

Moving Pattern-based Approach to Modeling of a Class of Complex Production Processes

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Abstract—For a class of complex production processes, based on the actual running status data, a new modeling approach based on moving pattern is presented by constructing pattern moving space and defining moving variable-pattern class variable in it. The dynamics of a class of complex production processes is characterized by the movement of pattern class variable in pattern moving space. For characterizing pattern class variable quantitatively, in this paper, interval number is used as its metric form, and our previous proposed interval T-S fuzzy model (ITSFM) is adapted to model its movement in pattern moving space. Experimental results are then presented that indicate the validity and applicability of the proposed approach.

Keywords: moving pattern, pattern moving space, pattern class variable, interval arithmetic, Takagi-Sugeno fuzzy model, interval time series

I. INTRODUCTION

In real world, there are many complex production processes in metallurgy, chemical industry and building materials etc (e.g. blast furnace, sintering machine, cement rotary kiln and so on.) For this class of production processes, there are the same characteristics as follows[1]. Therein, there is a series of physical chemistry reactions of heat transfer and matter transfer, burning thermodynamics and chemistry reaction dynamics, moving boundary, hydrodynamics and aerodynamics. It is difficult to characterize the dynamics. In addition, the mapping relationships between inputs and outputs can't be described by classic Newton's laws of mechanics, but be described only by statistics. For example, even under the same experimental conditions, the obtained data usually differ from one to another. Thus, the traditional modeling approach based on input/output data characterized in Euclidean space is not appropriate for modeling the relationship between inputs and outputs of a complex industrial process.

For this class of complex production process systems, there is lack of effective dynamics description methods. We try to give a new method to describe the movement law obeying statistics by using statistical principal, pattern recognition and control theory.

For modeling of complex dynamical systems, an pattern-based process identification approach emulating human in dealing with process response was originally introduced in [2].

Generally, the existing methods for pattern-based process identification can be divided into four classes [3], namely the key-values approach [4][5], the qualitative evaluation approach [6], the elementary pattern recognition approach [7], and the cure fitting approach [8] [9]. In these methods, Pattern recognition is mainly used to solve system model identification or system state estimation problems. After that, the design of control law is still based on the time-domain model. Here pattern is not considered as a moving variable.

In this paper, in contrast to traditional modeling approach to characterizing dynamical systems in Euclidean space, the dynamics of complex production processes is characterized by the moving of running status pattern from one pattern class to another in pattern moving space. First, the collected multi-dimensional actual running status data of complex production processes are reduced to one dimensional data. Then, the one dimensional data are partitioned into C pattern classes constructing the pattern moving space, and pattern class variable is defined in it. Each pattern class represented by an interval number can be considered as a scale value of pattern moving space. The pattern samples belonging to the same pattern class have the same scale value in pattern moving space, and are represented by the same interval number. That is, we view the considered systems at the level of pattern class and capture only the dominant characteristics of the process. We are not concerned about the exact value of the running status data of the complex production processes, but concerned about the pattern classes which the running status data of complex production processes belong to. After pattern moving space is constructed and pattern class variable is defined in this space, the prediction model is built as follows:

$$\begin{aligned} dx(k) &= F(\tilde{dx}(k)) \\ &= F(f(dx(k-1), dx(k-2) \cdots dx(k-m_y), \\ &\quad u(k-1), u(k-2), \cdots, u(k-m_u))) \end{aligned} \quad (1)$$

Where $dx(k)$ is pattern class variable, $F(\cdot)$ denotes classification, $\tilde{dx}(k)$ is the initial prediction output of pattern class variable and $\tilde{dx}(k) = f(\cdot)$ is a kind of initial prediction model. This is a prediction process including two steps. The first step is to obtain the initial prediction output $\tilde{dx}(k)$ based

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on the initial prediction model $\hat{dx}(k) = f(\cdot)$ modeled by our previous proposed interval T-S fuzzy model (ITSFM). The second step is to obtain the final output pattern class variable $dx(k)$ by classifying the initial prediction output $\hat{dx}(k)$.

