Horizon-Varying Model Predictive Control for Accelerated and Controlled Cooling Process

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***Abstract*—In accelerated and controlled cooling (ACC) processes, the relationship between the plate velocity and the final temperature of plate point is complicated and implicitly expressed, with undetermined ending time of the plate cooling. It is difficult to obtain the optimal plate velocity to accurately control the final temperature. A novel control methodology is proposed to improve the accuracy of the final temperature. The technical targets are transformed first into several location-dependent temperatures to simplify the ACC process as a linear system. Then, a horizon-varying model predictive control algorithm is developed to obtain the optimal final temperature of the entire plate. The optimization horizon is estimated according to the plate length and the prediction of future input sequence in each control period. The experimental results show the effectiveness of the proposed method.**

***Index Terms*—Accelerated cooling, laminar cooling, model predictive control (MPC), plate steel.**

I. Introduction

TO IMPROVE the metallurgical properties of hot-rolled plates, manufacturers usually use the accelerated and controlled cooling (ACC) process to cool the plate steel from the austenitic starting temperature (750 °C–850 °C) down to the final temperature (500 °C–600 °C) for producing a refined final microstructure and favoring the formation of the plate steel. The final temperature and cooling rate are important parameters that determine the performance and the physical and mechanical properties of the products [1]–[3]. In ACC, there are many disturbances and constraints, and the relationships between the inputs and the outputs are complicated and can hardly be presented explicitly. All of them make it difficult to improve the accuracy of the final temperature.

The control of ACC processes can be broadly divided into two parts: the supervisory controller and the dynamic controller. The supervisory controller calculates the cooling-water flux and the number of cooling headers opened according to the grade of the plate steel and the reference cooling rate. The dynamic controller computes the optimal velocity sequence to obtain an accurate final temperature of each plate point. Literature works [4]–[6] present various effective approaches to design a supervisory controller, while there are few research activities on the dynamic controller. In industrial manufactories, the existing dynamic control method assumes that the cooling rate equals a desired constant, calculates the average velocity of each plate point according to the difference between the starting temperature of each plate point and the desired final temperature, and transforms these average velocities of plate points into a velocity sequence in time order. In fact, the cooling rate of plate point is different from the desired cooling rate. The plate temperature and many other disturbances that affect the cooling rate are not taken into account; it lacks the accuracy in the procedure of transforming the average velocities of plate points into a velocity sequence in time order.

Model predictive control (MPC) is widely recognized as a practical control technology with high performance [7], [8], has been successfully applied to many various linear [8]–[10] and nonlinear [11]–[13] systems in the process industries, and is becoming more widespread [14]–[17]. Literature works [18]–[21] gave attempts to apply MPC to the metallurgy process. Since MPC offers good dynamic performance and caters for hard actuator limits and other system constraints in a straightforward manner, we will use it to optimize the ACC process.

However, the relationship between the plate velocity and the plate point's temperature is hardly expressed explicitly and accurately. On the other hand, the time instants that the plate's head and tail reach the controlled points are determined by the future plate's velocities, which gives a time-varying and undetermined optimization horizon of MPC if a uniform temperature of the whole plate is required. Wan and Kothare [22] presented a horizon-varying (HV) strategy to guarantee the controller feasibility. To our knowledge, no HV method has been proposed to address this problem.

In this paper, the technical targets are transformed into several location-dependent temperatures first, which enables the ACC process to be approximated as a linear system at the neighborhood of equilibria. Then, based on the model of transformed system, an HV-MPC algorithm is developed to obtain the optimal final temperature of the entire plate. The optimization horizon is estimated in HV-MPC through the prediction of the future plate velocity sequence to solve the problem of undetermined optimization horizon of MPC.

The contents are organized as follows. Section II describes the ACC process and the control problem. Section III presents the existing method. Section IV proposes a novel control method for the ACC, with an HV-MPC algorithm developed for

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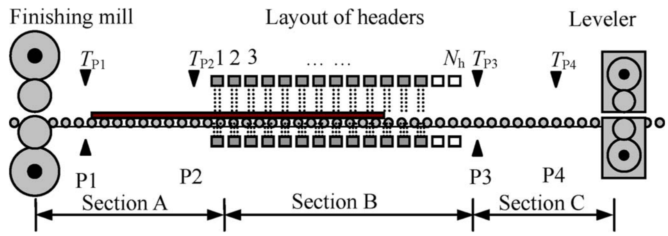


Fig. 1. ACC process for middle and heavy plates.

the dynamic controller in Section V. In Section VI, experiments are presented to demonstrate the effectiveness of the proposed control method. Section VII gives the conclusion of this paper.

II. Problem Statement

A. System Description

The ACC process, shown in Fig. 1, consists of three sections: air cooling section (51.5 m), water cooling section (24 m), and re-reddening section, labeled with A, B, and C, respectively. Fifteen groups of cooling headers are uniformly distributed along section B. Four parameters T_{P1}–T_{P4} are located after the finishing mill, at the entry to section B, at the exit from section B, and before the leveler to measure the surface temperatures of the slab, respectively. Speed tachometers are mounted in the roller motors to track the plate speed.

