# A Novel Grey-fuzzy Predictive Control Algorithm Based on Physical Mode for Roller Kiln

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**Abstract**

This paper proposes a novel grey-fuzzy predictive control (GFPC) strategy using an on-line dynamic switching mechanism for controlling the sintering process of ceramic roller kiln. The grey predictor is applied to extract key information such as temperature parameters and gas pressure, and send the prediction information to the controller of actuator. The mathematical model which based on physical and heat conduction theory is derived and the real-time fuzzy controller is designed to make the output temperature in the sintering area follow the temperature-curve accurately. To achieve excellent transient performance and steady-state response, an on-line switching mechanism is adopted to regulate the forecasting step size of the grey predictor appropriately according to the error between reference value and real temperature of the kiln. Additionally, this kind of method can control the temperature of kiln without accurate mathematical models for the kiln effectively. To verify the GFPC strategy, the control module based on Matlab is presented. When the sintering operating condition is stable, it is a kind of effective control strategy for temperature of roller kiln.

**Keywords** Roller kiln, Grey-fuzzy predictive control, Firing process, Physical mode, Heat conduction

## 1 Introduction

Chinese construction industrial is booming, the ceramic tile manufacturing industry is one important industry related to this field. Ceramic tile manufacturing line is a very complicated process which contained pressing machine, vertical dryer, enameling, firing kiln, sorting line, and packaging. Roller kiln have important applications in ceramic industry and shows superiority over other intermittent kilns in process flexibility, production efficiency and energy consumption. Roller kiln is nearly the last station and its performance is key process which control final tile quality. Therefore, the finished ceramic tile has to satisfy the engineering parameters such as shape, size, durability and deformation as much as possible. If temperature values in roller kiln do not follow the reference curve accurately, then many serious defects, such as cracks and fractures, black heart, insufficient firing and over firing, tonality variations of the glaze will occur in the finished ceramic tiles [1]. However, if there are any flaws at the firing process all efforts of the preceding stations will become the waste. In view of these factors, in order to avoid the defects and obtain better quality, good controller is required to improve the control accuracy of temperature process.

An appropriate control system designed to make temperature process control in roller kiln as accurate as possible. So far, researches on roller kiln have concentrated most on the kiln construction, linging material, loading and unloading machinery, and other installations. Only a few studies considered the how to make the output temperature of roller kiln track the set-point values closely is a key factor affecting the firing process and the products quality. Huang and Fang [2] design the distributed intelligent control system for roller kiln, which using auto-tuning method based on relay feedback theory in order to decide the PID's control parameter, and using the fuzzy control theory on this foundation. Chen et al. [3] present logic control algorithm based on Panboolean algebra, the control scheme relies on the correlation between E and EC of temperature. However, to be able to control this temperature process, in this study such as PID controller and Fuzzy logic controller, for the best response characteristic of the system in time domain, you need choose the precision parameters.

Therefore, fuzzy logic controller improves the intelligent behavior, robustness, response speed, and accuracy of control system. Due to the complexity of physical behaviors of temperature process in roller kiln, one of the ways to improve the system is by collecting the input-output data of plant and these details used to train NN or neuro-fuzzy model. Thus, Nguyen *et al.* present a comparative study using ANNs and co-active neuro-fuzzy inference system (CANFIS) in modeling a real, complicated multi input multi output (MIMO) nonlinear temperature process of roller kiln used in ceramic tile manufacturing line[1].

In consideration of previous studies, to improve the systems performance, we proposed a novel control algorithm based on grey-fuzzy theory. The reason for using grey prediction in a fuzzy control system is that the grey predicted output from an unknown plant could always provide us some useful information for better control of the system before the system behavior runs into bad situations.

The rest of this paper is organized as follows. In Section 2 and 3, the structure and the mathematical model for roller kiln based on grey-fuzzy predictive control is presented. In Section 4, Matlab program with the proposed control scheme are obtained. Finally, conclusion remarks and future work are presented in Section 4.

## 2 Grey Prediction Model

It has been more than twenty years since the grey system theory proposed by a Chinese professor Julong Deng in the 1980s. The grey predictive method has been successfully used to model the dynamic systems in different fields such as agriculture, ecology, economy, statistics, meteorology, industry, environment, and so on [4]. Grey system theory has classified its research objects into three kinds of 'black', 'white' and 'grey', according to some cognitive hierarchy.

The general form of a grey differential model is GM (i, j), where i is the order of the ordinary differential equation and j the number of grey variables. The grey model GM (1, 1) with a single parameter has been most widely applied, therefore the model can be derived by the following basic steps in the following [5-6].

