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CBR Applications in Combustion Control of Blast Furnace Stoves

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***Abstract*—Since its appearance, CBR methodology has drawn many research attentions and already proved its potentials in different industrial applications. However the related applications up to now are mainly focused on non real-time targets. In our work, CBR methodology was introduced for solving practical real-time process control problems. Its deployments in combustion control of blast furnace stoves are provided in this paper. Two examples, the dome temperature control and the blast temperature prediction applying CBR method, are presented respectively.**

***Index Terms*—Case-based reasoning, Combustion control, Blast furnace stoves, Real-time, Prediction**

I. Introduction

Case-based reasoning is a method that compares the present problem with previous ones and applies the problem solving of the past to the present problem. In other words, we can reuse the problem solving technique that was used in the past and apply it to the present problem [1, 2]. Case-based reasoning has been used to solve problems in diverse areas including decision support, help desk support, product cataloguing and maintenance support, etc. In this article, CBR applications in combustion control of blast furnace stoves, which is a typical real-time process control problem, are presented.

A blast furnace is used to produce molten pig iron from iron oxides, coke and flux. One of the major sources of energy for this process is the sensible heat coming from the preheated air, referred to as blast air, which is injected into the furnace. This air is preheated in tall, cylindrical, refractory-filled thermal regenerators called *Blast Furnace Stoves* (BFS). Since a BFS has inherently time-delay, time-varying and non-linear characteristics, traditional control strategies such as PID are no longer in force while confronting the combustion control problem of BFSs, because there are no exact mathematical models for describing the stoves' characteristics. Therefore some advanced control strategies have been researched and implemented for solving this combustion control problem, such as fuzzy control or expert control methods reported in literatures [3, 4]. But the natures of these intelligent control strategies are of rule-based, consequently the obstacle or so called "bottle neck" for gaining the expert knowledge, which is the basis for realizing the above mentioned strategies, is inevitable eventually. So a novel control strategy was proposed [5], which utilizes CBR rather than RBR as its reasoning machine for getting control decisions, and this method has been proved to be effective and easy to be implemented in several in-situ applications.

Iron manufacturing in blast furnace requires a large, continuous flow of air preheated at high temperature (above 1000℃). A battery of 3~4 BFSs, operated cyclically, is located in the vicinity of the furnace. From the view point of a total blast process, each one in a battery of BFSs works in a discontinuous or sequential batch mode, and an entire continuous on-blast process is guaranteed by each stove's cyclic and alternating operation. Since the heat energy accumulated during the on-gas phase could not be measured directly and easily, a fixed on-gas and on-blast duration and its correspondent changeover cycle are pre-determined for each stove according to formerly manual monitoring experiences. Because the blast stoves and their related auxiliaries have inherently different characteristics, and the quality of their fuel (BFG) is changing frequently, such an operation mode with a fixed on-gas and on-blast cycle may cause the blast air temperature fluctuate dramatically, and the stove just over a better on-gas phase could not thoroughly send out its stored heat during the on-blast phase. For coping with this problem, a variable cycle control strategy was proposed and implemented [5]. This strategy takes the whole blast temperature as its control target. The next on-blast stove's heating intensity is adjusted dynamically according to the blast temperature prediction of the stove just terminated its on-gas phase. The blast temperature prediction is also realized based up CBR methodology.

The article is structured as follows. Section II presents the CBR method for controlling the dome temperature. Section III describes the blast temperature prediction based-on CBR methodology. Section V ends with the conclusions.

II. Dome Temperature Control

Because a BFS's heat level could not be directly and simply measured, the automatic control system usually takes two indirect parameters as its controlled variables, which are the BFS's dome temperature and its waste air temperature. The adjusted variables are the air flow rate and the fuel (BFG) flow rate, and a suitable ratio of air/fuel should be maintained to ensure an optimal and energy-saving combustion status.

The method for controlling the BFS's dome temperature using CBR is described as follows.

A. Case Representation

Each sample case while using CBR is described as a vector form which includes three elementary components,

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that is: a problem description, a solution description and an effect description. Before the reasoning mechanism is put into on-line operation, its case representation should be carefully researched and constructed.

