{\lambda}\left[\boldsymbol{I} - \boldsymbol{K}(k+1)\boldsymbol{\phi}^{\mathrm{T}}(k+1)\right]\boldsymbol{P}(k) \end{aligned} \tag{9}$$

where the initial value $\hat{\boldsymbol{\theta}}(0)$ is a zero vector or sufficient small positive vector, $\boldsymbol{P}(0) = (10^4 \sim 10^{10})\boldsymbol{I}$, the forgetting factor λ is close to 1, generally no less than 0.9.

2.3 Model switching strategy

The multi-agent switching strategy is a method that determines which model in the multi-model is most matched with the system′s working condition at the present moment by a kind of performance index online[20]. Based on the principle of the minimum accumulated error in the model at each sampling time, the system automatically chooses the optimal sub-model which minimizes the performance index. The objective function of global switching for multi-agent system is shown as

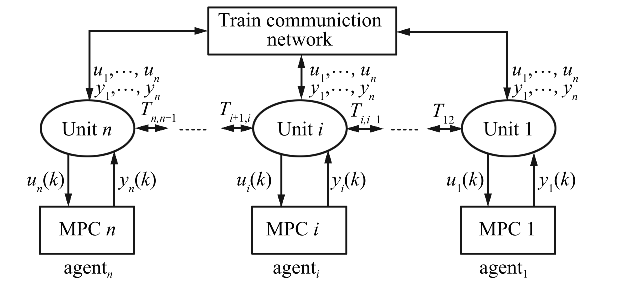
$$\begin{aligned} \boldsymbol{\delta}(k) =& \sum_{i=1}^{n}\boldsymbol{\delta}_i(k) = \sum_{i=1}^{n}\sum_{t=k-h}^{k}\frac{\|\boldsymbol{e}_{il}(t)\|^2}{1+\boldsymbol{\phi}_{il}(t)^{\mathrm{T}}\boldsymbol{\phi}_{il}(t)} = \\ & \sum_{i=1}^{n}\sum_{t=k-h}^{k}\frac{\|\boldsymbol{y}_{il}(t) - \hat{\boldsymbol{y}}_{il}(t)\|^2}{1+\boldsymbol{\phi}_{il}(t)^{\mathrm{T}}\boldsymbol{\phi}_{il}(t)} \end{aligned} \tag{10}$$

where $\boldsymbol{e}_{il}(t) = \boldsymbol{y}_{il}(t) - \hat{\boldsymbol{y}}_{il}(t) = \boldsymbol{y}_{il}(t) - \hat{\boldsymbol{\theta}}_{il}^{\mathrm{T}}\boldsymbol{\phi}(t)$ is the deviation between the actual output of agent i and the output of the lth linear model in agent i, $h > 1$ denotes the limited time length, $\boldsymbol{\phi}_{il}(t)$ denotes data vector, $\boldsymbol{y}_{il}(t)$ is the output of the lth linear model in agent i, and n denotes the number of agents.

3 Distributed model predictive control (DMPC) algorithm based on multi-agent model

3.1 The distributed predictive controller structure of EMUs

The agent model structure of EMUs is shown in (6). We should build predictive models and objective function for each agent. When the DMPC of local coordination and the decentralized model predictive control based on network establish the performance index, the influence on optimal control action of this subsystem by the output of other related subsystems is neglected. The control method based on global performance index can improve the whole performance of the system. But with this approach, each local controller should exchange information with all local controllers when using the global performance index, leading to a big load to the network. The complex controller algorithm is not convenient for engineering application. To take into account the structure of EMUs, the real-time of control algorithms and requirements of control objectives, this paper uses a DMPC system structure based on neighborhood optimization, as shown in Fig. 3.



