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Data-Driven Quality Monitoring Techniques for Distributed Parameter Systems With Application to Hot-Rolled Strip Laminar Cooling Process

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ABSTRACT Distributed parameter systems (DPS) widely exist in the large-scale industrial production industry. Techniques developed for DPS can further demonstrate the complexity of the industrial process, such as the hot-rolled strip laminar cooling (HSLC) process. Due to the infinite dimensional of states variables and manipulated variables, it is a challenging work to model and monitor for DPS in practice. In this paper, a data-driven approach for process modeling and quality monitoring of DPS is obtained. A second-order partial differential equation (PDE) is transformed into finite-dimensional model of ordinary differential equation (ODE) with finite element method (FEM) and Galerkin method. Then, this model is described by state space with time-space separation. To realize the proposed scheme by the data-driven approach, we use the industrial process data to estimate the parameters in the model and basic functions by recursive least squares method. Based on this model, a kernel representation of DPS for residual generation is obtained in the statistical framework. T^2 statistic is employed to evaluate the residual and the threshold is determined by the use of noncentral χ^2-distribution. Finally, the effectiveness of the proposed scheme is demonstrated by conducting a simulation on the production process of HSLC.

INDEX TERMS Quality monitoring, fault diagnosis, data-driven, distributed parameter system, laminar cooling process.

I. INTRODUCTION

With the increasing demands on production efficiency, economic requirement and process safety, modern industrial processes are more complicated in both structure and automation degrees [1], which raises more possibility and harmfulness of the failure. Therefore, process monitoring and fault detection become two of the most critical aspects in industrial process. On the one hand, the intensive competition in the industrial market leads to higher requirements for the accuracy of the results [2], [3]. On the other hand, due to the high dimensional data, the strong correlation of variables and the effects of abnormal conditions, it is difficult to excavate and analyze available information from the historical data [4].

In order to ensure the accuracy of process data and the correctness of the results, modeling is difficult but essential to simulation, control and optimization. Techniques of modeling in lumped parameter systems (LPS) have been widely studied [5], [6]. However it ignores the spatial distribution characteristics of the controlled object. As a result, it can't reflect a real system [7], [8]. Distributed parameter systems (DPS) have the degrees of freedom with infinite dimensions. That means the DPS can further demonstrate the complexity of the physical phenomena. It is more suitable for real-time modeling and controlling. Many industrial processes such as biotechnology, material engineering and chemical engineering belong to DPS [9]. For example, the hot-rolled strip laminar cooling (HSLC) process, where the input, output and even parameters can vary both temporally and spatially, is usually described in partial differential equations (PDE). The dynamic characteristics of HSLC process will be restricted if it has been described by LPS. Actually, it is only an approximate description of DPS.

Based on the nature of time-space coupled, modeling of DPS can be classified into two types: modeling of grey box and modeling of black box [5]. For grey box modeling, the PDE description of DPS is known. It can be easily transformed into a finite-order of ordinary differential equations (ODE) or difference equations (DE). As reported in [10] and [11], problems of modeling in DPS can be synthesized into a time-space separation framework with boundary conditions. Such infinite-dimensional systems need to be approximated into finite-dimensional systems with the model reduction methods [12]. If the structure of DPS is not available, namely the black box modeling, it requires system identification and parameter estimation of DPS [13], [14]. Data-driven based methods are widely applied in the modeling of black box in DPS. The mapping relations between the output variables and the measurable variables in the other processes are established with the sample data which are generated in the production process [15], [16]. The model identification of DPS is an important area in the field of system identification [17], [18].

Compared with it in LPS, the problems of monitoring and fault detection become more challenging and attract much research interest in DPS. However, these models described by PDE are usually approximated into a finite-dimensional system to solve these problems [19]–[23], just like modeling of DPS. When fault occurs, the characteristic parameters in the system will change and the LPS description is inaccurate. It may lead to errors and unreliability [24]. In addition, DPS also belongs to a two-dimensional (2-D) system because of its time-space coupled nature. In [25] and [26], some methods have been proposed to solve the problems of fault diagnosis and process monitoring in 2-D system. These methods are only applied in the batch process, but it provides the basis for solving the problem of process monitoring in DPS.

In this paper, a data-driven approach for process modeling and quality monitoring of DPS is proposed. The main contributions of this paper are summarized as follows:

(1) The second-order PDE is transformed into finite-dimensional model of ODE with finite element method (FEM) and Galerkin method, which is described by the state space model with time-space synthesis.

(2) Based on the state space model, a kernel representation of DPS for residual generation is obtained in the statistical framework. T^2 statistic is employed to evaluate the residual and the threshold is determined using noncentral χ^2-distribution.

The rest of this article is organized as follows. In section II, the methods of modeling in DPS are reviewed, while the DPS model of laminar cooling process is transformed into a finite-dimensional system of ODE. In section III, a residual generator is constructed in detail, and the residual evaluation and threshold setting are proposed. In section IV, the application results on industrial benchmark of laminar cooling process are provided. This article ends with concluding remarks in the last section.