For controlling a BFS's dome temperature during its heat storing stage, in addition to the directly related adjusting variables (like its gas flow rate and air flow rate), other relevant parameters should also be taken into consideration. In our work, the case-base's case representation is constructed based on the following considerations:

(a) The suggestions of experienced operators and the analysis of historical data should be taken into account first of all.

(b) Secondly, the selected variables or attributes should come out of easy to be measured or calculated process parameters.

Finally, the case representation for stable dome temperature control applying CBR methodology is determined，and described as in the following Table 1.

Table 1 Case representation

No.	Name	Symbol	Description
1	On-gas duration	$t_{ON\text{-}GAS}$	On-gas Duration from the beginning to the current time
2	Dome temperature	T_{DOME}	Current dome temperature
3	Change of dome temperature	ΔT_{DOME}	Difference between the current dome temperature and the precedent one
4	Waste gas temperature	$T_{EX\text{-}AIR}$	Current waste air temperature
5	Change of waste air temperature	$\Delta T_{EX\text{-}AIR}$	Difference between the current waste air temperature and the precedent one
6	Pressure of BFG	P_{BFG}	Current pressure of BFG (gas)
7	Flow rate of gas	F_{BFG}	Current flow rate of BFG
8	Flow rate of air	F_{AIR}	Current flow rate of combustion air
9	Ration of gas/air	$R_{GAS\text{-}AIR}$	Current ratio of BFG/air
10	Position of gas valve	V_{GAS}	Precedent position of gas valve
11	Position of air valve	V_{AIR}	Precedent position of air valve
12	Increment of gas valve	ΔV_{GAS}	Increment of gas valve of this adjustment
13	Increment of air valve	ΔV_{AIR}	Increment of air valve of this adjustment
14	Adjust effect	E_{adj}	1: normal, 2:better

After the case representation is determined and checked, it should be filled up originally with sufficient sample cases before being put into on-line operation. These sample cases are called the *initial seed* [6].

B. On-Line Operations

Differed from the non real-time applications, the CBR method for controlling the dome temperature should do its retrieving, reusing and revising as fast as possible because of its real-time requirement. Thus some complicated similarity calculation methods are unsuitable to such an application. Therefore the simple k-nearest neighbour algorithm is used to realize searching and matching of the similar cases. The essential idea of k-nearest neighbour is defining a certain space distance between a query case to be matched and each example case stored in the case-base, and taking the distance as a definite similarity degree measure. In our work, a threshold value is pre-determined before the on-line retrieving procedure is doing. If one or more cases with their respective distances less than the threshold are found, then the sample case which has the smallest distance is taken as the retrieved and reused sample.

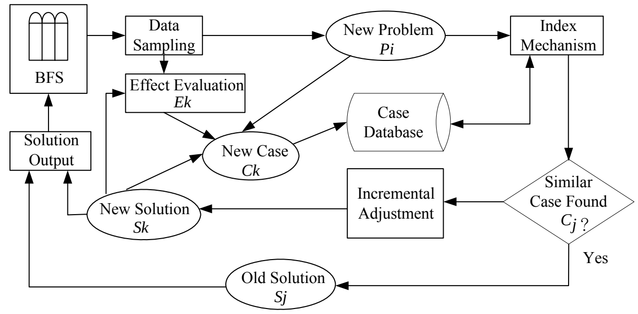

Fig.1 Flow chart of on-line operations

As shown in Figure 1, the tasks of the CBR method for controlling the dome temperature of a BFS in its on-line operation phase are just like a typical CBR cycle, which can be divided into the following steps:

(a) Getting data and submitting problem. Firstly the real-time data reflecting the controlled object's operation status and technique parameters are sampled. If some problems are found from the on-line data, such as a bias between a required temperature value and the measured one is greater than a pre-determined threshold, they will be taken as a new problem and submitted to the CBR reasoning mechanism in the form of a problem description vector to look for a suitable solution.