B. Control Problem

The technical targets of the ACC process are as follows.

1) Control the cooling rate R_C to be consistent with the set point R_C^o;
2) Control the final temperature T_e to be consistent with the set point T_e^o.
3) Obtain the uniform temperature evolution of each plate point.

The manipulated variables are as follows:

1) flux of cooling water: F;
2) plate velocity: $v(t)$;
3) number of opened cooling headers: N_h^o.

The relationship between the plate velocity and the plate point's temperature is very hard to be presented explicitly and accurately. This makes it difficult to apply the classical optimization methods to ACC directly and obstruct the improvement of control accuracy.

III. Existing Control Method

The existing control method of ACC is shown in Fig. 2. It consists of a supervisory controller, 30 PI controllers, and a velocity optimizer.

The supervisory controller calculates the set point of cooling-water flux F^o, the number of opened cooling headers N_h^o, and average velocity u^o according to the grade of the plate. The set point F^o is determined by the desired cooling rate R_C^o. The initial average velocity u^o and N_h^{fo} satisfy

$$N_h^o \times l_h = \frac{T_s^o - T_e^o}{R_C^o} \cdot u^o \tag{1}$$

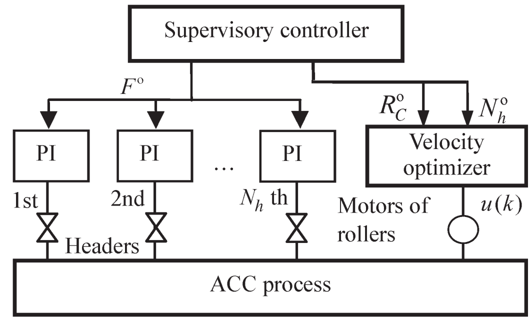


Fig. 2. Existing control method for ACC.

where $l_h = 1.6$ m is the space between two headers and T_s^o and T_e^o are the average starting temperature and the desired final temperature, respectively.

The PI controllers regulate the cooling-water flux of each cooling header to be consistent with the set point.

The velocity optimizer controls the final temperature of each plate point through adjusting the plate velocity. It divides the plate into n segments named as "plate point." Then, the average velocity of each plate point is obtained through minimizing

$$\min_{v_i} \sum_{i=1}^{n} \left\| \frac{(T_i - T_e^o) \cdot v_i}{L} - R_C^o \right\|_2^2 \tag{2}$$

where T_i is the starting temperature of the ith plate point, which refers to the ith plate point's temperature at position P2, v_i $(i = 1, \ldots, n)$ is the optimal average velocity of the ith plate point, and L is the length of the water cooling section. Since there is no causal relationship between the plate velocity and the cooling rate, optimization problem (2) assumes that the cooling rate equals R_C^o, and then, the velocity of each plate point is calculated such that the final temperature of each plate point equals the desired final temperature.

Connect the plate-point average velocities in position order as a curve, which is treated as a velocity sequence, and feed the plate in this velocity curve. When the last plate point enters the cooling section, the velocity of the plate keeps constant.

The limitations of this method are as follows.

1) The assumption that the cooling rate is always equal to R_C^o is not always true since the cooling rate is affected by many disturbances, e.g., the flux and temperature of the cooling water, and plate skidding on roller.
2) The velocity sequence in time order is approximated without any restricted deduction. To control the final temperature accurately, a new control concept for ACC is proposed in the next section.

IV. Novel Control Method Based on HV-MPC

A. Technical-Target Transformation

This paper studies the overall system of the cooling section from the viewpoint of the geometrically distributed setting system. As shown in Fig. 3, the desired cooling curve can be transformed into a location-dependent temperature profile from point P2 to point P4 under the assumption of the plate going through the cooling section with a constant velocity of u^o. Since

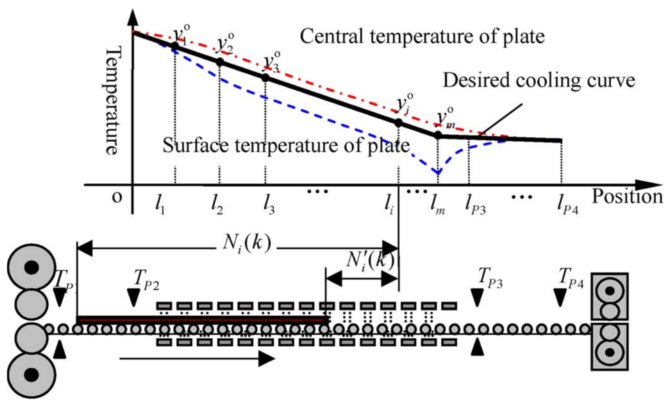


Fig. 3. Reference temperature and the optimization horizon.