II. PROCESS DESCRIPTION

A. MODELING OF DISTRIBUTED PARAMETER SYSTEMS DESCRIPTION

The DPS includes PDE, functional differential equation (FDE), integral equation (IE) and the abstract differential equation in Banach or Hilbert space. We consider the DPS described by the following equations [20],

$$\begin{aligned} A(x)\frac{\partial^2 z(x,t)}{\partial t^2} &+ B(x)\frac{\partial^2 z(x,t)}{\partial t \partial x} + C(x)\frac{\partial^2 z(x,t)}{\partial x^2} \\ &+ D(x)\frac{\partial z(x,t)}{\partial t} + E(x)\frac{\partial z(x,t)}{\partial x} + F(x)z(x,t) \\ &+ G(x)y(x,t) + \eta(x,t) = 0, \quad \alpha \le x \le \beta, t \ge 0 \quad (1) \end{aligned}$$

The conventional form is

$$H(x, t, z_x, z_t, z_{xx}, z_{xt}, z_{tt}) = 0 \tag{2}$$

which are subject to either the Dirichlet boundary conditions

$$z(\alpha, t) = z_\alpha(t), z(\beta, t) = z_\beta(t) \tag{3}$$

or the Neumann boundary conditions

$$\begin{aligned} \left.\frac{\partial^j z(x,t)}{\partial x^j}\right|_{x=a_j} &= z_{\alpha_j}(t) \\ \left.\frac{\partial^j z(x,t)}{\partial x^j}\right|_{x=\beta_j} &= z_{\beta_j}(t), \quad j = 1, 2. \end{aligned} \tag{4}$$

and the initial condition

$$z(x, t) = z_0(x) \tag{5}$$

where $z(x,t) = [z_1(x,t) \cdots z_n(x,t)]^T$ denotes a vector of the state variables in the Hilbert space. $A(x)$, $B(x)$, $C(x)$, $D(x)$, $E(x)$, $F(x)$ and $G(x)$ are matrices of functions with approximate dimensions, $x \in [\alpha, \beta]$ denotes the spatial coordinate and t denotes the time.

Model reduction is essential to obtain a finite-order model for practical application based on the time-space coupled nature. The basic idea is generated from the Fourier transform. It is well known that a continuous function can be approximated using the Fourier series [6], [28]. The framework of time-space separation is illustrated in Fig.1. Based on that, the spatio-temporal variable $T(x,t)$ of DPS can be expanded by a set of spatial basic functions (BFs) $\{\phi_i(x)\}_{i=1}^{\infty}$ and time-domain function $\alpha_i(t)$ as follows,

$$T(x, t) = \sum_{i=1}^{\infty} \alpha_i(t)\phi_i(x) \tag{6}$$

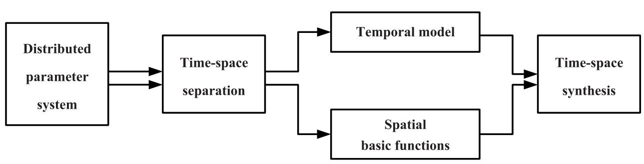

FIGURE 1. Framework of time-space separation in DPS.

The weighted residual method (WRM) is a frequently-used method for model reduction [29]. In recent years, a number of approaches have been developed for WRM based on the selection of weighted functions. The selection of spatial basic functions also has a great effect on the modeling performance [21]. The classification of spatial basis functions is shown in Table 1.

TABLE 1. Classification of spatial basis functions.

Type of BFs	
Local BFs	. Low-order piecewise . Splines . Wavelets... . Dirac delta functions
Global	. Fourier series . Eigenfunctions . Orthogonal polynomials . left or right singular functions

As shown in Table 1, the spatial BFs can be classified into local and global types. Fig.2 shows the geometric interpretation of time-space separation when $n = 3$. After the selection of BFs, the spatio-temporal will be approximated to the finite-dimensional model through the time-space synthesis. The most popular approaches appear to be Galerkin method [30] and Collocation method [31], which belong to WRM. Galerkin methods are a class of methods for converting a continous operator problem to a discrete problem [32]. The residual in the model is made orthogonal to each BFs. It does not need to find other weighting functions.

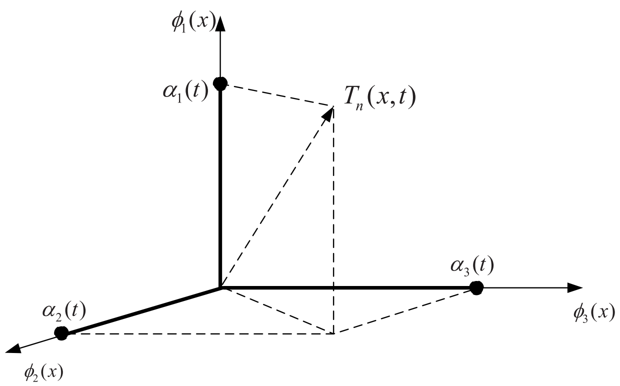

FIGURE 2. Geometric interpretation of WRM when $n = 3$.

Similar to Fourier series, the spatial BFs are often ordered from slow to fast in the spatial frequency domain. Because the fast modes contribute little to the whole system, only the first n slow modes in the expansion will be retained in practice [6]. This approach is referred to Galerkin method because the residual modes are completely ignored. As a result, Galerkin method will be used for model reduction in this paper.

