Case-based reasoning intelligent prediction model of rotary kiln temperature

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Abstract

Temperature is a key technical index in rotary kiln combustion process, which is so difficult to measure directly online. The offline analysis has large-time delay and poor precision. An intelligent prediction model of rotary kiln temperature based on case-based reasoning was developed, which consists of four modules: data collection and pre-treatment, prediction, online modification and effect estimate. The practical data of some rotary kiln were simulated. The industrial application results show that the prediction model can reflect the actual operation condition and meet the requirement of real-time control .Its effectiveness is proved evidently.

*Keywords: c*ase-based reasoning, intelligent prediction, temperature control, rotary kiln

1 Introduction

Rotary kiln is being widely used in many industrial departments .But the biggest shortcoming of it is its high energy consumption and low thermal efficiency. The backward method to test and control it is the main cause. At present, the estimation of its thermal state is still dependent on the fire workers keeping observing the "ring of fire" of the rotary kiln. The workers' mental state, technological literacy, responsibility and many other factors would affect them .The large randomness make it hard for the rotary kiln to save energy. Besides, the rotary kiln is a typical multivariable, time varying and distributed parameters nonlinear system. The thermo technical process is so complex that it's very difficult to build a mathematical model for it. Using soft-sensing technique to online test the temperature of rotary kiln is of great significance to control the combustion process of rotary kiln. At present, as an effective way to estimate the uncertain variables of industrial process, soft-sensing technique is being more and more widely used. It is mainly aimed at building mathematical model for process variables. It can be named prediction model according to its characteristic and function.

2 Modelling method based on case-based reasoning technology

CBR is a methodology using past experience to simulate human brain judging things. It expresses and stores a large number of problems and their solutions in the form of case. When meet a new problem (case), the system will match similar cases from its case library and retrieve the most similar one, then adjust their solutions to solve it. The new case with high typicality will be stored. And in that way, the CBR system is improved.

The Figure 1 shows an intelligent prediction model structure. It can forecast key variables of a complex industrial process. $\hat{X}$ is the output of the case-based reasoning prediction module, $\overline{X}$ is the correction output, Σ is the process data set from the distributed control system (DCS), Θ is the artificial measurement data set obtained by the measure model, e is the online correction parameter from the online correction module, u is the control input, y is the output of the controlled object.

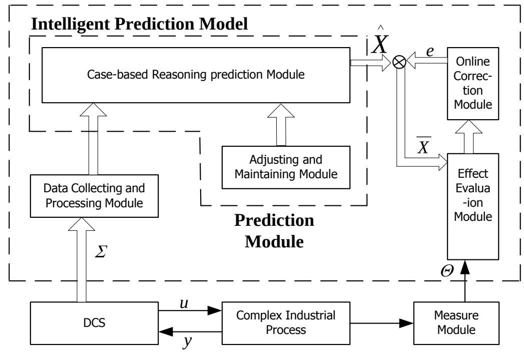

FIGURE 1 The structure of the intelligent prediction model

2.1 DATA COLLECTING AND PROCESSING MODULE

Data collected from the working site always accompanied with various kinds of interference noise. To furthest avert them, we need converse the data and deal with the errors. Under some conditions, we need also deal with the output of the prediction model appropriately. As the model is built on the premise of a series of hypotheses, it can't be

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all the fours with the practical situation. There are some model errors.

2.2 PREDICTION MODULE

Firstly, prediction model reads the current working condition and retrieves similar cases from the case library. Then the retrieved cases will be matched and reused according to their similarity threshold to get the solution, which is the dominant variable soft measurement value that needs to be estimated. Analyse the error between the actual measured value and the soft measured value, assess the precision of the soft measuring model precision. If a case cannot reach the prospective accuracy, adjust it. Else store it into the case library by corresponding rules.

When the case-based reasoning module is working, as the object's technological parameters and other condition changing, the original useable cases may not be appropriate any more. In order to make sure the case-based reasoning module can get the object's changing information and obtain the right result, the case-based reasoning system need to adjust and maintain. That is the function of the adjusting and maintaining module.