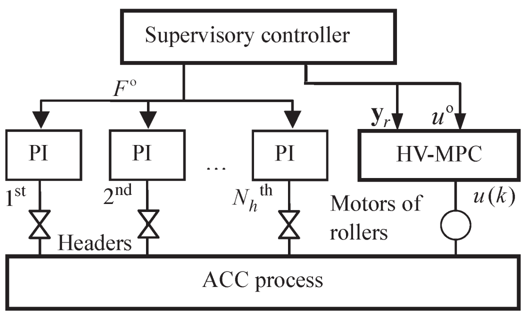


Fig. 4. HV-MPC-based control method for ACC.

the plate surface temperature is different from its central one, the temperature at the desired cooling curve is the plate average temperature along the thickness direction.

Since the temperature drop is mainly caused by the cooling water, the temperatures at positions $l_1, l_2, \ldots, l_m$ are selected as reference temperatures and denoted as

$$\mathbf{y}_r = [\,y_1^o \quad y_2^o \quad \cdots \quad y_m^o\,]^{\mathrm{T}}. \tag{3}$$

It means that the plate temperature should be $y_i^o, i = 1, \ldots, m$, when the plate reaches to l_i.

This transformation promises a very small range of each output. It means that the differences of the physical parameters among plate points are small at positions l_i $(i = 1, \ldots, m)$. Thus, we assume that the specific heat capacity, the heat conductivity, and the density of the plate are constant at positions l_i $(i = 1, \ldots, m)$. Then, the ACC process can be approximated by a linear model at the neighborhood of $\mathbf{y}_r$. This model implies the relationship between the plate velocity and the cooling curve (the cooling rate and the final temperature). Consequently, some model-based optimization methods can be applied to the dynamic control of the ACC process.

B. Control Method

As shown in Fig. 4, compared with the existing method, the technical-target transformation is added into the supervisory controller, and the velocity optimizer in the existing method is substituted by an HV-MPC. The HV-MPC regulates the transient temperature of the plate for consistency with $\mathbf{y}_r$ by adjusting the plate velocity.

TABLE I
INPUTS AND OUTPUTS OF HV-MPC

Item	Value
Outputs	y_i : plate temperature at position l_i, $i = 1, \ldots, m$
Manipulated variable	u : plate velocity
Measurable disturbance	w : measurement of T_{P2}

Since a uniform final temperature in the length direction is required to obtain a flat plate, as shown in Fig. 3, the optimization horizon of HV-MPC should start from the time that the plate head reaches l_i to the time that the plate tail reaches l_i [from $N_i(k)$ to $N_i'(k)$]. However, $N_i(k)$ and $N_i'(k)$ are time varying and undetermined at time k since the plate velocity is time varying. The VH-MPC is designed to solve this problem.

V. HV-MPC FOR ACC

A. Inputs and Outputs

Since the starting temperature contributes much to the plate's transient temperature, set the measurement of T_{P2} to be a measurable disturbance. The inputs and outputs of HV-MPC are listed in Table I.

B. Predictive Model

The predictive model of HV-MPC can be achieved by the data produced from the hybrid mechanism model detailed in [23]. It can be expressed as

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\Delta u(k) + \mathbf{W}\Delta w(k) \\ \mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) \end{cases} \tag{4}$$

$$y_i(k) = \mathbf{C}_i \mathbf{x}(k), \qquad i = 1, 2, \ldots, m \tag{5}$$

where $\mathbf{x} \in \mathbb{R}^{n_x}$ is the state vector; $\mathbf{y} = [\,y_1 \quad y_2 \quad \cdots \quad y_m\,]^{\mathrm{T}}$, $\mathbf{y} \in \mathbb{R}^m$ is the output vector; $\Delta u(k) = u(k) - u(k-1)$ and $\Delta w(k) = w(k) - w(k-1)$ are the increments of the manipulated variable and measurable disturbance; $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, and $\mathbf{W}$ are coefficient matrices with

$$\begin{aligned} \mathbf{A} &= \text{block-diag}(\mathbf{A}_1, \ldots, \mathbf{A}_m) \\ \mathbf{C} &= [\,\mathbf{C}_1^{\mathrm{T}} \quad \cdots \quad \mathbf{C}_m^{\mathrm{T}}\,]^{\mathrm{T}} \\ \mathbf{B} &= [\,\mathbf{b}_1^{\mathrm{T}} \quad \cdots \quad \mathbf{b}_m^{\mathrm{T}}\,]^{\mathrm{T}} \\ \mathbf{W} &= [\,\mathbf{d}_1^{\mathrm{T}} \quad \cdots \quad \mathbf{d}_m^{\mathrm{T}}\,]^{\mathrm{T}} \\ \mathbf{A}_i &= [\,\mathbf{0}^{(N-1)\times 1} \quad \mathbf{I}_{N-1}\mathbf{0}^{1\times(N-1)} \quad 1\,] \\ \mathbf{C}_i &= [\,\mathbf{0}^{1\times(i-1)} \quad 1 \quad \mathbf{0}^{1\times(N-i)}\,] \end{aligned}$$

with $b_i(j)$, $j = 1, \ldots, N$, denoting the sample signal of the ith output for a unit-step manipulated variable at time instant j, and $\mathbf{b}_i = [\,b_i(1) \quad \cdots \quad b_i(N)\,]^{\mathrm{T}}$. $d_i(j)$ denotes the sample signal of the ith output for a unit-step measurable disturbance at sampling time j, and $\mathbf{d}_i = [\,d_i(1) \quad \cdots \quad d_i(N)\,]^{\mathrm{T}}$. N is the modeling horizon and equals the time instant when the system becomes stable with the step signals. $\{\mathbf{C}, \mathbf{A}\}$ is observable.

