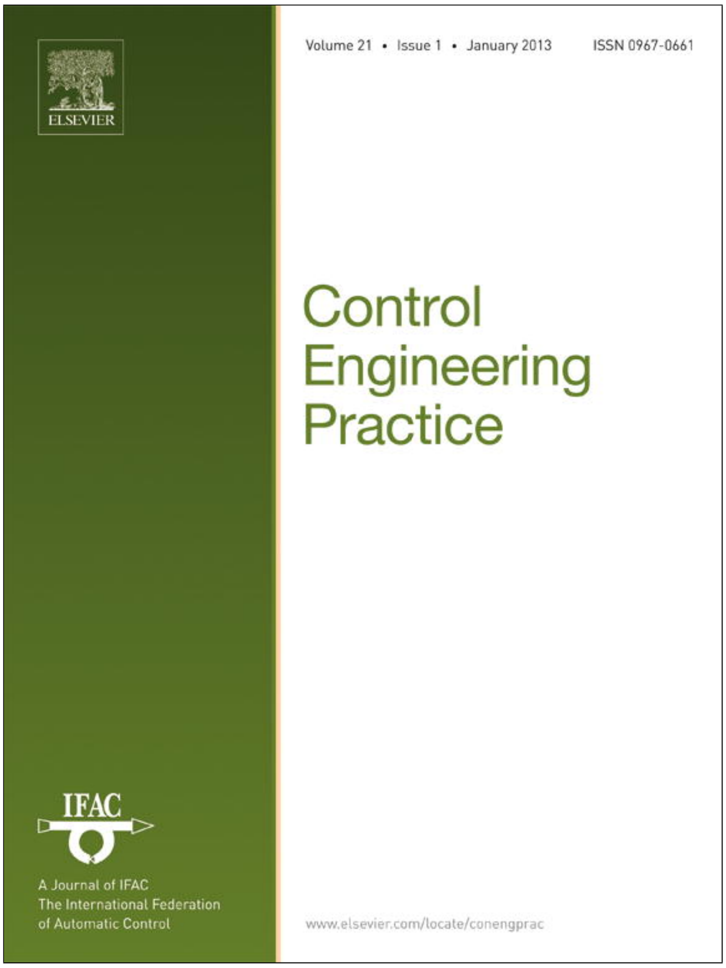
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Hot-rolled strip laminar cooling process plant-wide temperature monitoring and control

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ABSTRACT

The hot-rolled strip laminar cooling (HSLC) process is important to the production quality in hot-rolled strip product line. How to monitor the strip's transient temperature and accurately control the coiling temperature (CT) are the problems in HSLC since the strip temperature can hardly be measured inside the cooling section. In this paper, a modified EKF with trade-off feed-back coefficient is implemented to reconstruct the spatial distribution of strip temperature. It has the advantages of simple designation, having reasonable convergence rate and stability. Then a novel control strategy based on the designed EKF and model predictive control (MPC) is proposed for HSLC to improve the precision of CT. In MPC, a predictor is employed to predict the future temperature sequence at the inlet of fine cooling zone to further improve the performance of MPC. Finally, the reliability and performance of the proposed monitoring and control method were demonstrated by the experimentations in one HSLC manufactory.

1. Introduction

Recently, with the increasing of customers' requirements on the quality of hot-rolled strip, the operating performance of hot-rolled strip laminar cooling (HSLC) processes becomes more and more important in hot-rolled strip manufactory, since HSLC is crucial to the quality of production except of alloying elements and the mechanical properties of strip are directly determined by the cooling curve and coiling temperature (CT) of strip (Ding, Tang, Li, Wang, & Song, 2006). Thus, highly precise control of HSLC is extremely important. To precise control HSLC processes, one necessary condition is that the spatial distribution of strip temperature must be given. However, in real plant, the strip temperature can hardly be measured inside the cooling section due to the difficult ambient conditions. Thus, one part of this paper focuses on estimating the spatial distribution of whole strip's temperature with several temperature measurements, and the other part concentrates on the control method design for getting precise CT.

Some studies in estimating strip temperature are available in the literatures. Most of the existing methods use the thermodynamic model to estimate the spatial distribution of strip temperature (Han, Lee, Kim, & Jin, 2002; Serajzadeh, 2003). Since the measurements, e.g. CT, are not used to correct the dynamic model's outputs, the precision of the thermodynamic model has to be severely high. However to get very precise HSLC model is a very hard and expensive work since the shape and grade of strip, and the environment temperature, etc. greatly affect the cooling process. In order to precisely estimate the spatial distribution of strip transient temperature, one effective method is to use measurement signals to correct the results estimated only by model, and then to restrain the disturbances. Fortunately, this class of problems, the design of observers for nonlinear systems, is widely studied in the process control community (Grip, Saberi, & Johansen, 2012; Karafyllis & Kravaris, 2012). And Zheng and Li (2011) present an idea of using extended Kalman filter (EKF) to deduct these disturbances, but some details of the method and how to design the controller based on this method are not discussed.

As for the control of HSLC, the existing method in manufactory uses the layout and constant water flux in main cooling zone to control the cooling rate (CR) of strip, and uses PID controller to adjust the water flux in fine cooling zone for regulating CT. Since the strip temperature at the inlet of fine cooling zone dramatically fluctuates, the PID controller is not competent for the increasing requirements of strip quality. Model predictive control (MPC) is naturally a good method to take this task since it could directly treat with measurable disturbances, and has been widely recognized as a practical control technology with high performance (Qin & Badgwell, 2003; Richalet, 1993). In MPC, a control action

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sequence is obtained by solving, at each sampling instant, a finite horizon open-loop receding optimization problem and the first control action is applied to the processes (Zheng, Li, & Qiu, in press). It has been applied successfully to various linear, nonlinear systems in process industries and is becoming more widespread (Lee, Kumara, & Gautam, 2008; Li, Zheng, & Wang, 2008; Maciejowski, 2002; Peng, Nakano, & Shioya, 2007; Zheng, Li, & Wang, 2011). This stimulates to design an MPC for HSLC processes.

Considering the high order and the nonlinear characteristics of the lumped state space model of HSLC, in this paper, the EKF is chosen to monitor the strip temperature in cooling zone since EKF is convenient designation for high dimension system. Moreover, a trade-off feed-back coefficient is designed in EKF to coordinate the convergence rate and stability of EKF. In addition to the design of EKF, an EKF and MPC based control strategy is developed to improve the precision of CT. In main cooling zone, a predictor is designed to predict the future temperature sequence at the inlet of fine cooling zone according to system models and current temperature obtained from EKF. Then this predictive sequence is feed to the MPC, and the MPC optimizes the water flux in fine cooling zone to improve the control accuracy of CT. Moreover, the implementation of EKF and MPC to an HSLC process in manufactory is conducted to validate their performance.

