Distributed Model Predictive Control for Automatic Train Regulation in Metro Lines

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***Abstract*—In high-frequency metro lines, unexpected disturbances often occur to cause train delays, which will influence the application of pre-optimized timetables. Real-time train regulation adjusting running and dwell times is an effective method to suppress train delays. This paper investigates a real-time metro train regulation method combining the distributed model predictive control (DMPC) algorithm, which is motivated by the technology of vehicle-based train control system. In the vehicle-based system, each train is self-organized with the capability of communication and computation. Firstly, an optimal control model is established for the metro train regulation process considering the train traffic dynamics, system constraints and objectives. Then, a distributed control framework is proposed to solve the optimal control model. In addition, DMPC algorithms with no information transmission, single-direction and bi-direction information transmission are designed, aiming to analyze the influence of the communication modes on the DMPC algorithms. Finally, the proposed algorithms were subjected to numerical validation to assess their efficacy. The results show that the DMPC algorithm with bi-direction information transmission achieved significant performances in reducing computation costs and suppressing train delays.**

Keywords*—*Urban rail transit, Train rescheduling, Distributed model predictive control, Quadratic programming

I. INTRODUCTION

Metro traffic is one of the most important components of public transportation, since it is regarded as an efficient transportation mode with high security, large capacity and low energy consumption. Metro trains are usually running with high-frequency to transport a large number of passengers. Metro traffic is inherently unstable: any deviation from the nominal timetable of a train will amplify over time and disturb the operation of other trains [1]. In real-time operations of a metro traffic system, unexpected disturbances often affect the orderly operation of trains, which will result in train delays. Once the train delays cannot be effectively mitigated, they will have a negative impact on the quality of service and even cause serious interferences during peak hours [2]. In order to reduce the influences of disturbances, train regulation is necessary to recover train delays and to keep the stability of metro traffic systems [3].

At present, train regulation is carried out in a centralized way, in which a dispatcher is in charge of all traffic management covering a specific control area. Meanwhile, related decision support tools providing optimal control strategies for train regulation consider a centralized decision making [4]. With the development of vehicle based train control technology in metro traffic systems, trains are autonomous and connected with the capability of making self-organized regulation decisions and communicating with other trains [5]. Then, the central train regulation decision-making tasks are broken down to each intelligent train. These trains adjust the running and dwell times to recover train delays according to the system states information they can obtain, including their own states and information transmitted by other trains. However, this decentralized way can only deal with disturbances, not disruptions [4]. Disruptions refer to large incidents, requiring both the timetable and the planning of train service to be modified (e.g., cancelling or adding train services). In this paper, we only focus on the train regulation problem under disturbances, which can be dealt with by adjusting the running and dwell times.

Although some researchers in studies [5]-[7] begin to solve this problem in a decentralized method with connected and autonomous trains, there is typically a lack of systematic analysis. In general, the lack of this method mainly includes the following aspects. 1) In a decentralized control problem, the mode of communication is critical, which will influence the control effect [8]. However, the related studies only consider the situation that each train can communicate with its predecessor. It is necessary to consider and analyze the performances of decentralized train regulation controllers under different information interaction modes, like no-communication and bi-direction communication. 2) To address the decentralized train regulation problem, it is necessary to propose a more appropriate model and algorithm considering various communication modes.

This paper aims solve the problem of metro train regulation problem by making the following contributions. 1) A decentralized train regulation model, which considers different modes of information interaction between trains, is formulated. The purpose is to describe train regulation problem with different MPC architectures. Previous related works [5]-[7] have only built a decentralized train regulation model with single-direction information transmission. To analyze the decentralized train regulation problem more comprehensively, models with different modes of

This work was supported by the Independent Research Project of Zhejiang Scientific Research Institute of Transport under grant no. ZK202321.

2023 China Automation Congress (CAC) | 979-8-3503-0375-9/23/$31.00 ©2023 IEEE | DOI: 10.1109/CAC59555.2023.10451926

information interaction should be built. 2) DMPC algorithms are designed to generate real-time optimal control actions while minimizing the impact of disturbances.. At each control cycle, a local control action is obtained by solving the subproblem of each train. Furthermore, the effectiveness of the proposed approaches is validated through the implementation of numerical examples based on one of the metro lines in Guangzhou.