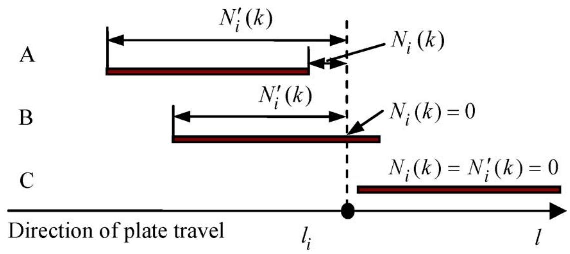


Fig. 5. Cases of plate position.

All the elements in $\mathbf{x}(k)$ are not directly measurable except the elements which equal the output, and a state observer can be constructed to estimate them as follows:

$$\hat{\mathbf{x}}(k+1) = \mathbf{A}\hat{\mathbf{x}}(k) + \mathbf{B}\Delta u(k) + \mathbf{W}\Delta w(k) + \mathbf{V}\left(\mathbf{y}(k+1) - \hat{\mathbf{y}}(k+1)\right) \quad (6)$$

$$\hat{\mathbf{y}}(k+1) = \mathbf{CA}\hat{\mathbf{x}}(k) + \mathbf{CB}\Delta u(k) + \mathbf{CW}\Delta w(k) \quad (7)$$

where $\mathbf{V} \in \mathbb{R}^{mN \times m}$ is the observer feedback matrix. Defining $\tilde{\mathbf{x}}(k) = \mathbf{x}(k) - \hat{\mathbf{x}}(k)$, the observer dynamics can be described as

$$\tilde{\mathbf{x}}(k+1) = (\mathbf{I} - \mathbf{VC})\mathbf{A}\tilde{\mathbf{x}}(k). \quad (8)$$

It can be seen that $\hat{\mathbf{x}}(k)$ will converge to $\mathbf{x}(k)$ under proper selection of $\mathbf{V}$. The stability for prediction error correction can be guaranteed by analyzing the observer dynamics.

Remark 1: Due to the difficult ambient condition, the plate temperatures at l_i, $i = 1, \ldots, m$, are usually measured by soft sensors. Here, the thermodynamic model [23] is used, which has enough accuracy and applied on the hot-rolled strip mill [23]–[25].

C. Optimization Index

As shown in Fig. 5, since $N_i(k)$ and $N_i'(k)$ are integers, the optimization horizon for the ith output at current time k should be as follows:

1) from time instant $k + N_i(k)$ to time instant $k + N_i'(k)$ in case A, where $N_i(k)$ minimizes the distance from l_i to the plate head at time instant $k + N_i(k)$, and $N_i'(k)$ minimizes the distance from l_i to the plate tail at time instant $k + N_i'(k)$;
2) from time instant k to time instant $k + N_i'(k)$ that minimizes the error between l_i and the position of the plate tail after $N_i'(k)$ control period in case B;
3) zero in case C.

In conclusion, $N_i(k)$ and $N_i'(k)$ can be obtained by solving the following optimization problems, respectively:

$$\min_{N_i(k)} \left\| \frac{l_i - l_P}{\Delta t} - \sum_{i=1}^{N_i(k)} u(k+i-1) \right\|_2$$
$$\text{s.t.} \quad 0 \le N_i(k) \le N_0 \quad N_i(k) \in \mathbb{N} \quad (9)$$

$$\min_{N_i'(k)} \left\| \frac{l_i - l_P + L_P}{\Delta t} - \sum_{i=1}^{N_i'(k)} u(k+i-1) \right\|_2$$
$$\text{s.t.} \quad 0 \le N_i'(k) \le N_0 \quad N_i(k) \in \mathbb{N} \quad (10)$$

where $\mathbb{N}$ is the set of positive integers, N_0 is the maximum prediction horizon, $l_P = \sum_{j=0}^{k-1} u(j)$ is the position of the plate's head, L_P is the length of the plate, and Δt is the control period.

In addition, if the plate is far away from l_i so that the plate cannot reach l_i even after N_0 step, the optimization horizon will be set to zero. That is, if $N_i' = N_i = N_0$, then set $N_i' = N_i = 0$.

Remark 2: At time k, l_P can be measured by an encoder and the speed tachometers, and L_P and l_i are given; thus, it is easy to find $N_i(k)$ and $N_i'(k)$ in problems (9) and (10) online through many line search methods.