Unit1 1~n: Unit; $u_1,\cdots,u_n$: Input vector; $y_1,\cdots,y_n$: Output vector; T : Elastic force

Fig. 3 DMPC structure of EMUs

3.2 DMPC algorithm

In the EMUs multi-agent model, while each agent does its local performance optimization, it will inevitably lead to the performance diversification of its adjacent agent controller. And then it affects the overall performance. So, while agent does local optimization in multi-agent systems, it should take into account the impact of its adjtacent agent. Based on the above analysis, each agent of the EMUs solves the performance index in the case of neighborhood optimization in this paper. According to (6), the predicted output of the ith agent can be written as

$$\begin{aligned} \hat{\boldsymbol{y}}_i\,(k+j|k) =& \sum_{j=1}^{n}W_{ij}(z^{-1})\Delta u_j(k+j-1) + \\ & \sum_{j=1}^{n}W_{pij}(z^{-1})\Delta u_j(k-1) + W_0(z^{-1})y_i(k) \end{aligned} \tag{11}$$

On the right of (11), the first is the output predictive values impacted by the future control action, and the remaining two are the output predictive values impacted by the past control action.

Performance index based on neighborhood optimization can be described as

$$\min J_i(k) = \min_{\mathrm{Nash}} J_i(k) + \min_{V_{\mathrm{in}}(i)\to i} J_i(k) + \min_{V_{\mathrm{out}}(i)\to i} J_i(k) \tag{12}$$

where $\min_{\mathrm{Nash}} J_i(k)$ is local performance index of agent i in view of the Nash optimal solution and can be written as

$$\begin{aligned} \min_{\mathrm{Nash}} J_i(k) =& \sum_{j=1}^{P}\|y_i(k+j) - w_i(k+j)\|_{Q_i}^2 + \\ & \sum_{j=1}^{M}\|\Delta u_i(k+j-1)\|_{R_i}^2 \end{aligned} \tag{13}$$

$\min_{V_{\text{in}}(i)\to i} J_i(k)$ is the performance index influenced by the adjacency input agent i and can be expressed as

$$\min_{V_{\text{in}}(i)\to i} J_i(k) = \sum_{\alpha\in V_{\text{in}}(i)}^{P} \left(\sum_{j=1}^{P} \|y_\alpha(k+j) - w_\alpha(k+j)\|_{Q_\alpha}^2 + \sum_{j=1}^{M} \|\Delta u_\alpha(k+j-1)\|_{R_\alpha}^2\right) \tag{14}$$

$\min_{V_{\text{out}}(i)\to i} J_i(k)$ is the performance index of agent i influenced by the adjacency output agent and can be written as

$$\min_{V_{\text{out}}(i)\to i} J_i(k) = \sum_{\alpha\in V_{\text{out}}(i)} \sum_{j=1}^{P} \|y_\alpha(k+j) - w_\alpha(k+j)\|_{Q_\alpha}^2 \tag{15}$$

According to (13) ~ (15), (12) can be expressed as

$$\begin{aligned} \min J_i(k) = \min \sum_{\beta} &\left(\sum_{j=1}^{P} \|y_\beta(k+j) - w_\beta(k+j)\|_{Q_\beta}^2 + \sum_{j=1}^{M} \|\Delta u_\beta(k+j-1)\|_{R_\beta}^2\right) \\ \text{s.t.}\quad & u_{\min} \le u_\beta \le u_{\max} \\ & \Delta u_{\min} \le \Delta u_\beta \le \Delta u_{\max} \\ & 0 \le y_\beta \le y_{\max} \end{aligned} \tag{16}$$

where $\begin{cases} i = 1, & \beta = 1, 2 \\ 1 < i < n, & \beta = i-1, i, i+1 \\ i = n, & \beta = n-1, n \end{cases}$, P is prediction horizon, M refers to the control horizon.

Equation (18) is a constrained optimization problem, and it should be solved by the interior point method, Lemke method, ellipsoid algorithm and so on. But they are difficult to obtain the analytical solution. In this paper, the engineering optimization method is used. In this way, the unconstrained quadratic programming is solved primarily. And then the solutions obtained are verified whether they meet the requirements of the EMUs actual operations. According to $\frac{\partial J_i}{\partial \Delta U_i}$, we have the optimal control. The output predictive value is described as

$$\hat{y}(k+j) = [\hat{y}_1(k+j), \cdots, \hat{y}_i(k+j), \cdots, \hat{y}_n(k+j)]^{\mathrm{T}} \tag{17}$$

$y_r(k+j) = [y_{r1}(k+j), \cdots, y_{ri}(k+j), \cdots, y_{rn}(k+j)]$ denote the future output reference vector.