Step 1 : RC and AGO (accumulated generating operation)

Considering a temperature sequence as the original data, we have $\eta$

$$S^{(0)} = \{T^{(0)}(1), T^{(0)}(2), \ldots, T^{(0)}(m)\} \tag{1}$$

where m=2,. . . ,$\eta$,$\eta \geq 4$

Wherein (0) represents original data of grey prediction. The data sequence proceeded by AGO once is

$$S^{(1)} = AGO \circ S^{(0)} = \{T^{(1)}(1), T^{(1)}(2), \ldots, T^{(1)}(m)\}, m = 1, 2, \ldots, \eta, \eta \geq 4 \tag{2}$$

which

$$T^{(1)}(1) = T^{(0)}(1)$$

$$T^{(1)}(m) = T^{(1)}(m-1) + T^{(0)}(m), m = 2, 3, \ldots, \eta, \eta \geq 4 \tag{3}$$

Step 2: Build grey model GM (1,1)

The GM (1,1) model can be constructed by establishing a first order differential equation as follows:

$$\frac{dT^{(1)}(x)}{dx} + aT^{(1)}(x) = b \tag{4}$$

Where a and b are estimation parameters.$Z^{(1)}(m)$ is affected by $T^{(1)}$

$$Z^{(1)}(m) = \alpha_m T^{(0)}(m) + T^{(1)}(m-1) \tag{5}$$

$$m = 2, 3, \ldots, \eta, \eta \geq 4$$

However,the selection of $\alpha_m$ value will influence the accuracy of predicted value. The solution for Eq.(3) with discretization is

$$\widehat{T}^{(1)}(m+1) = (T^{(0)}(1) - \frac{b}{a})e^{-am} + \frac{b}{a} \tag{6}$$

$$m \geq 0$$

Wherein$\widehat{\ }$represents Grey forecast and $\widehat{T}^{(1)}(m+1)$ is the grey predicted value of the $S^{(1)}$ .

Here, we set

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ ... & ... \\ -z^{(1)}(m) & 1 \end{bmatrix}, T = \begin{bmatrix} T^{(0)}(2) \\ T^{(0)}(3) \\ ... \\ T^{(0)}(m) \end{bmatrix} \tag{7}$$

$$M = \begin{bmatrix} a \\ b \end{bmatrix}, m = 2, 3, \ldots, \eta, \eta \geq 4$$

So, Eq.(4) can be substituted as

$$T_N = BM \tag{8}$$

Then the optimal parameter M can be obtained by using the minimum least-square estimation algorithm

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T T \tag{9}$$

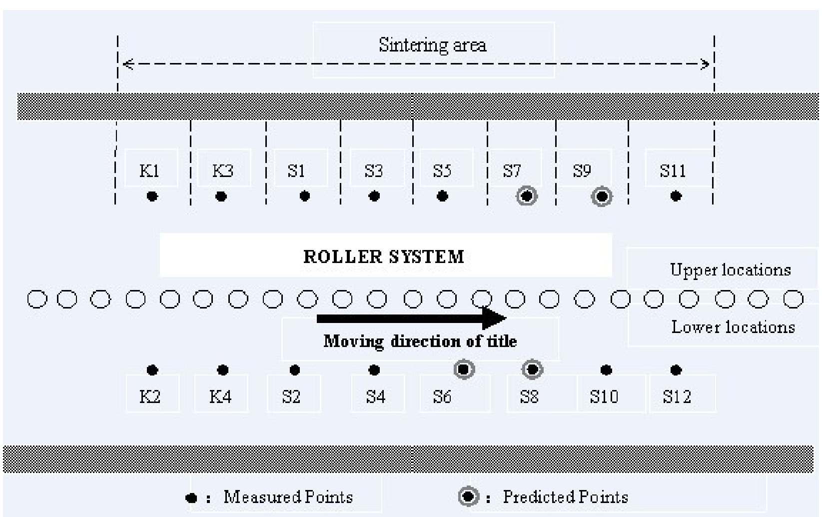


**Fig.1** Measured points and predicted points for the temperature in roller kiln

## 3 Modeling of Grey-Fuzzy Predictive Control

### *3.1 The Derivation of Physical Model for Roller Kiln*

As shown in Fig.1, in the ceramic roller kiln, dozens of nozzles distributed upper locations and lower locations alone roller kiln which controlled the temperature at considered point within a limited range.

The kiln shows non-linearity, due to the different behavior in the heating and in the cooling phases. However, it is very difficult, even impossible to build an accurate and perfect mathematical model for temperature process in ceramic roller kiln. So, With reference to Fig. 1, our research assumes that the kiln has been wrapped up by the insulated materials and there is no any heat source besides nozzle inside such target.

The governing equation for the one dimensional transient heat conduction is given by

$$\frac{\partial T}{\partial t} = \frac{\partial}{\partial x}(k\frac{\partial T}{\partial x}) \tag{10}$$

Namely,

$$\frac{\partial T}{\partial t} = k\frac{\partial^2 T}{\partial x^2} + \frac{\partial k}{\partial x}\frac{\partial T}{\partial x} \tag{11}$$

T means the temperature, t indicates the time, x indicates the positional parameter, and k indicates the thermal conductivity.