The rest of this paper is organized as follows. Section 2 provides an overview of the metro train rescheduling problem. In Section 3, we present our proposed methodology for the metro train regulation problem. Section 4 tests the practical application of our proposed approaches through two numerical examples. These examples include a single disturbance case and a multiple disturbances case. Finally, in Section 5, we conclude this paper, summarizing the key findings and potential avenues for future research.

II. Optimal Train Regulation Problem

A metro line with I stations, where J trains orderly running through stations is considered, as shown in Fig. 1. In real-time operation of metro lines, the timetables are unable to keep the pre-scheduled settings and train regulation strategies should be taken to make the disturbed timetables revert to the pre-scheduled ones. The metro line traffic dynamics, regulation objectives and system constraints should be considered to generate the optimal train regulation problem.

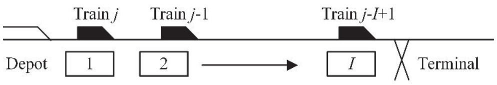

Fig. 1. The illustration of the considered metro line

To conduct a more rigorous study of the train regulation problem, certain assumptions are formulated based on the operational characteristics of metro lines. These assumptions are as follows:1) The overtaking operation is not considered, trains are following the manner of first-in-first-out; 2) The skip-stop operation is not considered, trains stop at all stations among the line.

A. Traffic dynamics

The discrete-event train regulation mode is built based on the study [9]. The actual departure time can be described as:

$$t_{i+1}^j = t_i^j + r_i^j + d_{i+1}^j \tag{1}$$

where, i is the index of stations, $1 \le i \le I$; j is the index of trains, $1 \le j \le J$; t_i^j is the actual departure time of train j at station i; r_i^j is the actual running time of train j from station i to station $i+1$; d_i^j is the actual dwell time of train j at station i.

The actual running time and dwell time can be described as:

$$r_i^j = R_i + ur_i^j + wr_i^j \tag{2}$$

$$d_{i+1}^j = D_{i+1} + ud_{i+1}^j + wd_{i+1}^j \tag{3}$$

where, R_i is the nominal running time from station i to station $i+1$; ur_i^j is the control action of running time of train j from station i to station $i+1$; wr_i^j is the disturbance of running time of train j from station i to station $i+1$; D is the nominal dwell time at station i; ud_i^j is the control action of dwell time of train j at station i; wd_i^j is the disturbance of dwell time of train j at station i.

The train traffic dynamics model can be described by combining Eq. (1)-(3):

$$t_{i+1}^j = t_i^j + R_i + D_{i+1} + ur_i^j + ud_{i+1}^j + wr_i^j + wd_{i+1}^j \tag{4}$$

where , the running time and dwell time are affected by uncertain disturbances, and control actions are implemented to mitigate the effects of disturbances.

B. Regulation objectives

The train regulation problem aims to achieve several objectives, including reducing timetable deviation, headway deviation, cost of control actions. The objective function can be described as:

$$J = p_1\sum_{i,j}(x_i^j)^2 + p_2\sum_{i,j}(x_i^j - x_i^{j-1})^2 + p_3\sum_{i,j}(ur_i^j)^2 + p_3\sum_{i,j}(ud_i^j)^2 \tag{5}$$

where, p_1, p_2 and p_3 are the weight coefficients. In the objective function (5), the first part represents the total timetable deviation (TTD). As an important metric, the deviation from the nominal timetable can be defined as:

$$x_{i+1}^j = t_{i+1}^j - T_{i+1}^j \tag{6}$$

where, x_i^j is the deviation of train j from nominal departure time at station i; T_i^j is the nominal departure time of train j at station i. The second component of objective function (5) pertains to the minimization of total headway deviation (THD), which is crucial for ensuring the regularity of headway, as emphasized in previous study [10]. The headway deviation is defined as the difference between the interval between successive trains and the nominal headway H, which can be defined as:

$$(t_{i+1}^j - t_{i+1}^{j-1}) - H = x_{i+1}^j - x_{i+1}^{j-1} \tag{7}$$

The third and fourth components of the objective function (5) represent the total magnitude of control actions. Minimizing these components aims to reduce the overall control cost and discourage excessive control actions.