This paper is organized as follows: Section 2 presents the HSLC process and its thermodynamic model with a reasonable accuracy; Section 3 designs the strip temperature monitoring method. Section 4 is dedicated to develop the proposed MPC for HSLC based on the designed EKF. Section 5 discusses the numerical and experimental results. Finally, conclusions are stated in Section 6.

2. HSLC process

2.1. Process description

The HSLC process studied here is illustrated in Fig. 1. The steel strip with length of 200–1100 m arrives at the inlet of laminar cooling equipment at finishing rolling temperature (FRT) of 750–900 °C, and is cooled down to CT 400–600 °C by the laminar cooling equipment. There are 90 top headers and 90 bottom headers in laminar cooling equipment. These headers are grouped by 12 banks, first nine banks for the main cooling zone and last three banks for the fine cooling zone. The gauge of strip is measured by the X-ray gauge installed after finishing mill. Coiling speed is measured by the speed tacho-meters installed on the rollers' motors and the coilers' mandrels. FRT and CT are measured by pyrometers installed after the finishing mill and before the coiler, respectively.

The control objective is to control CR and CT of each strip point to be consistent with a predefined values.

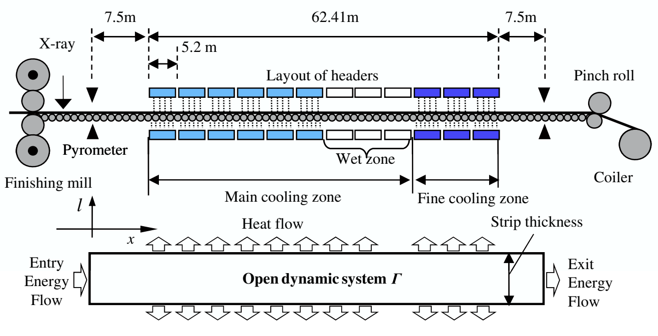

Fig. 1. The schematic of hot-rolled strip laminar cooling process.

The manipulated variables are the fluxes of cooling water at the banks of spraying headers and all of them are separately adjustable.

2.2. First principle model

The location of finishing mill, bottom surface of strip, the location of coiler, and the top surface of strip, as shown in Fig. 1, enclose a open thermodynamic system Γ. Then combining the research results in Zhang, Wang, Li, and Li (2007), Liu, Zhang, Sun, GaoPeng, and Su (2012), and Zheng, Li, and Wang (2010), the HSLC process can be modeled as

$$\dot{T} = -\frac{\lambda(T)}{\rho(T)\cdot cp(T)}\cdot\frac{\partial^2 T}{\partial l^2} - \dot{x}\cdot\frac{\partial T}{\partial x} \tag{1}$$

with the boundary conditions on the top and bottom surfaces

$$\pm\lambda(T)\frac{\partial T}{\partial l} = h(T-T_\infty) \tag{2}$$

where

$$h = h_w\frac{T-T_w}{T-T_\infty} + \sigma_0\varepsilon\frac{T^4-T_\infty^4}{T-T_\infty} \tag{3}$$

$$h_w = \alpha\frac{2186.7}{10^6}\left(\frac{T}{T_0}\right)^a\left(\frac{v}{v_0}\right)^b\left(\frac{F}{F_0}\right)^c \tag{4}$$

In (4), $T_0 = 1000$ °C, $v_0 = 20$ m/s, $a = 1.62$, $b = -0.4$, $c = 1.41$. This first principle model assumes that $\lambda(T)$ is no direction dependency heat conductivity, the heat transfer in width direction and length direction is neglected. The latent heat of phase transformation is considered through the temperature-dependent thermal property (Pehlke, Jeyarajan, & Wada, 1982; Zheng & Li, 2011). In (3), the first right term is zero when the strip is out of water cooling section, and the second term is zero when the strip is cooled by cooling water.

Though these models could estimate the strip temperature in straightforward approach, the accumulate errors caused by iterative hampers precisely monitoring strip temperature and make it hard to directly be used in real-time control. Thus it is necessary to develop a monitoring method to observe the strip transient temperature in water cooling zone for the better control of HSLC.

3. EKF based monitoring method

3.1. State space model of HSLC

Observers are usually used to infer the unmeasured states from measurements. It is just what the monitoring method wants to be realized. For easy design the observer of HSLC, the (1) should firstly transform into lumping parameter model.

Using 2D finite volumes method (Welty, Wicks, Rorrer, & Wilson, 2009), model (1) can be reduced into a finite dimensional problem. Divide the open thermodynamic system Γ into $n\times m$ volumes, as shown in Fig. 2, where δx and δl are the length and thickness of each volume, respectively.

Define that $T_{i,j}$ as the temperature of ith in l-direction and jth in x-direction volume. Applying energy balance to the up and

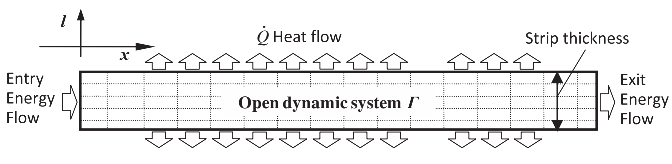

Fig. 2. The spatial meshing of the open dynamic system.

bottom surface volumes leads to

$$\dot{T}_{1,j} = -\frac{\lambda(T_{1,j})}{\rho(T_{1,j})cp(T_{1,j})}\left(\frac{1}{\delta l^2}(T_{2,j}-T_{1,j}-\delta l\frac{h_{1,j}}{\lambda(T_{1,j})}(T_{1,j}-T_\infty))\right) - \frac{1}{\delta x}\cdot v(T_{1,j}-T_{1,j-1}) \quad (5)$$

$$\dot{T}_{m,j} = -\frac{\lambda(T_{m,j})}{\rho(T_{m,j})cp(T_{m,j})}\left(\frac{1}{\delta l^2}(T_{m-1}-T_m-\delta l\frac{h_{m,j}}{\lambda(T_{m,j})}(T_{m,j}-T_\infty))\right) - \frac{v}{\delta x}\cdot(T_{m,j}-T_{m,j-1}) \quad (6)$$

for the other volumes

$$\dot{T}_{i,j} = -\frac{1}{\delta l^2}\frac{\lambda(T_{i,j})}{\rho(T_{i,j})cp(T_{i,j})}(T_{i+1,j}-2T_{i,j}+T_{i-1,j}) - \frac{1}{\delta x}\cdot v(T_{i,j}-T_{i,j-1}) \quad (7)$$

where $v=\dot{x}$ is the velocity of strip.