This paper is organized as follows. After the introduction the preliminary knowledge about interval arithmetic is presented in Section II. In Section III, moving pattern-based modeling approach of a class of complex production process is proposed. In Section IV, the example is considered to demonstrate the validity and applicability of the proposed approach. Finally, Section V concludes this paper.

II. PRELIMINARY KNOWLEDGE

In this section, we briefly look at some important formulations in interval arithmetic[10].

A. Interval arithmetic

An interval number can be represented by its lower and upper bounds as $A = [a^L, a^U]$, or, equivalently, by its midpoint and radius as $A = (a^C, a^R)$, where $a^C = (a^L + a^U)/2$ and $a^R = (a^U - a^L)/2$. Let A and B be two intervals represented by its lower and upper bounds, the operations defined on the interval numbers are, respectively.

$$A + B = [a^L + b^L, a^U + b^U] \quad (2)$$

$$A - B = [a^L - b^U, a^U - b^L] \quad (3)$$

$$\lambda \cdot A = [\lambda \cdot a^L, \lambda \cdot a^U] \quad (4)$$

Where λ is a constant and $\lambda > 0$.

If the interval number A and B are represented by its midpoint and radius, the operations defined on the interval numbers are respectively:

$$A + B = (a^C + b^C, a^R + b^R) \quad (5)$$

$$A - B = (a^C - b^C, a^R + b^R) \quad (6)$$

$$\lambda \cdot A = (\lambda \cdot a^C, |\lambda| \cdot a^R) \quad (7)$$

B. Hausdorff distance

The Hausdorff distance is often used to measure the distance between two interval data. The concept of Hausdorff distance is stated as follows. Assume that two interval numbers X_1 and X_2 , $X_1 = (a_1, c_1)$, $X_2 = (a_2, c_2)$, a_1 and c_1 are the center and radius of interval number X_1 , respectively, a_2 and c_2 are the center and radius of interval number X_2 , respectively. The distance between X_1 and X_2 is defined as:

$$D(X_1, X_2) = |a_1 - a_2| + |c_1 - c_2|$$

III. MODELING OF COMPLEX PRODUCTION PROCESSES BASED ON MOVING PATTERN

In this paper, the dynamics of complex production processes is characterized by the move of operating condition

patterns in pattern moving space. So, we need to construct pattern moving space firstly.

A. Construction of pattern moving space

Firstly, the multi-dimensional running status data are reduced to one dimensional data using principal component analysis. This can be considered as a process of feature extraction. Then, by fuzzy c-mean (FCM) clustering algorithm, the one-dimensional running status samples are partitioned into C pattern classes, that is, $P_1, P_2, \dots, P_C$. The collection of those classes forms pattern moving space which corresponds to the considered complex production process. An explanatory example for demonstrating the constructed pattern moving space is shown in Fig.1. Each pattern class in pattern moving space can be considered as a qualitative "scale". The pattern samples belonging to the same pattern class have same "scale" value in pattern moving space.

If the data is collected in a long enough period of time, the pattern moving space constructed based on these actual running status data can be considered as the running subspace of the system. Dynamics description and control problems can be discussed in this space. When the actual running status sample is out of the pattern moving space, the pattern moving space can be expanded by using the following method.

When a new pattern sample is classified into its belonging class, the distance between the pattern sample and this class center is calculated. If this distance is more than the class radius, then a new pattern class generates. In this paper, the new pattern sample is used as a new class center and the membership function can be computed for the new pattern class.

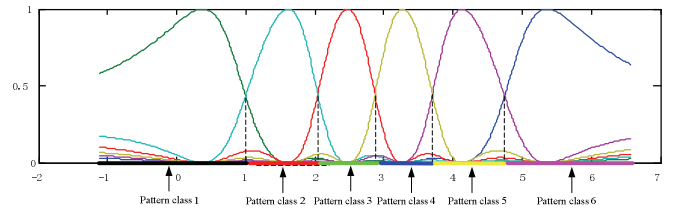


Fig.1 Pattern moving space composed of six pattern classes. The horizontal axis denotes the values of dimension reduced running status samples, and vertical axis denotes membership function values corresponding to dimension reduced running status samples.