To guarantee only one optimal solution for the problem (13) introduced thereinafter, the control horizon $M(k)$ should satisfy

$$M(k) = \min\left(M_0, \max_i \left(N_i'(k), \sum_{j=1}^{m}\left(N_j'(k) - N_j(k)\right)\right)\right) \quad (11)$$

where $i = 1, 2, \ldots, m$ and M_0 is the upper boundary of the control horizon. Then, the cost function of the whole system at time k can be expressed as

$$J(k) = \sum_{\substack{i=1,\\ i \notin \Omega}}^{m} \sum_{l=N_1(k)}^{N_i'(k)} \left\| y_i(k+l|k) - y_i^r \right\|_{q_{i,l}} + \sum_{h=1}^{M(k)} \left\| \Delta u(k+h-1) \right\|_{r_h} \quad (12)$$

where J is the cost function, $q_{i,l} \in \mathrm{R}$, $q_{i,l} > 0$, is the weighting coefficient, and $r_h \in \mathrm{R}$, $r_h > 0$, is the weighting matrix. Generally, to guarantee the accuracy of the final temperature, set $q_{1,l} \le q_{2,l} \le \cdots \le q_{m,l}$.

D. Optimization Problem

Considering the constraints of the manipulated variables, the outputs, the increments of the manipulated variables, and the increments of the outputs, the optimization problem of MPC at each sampling time k becomes

$$\min_{\Delta\mathbf{U}(k)} J(k) = \min_{\Delta\mathbf{U}(k)} \left(\sum_{\substack{i=1,\\ i \notin \Omega}}^{m} \sum_{l=N_i(k)}^{N_i'(k)} \left\| y_i(k+l|k) - y_i^r \right\|_{q_{i,l}} + \sum_{h=1}^{M(k)} \left\| \Delta u(k+h-1) \right\|_{r_h} \right)$$

s.t.

$$\begin{array}{l} \text{Eq. (4); Eq. (5); Eq. (11)} \\ N_i'(k) = \arg\left(\text{problem (10)}\right) \\ y_{i,\min} \le y_i(k+l|k) \le y_{i,\min} \\ \Delta y_{i,\min} \le \Delta y_i(k+l|k) \le \Delta y_{i,\min} \\ u_{\min} \le u(k+h-1|k) \le u_{\max} \\ \Delta u_{\min} \le \Delta u(k+h-1|k) \le \Delta u_{\max} \end{array} \quad (13)$$

where $\Delta\mathbf{U}(k) = [\,\Delta u(k|k)^{\mathrm{T}} \quad \cdots \quad \Delta u(k+M(k)-1|k)^{\mathrm{T}}\,]^T$ is the input increment sequence at time k. $\{u_{\min}, u_{\max}\}$, $\{y_{i,\min}, y_{i,\max}\}$, $\{\Delta u_{\min}, \Delta u_{\max}\}$, and $\{\Delta y_{i,\min}, \Delta y_{i,\max}\}$ are the boundaries of the manipulated variable, the output, the increment of the manipulated variable, and the increment of the output, respectively.

Remark 3: The constraint of $\Delta\mathbf{y}$ in problem (13) is used to avoid the plate's temperature changes sharply in the length direction and then to guarantee the plate uniform properties.

If $N_i(k)$, $N_i'(k)$, and $M(k)$ are given, problem (13) can be cast as a quadratic programming with $M(k)$ optimized vector. However, the optimization horizon is available in time k, so an iterative algorithm is developed to solve this problem.

E. HV-MPC Algorithm

Denote the future input sequence at time k with

$$\mathbf{U}(k) = [\,\mathbf{u}(k|k)^{\mathrm{T}} \quad \mathbf{u}(k+1|k)^{\mathrm{T}} \quad \cdots\,]^{\mathrm{T}}. \tag{14}$$

Denote the optimal input sequence as $\mathbf{U}^*(k)$ and the optimal input sequence at iteration l as $\mathbf{U}^{*(l)}(k)$. Express the estimations of $N_i(k)$, $N_i'(k)$, and $M(k)$ in the lth iteration as $\hat{N}_i^{(l)}(k)$, $\hat{N}_i'^{(l)}(k)$, and $\hat{M}^{(l)}(k)$, respectively. Then, the detail of the *HV-MPC algorithm* can be described as follows.

Step 1) *Initialization:* At time k, initialize the maximum control horizon M_0, the maximum prediction horizon N_0, and the maximum iteration l^*. Set the iterative index $l = 1$

$$\hat{N}_i^{(1)}(k) = \arg\left(\text{problem (9)}\right)\big|_{\mathbf{U}(k)=\mathbf{U}^*(k-1)}$$
$$\hat{N}_i'^{(1)}(k) = \arg\left(\text{problem (10)}\right)\big|_{\mathbf{U}(k)=\mathbf{U}^*(k-1)}.$$

Calculate $\hat{M}^{(0)}(k)$ by (11).

Step 2) *Problem* (13) *optimization:* Let

$$\Delta\mathbf{U}^{*(l)}(k) = \arg(\text{problem (13)})\Big|_{\substack{N_i(k)=\hat{N}_i^{(l)}(k), N_i'(k)=\hat{N}_i'^{(l)}(k),\\ M(k)=\hat{M}^{(l)}(k).}}$$

Calculate $\mathbf{U}^{*(l)}(k)$ by $u(k) = u(k-1) + \Delta u(k)$.