Denote the measurable disturbance, FTR, as

$$\mathbf{T}_0(t) = [T_{1,0}\ \ T_{2,0}\ \ \cdots\ \ T_{m,0}]^{\mathrm{T}} \quad (8)$$

Set the heat transfer coefficients be mediate inputs, and

$$\mathbf{u}(t) = [h_{1,1}(t)\ \ h_{m,1}(t)\ \ h_{1,2}(t)\ \ h_{m,2}(t)\ \ \cdots\ \ h_{1,n}(t)\ \ h_{m,n}(t)]^{\mathrm{T}} \quad (9)$$

where $h_{1,i}(t)$ and $h_{m,i}$, $i=1,2,\ldots,n$ are heat transfer coefficients of the corresponding volumes. Define each volume' temperature as the state of system, the CT (both the top surface of strip and the bottom surface of strip) as the outputs of system:

$$\mathbf{T} = [\mathbf{T}_1^{\mathrm{T}}\ \ \mathbf{T}_2^{\mathrm{T}}\ \ \cdots\ \ \mathbf{T}_n^{\mathrm{T}}]^{\mathrm{T}}$$
$$\mathbf{T}_j = [T_{1,j}\ \ T_{2,j}\ \ \cdots\ \ T_{m,j}]^{\mathrm{T}} \quad (j=1,2,\ldots,n) \quad (10)$$

$$\mathbf{y}(t) = [T_{1,n}\ \ T_{m,n}]^{\mathrm{T}} \quad (11)$$

Define that $a(T_{i,j}) = -\lambda(T_{i,j})/(\delta l^2\rho(T_{i,j})cp(T_{ij}))$, $\gamma = v/(2\delta x)$, and $\beta(T_{i,j}) = a(T_{i,j})/\lambda(T,i,j)$, and substitute them into (5), (6) and (7), then a nonlinear state space model of HSLC can be expressed as

$$\dot{\mathbf{T}} = \mathbf{f}(\mathbf{T})\cdot\mathbf{T} + \mathbf{g}(\mathbf{T})\cdot\mathbf{u}(t) + \mathbf{D}\mathbf{T}_0(t)$$
$$\mathbf{y}(t) = \mathbf{H}\mathbf{T} \quad (12)$$

where

$$\mathbf{f}(\mathbf{T}) = \begin{bmatrix} \mathbf{\Phi}_1(\mathbf{T})\mathbf{\Lambda} & 0 & \cdots & 0 \\ 0 & \mathbf{\Phi}_2(\mathbf{T})\mathbf{\Lambda} & & \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{\Phi}_n(\mathbf{T})\mathbf{\Lambda} \end{bmatrix} + \begin{bmatrix} -\gamma\mathbf{I}_m & 0 & \cdots & 0 \\ \gamma\mathbf{I}_m & -\gamma\mathbf{I}_m & & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & \gamma\mathbf{I}_m & -\gamma\mathbf{I}_m \end{bmatrix} \quad (13)$$

$$\mathbf{g}(\mathbf{T}) = \begin{bmatrix} \mathbf{\Psi}_1(\mathbf{T}) & 0 & \cdots & 0 \\ 0 & \mathbf{\Psi}_2(\mathbf{T}) & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{\Psi}_n(\mathbf{T}) \end{bmatrix} \times \begin{bmatrix} \mathbf{B}_1(\mathbf{T}) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{B}_n(\mathbf{T}) \end{bmatrix} \quad (14)$$

$$\mathbf{D} = [\gamma\mathbf{I}_m\ \ 0^{m\times m}\ \ \cdots\ \ 0^{m\times m}]^{\mathrm{T}} \quad (15)$$

$$\mathbf{H} = \begin{bmatrix} 0^{1\times(n-1)m} & 1 & 0^{1\times(m-1)} \\ 0^{1\times(n-1)m} & 0^{1\times(m-1)} & 1 \end{bmatrix} \quad (16)$$

and

$$\mathbf{\Phi}_j(\mathbf{T}) = \begin{bmatrix} a(T_{1,j}) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a(T_{m,j}) \end{bmatrix}$$

$$\mathbf{\Psi}_j(\mathbf{T}) = \begin{bmatrix} \beta(T_{1,j}) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta(T_{m,j}) \end{bmatrix}$$

$$\mathbf{B}_j(\mathbf{T}) = \begin{bmatrix} (T_{1,j}-T_\infty) & 0^{(m-2)\times 1} \\ 0^{(m-2)\times 1} & 0 \\ 0 & (T_{m,j}-T_\infty) \end{bmatrix}$$

$$\mathbf{I}_m \in R^{m\times m}$$

$$\mathbf{\Lambda} = \begin{bmatrix} -1 & 1 & 0 & \cdots & 0 \\ 1 & -2 & 1 & \cdots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & 1 & -2 & 1 \\ 0 & \cdots & 0 & 1 & -1 \end{bmatrix}$$

Given the initial spatial distribution of strip temperature, the strip's FRT and the heat transfer coefficients, the future spatial distribution of strip temperature can be calculated through the above equations. However the states of system model are unknown. It demonstrates that to design an observer to reconstruct the temperature distribution of strip is necessary.

3.2. Design of EKF

For nonlinear system, one class of first-order observers linearize the nonlinear systems at current operating point and design observer based on the linearized model, e.g. the EKF (Gryzlov, Leskens, & Mudde, 2011; Ljung, 1979) and extended Luenberger observer (Zeitz, 1987). Another class of approaches transform the nonlinear models into an observable canonical form and then design the observer based on the canonical form, e.g. the "high-gain observers" (Boizot, Busvelle, & Gauthier, 2010; Tornambé, 1992). Moreover, there are some methods which are designed based on presenting the uncertainty on the structure and/or the parameters of model, e.g. asymptotic observers (Dochain, Perrier, & Ydstie, 1992), sliding-mode observers (Davila, Fridman, & Levant, 2005; Edwards, Spurgeon, Tan, & Patel, 2007; Tan, Yu, & Man, 2010), adaptive observers (Farza, M'Saad, Maatoug, & Kamoun, 2009; Marino, 1990). As for HSLC processes, to get an accurate HSLC model using finite volumes method, a high dimension of system model would be inevitable. If using high gain methods, the observer will be too frangible. Though the EKF is more convenient to design, it is difficult to tune the rate of convergence.