2.3 ONLINE CORRECTION MODULE

After the prediction module come into using, the output of the module may drift if the object's situation and working location changed. To ensure the prediction value's veracity, it needs correction.

$$e=\frac{1}{n}\sum_{i=1}^{n}\left(X_i^*-\hat{X}_i\right), \tag{1}$$

e is the online correction parameter, $\hat{X}_i$ is the output of the prediction model, X_i^* is the actual measured value, n is the sample size. The corrected output is

$$\bar{X}=\hat{X}+e. \tag{2}$$

This method is easy to realize. We can adjust the output of the prediction module with type (1) and type (2) to facilitate the output result drifting and ensure the accuracy.

2.4 EFFECT EVALUATION MODULE

This module compares the output of the case-based reasoning prediction module with the artificial measured data from the measure module to evaluate the prediction accuracy.

3 Rotary kiln temperature intelligent prediction model based on case-based reasoning

When building a temperature prediction model of rotary kiln, the temperature of rotary kiln should be analysed in consideration of the periodically statistics of rotary kiln temperature, the combustion chamber draft, the heating gas flow, the heating gas pressure and the calorific value of gas. Intelligent prediction will be operated based on case-based reasoning technology. Figure 2 is the model structure. The rotary kiln temperature intelligent prediction model consists of case-based reasoning prediction model, self-adjusting model and so on. There is the measure data set of rotary kiln combustion process. There is the output of the case-based reasoning prediction model, There is the measure value of rotary kiln during a time interval. There is the statistic of the artificial measured temperature values. There is the error between the output of the case-based reasoning prediction model and the artificial measured temperature value, (>0) there is the presupposed error limitation. There is the adjusted output of rotary kiln temperature value. After the model selector obtain the test data from rotary kiln combustion process, the case-based reasoning prediction model will accomplish the prediction and get the value. The result will be adjusted according to the artificial testing temperature statistic obtained by the self-adjusting model. Then we can get the desired value.

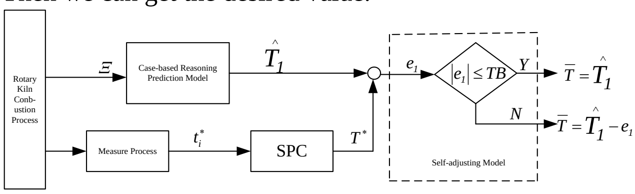

FIGURE 2 The complex intelligent prediction model of rotary kiln

3.1 CASE-BASED REASONING ALGORITHM

3.1.1 Presentation of the case

The prediction model of rotary kiln temperature is based on case-based reasoning prediction algorithm. Analyse the operating parameters with visible controllable analysis and use correlation analysis to compare them with other variables. In consideration of variable simplification, choose the parameters below as the auxiliary variables of the soft-sensing model of rotary kiln temperature: the heating gas flow *u*, the calorific value of gas *h*, the heating gas pressure *p* and the combustion chamber draft *n*. The cases of rotary kiln are stored into computer in form of data base. The data base is composed of several case records, presented as the Table 1.

TABLE 1 The case of rotary kiln temperature

Time	Working Condition				Solution
	Heating Gas Flow	Calorific Value of Gas	Heating Gas Pressure	Combustion Chamber Draft	Rotary Kiln Temperature Prediction Value

3.1.2 Case retrieval

Case retrieval is of great importance to case-based reasoning. Retrieve the case library according to the new case and find the best solution. If the current working state is described as $X=\left(x_1,x_2,...,x_n\right)$, but the case in the case library is $X_k=\left(x_{1,k},x_{2,k},...,x_{n,k}\right)$, $k=1,...,m$, m is the number of the cases. The similarity between x_i $\left(1\le i\le n\right)$ and $x_{i,k}$ can be defined as:

$$Sim\left(x_i,x_{i,k}\right)=1-\left|x_i-x_{i,k}\right|/Max\left(x_i,x_{i,k}\right). \tag{3}$$

And the similarity between current working state C_c and the existing case C_k is:

$$Sim\left(C_r,C_k\right)=\sum_{i=1}^{n}w_i Sim\left(x_i,x_{i,k}\right). \tag{4}$$

The w_i in Equation (4) is characteristic weight parameter, $\sum_{i=1}^{n}w_i$ =1.