B. FINITE DIMENSIONAL APPROXIMATION FOR DISTRIBUTED PARAMETER SYSTEMS IN LAMINAR COOLING PROCESS

It is important to assess the production quality of HSLC process. The mechanical properties of hot coil depend on the finish rolling temperature (FRT), the coiling temperature (CT) and the cooling rate (CR). When the coiling temperature exceeds the required range, the microstructure and properties of the strip will be worse [33], [34]. Therefore, the way to monitor the strip's transient temperature and measure the strip temperature inside the cooling section accurately will be extremely important.

The schematic diagram of laminar cooling process is illustrated in Fig.3. There are 120 top headers and 120 bottom headers in laminar cooling equipment. These cooling headers are divided into 14 groups. The first nine groups are considered as the main cooling zone and the last five groups are the fine cooling zone. Strips enter cooling section after the finishing process at finishing rolling temperature of 820–920°C. After the water cooling section, the strips are cooled at coiling temperature of 500–650°C [34].

In recent years, the research of thermal conduction problem has made a great progress in the application of temperature field mathematic model. It is widely applied in laminar cooling equipment of plate mill and some hot-rolled strip mill. However, the factors considered are not complete and the data are lack of screening. The laminar cooling process also belongs to DPS as mentioned in section I. Different from modeling in LPS, the distributed characteristics of temperature in the HSLC process are considered. A two-order differential equation of heat conduction is calculated as

$$\frac{\partial}{\partial x}\left(\lambda\frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(\lambda\frac{\partial T}{\partial y}\right)+\frac{\partial}{\partial z}\left(\lambda\frac{\partial T}{\partial Z}\right)+\dot{Q}=\rho c\frac{\partial T}{\partial t} \tag{7}$$

with the boundary conditions

$$\begin{aligned}\lambda\left(\frac{\partial T}{\partial x}+\frac{\partial T}{\partial y}\right)&=F\sigma({T_f}^4-{T_\alpha}^4)\\ \lambda\left(\frac{\partial T}{\partial x}+\frac{\partial T}{\partial y}\right)&=\alpha(T_s-T_w)\end{aligned} \tag{8}$$

and the initial condition

$$T_{t=0}=f(x,y,z) \tag{9}$$

where T denotes the temperature, °C; t denotes the time, s; x, y, z denote the coordinate value of length, width and depth, m; ρ denotes the strip density, kg/m^3; λ denotes the thermal conductivity, $W/(m\cdot k)$; $\dot{Q}$ denotes the thermal conductivity of heat sources; c denotes the specific heat capacity of strip, $J/(kg\cdot k)$; F denotes the stripąŕs surface, m^2; T_f denotes the surface temperature, °C; T_α denotes the ambient temperature, °C; T_w denotes the water temperature, °C; $\sigma = 5.67\times10^{-8}W/(m^2 \ldotp k^4)$ denotes the Boltzmann's constant.

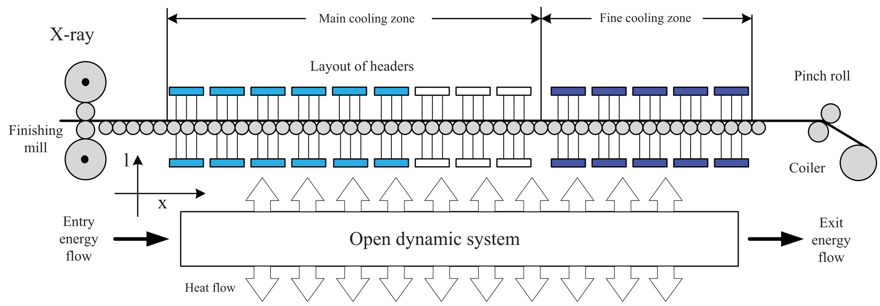

FIGURE 3. The schematic diagram of laminar cooling process in hot-rolled strip.

The model of HSLC process can be reduced into a finite dimensional model by FEM. It can be employed to handle complex geometries and boundaries with relative ease. The model is divided into the mesh with octahedral module. Referring to the related parameters in hot strip mill process, the basic model of the strip steel will be obtained with the mesh.

In order to reduce the complexity of modeling, a pair of water spray headers which are symmetric can be defined as a cooling action. Different heat transfer modes are adopted under different conditions with the change of switch in the cooling zone. The air or water cooling section can be determined by the switch state of the spray header groups.

By ignoring the temperature gradient in the width direction and considering the influence of latent heat of phase change, the equation can be simplified as follows

$$\frac{\partial}{\partial x}\left(\lambda\frac{\partial T}{\partial x}\right)+\dot{Q}=\rho c\frac{\partial T}{\partial t} \tag{10}$$

Firstly, the steel plate are divided into n sections and normalized in its length direction,

$$0<x_1<x_2<\ldots\ldots x_{n-1}<x_n<1. \tag{11}$$

Then orthogonal polynomials are selected as the basic functions

$$\varphi_i(x)=\begin{cases}\dfrac{x-x_{i-1}}{x_i-x_{i-1}} & x\in[x_{i-1},x_i]\\ \dfrac{x-x_{i+1}}{x_i-x_{i+1}} & x\in[x_i,x_{i+1}]\end{cases},\quad 1\le i\le n \tag{12}$$

which is indicated in the coordinate axis in Fig.4.