Fortunately, Boutayeb and Aubry (1999) presents a modified method which could significantly improve the convergence of the EKF using a trade-off matrix $\mathbf{R}(t)$. Thus, the EKF with the trade-off matrix is chosen since it is more convenient to design in this case.

The EKF with trade-off matrix observer is given by the following structure (Jazwinski, 1970):

$$\dot{\hat{\mathbf{T}}} = \mathbf{f}(\hat{\mathbf{T}})\hat{\mathbf{T}} + \mathbf{g}(\hat{\mathbf{T}})\mathbf{u}(t) + \mathbf{D}\mathbf{T}_0(t) + \mathbf{K}(t)(\mathbf{y}(t) - \mathbf{H}\hat{\mathbf{T}})$$
$$\mathbf{K}(t) = \mathbf{P}(t)\mathbf{\Lambda}^{\mathrm{T}}(t)\mathbf{R}^{-1}(t) \quad (17)$$

where $\mathbf{K}(t)$ is the resulting observer's gain, and the following *Riccati* equation must be satisfied:

$$\dot{\mathbf{P}}(t) = \mathbf{\Gamma}(\hat{\mathbf{T}})\mathbf{P}(t) + \mathbf{P}(t)\mathbf{\Gamma}^{\mathrm{T}}(\hat{\mathbf{x}}) + \mathbf{Q}(t) - \mathbf{P}(t)\mathbf{\Lambda}^{\mathrm{T}}(\hat{\mathbf{T}})\mathbf{R}^{-1}(t)\mathbf{\Lambda}(\hat{\mathbf{x}})\mathbf{P}(t) \quad (18)$$

where

$$\boldsymbol{\Gamma}(\hat{\mathbf{T}}) = \frac{\partial[\mathbf{f}(\mathbf{T})\cdot\mathbf{T}+\mathbf{g}(\mathbf{T})\cdot\mathbf{u}]}{\partial \mathbf{T}}\bigg|_{\mathbf{T}(t)=\hat{\mathbf{T}}(t)} \qquad \boldsymbol{\Lambda}(\hat{\mathbf{T}})=\mathbf{H} \tag{19}$$

$\mathbf{Q}(t)>0$ and $\mathbf{R}(t)>0$ are symmetric matrices. It should be noted that, with the increasing of $\mathbf{R}(t)$, the system would be more stable but the convergence rate of EKF would be more slow (Boutayeb & Aubry, 1999). Thus, a trade-off between stability and rate of convergence can be obtained by

$$\mathbf{R}(t)=\mu\mathbf{K}^{\mathrm{T}}(t)\mathbf{P}(t)\mathbf{K}(t)+\zeta\mathbf{I}_p \tag{20}$$

where ζ and μ are design parameters with $\zeta>0$ and $\mu>0$; p is the outputs dimension.

Now, the design of HSLC model and the EKF based monitoring method is completed. Based on the observed spatial distribution of strip transient temperature, the real-time controller is designed in the next section.

4. Control of HSLC

4.1. Exiting method

In manufactory, as shown in Fig. 3, the strip runs from left to right with a constant coiling velocity v_c. The cooling water flux in main cooling zone is used to roughly control CR and CT. The cooing water flux in fine cooling zone is used to improve the precision of CT.

In main cooling zone, the water flux of each opened bank equals to each other, and is controlled by a PI controller. Its' set point F_m^* is determined by the desired CR, R_C^*, and is obtained by lookup table. The number of opened banks N_o is calculated by the following equation:

$$N_o=\frac{v_c}{l_h}\cdot\frac{\overline{T}_F-T_C^*}{R_C} \tag{21}$$

where $\overline{T}_F$ is the average FRT, T_C^* is the CT set point, l_h is the length in run-out table corresponding to one header bank and R_C^* is the CR set point.

In fine cooling zone, as shown in Fig. 3, the process variable of PID controller is T_C and output of the controller is the set point of the flux of each bank in fine cooling zone. The flux of each bank F_f is regulated by a PI controller.

Since CT is dramatically effected by the strip temperature after main cooling zone, this disturbance cannot be well deducted by the PID controller. Therefore a new approach which could improve the precision of CT is needed.

4.2. Proposed method

Since MPC offers good dynamic performance, handles measurable disturbances and caters for hard actuator limits and other

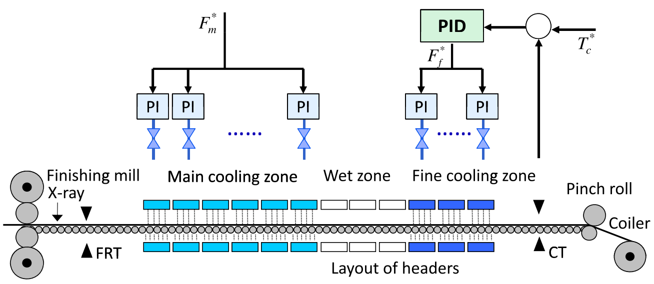

Fig. 3. Schematic of existing control method for HSLC.

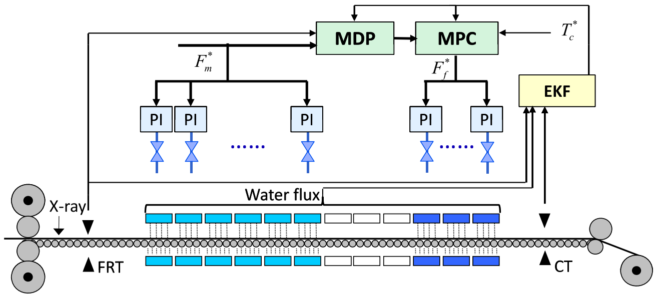

Fig. 4. Schematic of MPC based controller for HSLC.

system constraints in a straightforward manner, an MPC based control algorithm is developed for HSLC.

The control schematic is shown in Fig. 4. The difference between the proposed method and existing method focuses on the control in fine cooling zone. The proposed method consists of three parts, the EKF, the measurable disturbance predictor (MDP) and the MPC. The EKF estimates the current temperature distribution of strip along run-out table. Then the MDP predicts the future strip temperature sequence at the inlet of fine cooling zone and sends them to MPC. Finally the MPC calculates the optimal water flux in the fine cooling to optimize the CT according to the feeding measurable disturbance sequence from MDP and the current strip temperature distribution estimated by EKF. The details of the MDP and MPC are presented in the below context.