Control increment of all agents is defined as

$$\Delta u(k+j-1) = [\Delta u_1(k+j-1), \cdots, \Delta u_n(k+j-1)]^{\mathrm{T}} \tag{18}$$

R and Q are weight matrixes. Using the forecast model (11), we can obtain all control increments when the performance is optimal:

$$\Delta \boldsymbol{u}_i = D(\boldsymbol{y}_{ri} - \boldsymbol{f}_i) \tag{19}$$

$$D = (W^{\mathrm{T}}RW + Q)^{-1}W^{\mathrm{T}}R \tag{20}$$

$$\boldsymbol{f}_i(k) = \sum_{j=1}^{n} W_{pij}(z^{-1})\Delta u_j(k-1) + W_0(z^{-1})y_i(k) \tag{21}$$

where W is an $n \times n$ order matrix, whose value is solved by Diophantine equation recursion. Let $\boldsymbol{d}^{\mathrm{T}}$ is the first line of the matrix D.

$$u_i(k) = u_i(k-1) + \boldsymbol{d}^{\mathrm{T}}(\boldsymbol{y}_{ri} - \boldsymbol{f}_i) \tag{22}$$

The whole control process is repeatedly run online through rolling optimization.

3.3 Smooth control strategies in start-up condition of EMUs

Because the start point of GPC is behind the maximum prediction horizon, the actual output before simulation cannot track the reference trajectory, which results in error jumps existing in the initial period of force control and acceleration curves. To address the problem, a compound control of PID and GPC methods is proposed to control each agent. By comparing the errors of PID and GPC methods in a consecutive time, switching of the two methods is realized. When (25) is met and this trend lasts a period of time τ, we choose GPC method to control the EMUs. Conversely, the PID approach is adopted. The switching law is

$$\begin{aligned} &\delta_{GPC}(k) < \delta_{PID}(k) \\ &\delta_{GPC}(k-1) < \delta_{PID}(k-1) \\ &\cdots \\ &\delta_{GPC}(k-\tau) < \delta_{PID}(k-\tau) \end{aligned} \tag{23}$$

where

$$\delta_{GPC}(k) = \sum_{i=1}^{n} \frac{\left(\sum_{j=1}^{h} \|y_i(k-j) - w_i(k-j)\|^2\right)}{h}$$

$$\delta_{PID}(k) = \sum_{i=1}^{n} \frac{\left(\sum_{j=1}^{h} \|yPID_i(k-j) - w_i(k-j)\|^2\right)}{h}$$

4 Simulation and analysis

In this paper, we illustrate our methods in CRH380A EMUs which consist of two carriages ($T1$, $T8$) and six locomotives. According to the structural characteristics of the power unit, the CRH380A train can be described using three agents. Agent 1 is composed of the first, second and third vehicles, Agent 2 is composed of the fourth and fifth vehicles, Agent 3 is composed of the sixth, seventh and eighth vehicles. The network topology structure among various agents of the CRH380A EMUs is shown in Fig. 4. We adopt the distributed coordination control algorithm to guarantee synchronous speed tracking of the agents.

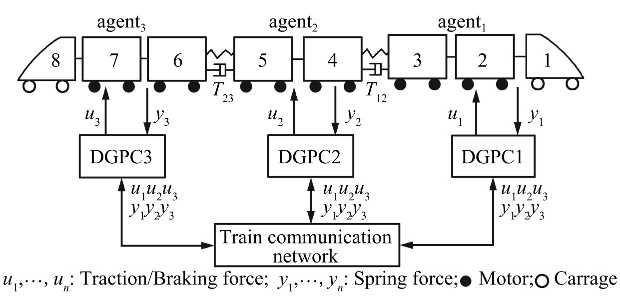


Fig. 4 The network topology structure for the agents

Simulation study is carried out according to the traction/brake characteristic curve[23] and 15 000 groups of data during EMUs running. The control forces of all agents as samples are analyzed with the subtractive clustering method. Clustering centers of each agent are shown in Table 1.