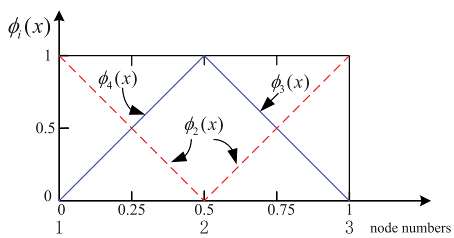

FIGURE 4. Orthogonal polynomial basic function.

Next, solve the weak solution of Eq.10. Given a full column-rank matrix V of BFs and $V=span\{\Phi_1(x),\Phi_2(x),\Phi3(x),\ldots\ldots\Phi_n(x)\}$. Then the spatio-temporal varible $T(x,t)$ can be expanded with time-space separation as follows

$$T_n(x,t)=\sum\nolimits_{i=2}^{n}\alpha_i(t)\Phi_i(x) \tag{13}$$

Let us denote $g(x)\in V$. Multiply $g(x)$ and integrate on both sides of Eq.10

$$\int_0^1\frac{\partial T}{\partial t}g(x)dx=\int_0^1 k\frac{\partial^2 T}{\partial x^2}g(x)dx+p\int_0^1 g(x)dx \tag{14}$$

where $k=\frac{\lambda}{\rho c}$, $p=\frac{\dot{Q}}{\rho c}$, and denote $f(x,t)=\frac{\partial T}{\partial x}$,

$$\begin{aligned}&\int_0^1 k\frac{\partial^2 T}{\partial x^2}g(x)dx\\&=-\int_0^1 f(x,t)\frac{dg(x)}{dx}dx+kg(1)\left(\sum\nolimits_{i=1}^{n}\alpha_i(t)\frac{d\Phi_i(x)}{dx}\bigg|_{x=1}\right)\\&\quad-kg(0)\left(\sum\nolimits_{i=1}^{n}\alpha_i(t)\frac{d\Phi_i(x)}{dx}\bigg|_{x=0}\right)\end{aligned} \tag{15}$$

$$\begin{aligned}&\sum\nolimits_{i=1}^{n}\frac{d\alpha_i(t)}{dt}\int_0^1\Phi_i(x)g(x)dx\\&=-\sum\nolimits_{i=1}^{n}\alpha_i(t)\int_0^1\frac{d\Phi_i(x)}{dx}\frac{dg(x)}{dx}dx+p\int_0^1 g(x)dx\\&\quad+\sum\nolimits_{i=1}^{n}\alpha_i(t)\left\{kg(1)\frac{d\Phi_i(x)}{dx}|_{x=1}-kg(0)\frac{d\Phi_i(x)}{dx}|_{x=0}\right\}\end{aligned} \tag{16}$$

by substituting $\Phi_j(x)$ into $g(x)$, we have

$$\begin{aligned}&\sum\nolimits_{i=1}^{n}\frac{d\alpha_i(t)}{dt}\int_0^1\Phi_i(x)\Phi_j(x)dx\\&=-\sum\nolimits_{i=1}^{n}\alpha_i(t)\int_0^1\frac{d\Phi_i(x)}{dx}\cdot\frac{d\Phi_j(x)}{dx}dx+p\int_0^1\Phi_j(x)dx\\&\quad+\sum\nolimits_{i=1}^{n}\alpha_i(t)\left\{k\Phi_j(1)\frac{d\Phi_i(x)}{dx}|_{x=1}-k\Phi_j(0)\frac{d\Phi_i(x)}{dx}|_{x=0}\right\}\end{aligned} \tag{17}$$

Finally, a linear state space model of HSLC can be expressed as

$$\begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,n} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,n} \\ \vdots & \vdots & m_{i,j} & \vdots \\ m_{n,1} & m_{n,2} & \cdots & m_{n,n} \end{bmatrix} \begin{bmatrix} \dot{\alpha_1}(t) \\ \dot{\alpha_2}(t) \\ \vdots \\ \dot{\alpha_n}(t) \end{bmatrix} = \begin{bmatrix} k_{1,1}+N_{1,1} & k_{1,2}+N_{1,2} & \cdots & k_{1,n}+N_{1,n} \\ k_{2,1}+N_{2,1} & k_{2,2}+N_{2,2} & \cdots & k_{2,n}+N_{2,n} \\ \vdots & \vdots & k_{i,j}+N_{i,j} & \vdots \\ k_{n,1}+N_{n,1} & k_{n,2}+N_{n,2} & \cdots & k_{n,n}+N_{n,n} \end{bmatrix} \cdot \begin{bmatrix} \alpha_1(t) \\ \alpha_2(t) \\ \vdots \\ \alpha_n(t) \end{bmatrix} + \begin{bmatrix} g_1(x) \\ g_2(x) \\ \vdots \\ g_n(x) \end{bmatrix} \tag{18}$$

where

$$m_{i,j} = \int_0^1 \Phi_i(x)\Phi_j(x)dx, \quad k_{i,j} = -\int_0^1 \frac{d\Phi_i(x)}{dx}\frac{d\Phi_j(x)}{dx}dx,$$

$$g_i(x) = p\int_0^1 \Phi_j(x)dx,$$

$$N_{i,j}(x) = k\Phi_j(1)\frac{d\Phi_i(x)}{dx}|_{x=1} - k\Phi_j(0)\frac{d\Phi_i(x)}{dx}|_{x=0}, \quad 1 \le i,j \le n.$$