4.2.1. Subsystem model

The division of whole HSLC system is based on the layout of cooling water spraying headers. Set the system from FRT sensor to the inlet of water cooling section be the 1st subsystem, each area under each spraying header bank be one individual subsystem, and the area from the outlet of water cooling section to coiler be the last subsystem. Denote the sth subsystem with $\mathcal{S}_s$. According to (12) and Euler method, the discrete subsystem model of $\mathcal{S}_s$ can be directly written as follows (Zheng & Li, 2011; Zheng, Li, & Li, 2011):

$$\begin{cases}\mathbf{T}^s(k+1)=\mathbf{A}_{ss}\mathbf{T}^s(k)+\mathbf{B}_{ss}u^s(k)+\mathbf{D}_{s,s-1}\mathbf{T}^{s-1}(k)\\ y^s(k)=\mathbf{C}_{ss}\mathbf{T}^s(k)\\ s=1,2,\ldots,N\end{cases} \tag{22}$$

where N is the number of subsystems; $\mathbf{A}_{ss}$, $\mathbf{B}_{ss}$, $\mathbf{D}_{s,s-1}$ and $\mathbf{C}_{ss}$ are coefficient matrices of $\mathcal{S}_s$; $\mathbf{T}^s=[(\mathbf{T}_{j_{s1}})^{\mathrm{T}}\ (\mathbf{T}_{j_{s2}})^{\mathrm{T}}\ \cdots\ (\mathbf{T}_{j_{sn}})^{\mathrm{T}}]^{\mathrm{T}}$ is the state vector of $\mathcal{S}_s$, $j_{s1}\ldots j_{sn}$ are the columns that $\mathcal{S}_s$ owned; y^s is the average strip temperature in thickness direction at the outlet of $\mathcal{S}_s$, u^s is the input of $\mathcal{S}_s$ and there is a fixed relationship between u^s and the water flux in $\mathcal{S}_s$ as follows:

$$\begin{cases}u^s=2186.7\times10^{-6}\times a\left(\dfrac{v}{v_0}\right)^b\left(\dfrac{F_s}{F_0}\right)^c, & \mathcal{S}_s\in\mathcal{C}_W\\ u^s=1, & \mathcal{S}_s\in\mathcal{C}_A\end{cases} \tag{23}$$

where $\mathcal{C}_W$ is the set of subsystems in which strip is cooled by water; $\mathcal{C}_A$ is the set of subsystems in which strip is cooled major through radiation; F_s is the water flux of the water spraying header in $\mathcal{S}_s$; a, b, c, F_0 and v_0 are constants, and their detailed definitions are available in Zheng et al. (2010) and Zheng and Li (2011).

4.2.2. Measurable disturbance predictor

From (22) and (23), the future states of each subsystem in main cooling zone can be expressed as

$$\hat{\mathbf{T}}^s(k+i)=\mathbf{A}_{ss}^i\mathbf{T}^s(k)+\sum_{h=0}^{i-1}\mathbf{A}_{ss}^h\mathbf{B}_{ss}u_m$$

$$+\sum_{h=0}^{i-1}\mathbf{A}_{ss}^{h}\mathbf{D}_{s,s-1}\mathbf{T}^{s-1}(k+h) \tag{24}$$

where the state of $\mathbf{T}_s(k)$ can be obtained from EKF, and

$$\begin{cases} u_m = 2186.7\times 10^{-6}\times a\left(\dfrac{v}{v_0}\right)^{b}\left(\dfrac{F_m^*}{F_0}\right)^{c}, & s=2,3,\ldots,N_o+1 \\ u_m = 1 & s=1,N_o+2,\ldots,10 \end{cases}$$

Cascade calculate the states of subsystems from left to right, then the future temperature sequence at the inlet of fine cooling zone is obtained.

4.2.3. MPC formulation

The objective of MPC is to optimize CT through the water flux in fine cooling zone. Since $\mathbf{T}^s(k)$ can be observed by the designed EKF at time k, assume that $\mathbf{T}^s(k)$ is available. $\hat{\mathbf{T}}^{10}(k+i|k)$ can be obtained from MDP. Handling the constraints of manipulated variables, the increments of manipulated variables, CT and the increments of CT. Then the MPC becomes solving the following optimization problem at each sampling time instant k:

$$\begin{aligned}
&\min_{\Delta\mathbf{U}(k)} \sum_{i=1}^{P}\|T_c^* - \hat{T}_c(k+i|k)\|_{q_i}^2 + \sum_{j=1}^{M}\|\Delta u_f(k+j-1|k)\|_{g_i}^2 \\
&\text{s.t.}\quad \hat{\mathbf{T}}^{s}(k+i) = \mathbf{A}_{ss}^{i}\mathbf{T}^{s}(k) + \sum_{h=0}^{i-1}\mathbf{A}_{ss}^{h}\mathbf{B}_{ss}u_f(k+h|k) \\
&\qquad + \sum_{h=0}^{i-1}\mathbf{A}_{ss}^{h}\mathbf{D}_{s,s-1}\hat{\mathbf{T}}^{s-1}(k+h), \quad s=11,12,13 \\
&\hat{\mathbf{T}}^{N}(k+i) = \mathbf{A}_{NN}^{i}\mathbf{T}^{N}(k) \\
&\qquad + \sum_{h=0}^{i-1}\mathbf{A}_{ss}^{h}\mathbf{B}_{ss} + \sum_{h=0}^{i-1}\mathbf{A}_{NN}^{h}\mathbf{D}_{N,N-1}\hat{\mathbf{T}}^{N-1}(k+h) \\
&\hat{T}_c(k+i|k) = \mathbf{C}_{NN}\hat{\mathbf{T}}^{N}(k+i) \\
&\Delta u_f^{\min} \le \Delta u_f(k+j-1) \le \Delta u_f^{\max} \\
&\Delta u_f^{\min} \le \Delta\overline{u}_f(k+j-1) \le \Delta u_f^{\max} \\
&T_c^{\min} \le \hat{T}_c(k+p|k) \le T_c^{\max} \\
&\Delta T_c^{\min} \le \hat{T}_c(k+p|k) - \hat{T}_c(k+p|k) \le \Delta T_c^{\max}
\end{aligned} \tag{25}$$

where $\Delta\mathbf{U}(k) = [\Delta u_f(k)\ \Delta u_f(k+1)\ \cdots\ \Delta u_f(k+M)]^{\mathrm{T}}$; $\{u_f^{\min},u_f^{\max}\}$, $\{\Delta u_f^{\min},\Delta u_f^{\max}\}$, $\{T_c^{\min},T_c^{\max}\}$ and $\{\Delta T_c^{\min},\Delta T_c^{\max}\}$ are boundaries of manipulated variable, increment of manipulated variable, CT and increment of CT, respectively; q_i and g_j are the weight coefficients; $N=14$. In each sampling time, MPC solves problem (25) and applies $u_f(k) = u_f(k-1) + \Delta u_f^*(k)$ to HSLC process to control the water flux of the headers in fine cooling zone, where $\Delta u_f^*(k)$ is the first element of optimal solution of problem (25).