B. The representation of pattern classes

In fact, each pattern class obtained in the above section is a qualitative description about pattern. In order to characterize quantitatively the dynamics of complex production processes in pattern moving space, each pattern class must be represented quantitatively. In this paper, we adopt interval numbers to represent pattern classes.

First, finding the maximum I_i^U and minimum I_i^L among the samples belonging to the same pattern class P_i , $i = 1, \dots, C$, where C is the number of pattern classes constructing the pattern moving space. Then, the maximum I_i^U and minimum I_i^L are used to construct an interval number

$I_i = [I_i^L, I_i^U]$. Thus, $I_i = [I_i^L, I_i^U]$ is the interval number characterizing pattern class P_i quantitatively. Let $I = \{I_1, I_2, \dots, I_C\}$, it is the quantitative pattern moving space corresponding to pattern moving space P defined in above section. Here, quantified pattern classes are ordered from small to big in terms of the center values of I_i s. That is,

$$a_1 < a_2 < \dots < a_C, \text{ where } a_i = \frac{I_i^L + I_i^U}{2}, i = 1, \dots, C.$$

C. The definition of pattern class variable

In order to describe the movement of system in pattern moving space, a variable called pattern class variable is defined.

Assuming that $\{sx(k)\}$ and $\{mx(k)\}$ denotes measurement sample time series and pattern sample time series, respectively. Then pattern class variable must satisfy the following transformation:

$$mx(k) = T(sx(k)) \quad (8)$$

$$dx(k) = F(mx(k)) \quad (9)$$

Where $T(\cdot)$ and $F(\cdot)$ denote feature extraction and classification, respectively, $dx(k)$ is the pattern class variable.

Obviously, pattern class variable has two main characteristics:

(i) It is a variable over time.

(ii) It has the class attribute.

Pattern class variable is used to describe the variation of pattern class to which running status data belong over time in pattern moving space. And it together with pattern moving space forms the basis of the proposed modeling approach. The pattern class variable's metric form is not unique. In this paper, interval number is used as its metric form. That is, given at time instant t , $mx(k)$ is classified into pattern class i , and then let $dx(t) = I_i = [I_i^L, I_i^U]$. Thus, a pattern sample time series in Euclidean space is transformed into a pattern class variable time series in pattern moving space.

D. Modeling of Complex Production Processes based on moving pattern

In this paper, as interval numbers is used as the pattern class variable's metric form, so, in fact pattern class variable time series is an interval number time series. The dynamics of complex production processes is characterized by the transition of pattern class variable $dx(k)$ in pattern moving space. The dynamic model based on moving pattern is as follows:

$$\begin{aligned} dx(k) &= F(\tilde{dx}(k)) \\ &= F(f(dx(k-1), dx(k-2) \dots dx(k-m_y) \\ &\quad u(k-1), u(k-2), \dots, u(k-m_u))) \end{aligned} \quad (10)$$

m_y and m_u , the orders of the considered dynamic systems; in

this paper, m_y and m_u are assumed to be known priorly. $dx(t)$ is the pattern class variable, $F(\cdot)$ denotes classification, $\tilde{dx}(t)$ is the initial prediction output of pattern class variable and $\tilde{dx}(t) = f(\cdot)$ is a kind of initial prediction model. $u(k)$ is general system input represented by crisp real numbers, $u(k) \in R$.

The proposed moving pattern based modeling approach is composed of two steps.

1) Constructing the initial prediction model using the adapted interval T-S fuzzy model (ITSFM).