(b) Retrieving and matching. Then the CBR reasoning machine compares the submitted problem with each sample case stored in the case-database to find a similar one. The similar case is defined as a sample case which has the smallest space distance between it and the submitted problem vector. And the space distance is calculated using the k-nearest neighbour algorithm.

(c) Adopting and reusing. If the similar case's distance calculated in the above step *b* is less than a pre-determined threshold, meaning a similar case is found, this case's solution description will be adopted and reused, and taken directly as the reasoning result or the final control decision. This control decision is sent to the actuator to execute the adjusting action

(d) Learning and revising. If no sample case's distance in the case-base is less than a pre-determined threshold, meaning no similar case is found, then an incremental or trial adjustment will be taken as the definite control decision. This trial adjustment is made based on some known control rules. And this new problem and new solution will be evaluated later and then added to the sample case-base to further extend the problem solving ability of the CBR reasoning mechanism.

C. Control result

An adjustment example using CBR method is given out in Table 2. At the 4^{th} sampling time, the dome temperature is 2℃ lower than the required value (1285℃) and the difference is bigger than **ε** (1.5℃), so the CBR mechanism is activated. This new problem is described as a vector: (22, 1283.0, -2.0, 253.1, 1.0, 21538, 9940, 2.17, 5.21, 51, 60). After the space distance calculations with each sample case in the case-base, a similar case is found, which is: C_{39} = (22, 1283.1, -1.9, 265.9, 1.6, 21683, 9824, 2.21, 5.27, 52, 58, -3,

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0). Therefore this case's solution description is reused and put into the actuators as the control decision, which is the gas valve's increment (-3, 0), meaning an open variation of the gas valve from 51% to 48%.

Table 2 Adjustment Example

No.	T_{DOME}	$T_{EX\text{-}AIR}$	F_{BFG}	F_{AIR}	P_{BFG}	V_{GAS}	V_{AIR}
1	1284.5	252.1	20904	10191	5.06	51	60
2	1284.2	252.7	21100	9971	5.13	51	60
3	1283.8	253.2	21372	9858	5.20	51	60
4	1283.0	253.1	21538	9940	5.21	51	60
5	1283.0	252.9	20276	10345	5.01	50	60
6	1283.7	253.3	20647	9913	5.05	49	60
7	1282.8	253.9	21130	9920	5.08	48	60
8	1283.2	255.3	20964	9851	5.09	48	60
9	1283.9	255.5	20939	9910	5.08	48	60
10	1284.8	255.7	20198	9991	5.09	48	60

III. BLAST TEMPERATURE PREDICTION

To ensure efficient furnace operation, the required flow-rate and temperature of the blast air must be maintained. A common disadvantage of the combustion control methods for BFSs presented before is that they take into account only the individual stove's control problem, not considering a battery of BFSs as a whole system. In reality, each stove's heat storage ability in a blast system is different inherently, and the caloricity of BFG ejected from BF as the main fuel for blast stoves is changing frequently, therefore a total optimal blast effect could not be guaranteed while applying a fixed cycle operation. Therefore, a variable cycle operation mode was proposed and implemented. It dynamically changes the heating intensity of the next on-blast BFS according to the predicted blast temperature of the BFS just beginning its on-blast phase..

Obviously, the key factor for implementing the variable cycle strategy is how to predict the blast temperature timely and correctly based on the measured and/or calculated data. Some study on predicting the blast air temperature profile of the BFSs that just over on-gas phase have been presented in literatures. There are the methods based on the mathematic model [7, 8] or data reconciliation [9]. However, these methods are difficult to be applied because they need the craft parameters, which reflect the characteristics of the BFS itself and its refractory bricks, and the predicted result is not ideal because these parameters are commonly uncertain. Unlike the above mentioned methods, the presented one in this article is using CBR methodology as an effective predicting tool and based on the statistical data (not real-time data) during the on-gas phase.

A. *Case Representation*

Before doing the prediction, the case description and the case-base structure should be defined first of all, and then draw out sufficient cases from the precedent on-gas and on-blast cycles and put them into the case-base.