The state space model can be represented as

$$U[\dot{\alpha}(t)] = K[\alpha(t)] + G \tag{19}$$

where

$$U = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,n} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,n} \\ \vdots & \vdots & m_{i,j} & \vdots \\ m_{n,1} & m_{n,2} & \cdots & m_{n,n} \end{bmatrix},$$

$$K = \begin{bmatrix} k_{1,1}+N_{1,1} & k_{1,2}+N_{1,2} & \cdots & k_{1,n}+N_{1,n} \\ k_{2,1}+N_{2,1} & k_{2,2}+N_{2,2} & \cdots & k_{2,n}+N_{2,n} \\ \vdots & \vdots & k_{i,j}+N_{i,j} & \vdots \\ k_{n,1}+N_{n,1} & k_{n,2}+N_{n,2} & \cdots & k_{n,n}+N_{n,n} \end{bmatrix},$$

$$G = \begin{bmatrix} g_1(x) \\ g_2(x) \\ \vdots \\ g_n(x) \end{bmatrix}$$

Remark: Matrix U is used to denote the part of unsteady heat conduction. K denotes the part of steady heat conduction. G denotes the hot-splitting of node matrix. Eq.18 is a finite-dimensional model which is approximated by the PDE.

The state space description of DPS has been obtained by model reduction. To realize the proposed scheme by the data-driven approach, we can use the traditional method to estimate the parameters in state space model and basic functions such as partial least squares (PLS) method [35] and subspace method [36].

III. MODEL-BASED DESIGN OF RESIDUAL GENERATOR FOR DPS

A. MODEL-BASED DESIGN OF RESIDUAL GENERATOR FOR DPS

Model reduction by FEM often generates a model with high-order description. It may bring large computation. In order to design an implementable monitoring system, the order of state variables must be reduced to a lower one. The realization of the dimensional reduction for state space is based on the idea of projection. To simplify notations, let us define the following operations,

$$(m(x), n(x)) = \int_\alpha^\beta m(x)n(x)dx \tag{20}$$

And then the model can be rewritten into discrete-time form as

$$\hat{\alpha}(k+1) = A_d\hat{\alpha}(k) + B_d(\hat{v}(x), T(x,k)) + E_d(\hat{v}(x), \eta(x,k)) \tag{21}$$

$$\theta(x,k) = C_d(x)\alpha(k) + \xi(x,k) \tag{22}$$

where $A_d = U^{-1}K$, $B_d = G$, $C_d = (L(x), \theta(x,k) - \hat{\theta}(x,k))$ represents the measurement matrix, $\hat{v}(x) = \left[v_1(x) \cdots v_n(x)\right]^T \in V(x)$, η and ξ are uncorrelated white noise sequences which are uncorrelated with $\hat{\alpha}_0$ ($\hat{\alpha}_0$ is the initial condition of the system), $\theta(x,k)$ denote the manipulated low-level outputs variables.

Based on the lumped description with low-dimensional representation, a data-driven design of the model-based process monitoring system is established in this section. Design the following observer,

$$\tilde{\alpha}(k+1) = A_d\tilde{\alpha}(k) + B_d(\tilde{v}(x), T(x,k)) + (L(x), \theta(x,k) - \tilde{\theta}(x,k)) \tag{23}$$

$$r(x,k) = \theta(x,k) - \hat{\theta}(x,k) \tag{24}$$

where

$$L(x) = \begin{bmatrix} l_{1,1}(x) & \cdots & l_{1,l}(x) \\ \vdots & \ddots & \vdots \\ l_{2n\gamma,1}(x) & \cdots & l_{2n\gamma,l}(x) \end{bmatrix} \tag{25}$$

is an appropriately chosen observer gain matrix in H-space. The error $r(x,k)$ will serve as the residual signal used for monitoring. The major-objective is also to construct the I/O data model. Based on the residual generator Eq.24, an I/O data model can be constructed as

$$\Theta_{k,k+s} = \Gamma_s\hat{\alpha}_k + H_{y,s}Y_{k,k+s} + H_{r,s}R_{k,k+s} \tag{26}$$

where $\Theta_{k,k+s}$ is built from $\theta(k)$, $k = 1, \cdots, k+s+n-1$ as

$$\Theta_{k,k+s} = \begin{bmatrix} \theta(k) & \cdots & \theta(k+N-1) \\ \vdots & \ddots & \vdots \\ \theta(k+s) & \cdots & \theta(k+s+N-1) \end{bmatrix} \in R^{(s+1)l\times N}, \tag{27}$$

$Y_{k,k+s}$ and $R_{k,k+s}$ are built in the same way as $\Theta_{k,k+s}$. Γ_s is represented as C and A as

$$\Gamma_s = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} \in R^{(s+1)l\times n}, \tag{28}$$

$H_{r,s} \in R^{(s+1)l\times(s+1)l}$ is represented by (A, L, C, I) as

$$H_{r,s} = \begin{bmatrix} I & 0 & \cdots & \cdots & 0 \\ CL & I & 0 & \cdots & 0 \\ CAL & CL & I & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ CA^{s-1}L & \cdots & CAL & CL & I \end{bmatrix}. \tag{29}$$

Different from the scheme developed for LPS, the I/O data are manipulated by integration over space instead of multiplication. Assume $L(x)$ can be designed based on $\hat{v}(x)$.