Step 3) *Optimization horizon and control horizon calculation:* Let

$$\hat{N}_i^{(l+1)}(k) = \arg\left(\text{problem (9)}\right)\big|_{\mathbf{U}(k)=\mathbf{U}^{*(l)}(k)}$$
$$\hat{N}_i'^{(l+1)}(k) = \arg\left(\text{problem (10)}\right)\big|_{\mathbf{U}(k)=\mathbf{U}^{*(l)}(k)}.$$

Calculate $\hat{M}^{(l)}(k)$ by (11).

Step 4) *Check and update:* Check if the terminal iteration condition is satisfied, i.e.,

$$\hat{N}_i^{(l+1)}(k) = \hat{N}_i^{l}(k) \qquad \hat{N}_i'^{(l+1)}(k) = \hat{N}_i'^{l}(k)$$

for all $i = 1, 2, \ldots, m$. If the terminal condition is satisfied at iteration l or $l \geq l^*$, then stop the iteration and go to *Step 5)*. Otherwise, let $l = l + 1$ and go to *Step 2)*.

Fig. 6. ACC experimental apparatus.

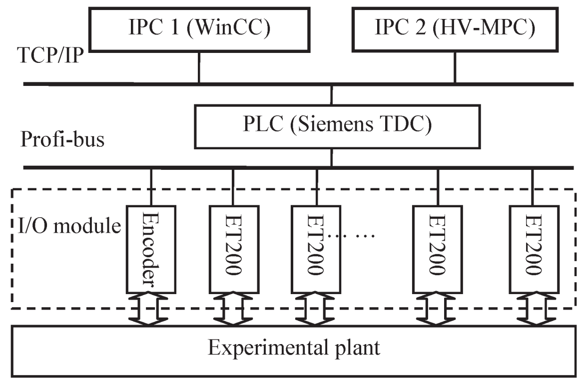


Fig. 7. Automation system of the experimental apparatus.

Step 5) *Assignment and implementation:* Compute the instant control law

$$\mathbf{u}^*(k) = [\,\mathbf{I}_{n_u} \quad \mathbf{0} \quad \cdots \quad \mathbf{0}\,]\,\mathbf{U}^{*(l)}(k)$$

and apply $\mathbf{u}^*(k)$ to the system.

Receding horizon: Move the horizon to the next sampling time, i.e., $k+1 \to k$, go to *Step 1)*, and repeat the aforementioned steps.

Remark 4: When applying the HV-MPC algorithm online, the predictive horizon is not always convergent. Thus, a maximum iteration l^* is used here to avoid endless iteration. If the iterative algorithm is convergent, an optimal solution can be achieved. Otherwise, an approximate optimal solution is obtained. Although the solution obtained by the HV-MPC algorithm is not optimal under the condition of $\hat{N}_i^{l*}(k) \neq N_i(k)$ or $\hat{N}_i'^{l*}(k) \neq N_i'(k)$, the performance of the closed-loop system with HV-MPC is still better than the basic MPC since the optimization index of HV-MPC is much closer to the requirements of the system than that of the basic MPC.

VI. Experimental Results

A. Experimental Apparatus

To illustrate the effectiveness of the proposed method, some experiments are conducted in the ACC experimental apparatus, as shown in Fig. 6. The automation system of the experimental apparatus (see Fig. 7) consists of two industrial personal computers (IPCs), one PLC, and many I/O modules.

The software of *WinCC* and an *OPC* sever running on IPC 1 are used to monitor the cooling process, and the PI controllers

TABLE II
PLATE PARAMETERS AND OPERATING POINTS

Item	Value
Thickness of plate	20.91 mm
Length of plate	25 m
Environment temperature	25 °C
Starting temperature	770 °C
Desired final temperature	509 °C
Desired cooling rate	17.5 °C/s
Water flux set point	368 l/(m^{2}min)
Average velocity of plate	1.3 m/s
Number of header opened	12
Sampling period	0.37 Sec

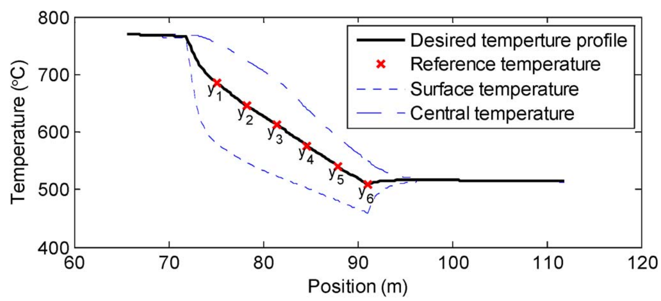
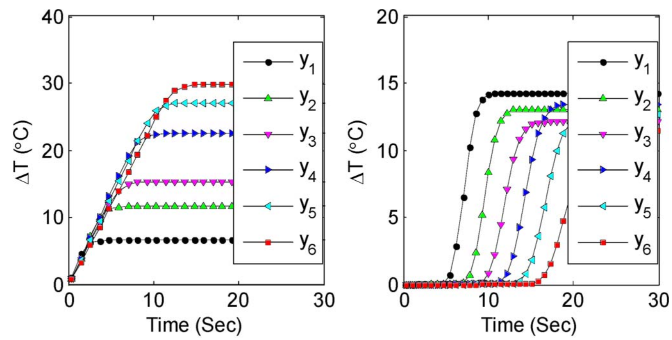


Fig. 8. Location-dependent reference temperature.