The combustion process of the BFSs is a kind of sequential batch process. It is demonstrated that the hot blast produced during the on-blast phase has a definite relation with the accumulative heating effect during its corresponding on-gas phase. Therefore 9 characteristic variables that appeared to be relative with the heating effect are taken as the problem description of the case representation. These 9 characteristic variables are easy to be calculated or summed up in terms of the measured process variables, they are: *even dome temperature* (EDT), *initial dome temperature* (IDT), *even exhaust-gas temperature* (EEGT), *heating time* (HT), *gas flux sum* (GFS), *combustion air sum* (AFS), *last blast temperature* (LBT), *initial blast dome temperature* (IBDT), and *even gas pressure* (EGP). The correlative measured process variables include: dome temperature, exhaust gas temperature, gas pressure, gas flow, combustion air flow and hot blast temperature, etc.

In order to fill up the case-base with various samples that covering nearly all the possible combustion situations, 100,000 measured sample data records were collected from the No.2 blast furnace control system at Baofeng Iron & Steel Company in Heibei, China. From these records, 48 cases representing both the on-gas and on-blast features were drawn out and chosen eventually, and stored in the case-base as the basis of the prospective reasoning.

B. *On-Line Operations*

In our study, the k-nearest neighbour algorithm is used to realize searching and matching of the similar cases. The specific predicting steps in our applications are described as follows:

(a) Sum up and record the above defined 9 attributes values from the gathered sample data after an on-gas phase having been terminated, and then take these values as a query case (or problem). This new query is an input to the CBR system, which generates the adequate problem descriptions by querying the case-base.

(b) Calculate the Euclidean distances that clarifies the similarity measure between the query case and each example case. Then choose k nearest example cases that have the smallest Euclidean distances, where k equals to $\lfloor \sqrt{n} \rfloor$ ("[ ]" means an integer operation), and n is the total number of example cases stored in the case-base. In our applications, n is 48, so k is 7.

(c) Do cluster analysis in the above k nearest cases to categorize them further into two parts, and choose the k′ nearest cases to be used in the next step from the smaller distance category.

(d) Finally calculate the arithmetic average values of the corresponding blast air temperature's time sequence of the k′ nearest example cases at each sample time, and take the averaged time sequence as the predicted blast air temperature profile.

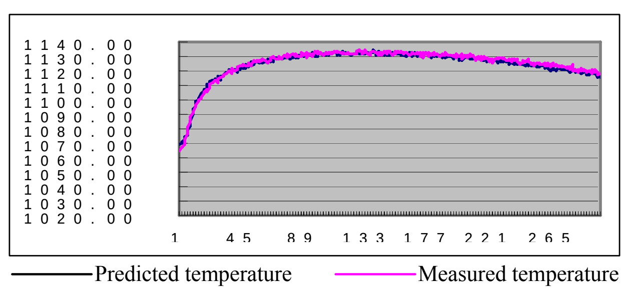

Fig.2 A good prediction result

C. *Predicting result*

The application results produced by this CBR method are very promising. Figure 2 shows an example for a good prediction of the blast temperature. We can see from the figure that the measured and predicted temperature curves are almost identical.

IV. CONCLUSION

(a) Compared with other intelligent control strategies, like fuzzy control or rule-based expert control, the presented case-based one has an obvious advantage: it is very easy to be implemented. The obstacle or bottle neck for obtaining the control rules is entirely overcome. And more importantly, since the control decisions in manual operations were made by the operators with taking into account several factors affecting the control results, and the decisions were fuzzy in some degree, thus the final control decisions using CBR based on the sample cases drawn out from experienced practices would inherit naturally the characteristics of both fuzzy and multi-factors.

(b) This article also presents a novel approach to predict the blast temperature without a mathematical or logic model, but only based on the measured and statistical data during the on-gas phase. Though this CBR method seems easier to be implemented than the other mathematical model methods, it has been shown that its temperature prediction precision is quite satisfied.

It is shown with the presented applications that the CBR methodology could be used for dealing with not only the reasoning of non real-time objectives, but also the real-time control of industrial processes. It is proved once again with the presented article that CBR is a powerful AI methodology, and it will be found more successful applications on more industrial domains in the future.

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