So far, the proposed HSLC monitoring method and control algorithm is designed. Does it work well? Section 5 gives the validation of this method.

5. Numeric and experimental results

5.1. Validation of system model

To validate the designed model, an experiment is performed with the parameters of strip steel shown in Table 1. Seven header banks are opened with water flux of 233 $\mathrm{m^3/(s\,m^2)}$ in main cooling zone, and all header banks are opened with water flux of 150 $\mathrm{m^3/(s\,m^2)}$ in fine cooing zone. The coiling speed is 10.5 m/s.

In the transformation of system model, the open dynamic system mentioned above is divided into five volumes of 1.2 mm in l-direction and 14 volumes of 5.4 m in x-direction.

Table 1
Parameters of strip.

Item, unit	Values
T_w,K	298.5
T_∞, K	298.5
$\lambda(T_{1,i})$, W/(m K)	$56.43-(0.0363-c(v-v_0))\cdot T_{1,i}$
$\lambda(T_{m,i})$, W/(m K)	$56.43-(0.0363-c(v-v_0))\cdot T_{m,i}$
a, $\mathrm{mm^2/s}$, $T_{i,j}\in[400,650)$	$8.65+\dfrac{(5.0-8.65)(T_{i,j}-400)}{250}$
a, $\mathrm{mm^2/s}$, $T_{i,j}\in[650,700)$	$5.0+\dfrac{(2.75-5.0)(T_{i,j}-650)}{50}$
a, $\mathrm{mm^2/s}$, $T_{i,j}\in[700,800)$	$2.75+\dfrac{(5.25-2.75)(T_{i,j}-700)}{100}$
a, $\mathrm{mm^2/s}$, $T_{i,j}\in[800,1000]$	$5.25+0.00225(T_{i,j}-800)$

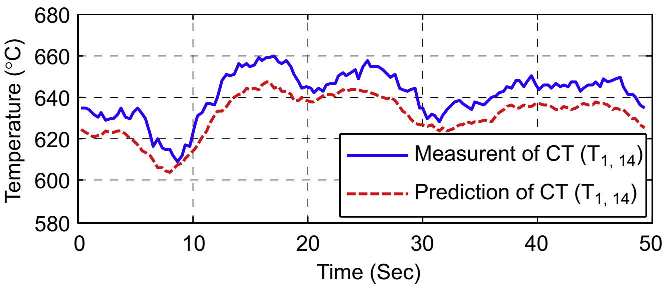

Fig. 5. The measurement and prediction of CT.

Fig. 5 shows the predictive CT by model (12) and the measurement of CT. The maximum bias between the prediction and the measurement is nearly 20 °C. It is because that, on the one hand, the predictive CT is obtained by the recursive of system model. The error of CT is enlarged large due to the accumulation of errors. On the other hand, it is too expensive to accurately model all types of strips since there are too many types of strips and each type of strip has different model coefficients, thus error exists in strip cooling model.

5.2. Validation of the monitoring method

5.2.1. Simulation

Two cases of simulations are carried out to validate the proposed monitoring method: (1) inputs varying and no measurement error, (2) inputs varying and the measurement disturbance existing in outputs. The covariance matrix $\mathbf{Q}$ in EKF was selected by try-and-error method. Set $\mu=0.2$ and $\zeta=1$, respectively.

*Case*1: In this case, different initial state vectors are used in process model and observer to validate the convergence of the monitoring method. The parameters given in Table 1 are used. Set the initial state vector of process model be the spatial distribution of strip temperature shown in Fig. 6(a), and set the initial state vector of observer be 30 °C higher than that of process model. As is shown in Fig. 6(b), the first six header banks in main cooling zone and the first two header banks in fine cooling zone are used to cooling strip. Set the flux of cooling water in main cooling zone and the flux of cooling water in fine cooling zone, as well as the FRT, all are time-varying, be those shown in Fig. 7. Set the coiling speed v be 9.96 m/s.

The simulation demonstrates, see Fig. 8, that even under the affection of FRT and the flux of cooling water in both main cooling zone and fine cooling zone, the results of observer could convergent to the results of system model.

*Case*2: In this case, a Gaussian random noise is added to the temperature sensor signals with zero mean and a standard deviation of $\pm 10\,^{\circ}$C to investigate the designed observer's characteristic of against noisy. The other design conditions are same as those in case 1 and are shown in Fig. 6 and Table 1.

The simulation results are shown in Fig. 9. Among these figures, (a)–(d) present the strip temperature estimated by observer and system model. These figures show that the noisy effects very small on the observer. Especially, it almost do nothing to the estimated strip temperature before the 11th header bank when using the proposed monitoring method. (e) and (f) give both the CT estimated by process model and the CT estimated by observer, as well as the CT with measurement noisy. These figures show that the EKF could effectively filter Gaussian random noise and give satisfactory estimates of the transient temperature of strip in HSLC processes.

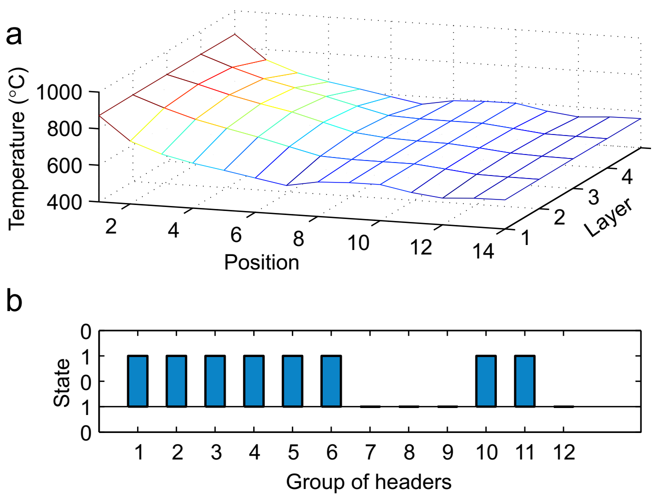

Fig. 6. (a)Initial spatial distribution of strip temperature in process model and (b) the states of header banks.