C. System constraints

To guarantee the safety and feasibility of regulation strategies, the following constraints should be considered.

1) The interval between the departure time of the preceding train and the arrival time of the following train at the same station should be larger than the minimum departure-arrival interval:

$$t_i^j - d_i^j - t_i^{j-1} \ge \Psi_{i,min} \tag{8}$$

where, $\Psi_{i,min}$ is the minimum departure-arrival interval at station i.

2) The dwell time at each station should be larger than the minimum value:

$$D_i + ud_i^j + \omega d_i^j \geq D_{i,min} \tag{9}$$

where, $D_{i,min}$ is the minimal dwell time at station i.

3) The running time at each section should be larger than the minimum value:

$$R_i + ur_i^j + \omega r_i^j \geq R_{i,min} \tag{10}$$

where, $R_{i,min}$ is the minimum running time from station i to station $i+1$.

4) The control actions should be within acceptable limits:

$$\begin{cases} UR_{i,min} \leq ur_i^j \leq UR_{i,max} \\ UD_{i,min} \leq ud_i^j \leq UD_{i,max} \end{cases} \tag{11}$$

where, $UR_{i,min}$ and $UR_{i,max}$ are the lower and upper bounds of the control action for the running time from station i to station $i+1$ respectively; $UD_{i,min}$ and $UD_{i,max}$ are the lower and upper bounds of the control action for the dwell time at station i respectively.

D. Optimal train regulation problem

By taking into account the traffic dynamics, the regulation objectives, and the system constraints, the optimal train regulation problem can be established as follows:

$$\min \sum_{i,j} [p_1 (x_i^j)^2 + p_2 (x_i^j - x_i^{j-1})^2 + p_3 (ur_i^j)^2 + p_3 (ud_i^j)^2] \tag{12}$$

s.t. Eq. (4), (6), (8)-(11).

III. Distributed Model Predictive Control for Train Regulation

In this section, four methods based on MPC are proposed to solve the proposed optimal train regulation problem. First, the centralized model predictive control (CMPC) method, which has been widely studied to solve the real-time optimal train regulation problem [1], [3], [10]-[12], is introduced. Then, a DMPC model handling different information transmission modes is proposed, and the related algorithm is designed to generate the optimal regulation strategy, as shown in Fig. 2.

A. Model predictive control problem

Let k represent the stage, t_k represent the state variables, ur_k and ud_k represent the decision variables, the proposed problem (12) can be transformed into the following MPC problem:

$$\min \sum_{i=0}^{L-1} \{p_1 x_{k+i+1}^T x_{k+i+1} + p_2 (x_{k+i+1} - x_{k+i})^T (x_{k+i+1} - x_{k+i}) + p_3 ur_{k+i}^T ur_{k+i} + p_3 ud_{k+i}^T ud_{k+i}\} \tag{13}$$

Subject to:

$$t_{k+i+1} = \Lambda t_{k+i} + T_{0,k+i} + R + ur_{k+i} + \omega r_{k+i} + D + ud_{k+i} + \omega d_{k+i} \tag{14}$$