(a) (b)

Fig. 9. System responses. (a) To the velocity step signal. (b) To the inlet temperature step signal.

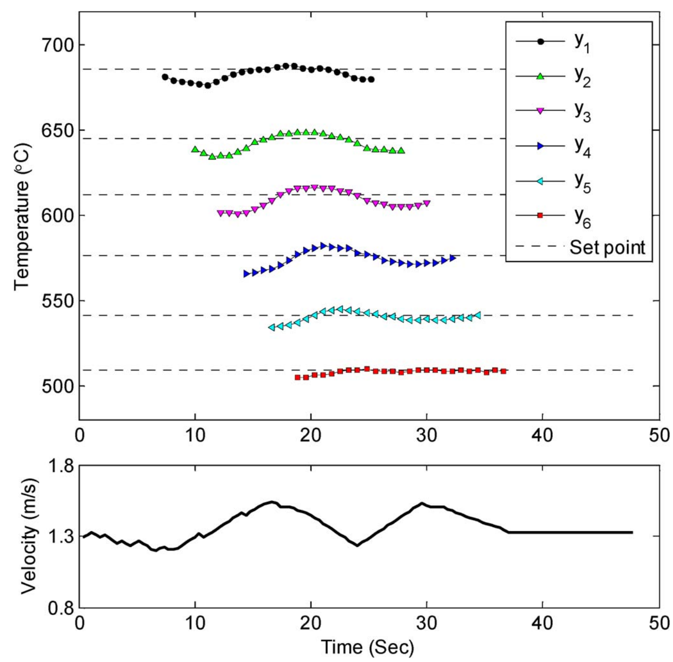


Fig. 10. Performance of the closed-loop system with the cooling-water step signal.

running on PLC are employed to control the water flux. The HV-MPC algorithm running on IPC 2 is developed in C++. The control signals of HV-MPC are transferred to the experimental apparatus through PLC, and the communication between the HV-MPC algorithm and PLC is realized through the *OPC* server installed on IPC 1.

B. Experimental Parameters

The parameters of the plate steel cooled in the experiments and the operating points calculated by the supervisory controller are listed in Table II. The cooling section (from P2 to P4) is separated into several segments, and the length of each segment is 1.6 m. The average temperatures of the 6th, 8th, 10th, 12th, 14th, and 16th segments are selected as the system outputs, and the reference outputs y_1^o, y_2^o, y_3^o, y_4^o, y_5^o, and y_6^o are shown in Fig. 8.

Fig. 9 shows the response signals of the open-loop system with a velocity step signal of 0.25 m/s and a starting-temperature step signal of 20 °C at equilibria. Then, the predictive model for HV-MPC is derived from (4) and (5). Set $N_0 = 100$ and $M_0 = 80$. Let the velocity constraint be $\{0.9, 1.7\}$ and the acceleration constraint be $\{-0.2, 0.2\}$.

C. Performance of HV-MPC

To demonstrate the validation of HV-MPC, various experiments with disturbances and uncertainties are conducted. Fig. 10 shows the disturbance handling of HV-MPC. The experiment adds a 10% water flux step signal into the system, and the accuracy of the final temperature y_6 is still guaranteed by HV-MPC. The errors between the outputs and the reference temperature decrease gradually from y_1 to y_6. Fig. 11 shows another example with plate skidding on run-out table from 10 to 14 s. The proposed method can also guarantee the final temperature with small errors between the outputs and the references.

D. Comparison With Existing Method

Comparison between the existing method and HV-MPC is presented to further verify the performance of HV-MPC. The experiments use the starting temperatures shown in Fig. 12 and the same physical parameters of the plate in Table II. The starting-temperature curves are also similar to guarantee the validation of the comparison.

The resulting final temperatures, cooling rates, and plate velocities are shown in Fig. 13. Fig. 13(a) shows that the plate's final temperature of the existing method is around 509 °C before 25 s, then increases to 515 °C, and stays in the

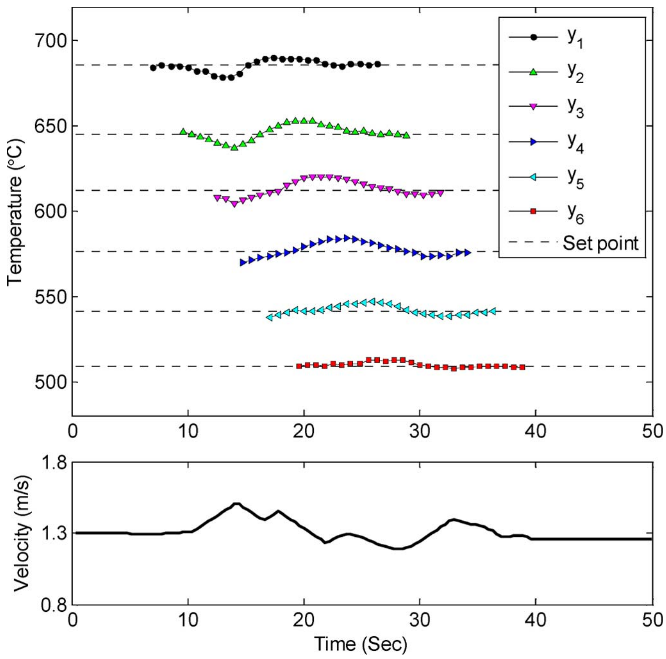


Fig. 11. Performance of the closed-loop system when plate skidding on run-out table exists.