For modeling the moving of pattern class variable in pattern moving space, our previous proposed interval T-S fuzzy model (ITSFM) [11] is adapted and applied to moving pattern based modeling of complex production processes. The adapted ITSFM used to model of complex production complex in pattern moving space is as follows:

R^i : If $dx_c(k-1)$ is A_1^i and $dx_c(k-2)$ is A_2^i , ..., $dx_c(k-m_y)$ is $A_{m_y}^i$ and $u(k-1)$ is B_1^i , and $u(k-2)$ is $B_2^i, \dots, u(k-m_u)$ is $B_{m_u}^i$

then

$$\begin{aligned} dx^i(k) &= \theta_0^i + \theta_1^i dx_c(k-1) + \dots + \theta_{m_y}^i dx_c(k-m_y) + \\ &\quad + \theta_{m_y+1}^i u(k-1) + \theta_{m_y+2}^i u(k-2) + \dots \\ &\quad + \theta_{m_y+m_u}^i u(k-m_u) \end{aligned} \quad (11)$$

Where A_j^i , B_q^i are the corresponding fuzzy sets. $dx_c(k-j)$ represents the center of pattern class variable $dx(k-j)$ at time instant $k-j$, that is, if the value of $dx(k-j)$ is equal to $I_i = [I_i^L, I_i^U]$ at time instant $k-j$, then $dx_c(k-j)$ is equal to $\frac{I_i^L + I_i^U}{2}$. $\theta_l^i = (a_l^i, c_l^i)$ is an interval number, a_l^i and c_l^i are the center and radius of θ_l^i , respectively. The membership grade $A_j^i(dx_c(k-j))$ and $B_q^i(u(k-q))$ are obtained by fuzzy c -means clustering algorithm in this paper, $l = 0, 1, 2, \dots, m_y + m_u$, $j = 1, 2, \dots, m_y$, $q = 1, 2, \dots, m_u$, $i = 1, 2, \dots, r$, r denotes the number of rules.

The predicted interval output of the improved ITSFM, that is, $\tilde{dx}(k)$ is inferred as

$$\tilde{dx}(k) = \frac{\sum_{i=1}^r \omega_i dx^i(k)}{\sum_{i=1}^r \omega_i}, \quad (12)$$

Where $\omega_i = \prod_{j=1}^{m_y} A_j^i(dx_c(k-j)) \prod_{q=1}^{m_u} B_q^i(u(k-q))$

Let $\tilde{\omega}_i = \frac{\omega_i}{\sum_{i=1}^r \omega_i}$, then

$$\begin{aligned}
d\tilde{x}(k) &= \sum_{i=1}^r \tilde{\omega}_i dx^i(k) \\
&= \sum_{i=1}^r \tilde{\omega}_i [\theta_0^i + \theta_1^i dx_c(k-1) + \dots + \theta_{m_y}^i dx_c(k-m_y) \\
&\quad + \theta_{m_y+1}^i u(k-1) + \theta_{m_y+2}^i u(k-2) + \dots \\
&\quad + \theta_{m_y+m_u}^i u(k-m_u)] \\
&= \sum_{i=1}^r \tilde{\omega}_i [(a_0^i, c_0^i) + (a_1^i, c_1^i) dx_c(k-1) + \dots \\
&\quad + (a_{m_y}^i, c_{m_y}^i) dx_c(k-m_y) + (a_{m_y+1}^i, c_{m_y+1}^i) u(k-1) \\
&\quad + (a_{m_y+2}^i, c_{m_y+2}^i) u(k-2) + \dots \\
&\quad + (a_{m_y+m_u}^i, c_{m_y+m_u}^i) u(k-m_u)] \\
&= \sum_{i=1}^r \omega_i (A_i^t \mathbf{x}(k), C_i^t | \mathbf{x}(k)) \\
&= (\sum_{i=1}^r \omega_i A_i^t \mathbf{x}(k), \sum_{i=1}^r \omega_i C_i^t | \mathbf{x}(k)) \quad (13)
\end{aligned}$$

Where

$$\begin{aligned}
A_i &= (a_0^i, a_1^i, \dots, a_{m_y+m_u}^i)^t, C_i = (c_0^i, c_1^i, \dots, c_{m_y+m_u}^i)^t, \\
\mathbf{x}(k) &= (1, dx_c(k-1), dx_c(k-2), \dots, dx_c(k-m_y), \\
&\quad u(k-1), u(k-2), \dots, u(k-m_u))^t, \\
|\mathbf{x}(k)| &= (1, |dx_c(k-1)|, |dx_c(k-2)|, \dots, |dx_c(k-m_y)|, \\
&\quad |u(k-1)|, |u(k-2)|, \dots, |u(k-m_u)|)^t
\end{aligned}$$