$$x_{k+i+1} = t_{k+i+1} - T_{k+i+1} \tag{15}$$

$$\Psi_{min} \leq t_{k+i+1} - D - ud_{k+i} - \omega d_{k+i} - t_{k+i} \tag{16}$$

$$D_{min} \leq D + ud_{k+i} + \omega d_{k+i} \tag{17}$$

$$R_{min} \leq R + ur_{k+i} + \omega r_{k+i} \tag{18}$$

$$UR_{min} \leq ur_{k+i} \leq UR_{max} \tag{19}$$

$$UD_{min} \leq ud_{k+i} \leq UD_{max} \tag{20}$$

Since several parameters in the proposed optimal control model (13)-(20), like ωr_k and ωd_k, are time-dynamics, and the optimal control model is a complex optimization problem with a nonlinear objective function, plenty of constraints and multiple decision variables. By leveraging a real-time rolling optimization framework, the MPC algorithm can handle nonlinear high-dimensional optimal control problem with dynamic disturbances. The MPC algorithm devised for addressing the proposed problem can be decomposed into three components.. 1) Prediction model: the model (4) can be used to predict the system states. 2) Optimization problem: the optimization problem (13)-(20) can be solved to obtain a set of optimal control sequence. Specifically, the optimization problem is a quadratic programming problem. 3) Rolling horizon: a set of optimal control sequence can be obtained at each time step, while simultaneously implementing the first control action to the system. At the next time step, the prediction horizon is shifted one step forward, and the optimization problem is solved again with updated parameters.

B. Centralized model predictive control algorithm

Optimal train regulation studies based on MPC mainly adopt the CMPC algorithm, where a centralized controller receives system states and decides on the optimal control sequence. The standard MPC formulation discussed in the previous section can be characterized as a sequence of static optimization problems $\{SP_k \mid k = 0, 1, 2, \ldots\}$ [13]:

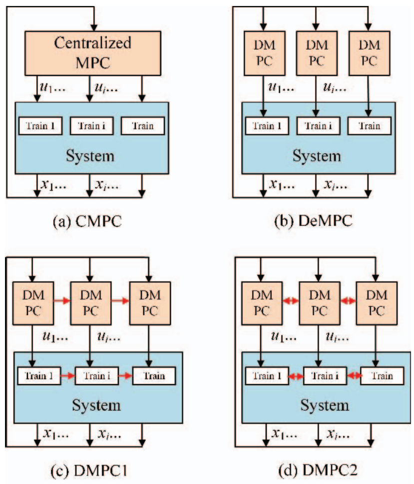

Fig. 2. Four model predictive control architectures. (a) CMPC: A single centralized controller receives information about the system's current state and determines the appropriate actions to take; (b) DeMPC: Local controllers independently receive system states and make decisions without exchanging information with other local controllers; (c) DMPC1: Local controllers receive system states and cooperate to make decisions with single-direction information transmission; (d) DMPC2: Local controllers receive system states and cooperate to make decisions with bi-direction information exchange [8].

$$\begin{cases} SP_k : \min_S & J(S,U) \\ \quad\quad \text{s.t.} & F(S,U) \le 0 \\ & G(S,U) = 0 \end{cases} \quad (21)$$

where, S is the vector of the state variables; U is the vector of decision variables over the prediction horizon; J is the objective function; F and G are the equality and inequality constraints matrices in the optimization problem (13)-(20) respectively.

The CMPC algorithm can be summarized in the following manner.

Algorithm 1: CMPC algorithm
Step 1: Formulate the optimization problem (21) at stage k .
Step 2: Obtain the optimal control sequence by solving the formulated optimization problem.
Step 3: Apply the first control action of the optimal control sequence to the system, and update the system states, set $k = k + 1$, go to Step 1.

C. Distributed model predictive control algorithm

By applying the DMPC algorithm, the optimization problem (21) in the CMPC algorithm can be divided into a set of subproblems $SP_{k,j}$:

$$\begin{cases} SP_{k,j} : \min_{S_j} & J_j(S_j, U_j, S_j^{obt}) \\ \quad\quad \text{s.t.} & F_j(S_j, U_j, S_j^{obt}) \le 0 \\ & G_j(S_j, U_j, S_j^{obt}) = 0 \end{cases} \quad (22)$$

where, S_j and U_j represent the state and decision variables allocated to the j-th subproblem respectively, which can be obtained by solving the subproblem $SP_{k,j}$; S_j^{obt} represents the obtained state variables from other DMPC controllers by information transmission allocated to the j-th subproblem; J_j, F_j and G_j represents the objective function, equality and inequality constraints matrices allocated to the j-th subproblem respectively. In the DMPC algorithm, the set of variables S is divided into three subsets: S_j, S_j^{obt} and S_j^{una}, with $S = S_j \cup S_j^{obt} \cup S_j^{una}$, where S_j^{una} represents the unacquirable variables.