Then write the similarity value into corresponding case library.

Assume the similarity threshold is Sim_{max} = $max(sim(c_{r,}c_k))$.

$$Sim_v=\begin{cases}J_v, Sim_{max}\ge J_v\\ Sim_{max}, Sim_{max}<J_v\end{cases}. \tag{5}$$

The threshold J_v is confirmed by engineers from the practical situation.

If similarity value between a retrieved case with the practical situation is $\ge Sim_v$, then the case is a matched case.

3.1.3 Case retrieval and matching

Case retrieval and matching is the key to case-based reasoning. Its main purpose is retrieving cases according to the description of new problems and finding out their solutions. Any case whose similarity value with the current practical situation is over the threshold Sim_t will be retrieved as matched case.

3.1.4 Case reusing

In general, the solutions of the retrieved matched cases can't be directly used as the solution of the current working situation. Assume the retrieved matched case set is $C_k=\left\{T_k,X_k,Y_k,Sim_k\right\}$, $k=1,2,...,l$, $l<m$. k is the number of matched cases, Sim_k is the similarity value between the case set C_k and the working situation. Suppose $\tilde{C}$ as a case set with biggest similarity value Sim_{max} and the solution as $\tilde{J}$. J_u is calculated solution reused according to the case set.

$$J_u=\sum_{k=1}^{l}\left(Sim_k\times Y_k\right)/\sum_{k=1}^{l}Sim_k. \tag{6}$$

The variables above are characterizing attributes. Their feature weights are determined to be 0.25, 0.25, 0.25, 0.25 according to expert experience. Based on the past cases from the temperature case library, the rotary kiln temperature can be predicted with case-based reasoning method.

3.2 SELF-ADJUSTING ALGORITHM

To ensure prediction accuracy, the initial predicted result needs to be self-adjusted. Suppose the artificial measuring data set as $\left\{t_i^*, i=1,2,...,k\right\}$. The data can be conducted with statistical process control (SPC) method.

$$T^*=\frac{\sum_{i=1}^{k}t_i^*}{k}. \tag{7}$$

$\hat{T}_1$ is the initial rotary temperature value obtained by case-based reasoning prediction model. The temperature prediction effect is evaluated with the type below.

$$e_1=\hat{T}_1-T^*, \tag{8}$$

e_1 is the error between the initial rotary temperature value obtained by case-based reasoning prediction model and the artificial test data. If $\left|e_1\right|>TB$, it means the output of the prediction model needs to be adjusted, e_1 is the adjusting parameter. Else, the output does not need to be adjusted and e_1 can be supposed to be 0. The adjusted output $\overline{T}$ is:

$$\overline{T}=\hat{T}_1-e_1. \tag{9}$$

4 Industrial application

Apply the intelligent prediction model of rotary kiln into an iron and steel complex's mineral processing intelligent control system. The temperature prediction is shown in Figure 3. Statistic suggests, if the odds, which the rotary kiln temperature prediction errors stay within ±10°C can reach 91.8%, it will meet the industrial production requirement.

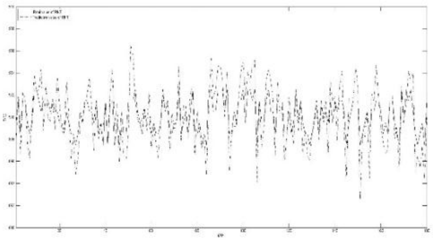

FIGURE 3 The prediction effective of the rotary kiln

5 Conclusions

The key parameters of a complex industrial production process can't be measured directly online. The intelligent prediction model based on CBR is aimed at solving the problem. In consideration of the rotary kiln temperature cannot be measured in real time, an intelligent prediction model of rotary kiln temperature can be built with the suggested modelling method. It has been applied to industrial production, the result is positive. That means the method is effective.

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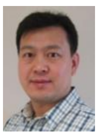

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