Denote $l_{i,j}(x) = \sum_{k=1}^{n} \alpha_{i,j,k} v_k(x), i = 1, 2, \cdots, 2n$, $j = 1, \cdots, n$, then we can derive

$$(L(x), C_d(x)) = L_L C_L \tag{30}$$

where

$$L_L = \begin{bmatrix} L_{L,1} & \cdots & L_{L,l} \end{bmatrix} \in R^{2n\gamma\times l\gamma},$$
$$C_L = \begin{bmatrix} C_{L,1} \\ \vdots \\ C_{L,l} \end{bmatrix} \in R^{l\gamma\times 2n\gamma},$$
$$L_{L,j} = \begin{bmatrix} \alpha_{1,j,1} & \alpha_{1,j,n} \\ \alpha_{2n,j,1} & \alpha_{2n,j,n} \end{bmatrix},$$
$$C_{L,j} = \begin{bmatrix} \left(v_1(x), c_{d,j,1}(x)\right) & \cdots & \left(v(x)_1, c_{d,j,2n\gamma}(x)\right) \\ \vdots & \ddots & \vdots \\ \left(v_\gamma(x), c_{d,j,1}(x)\right) & \cdots & \left(v_\gamma(x), c_{d,j,2n\gamma}(x)\right) \end{bmatrix},$$

with

$$C_d(x) = \begin{bmatrix} c_{d,j,1}(x) & \cdots & c_{d,j,2n}(x) \\ \vdots & \ddots & \vdots \\ c_{d,j,1}(x) & \cdots & c_{d,j,2n}(x) \end{bmatrix}, \quad j = 1, \cdots, l.$$

Assume that (A_d, C_L) is observable, the matrix L_L can be designed. Note that L_L contains the weighting coefficients for Eq.25. Based on it, the observer matrix $L(x)$ can be established as

$$L(x) = \begin{bmatrix} L_{L,1}\hat{v}(x) & \cdots & L_{L,l}\hat{v}(x) \end{bmatrix} \tag{31}$$

The residual generator is written as

$$\begin{aligned} r &= \theta(x,k) - \hat{\theta}(x,k) \\ &= \begin{bmatrix} -\hat{N}(p,x) & \hat{M}(p,x) \end{bmatrix} \begin{bmatrix} y(x) \\ \theta(x) \end{bmatrix} \\ &= \left(-\hat{N}(p,x), y(x)\right) + \left(\hat{M}(p,x), \theta(x)\right) \end{aligned} \tag{32}$$

where

$$\begin{aligned} \hat{N}(p,x) &= C_d(x)(pI - A_d)^{-1} B_d \hat{v}(x) \\ \hat{M}(p) &= I - C_d(x)(pI - A_d)^{-1} L(x) \end{aligned} \tag{33}$$

and p denotes the z-transformation operator, $y(x) \in R^n$ represents the low-level process vector.

B. RESIDUAL EVALUATION AND THRESHOLD SETTING

The residual generated by Eq.32 provides a measure of discrepancy between the evolution of the actual DPS and the approximated finite dimensional description. For residual evaluation, the test statistics T^2 is established as

$$T^2 = r^2/\sigma_r^2 \tag{34}$$

where

$$\sigma_r^2 = \frac{1}{N-1}\sum_{k=1}^{N}\left(r(k) - \frac{1}{N}\sum_{k=1}^{N} r(k)\right)^2 \tag{35}$$

and $\sum$ represents the covariance matrix of the steady-state residual vector and N is the length of evaluation window. The threshold is determined using noncentral χ^2-distribution as $J_{th} = \chi^2_{1-\alpha}\left(1, E(r)^2/\sigma_r^2\right)$ and the decision logic is as follows:

If $T^2 > J_{th}$, then faulty; otherwise, fault-free.

To sum up, the flow chart of the approach is shown in Fig.5.

IV. BENCHMARKY

In section II, we have obtained a state space representation for DPS of HSLC. Next, a simulation study is carried out to verify reliability and effectiveness of the model. Not only the unknown parameters can be estimated according to the process data, but also the state space model will be applied in the filed condition.

A. DATA-DRIVEN REALIZATION OF SYSTEM IDENTIFICATION FOR STATE SPACE REPRESENTATION

The data sets collected from s10132 CTC Engineering and the thermal properties of the low-alloy steel Q235B are listed in Table 2. Data in Table 2 are obtained by interpolation method due to the changes of temperature in laminar cooling process.