Each subproblem $SP_{k,j}$ is assigned to the optimal train regulation problem of train j at stage k . The local variables S_j and U_j are assigned to the state and control variables of train j respectively. The obtained variables S_j^{obt} is assigned to the state variables from the connected trains. Due to the different information transmission modes, the DMPC algorithms can be divided into three types: DeMPC, DMPC1 and DMPC2, as shown in Fig. 2. For the DeMPC, there is no exchanging information between local controllers, thus $S_j^{obt} = \varnothing$. And for the DMPC1, the local controller can only receive the information from the front controller, which means $S_j^{obt} = S_{j-1}$. Specially, for the DMPC2, the local controller can both receive the information from the front and latter controllers, which means $S_j^{obt} = \{S_{j-1}, S_{j+1}\}$. Then, three DMPC algorithms are proposed for the optimal train regulation problem:

Algorithm 2: DMPC algorithm
Step 1: Before train j departs from station, formulate the optimization problem (22). Specially, $S_j^{obt} = \varnothing$ in DeMPC algorithm; $S_j^{obt} = S_{j-1}$ in DMPC1 algorithm; and $S_j^{obt} = \{S_{j-1}, S_{j+1}\}$ in DMPC2 algorithm.
Step 2: Obtain the optimal control sequence by solving the formulated optimization problem.
Step 3: Apply the first control action of the optimal control sequence and update the system states. Meanwhile, train j transmits S_j to train $j + 1$ in DMPC1 algorithm; train j transmits S_j to train $j - 1$ and $j + 1$ in DMPC2 algorithm; nothing to do in DeMPC algorithm.
Step 4: Until train j arrives at the next station, go to Step 1.

IV. NUMERICAL EXAMPLES

A. Case study conditions

The case studies are based on one of the Guangzhou metro lines with 13 stations (i.e., $I = 13$). The up direction operation from station 1 to station 13 of the metro line is considered in the case studies. Given the frequent occurrence of disturbances during peak hours, the testing period for train regulation is selected to be the morning peak hours. The corresponding nominal timetable parameters are shown in Table 1.

TABLE 1. NOMINAL TIMETABLE PARAMETERS DURING MORNING PEAK HOURS

Station index	Nominal running time [s]	Minimum running time [s]	Nominal dwell time [s]	Minimum dwell time [s]
1	0	0	60	50
2	129	120	45	35
3	86	79	45	35
4	116	109	45	35
5	81	76	45	35
6	111	101	50	35
7	102	97	44	35
8	124	119	46	35
9	99	92	47	35
10	74	68	55	45
11	75	69	50	35
12	96	88	48	35
13	131	125	60	45

The nominal headway between trains H is set as 150s, in the morning peak hours. The prediction step horizon L is chosen as 4. The lower and upper bounds of the control action are respectively set as $UR_{i,min} = -30$s , $UR_{i,max} = 30$s, $UD_{i,min} = -20$s , $UD_{i,mmax} = 20$s , and the minimum departure-arrival interval $\Psi_{i,min}$ is set as 20s. In the case studies, the start time is 7:00 am setting as 0s ($k = 1$), and the end time is 7:50 am setting as 3000s. The departure time of the first train at station 1 is 10s, and the departure times of trains at station 1 is $[10,160,310,\ldots,3010]_{\times 20}$. At stage 1, the original timetable deviations are equal to zero. To maintain generality, the objective weights are set to be equal (i.e., $p_1 = p_2 = p_3 = 1$). The case studies are conducted within the MATLAB environment on a personal computer (Intel Core i5 2.30 GHz CPU and 8GB RAM). The quadratic programming problem is solved utilizing the quadprog function provided by MATLAB. In the case studies, five train regulation strategies are compared, namely: (a) Strategy NC: strategy without regulation; (b) Strategy CMPC:

strategy involves CMPC; (c) Strategy DeMPC: strategy involves DeMPC; (d) Strategy DMPC1: strategy involves DMPC1; (e) Strategy DMPC2: strategy involves DMPC2.