5.2.2. *Experimentation*

Apply the proposed monitoring method to the HSLC process at one steel Ltd. Co., China, and use a mobile pyrometer, which could work even in moisture, to measure the strip surface's temperature under 5th header bank. The result shown in Fig. 10 presents that the temperature measured by the mobile pyrometer and estimated by the proposed method are very close to each other.

5.3. *Performance of proposed controller*

To validate the performance of the proposed control method and further test the monitoring method, three tests are conducted in manufactory: (1) use the existing control method, (2) use the proposed control method but the result of EKF is not used in MDP, (3) use the proposed control method. Set the predictive horizon of MPC be 10, and the control horizon be 5. Experiences show that the computation in MPC could be accomplished within 0.2 s if the computer is not slower than the one with the 1.5 G CPU speed and 516 Mb memory. It is fast enough for the implementation, since the control period of HSLC is 0.37 s.

The experimental results are shown in Fig. 11–13. These figures show that the proposed method gets the best results, the amplitude of error of CT is less than 9 °C. And the result of test 2 is better than the result of test 1. That is because that the test 2 and test 3 handle the measurable disturbance in controllers. Moreover, the fact that the CT in test 3 is more accurate than that in test 2 also demonstrates that the EKF monitoring method do help to the control of HSLC process. In a conclusion, the EKF and MPC based control algorithm is an effective method for HSLC process, which could improve the precision of CT.

6. Conclusions

A method to monitor the spatial distribution of strip temperature and control the CT for HSLC processes is studied in this paper.

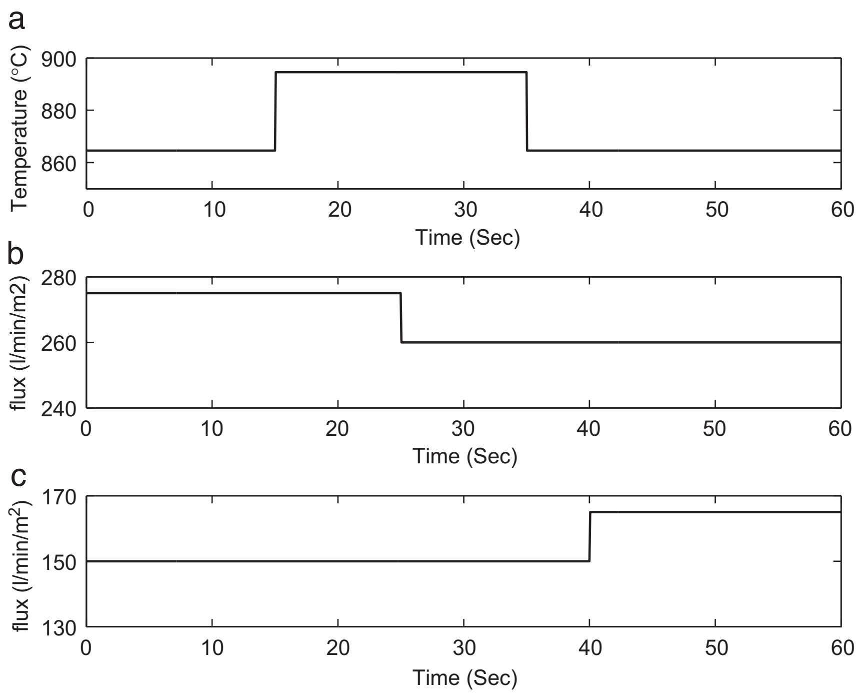

Fig. 7. (a) Strip's FRT, (b) flux of cooling water in main cooling zone, and (c) flux of cooling water in fine cooling zone.

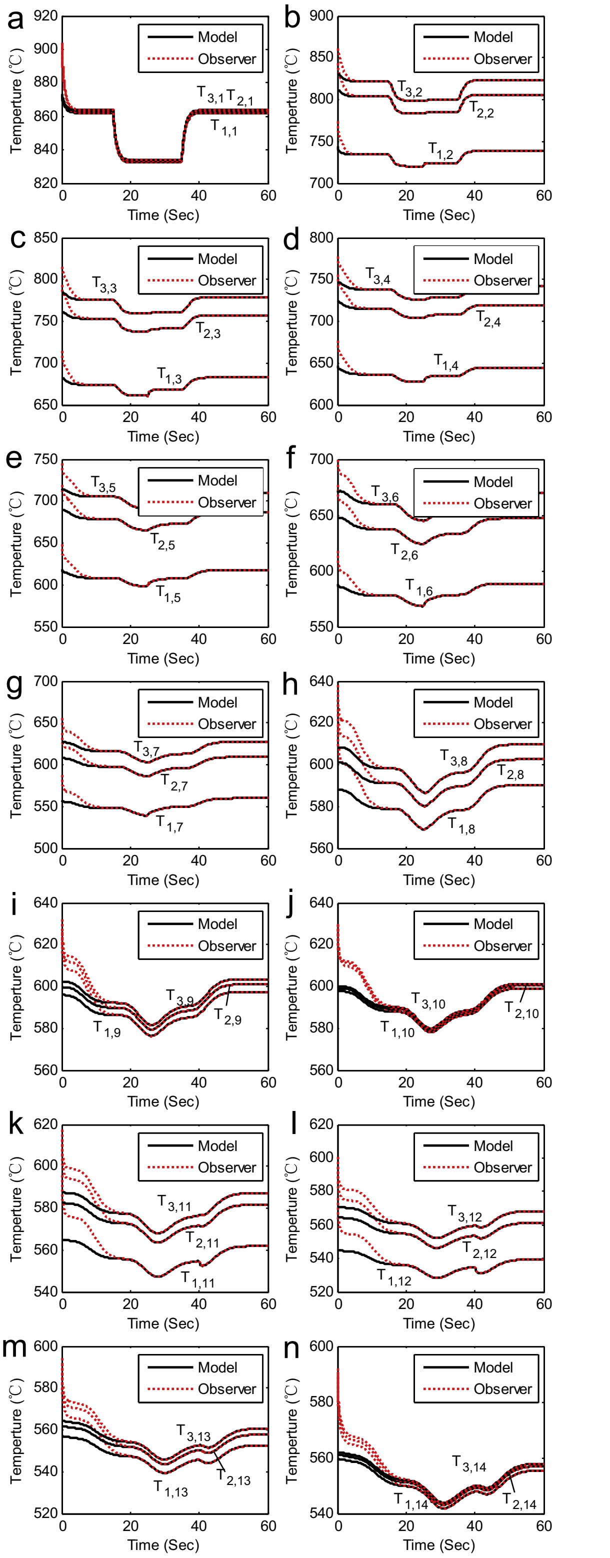

Fig. 8. Strip temperature calculated by process model and estimated by observer.