Furthermore, $\hat{p}(k)$ can be expressed as

$$d\tilde{x}(k) = (A^t \tilde{\mathbf{x}}(k), C^t | \tilde{\mathbf{x}}(k)) \quad (14)$$

Where $A = (A_1^t, A_2^t, \dots, A_r^t)^t$, $C = (C_1^t, C_2^t, \dots, C_r^t)^t$

$$\tilde{\mathbf{x}}(k) = (\tilde{\omega}_1 \mathbf{x}(k)^t, \tilde{\omega}_2 \mathbf{x}(k)^t, \dots, \tilde{\omega}_r \mathbf{x}(k)^t)^t$$

$$|\tilde{\mathbf{x}}(k)| = (\tilde{\omega}_1 |\mathbf{x}(k)|^t, \tilde{\omega}_2 |\mathbf{x}(k)|^t, \dots, \tilde{\omega}_r |\mathbf{x}(k)|^t)^t$$

$A^t \tilde{\mathbf{x}}(k)$ and $C^t | \tilde{\mathbf{x}}(k)$ are the center and radius of the initial predicted interval output $d\tilde{x}(k)$, respectively.

Different from our previous work [13], the parameters in (14) are obtained by minimizing the following objective function J in (15) subject to the constraints $c_j^i \geq 0$ as the radius of an interval is greater than or equal to zero, $i = 1, 2, \dots, r$, $j = 0, 1, 2, \dots, m_y + m_u$. Where $d\tilde{x}^L(k)$, $d\tilde{x}^U(k)$ are the lower and upper bound of the initial prediction output $d\tilde{x}(k)$, respectively, $dx^L(k)$, $dx^U(k)$ are the lower and upper bound of real pattern class variable $dx(k)$ at time instant k , respectively.

$$\begin{aligned}
\text{Min}_{A, C} \quad J &= \sum_{k=1}^N [dx^L(k) - d\tilde{x}^L(k)]^2 + \sum_{k=1}^N [dx^U(k) - d\tilde{x}^U(k)]^2 \\
\text{subject to} \quad c_j^i &\geq 0, i = 1, 2, \dots, r, j = 0, 1, 2, \dots, m_y + m_u \quad (15)
\end{aligned}$$

2) After obtaining the initial prediction output $d\tilde{x}(k)$, the final prediction output $d\hat{x}(k)$ can be obtained by classifying the initial prediction output $d\tilde{x}(k)$ into the pattern class which is nearest to the initial prediction output $d\tilde{x}(k)$ by calculating the Hausdorff distance between the initial prediction output $d\tilde{x}(k)$ and each pattern class I_i in pattern moving space. That is, if $j = \arg \min_{i=1, 2, \dots, C} (D(d\tilde{x}(k), I_i))$, then

the final prediction output $d\hat{x}(k)$ is equal to I_j , where $I_i = [I_i^L, I_i^U]$ is the quantified value of pattern class i , $i = 1, 2, \dots, C$, C is the number of pattern class in pattern moving space. $D(d\tilde{x}(k), I_i)$ denotes the Hausdorff distance between interval number $d\tilde{x}(k)$ and I_i .

IV. NUMERICAL EXAMPLE

In this chapter, one practical example- sintering process of Anyang (one city of Henan Province of China) iron and steel plant is given to verify the validity of the proposed moving pattern-based modeling approach.