HSLC process studied here is illustrated in Fig.6. '1' denotes the open state of the header bank and '0' denotes closed state of it. The temperature filed simulation in HSLC is established in COMSOL and the prediction of coiling temperature is obtained in filed simulation. When the model structure is known, least-squares method can be used to estimate parameters. After system identification, the state space model is loaded into MATLAB and calculated according to the process data. In order to prevent the fitting results with a

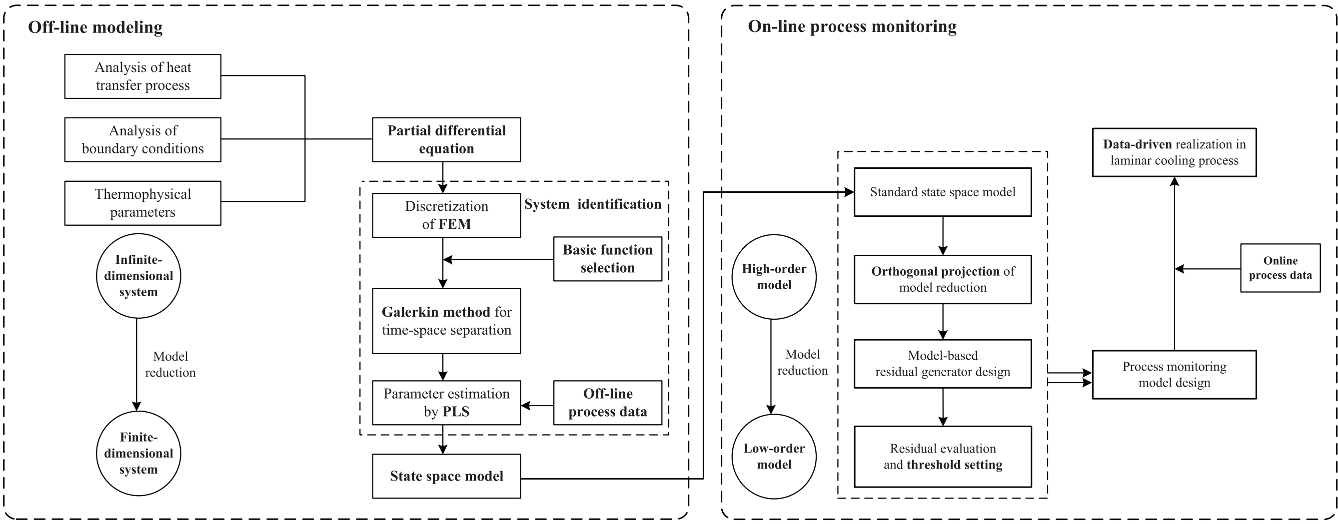

FIGURE 5. Flowchart of modeling and process monitoring for DPS in HSLC.

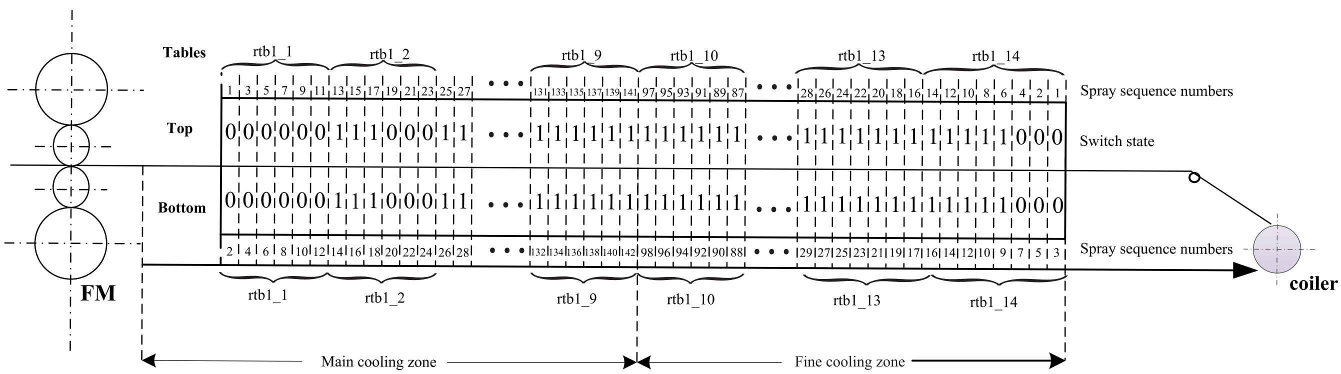

FIGURE 6. The state of spray header banks in HSLC.

TABLE 2. Q235b strip steel thermophysical parameters.

Temperature	200	300	400	500	600	700	800	900
Thermal conductivity	21.02	38.23	35.74	33.20	30.81	29.39	25.39	26.13
Specific heat	508	530	560	605	680	824	718	615

large error, we will further improve the basic functions,

$$\omega_i(x) = \begin{cases} \varphi_i(x) - 3\alpha_1 \dfrac{(x - x_{i-1})(x - x_i)}{(x_i - x_{i-1})^2}, & x \in [x_{i-1}, x_i] \\ \varphi_i(x) + 3\alpha_1 \dfrac{(x - x_i)(x - x_{i+1})}{(x_{i+1} - x_i)^2}, & x \in [x_{i+1}, x_i], \end{cases} \quad 1 \le i \le n \qquad (36)$$

Fig.7 shows the temperature variation curve of the measurement and prediction at the upper surface of the steel. The trend of the temperature change is the same. It can be seen that the maximum error between the prediction and the measurement is nearly $25°C$. It is because that the measurement of the temperature is obtained by the recursive of temperature filed simulation and the error of the temperature is enlarged due to the process data errors.