Table 1 Clustering center of each agent

Model	u_1 (kN)	u_2 (kN)	u_3 (kN)
1	53.1085	35.4608	53.2608
2	30.2013	20.1382	30.0856
3	18.6281	12.4216	18.0269
4	−21.3809	−14.0851	−21.2843
5	−51.0851	−34.0175	−51.2683
6	0.0783	0.0532	0.0809

For each clustering set, the corresponding linear model is built with the recursive least squares method. Model parameters of each agent are given from Table 2 to Table 4.

Table 2 Model parameters of Agent 1

Model	a_{1l_1}	b_{11l_1}	b_{12l_1}	b_{13l_1}
1	−0.9976	0.0038	0.0145	0.0032
2	−0.9835	0.0092	0.0256	0.0089
3	−0.9896	0.0063	0.0216	0.0061
4	−0.9921	−0.0023	−0.0126	−0.0023
5	−0.9929	−0.0025	−0.0052	−0.0026
6	−0.9782	−0.0047	0.0315	−0.0056

Table 3 Model parameters of Agent 2

Model	a_{2l_1}	b_{21l_1}	b_{22l_1}	b_{23l_1}
1	−0.9968	0.0039	0.0147	0.0032
2	−0.9841	0.0091	0.0252	0.0091
3	−0.9893	0.0062	0.0213	0.0062
4	−0.9921	−0.0023	−0.0126	−0.0023
5	−0.9931	−0.0025	−0.0051	−0.0025
6	−0.9785	−0.0045	0.0318	−0.0052

Table 4 Model parameters of Agent 3

Model	a_{3l_1}	b_{31l_1}	b_{32l_1}	b_{33l_1}
1	−0.9972	0.0038	0.0151	0.0033
2	−0.9842	0.0091	0.0256	0.0093
3	−0.9891	0.0065	0.0221	0.0065
4	−0.9929	−0.0021	−0.0128	−0.0024
5	−0.9932	−0.0023	−0.0053	−0.0028
6	−0.9791	−0.0048	0.0315	−0.0051

In Fig. 5, y_r describes the actual speed target of the CRH380A running from Jinan to Xuzhou East on certain day. The methods of this paper are employed to achieve the tracking control. $y_1 \sim y_3$ describe the tracking of the given speed processes of the three agents. The ranges of tracking error are given in Table 5.

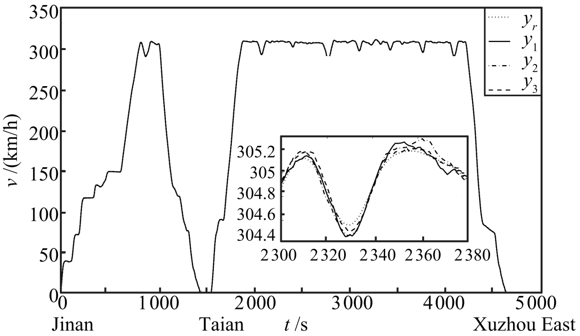


Fig. 5 Speed tracking curves of the agents

Table 5 Speed tracking error range of each agent

Number of agent	Error (km/h)
Agent 1	(−0.0763, 0.0759)
Agent 2	(−0.0861, 0.0748)
Agent 3	(−0.0713, 0.0506)

Each agent has satisfactory tracking ability, which meets the operation requirements at a relatively high precision and meets positioning speed measuring error requirements of the CTCS-3[24].