In the example, the actual running status data collected from sintering process of Anyang (one city of Shandong Province of China) iron and steel plant are used. The data consist of 864 pairs of input-output samples of a sintering process: the input $u(k)$ is the temperature of ignition hood and the output $y(k)$ is the first principal component of exhaust gas temperatures of three wind boxes, and the sampling time is 25s. In this example, the input and output data are normalized by statistical normalization, that

is, $Z = \frac{X - \mu}{\sigma}$, where μ and σ are the mean and standard

deviation of X , respectively. Fig.2 shows the 864 pairs of input-output samples. In this example, 864 running status samples $y(k)$ are used to constructing the pattern moving space by fuzzy c -means (FCM) clustering algorithm. Here, the cluster number is set to 20. The 20 pattern classes P_i represented by interval numbers are shown in Table I. The running status time series $y(k)$ in Euclidean space and the corresponding pattern class variable time series $\tilde{p}(k)$ characterized by intervals in pattern moving space are shown in Fig.3, $k = 1, 2, \dots, 100$. From Fig.3, we can see that the transition of pattern class variable from one pattern class to another in pattern moving space can also characterize change of running status $y(k)$ in general.

In this example, the first 500 pairs of input-output samples are used to train the proposed initial prediction model, the

others are used to validate the model. The initial prediction model based on ITSFM is as follows:

R^i : If $dx_c(k-1)$ is A_1^i and $dx_c(k-2)$ is A_2^i and $dx_c(k-3)$ is A_3^i and $dx_c(k-4)$ is A_4^i and $u(k-1)$ is B_1^i

Then:

$$dx^i(k) = \theta_0^i + \theta_1^i dx_c(k-1) + \theta_2^i dx_c(k-2) + \theta_3^i dx_c(k-3) + \theta_4^i dx_c(k-4) + \theta_5^i u(k-1)$$

Where $dx_c(k-1)$ is the center of $dx(k-1)$. The membership grade $A_1^i(dx_c(k-1))$ and $B_1^i(u(k-1))$ is obtained by fuzzy c -means clustering algorithm which was adopted in [12] for determining the premise structure of T-S fuzzy model. $\theta^i = [\theta_0^i, \theta_1^i, \theta_2^i, \theta_3^i, \theta_4^i, \theta_5^i]$ is the interval parameter vector in consequent part of ITSFM. Based on formula (15), the interval parameters in the consequent part of ITSFM are obtained and shown in Table II.

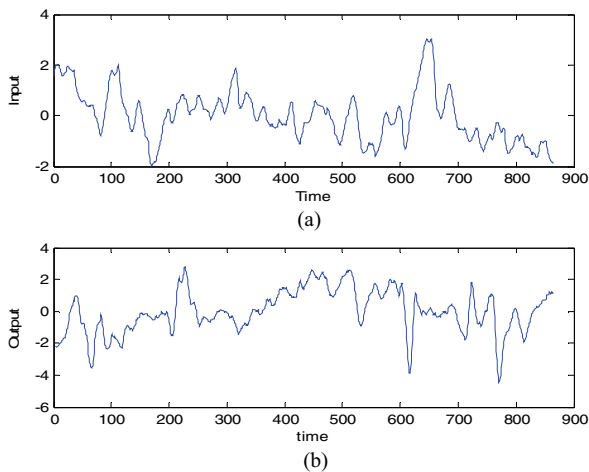


Fig.2 The input and output signals of the sintering process: (a) input $u(k)$; (b) output $y(k)$

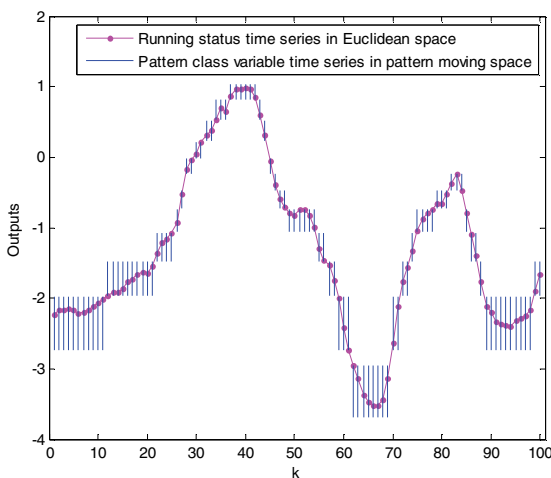


Fig.3 The running status time series $y(k)$ (dots) and the corresponding pattern class variable time series $dx(k)$ (segments) characterized by intervals