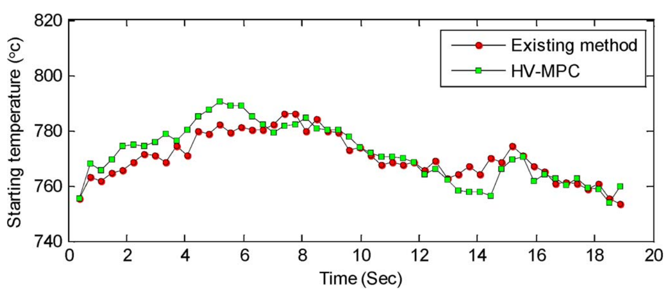


Fig. 12. Starting temperatures of the plates for experiments.

neighborhood of 515 °C, whereas the final temperature of the plate controlled by HV-MPC is always close to 509 °C, with the errors within ±3 °C. The HV-MPC can obtain the uniform and accurate final temperature.

In Fig. 13(b), the average cooling rates of the plate points in two plates are both close to 17.5 °C/s, with 17.5 °C/s for HV-MPC and 17.35 °C/s for the existing method. They are similar because the cooling rate is mainly determined by the cooling-water flux, which is the same in two experiments. The corresponding plate velocities are shown in Fig. 13(c).

In the ACC process, the cooling rate and the final temperature are the two main factors determining the physical and mechanical properties of the plate steel. According to the experimental results, the proposed method can improve the mechanical properties of the produced plate steel and guarantee the flatness of the plate. In addition, this control methodology can be extended to other metallurgy processes, e.g., the laminar cooling process of a hot-rolled strip.

VII. Conclusion

In this paper, a novel control method has been developed for the ACC process. With a technical-target transformation, the ACC process has been transformed first into a system that can be modeled by a linear model, and then, the HV-MPC method has been proposed to control the plate temperature. The optimization horizon of HV-MPC is recalculated to guarantee the optimization index, which includes the temperatures of the entire plate. As a result, the accuracy and consistency of the final temperature have been improved, as well as the physical and mechanical properties of the plate steel. The experiments have been conducted to show the potentials of the proposed method in this paper. Future work will be applying this method to industrial production line.

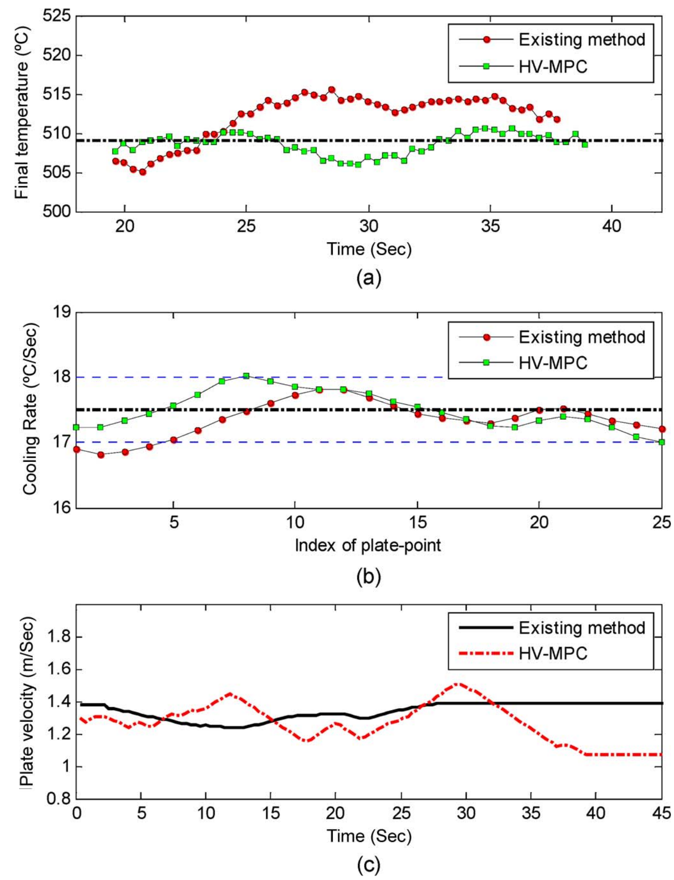


Fig. 13. Comparison between the existing method and HV-MPC. (a) Final temperature. (b) Cooling rate of each plate point. (c) Plate velocity.

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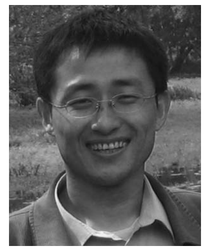

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