B. Single disturbance scenario

First, we set a single disturbance, $wr_2^5 = 70s$, to verify the effectiveness of the proposed control strategies. The control action and timetables are shown in Fig. 3 and 4 respectively. Specially, the control action in Fig. 3 is defined as $ur_i^j + ud_{i+1}^j$. Table 2 presents the performances of the five strategies under single disturbance scenario. Specially, TTD is defined as $[\sum_{i,j}(x_i^j)^2]^{\frac{1}{2}}$, and THD is defined as $[\sum_{i,j}(x_i^j - x_i^{j-1})^2]^{\frac{1}{2}}$.

TABLE 2. THE PERFORMANCES OF SINGLE DISTURBANCE SCENARIO

Type of strategy	NC	CMPC	DeMPC	DMPC1	DMPC2
TTD [s]	232.16	103.58	96.60	105.95	101.18
THD [s]	328.33	115.14	136.61	116.66	119.96
ACT [s]	/	0.06	0.01	0.01	0.01

As shown in Fig. 4, an initial delay of train 5 at station 3 leads to the propagation of delay to subsequent stations. Due to the differences in control strategies, the applied control actions of the five strategies are quite different, as shown in Fig. 3. In the strategy NC, no control action is implemented to mitigate the propagation of delays, as shown in Fig. 3 (a), thus the initial delay of train 5 is transmitted to subsequent stations without attenuation or mitigation, as in shown Fig. 4 (a). Meanwhile, without considering minimizing the headway deviation, the departure times of the successive trains, (i.e., train 4 and train 6), are not adjusted to keep the regularity of headway.

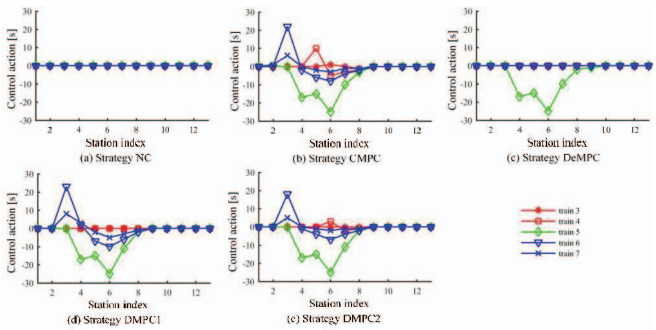

Fig. 3. Control actions of single disturbance case.

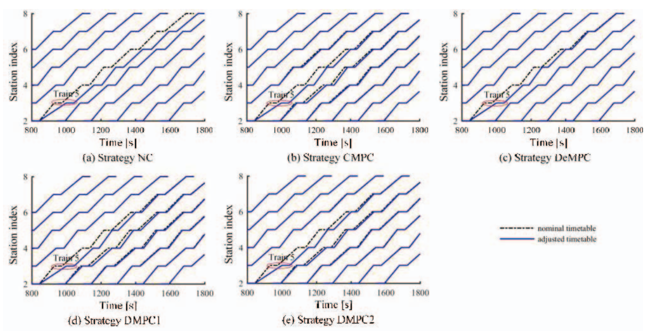

Fig. 4. Timetables of single disturbance case.

Considering the other four optimized strategies (CMPC, DeMPC, DMPC1 and DMPC2), control actions are applied to suppress train delay propagation, as shown in Fig. 3. In the strategy DeMPC, only the timetable of train 5 are adjusted to reduce the timetable deviation of train 5. As shown in Fig. 4 (c), the timetable deviation of train 5 is effectively reduced compared to the strategy NC. However, the timetables the front train (i.e., train 4) and the latter train (i.e., train 6) are not adjusted to minimize the headway deviation, it is because they cannot get the state information of train 5. From more holistic perspectives, the strategy CMPC, DMPC1 and DMPC2 perform better in reducing the headway deviation. In addition, the quantities of information that the controllers can obtain are different in these three control strategies. The centralized controller can obtain all the system state information in the strategy CMPC, the local controllers can obtain the state information of the successive trains and the controlled train in the strategy DMPC2, and the local controllers can only obtain the state information of the front train and the controlled train in the strategy DMPC1.