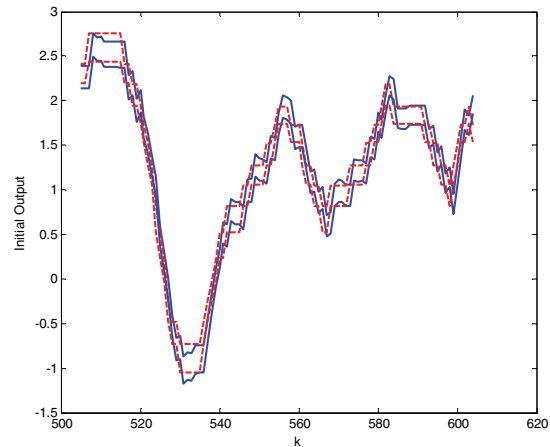


Fig.4 The initial prediction outputs $\tilde{dx}(k)$ (solid line) obtained by ITSFM and the real pattern class variable time series $dx(k)$ (dashed line).

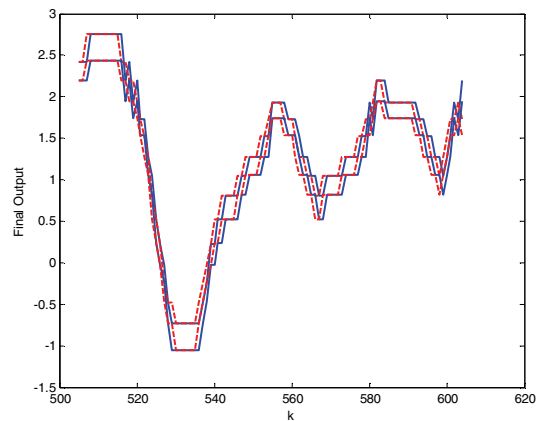


Fig.5 The final prediction outputs $\hat{dx}(k)$ (solid line) of the proposed model and the real pattern class variable time series $dx(k)$ (dashed line).

In Fig.4, the solid lines represent the initial prediction output $\tilde{dx}(k)$ obtained by the ITSFM with 4 fuzzy rules, and the dashed lines represent the real pattern class variable time series $dx(k)$ with time from 505 to 600. After the initial prediction output $\tilde{dx}(k)$ is classified, the final outputs $\hat{dx}(k)$ of the proposed model are obtained. In Fig.5, the solid lines represent the final outputs of the proposed model, the dashed lines represent the pattern class variable time series $dx(k)$ with time from 505 to 600. By comparing Fig.4 with Fig.5, we can see that the small difference between initial prediction output $\tilde{dx}(k)$ and the corresponding real pattern class variable time series $dx(k)$ at some time instant (for example $k=508-515$, $530-535$, $585-591$) is eliminated after $\hat{dx}(k)$ is classified.

V. CONCLUSION

In this paper, in contrast to traditional modeling approach to characterizing dynamical systems in Euclidean space, the dynamics of complex production processes is characterized by

TABLE II
THE IDENTIFIED INTERVAL PARAMETERS IN CONSEQUENT PART OF ITSFM

Rule i Interval parameters	$i=1$	$i=2$	$i=3$	$i=4$
θ_0^i	(0.1433, 0.0738)	(0.0001, 0.1217)	(-0.0558, 0.0644)	(-0.1388, 0.0373)
θ_1^i	(1.2793, 0.0068)	(1.1292, 0.0000)	(1.1333, 0.1147)	(0.8526, 0.1251)
θ_2^i	(-0.1925, 0.0000)	(0.0711, 0.0039)	(0.0932, 0.0000)	(0.3105, 0.0021)
θ_3^i	(0.0274, 0.0000)	(-0.0864, 0.0000)	(0.0757, 0.0000)	(-0.0547, 0.0000)
θ_4^i	(-0.1913, 0.0112)	(-0.1268, 0.0068)	(-0.3706, 0.0000)	(-0.2143, 0.0000)
θ_5^i	(-0.0102, 0.0000)	(-0.0352, 0.0082)	(0.0445, 0.0000)	(-0.0408, 0.0081)