The control force curves of the agents are shown in Fig. 6. The accelerated speed curves of the agents are indicated in Fig. 7. Control force and accelerated speed of each agent

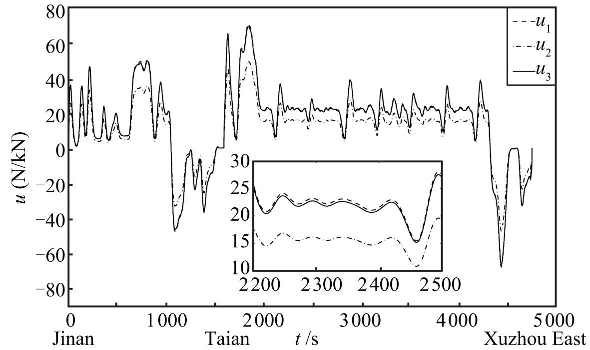


Fig. 6 Control force curves of the agents

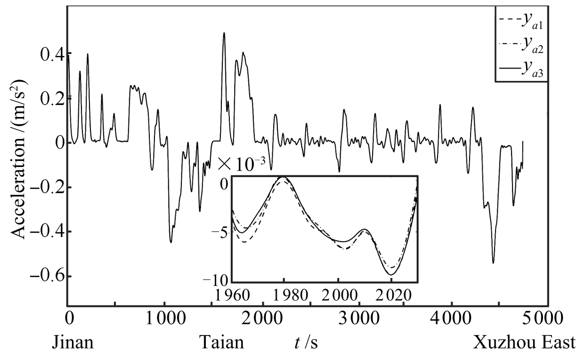


Fig. 7 Accelerated speed curves of the agents

are smooth and mitigated in all working conditions of the EMUs, which meets the requirements of the passenger comfort index.

We can observe that the EMUs track a given target displacement curve with a high precision in Fig. 8. The displacement deviations between each agent of the EMUs are also no more than 5 cm in Fig. 9, which conforms the control requirement[25].

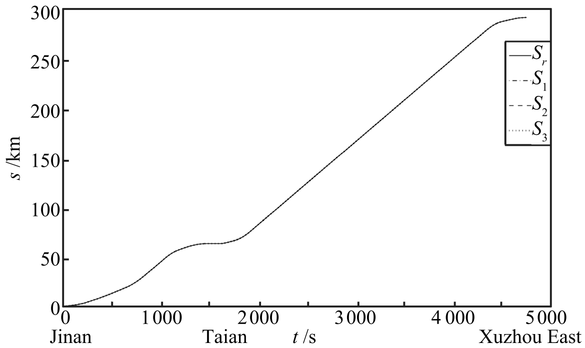


Fig. 8 Displacement of each agent

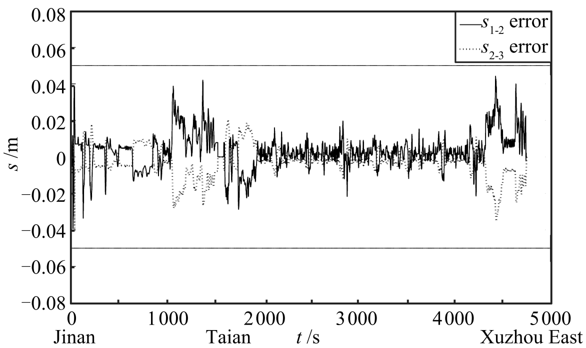


Fig. 9 Displacement deviation of each agent

5 Conclusion

A multi-agent model and distributed coordination predictive control method are proposed according to the structure and operation characteristics of the EMUs. We obtain the multiple model sets of each agent and a multi-model switching strategy based on the actual operation data of the CRH380A EMUs. We adopt distributed predictive control method based on the engineering optimization to realize the high-accuracy speed tracking control of each agent, and meet the safety, comfort, high-speed and punctuality of the EMUs.

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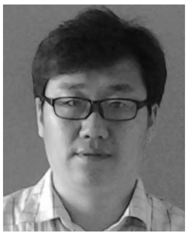

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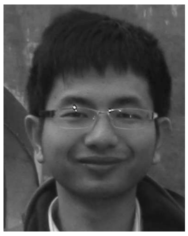

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