Considering the performances of the five strategies, the strategy NC performs the worst in terms of TTD and THD. In the strategy DeMPC, timetables are optimized without considering minimizing the headway deviation, thus the total deviation from the timetable is minimized to the greatest extent compared to other strategies. However, the total deviation in headway, or the time interval between consecutive trains, is larger compared to the other three optimized strategies. The strategies CMPC, DMPC1, and DMPC2 have demonstrated effective outcomes in reducing both TTD and THD. Furthermore, these distributed control strategies exhibit superior performance in terms of average computation time (ACT).

TABLE 3. THE DISTURBANCES OF MULTIPLE DISTURBANCE SCENARIO

Disturbance index	Disturbance type	Stage index	Station index	Intensity [s]
1	*wr*	6	3	70
2	*wr*	11	7	30
3	*wr*	15	10	30
4	*wr*	15	2	30
5	*wr*	18	5	40
6	*wd*	3	2	30
7	*wd*	7	3	30
8	*wd*	14	10	40
9	*wd*	15	5	40
10	*wd*	16	5	30

C. Multiple disturbances scenario

Second, we set multiple disturbances, as shown in Table 3, to verify the effectiveness of the proposed control strategies. Table 4 presents the performances of the five strategies under multiple disturbances scenario. The performances of the four optimized strategies vary due to the utilization of different control algorithms, as indicated in Table 4. Compared with the strategy NC, TTDs of the strategy CMPC, DeMPC, DMPC1 and DMPC2 are reduced by 55.8%, 62.7%, 54.0% and 57.5% respectively, and THD of the strategy CMPC, DeMPC, DMPC1 and DMPC2 are reduced by 60.3%, 55.4%, 59.5% and 59.1% respectively. These four optimized strategies achieve significant results in reducing TTD and THD. The strategy DeMPC performs best in reducing TTD However, the strategy DeMPC does not perform well in reducing THD because it does not consider the state information of successive trains. In terms of performances, the strategy DMPC2 is the most balanced strategy, TTD and THD of it are both reduced to lower levels. Thanks to the distributed control framework, ACTs of the strategy DeMPC, DMPC1 and DMPC2 are shorter compared to the strategy CMPC.

TABLE 4. THE PERFORMANCES OF MULTIPLE DISTURBANCE SCENARIO

Type of strategy	NC	CMPC	DeMPC	DMPC1	DMPC2
TTD [s]	393.68	173.83	146.92	180.95	166.97
THD [s]	398.33	158.03	177.45	161.16	163.02
ACT [s]	/	0.06	0.01	0.01	0.01

V. CONCLUSION

This paper focuses on investigating the real-time regulation problem of metro trains with the aim of mitigating the impact of disturbances. Considering the development of self-organized trains with the capability of communication and computation, we developed a decentralized train regulation optimization model, in which different information transmission modes are considered. To solve this real-time high-dimensional optimal control problem, this paper proposed efficient train regulation algorithms based on the DMPC framework.

To evaluate the effectiveness of the proposed approaches, two different scenarios are examined: the single disturbance scenario and the multiple disturbances scenario. These scenarios are employed to evaluate the performance of the proposed methods under different conditions. The computational results showed that, by applying the DMPC algorithm, the total timetable deviation and headway deviation could be effectively reduced around 54% to 63% and 55% to 60% respectively compared with the safe strategy without regulation, and the computation timetable could also be effectively reduced compared with the CMPC algorithm. Especially, the DMPC algorithm with bi-direction information transmission exhibited better performance in minimizing both the total timetable deviation and headway deviation when compared to other DMPC algorithms.

The current paper primarily addresses the train regulation problem under disturbances. Our forthcoming research will primarily concentrate on addressing the train regulation problem in the presence of disruptions.

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