In order to further verify the effectiveness of the model, different batches of data for same materials are used in the state space model. Fig.8 shows the predictive CT by model Eq.18 and the measurement of CT. The maximum error is nearly $10°C$ and the error decreases as the number of samples increases. The effectiveness of the state space model can be verified.

B. DATA-DRIVEN REALIZATION OF THE OBTAINED KERNEL REPRESENTATION IN HSLC

Based on the constructed residual generators, the abnormal conditions, including the descriptions of two faults description at different locations of spray header, as shown in Table 3, are used to verify the effectiveness of the proposed approach. If fault occurs, the coiling temperature measured is

TABLE 3. Variables of hot strip rolling process.

Faults No.	Description of faults	Occurrence location (header banks)
1	One of header banks in fine cooling zone can't be open	14
2	One of header banks in main cooling zone can't be closed	3,4

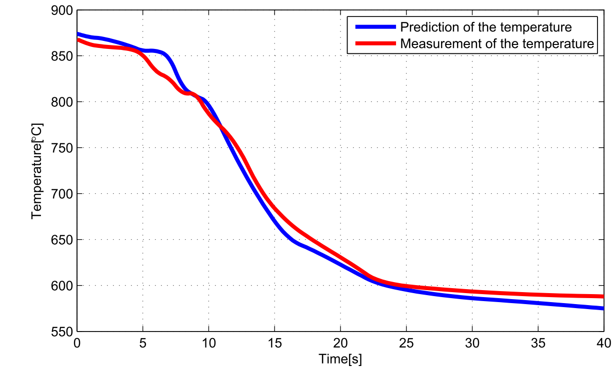

FIGURE 7. Temperature variations of the measurement and prediction at the upper surface of the steel.

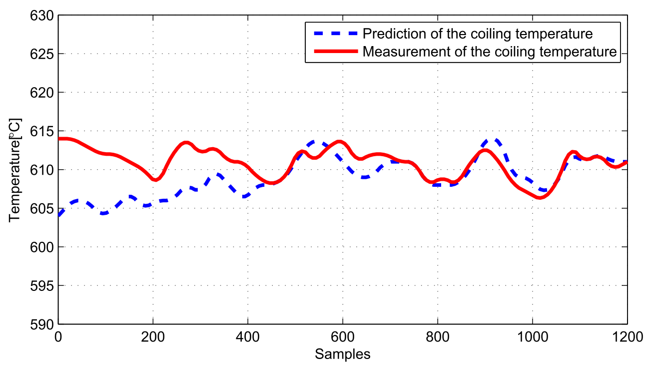

FIGURE 8. The measurement and prediction of coiling temperature.

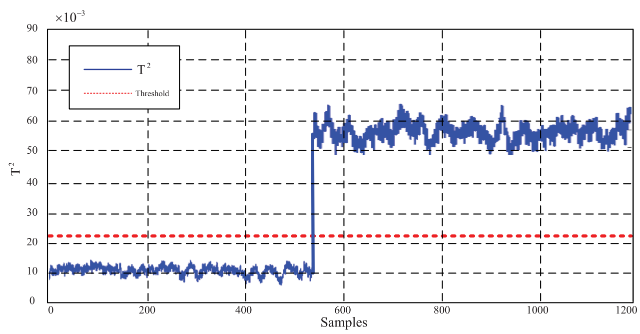

FIGURE 9. Process monitoring results of No.1 fault in main cooling zone.

different from that of setting. The open state of spray headers have a great impact on the coiling temperature and the cooling rate. The threshold settings are 0.02236 in main cooling zone and 0.02775 in fine cooling zone.

The monitoring results are shown in Fig.9 and Fig.10. It can be observed that the faults can be successfully detected without any delay. It builds the foundation for the research of fault location and fault causes in the future.

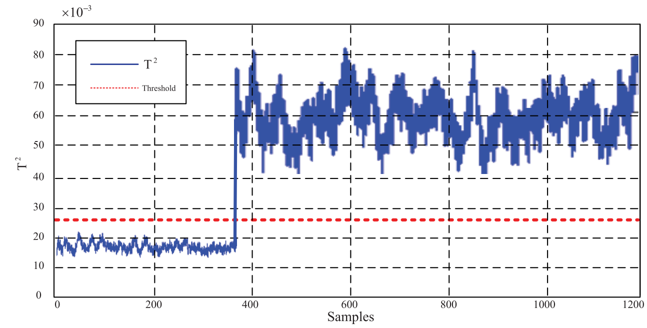

FIGURE 10. Process monitoring results of No.2 fault in fine cooling zone.

V. CONCLUSION

In this article, a data-driven based quality monitoring method is applied in DPS. Firstly, a method of modeling for DPS is proposed to describe the laminar cooling process. The problems of the DPS modeling are solved by model reduction and system identification. The main advantages of the scheme is that the description of state space model can excellently reconstruct the spatial distribution with initial and boundary conditions. The precision of modeling for HSLC is improved compared with traditional methods. Next, a data-driven process monitoring method is developed for the fault detection based on the state space model. Our approach is finally tested on an industrial benchmark of laminar cooling process and the satisfactory process monitoring performance is obtained.

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