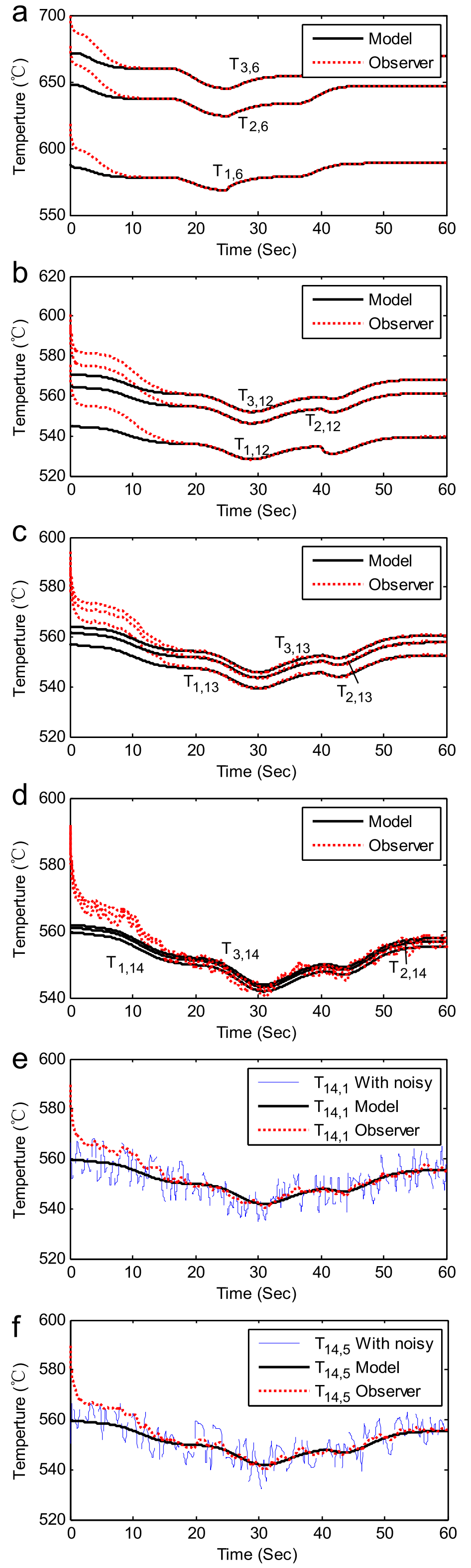

Fig. 9. (a)–(d) Strip temperature estimated by observer when measurement noise exist, strip temperature estimated by system model, (e), (f) CT estimated by observer with measurement noise, CT with measurement noise and CT estimated by process model.

Firstly, an accurate state space model is deduced to describe the evolution of strip temperature. Then a modified EKF, in which a time-varying trade-off matrix is designed to balance the stability and convergence speed of EKF, is developed to observe the spatial distribution of strip temperature in water cooling section. Finally, a MPC based control method is developed for the accurate control of CT. Experimentations and simulations prove that the proposed monitoring method could excellently reconstruct the spatial distribution of strip's temperature from several temperature measurements, even when the bias in initial temperature and/or measurement noise exist. And an improved precision of CT can be achieved by proposed control method.

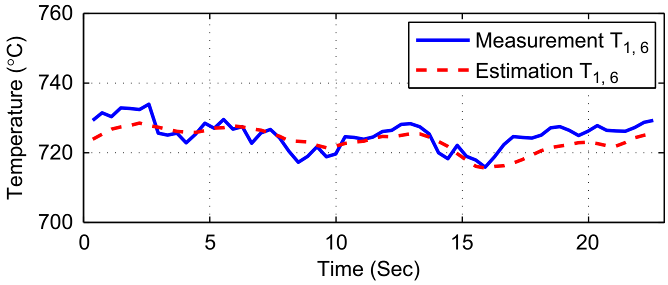

Fig. 10. Strip temperature measured by mobile pyrometer and estimated by proposed monitoring method.

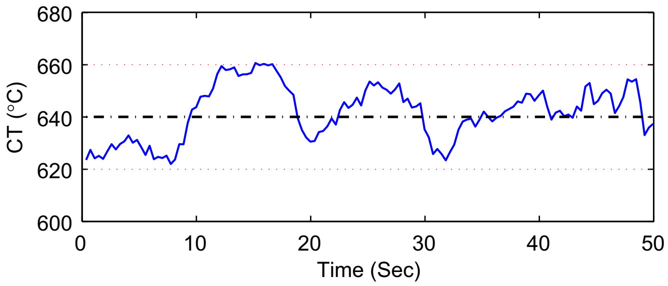

Fig. 11. The measurement CT under the control of existing method.

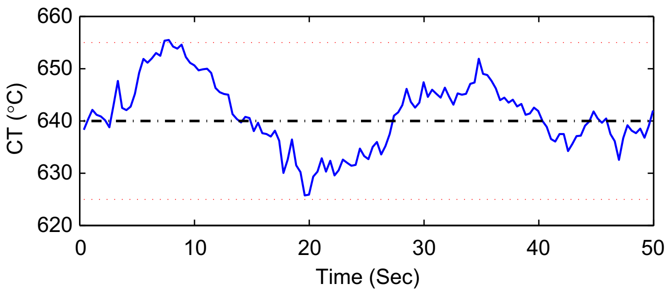

Fig. 12. The measurement CT under the control of MPC where the result of EKF is not used in MDP.

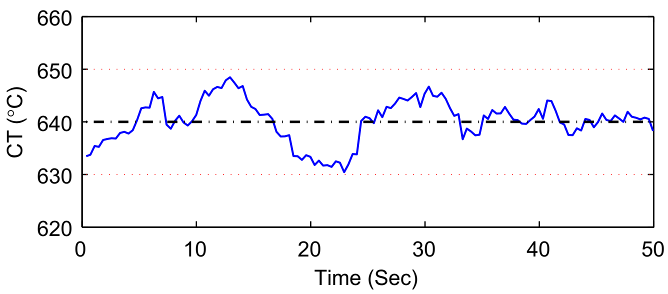

Fig. 13. The measurement CT under the control of proposed method.

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