TABLE I
REPRESENTATION OF PATTERN CLASSES BY INTERVAL NUMBER

P_i	$I_i = [\underline{I}_i, \overline{I}_i]$
1	[-4.4856, -3.8815]
2	[-3.6970, -2.9504]
3	[-2.7281, -1.9855]
4	[-1.9612, -1.4761]
5	[-1.4707, -1.0692]
6	[-1.0535, -0.7335]
7	[-0.7262, -0.4766]
8	[-0.4681, -0.2368]
9	[-0.2304, -0.0229]
10	[-0.0215, 0.2212]
11	[0.2330, 0.5212]
12	[0.5257, 0.8140]
13	[0.8200, 1.0430]
14	[1.0558, 1.2733]
15	[1.2774, 1.5243]
16	[1.5413, 1.7245]
17	[1.7445, 1.9327]
18	[1.9451, 2.1911]
19	[2.1939, 2.4154]
20	[2.4309, 2.7607]

movement of pattern class variable in pattern moving space. That is, we view the considered complex production the processes at the level of pattern class and capture only the

dominant characteristics of the process. Each pattern class in pattern moving space can be considered as a “scale”. Running status patterns belonging to the same pattern class are characterized (quantified) by the same pattern class label (interval number). Running status time series in Euclidean space is transformed into pattern class time series in pattern moving space.

REFERENCES

- [1] S.D.Qu, “Pattern recognition approach to intelligent automation for complex industrial processes,” *Journal of University of Science and Technology Beijing*, vol.20, pp.385-389, Aug.1998.
- [2] E.H.Bristol, “Pattern recognition: An alternative to parameter identification in adaptive control,” *Automatica*, vol.13, pp.197-202, Mar.1977.
- [3] Kar-Ann Toh and R.Devanathan, “Pattern-based identification for control applications,” *IEEE Trans.on Control Systems Technology*, vol.4, pp.641-648, Nov.1996.
- [4] Yu-Chu Tian, Futao Zhao, B.H.Bisowarno, and Moses O. Tade, “Pattern-based predictive control for ETBE reactive distillation,” *Journal of Process Control*, vol.13, pp.57-67, Feb.2003.
- [5] Rachelle Howard and Douglas Copper, “A novel pattern-based approach for diagnostic controller performance monitoring,” *Control Engineering Practice*, vol.18, pp.279-288, Mar.2010.
- [6] B. Porter, A. H. Jones and C. B. McKeown, “Real-time expert tuners for PI-controllers,” *IEE Proc., Part D*, vol. 134, pp. 260-263, Jul.1987..
- [7] M.Klein, T.Marczinkowsky, and M.Pandit, “An elementary pattern recognition self-tuning PI-controller,” in *Proc.IFAC Int.Symp.Intell.Tuning and Adaptive Contr*, Singapore, Jan.1991, pp.17-21.
- [8] M.S.Caceci and W.P.Cacheris, “Fitting curves to data,” *BYTE*, pp.340-362, May.1984.
- [9] A.G.Hill and W.Raksakij, “Process and disturbance identification by curve fitting the closed loop response,” in *Proc.Amer.Contr.Conf.*, Pittsburgh, PA, USA, Jun. 1989, pp.2206-2209.
- [10] Moore R E. *Methods and Applications of Interval analysis*, Englewood Cliffs: Prentice-Hall, 1979. 9-17
- [11] C.P.Sun and Z.G.Xu, “Extended T-S Fuzzy Model based on Interval Arithmetic and Its Application to Interval Nonlinear Regression Analysis,” in *Proc.18th IEEE Int. Conf. Fuzzy Syst.*, Jeju, South Korea, Aug. 2009, pp.1773-1778.
- [12] L.Wang and R.Langari, “Complex systems modeling via fuzzy logic,” *IEEE Transactions on System Man, and Cybernetics*, vol. 26, pp.100-106, Feb.1996.