Wherein, Eq.(11) can be discretizated into n-1 units as

$$\frac{{T_i}^{j+1} - {T_i}^j}{\Delta t} = {k_i}^j\frac{{T_i}^{j+1} - 2{T_i}^j + {T_{i-1}}^j}{(\Delta x)^2} + \frac{{k_{i+1}}^j - {k_{i-1}}^j}{2\Delta x}\frac{{T_{i+1}}^j - 2{T_{i-1}}^j}{2\Delta x} \tag{12}$$

From manuscript [7], we can deduce

$$AT = DC \tag{13}$$

And,

$$T = A^{-1}DC = EC, E = A^{-1}D \tag{14}$$

$$C = (E^T E)^{-1}E^T T_{grey} \tag{15}$$

Wherein $T_{grey}$ indicates the temperature acquired by the grey prediction.

According to Eq.(13)-(15),it is dispensable to measure the temperature at each dispersed point.

### *3.2 Grey-Fuzzy Predictive Controller of Roller Kiln*

Thus, in our control system, the control procedures are summarized as follows:

(1) Measure the temperature signal from thermocouples (sensors).

(2) Calculate output by using the control algorithm and switch the responses instantaneously.

The temperature control system of the ceramic roller kiln consists of thermocouples (sensors), valves, actuators, electrically-driven conveyors and other components to form realtime control. Schematic diagram of the proposed GFPC (greyCfuzzy predictive control) with an on-line dynamic switching mechanism is shown in Fig. 2.

r(t) is the reference value, T(t) indicates the measurement signal, $T*(t) = T_{grey}$ is the grey prediction value, u(t) is the output of the fuzzy controller, and $e^*(t)$ is the offset: $e^*(t) = r(t) - T^*(t)$.

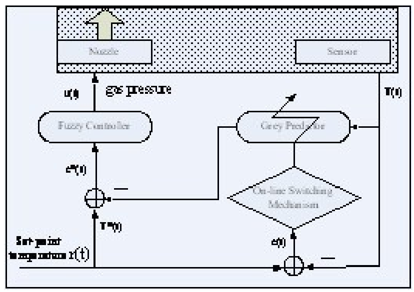


**Fig.2** The structure of grey-fuzzy predictive controller

In this paper the whole sintering will be dispersed into 8 units. According to Eq. (6), thus

$$\widehat{T}^{(1)}(5) = (T^{(0)}(1) - \frac{b}{a})e^{-4a} + \frac{b}{a} \tag{16}$$

Since the forecasting step size decides the predictive value and finally affects the control performance, an on-line switching mechanism is adopted to regulate the appropriate forecasting step size of the grey predictor [7].

This paper, we have also presented the comparison on selecting the measuring points for temperatures in order to reduce the synergistic effect on the grey prediction with errors of measurement.

Therefore, the grey predictor has the ability of predicting the "previous" behavior of the system based on different states of feedback responses by either increase or decrease of control signal applied to actuator. We have the following switching mechanism:

$$P = \begin{cases} P_1 < 0 & if \quad e(t) > e_1 \\ P_2 > 0 & if \quad e_\xi < e(t) < e_1 \\ P_3 < 0 & if \quad e(t) < e_\xi \end{cases} \tag{17}$$

In kiln temperature control system, E and EC (E means error between reference value and real temperature of the kiln, and EC means the differential coefficient of E) are typical variables. Any control rules of this temperature control system should be based on these variables [3].

Then, in our research, the input variables of the fuzzy controller are

$$e^*(t) = r(t) - T^*(t)$$

$$\Delta e^*(t) = [e^*(t) - e^*(t-T)]/T \tag{18}$$

where $e^*(t)$ and $\Delta e^*(t)$ are the output error and the error change, respectively.

## 4 Results and Discussion

Due to the characteristics of long time-delay, nonlinearity, coupling and incompletion of parameter information in sintering process, the grey predictive controller is established by using the Matlab. The algorithm is shown in Fig.3.

```
x=cumsum(Tt);      % T is the original data
% Create B matrix
for i=1:(dn-1)
    B(i)=- (x(i)+x(i+1))/2
End
% Create Y matrix vector
for i=1:(dn-1)
    y(i)=x(i+1)
End
y= y'
B=[B' ones(dn-t,l)]
au=(inv(B'*B))*B'*y
```

**Fig.3** Algorithm of grey predictive controller

## 5 Conclusions

In this paper, a control algorithm for temperature in the roller kiln has been proposed. From the study we concluded that this temperature process is too complicated to build a certain mathematical model for identification purpose. This work focused on analyzes the heat conductive feature. Basically, from the viewpoint of developing an effective control system, several key technologies were analyzed and the structure of controller was developed successfully in this paper. Besides, we created Matlab project to implement the predictive controller. However the limitation so far that all the control system are obtained by theory and simulation and in future we are planning to test the system for a pilot ceramic plant.

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