

## Operating-State-Based Intelligent Control of Combustion Process of Coke Oven<sup>\*</sup>

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**Abstract:** This paper describes a hierarchical intelligent integrated control method for controlling the combustion process in a coke oven. A key feature is the determination of the operating state of the oven from an analysis of the characteristics of the process. The system contains three layers: a decision layer, a temperature optimization and control layer, and a process control layer. An information fusion method is used in the decision layer to determine the operating state of the combustion process. The control strategy uses an outer and an inner loop. The outer loop uses fuzzy controllers to adjust the temperature, and to generate proper settings for the gas flow rate and air suction power for the inner loop. The parameters of the outer loop controllers are tuned by a multiple-objective optimization method with an adaptive genetic algorithm. The inner loop controllers keep the temperature of the coke oven in the proper range. A switching control strategy is used to select a suitable controller for the current operating state.

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### 1. INTRODUCTION

Coke, the product of a coking process, is an important raw material in the metallurgy industry and is widely used in iron-making blast furnaces, casting, and metal refining. The key process in making coke is combustion, which takes place in a coke oven. The oven temperature is defined to be the average of the flue temperatures of the combustion chambers; it is a key parameter that reflects the level of heating in the whole oven. Too low an oven temperature results in poor-quality coke and a short oven lifetime; while too high an oven temperature not only results in poor-quality coke, but also causes environmental pollution and wastes energy. So, it is very important to keep the temperature of the oven in the proper range, and this necessitates control of the combustion process (Sadaki et al. [1993]).

Combustion in a coke oven is a complicated process. It features a large time delay, strong nonlinearity, and time-varying characteristics. Three types of control systems for the combustion process have been reported: a coke oven temperature feedback control system (Nakazaki et al. [1987]), a heat supply feedforward control system (Vander et al. [1990]), and a two-degree-of-freedom (TDF) heat supply control system (Buss & Mccollum [1984]). Although many studies on the Smith predictor and predictive control have been reported (e.g., Vieira et al. [2003], Wang et al. [2006]), few are directly applicable to the combustion process of a coke oven because no exact mathematical model of the process is available. On the other hand,

since fuzzy control does not require an exact mathematical model of a plant and is very robust, it is widely used for process control in industry (Yanan et al. [2003], Ioannidis et al. [2006]). In actual practice, fuzzy control has already been shown to be effective in controlling the temperature of a coke oven (Gao et al. [2006]).

Industrial processes are generally becoming larger, more precise, and more complicated; and it is difficult to obtain satisfactory results with a single control method. One way to solve this problem is to combine intelligent methods; and in fact, this constitutes a new way to control the temperature of a coke oven. Simulation studies have demonstrated the validity of the method (Gao et al. [2005]). However, there are usually two problems with existing methods of controlling the combustion process of a coke oven:

- (1) Only tracking error information is utilized in the control of the oven temperature; and no consideration is given to the influence of discrete events, such as those arising from production planning and coking operations, even if they strongly affect process conditions.
- (2) The parameters of a fuzzy controller are selected based on operator experience and are not optimized.

In this study, the mechanism of the combustion process of a coke oven was analyzed from the standpoint of production planning in terms of the continuous physical variables of the process. Hybrid system theory provides an effective solution to the problem of controlling the temperature of a coke oven. Three layers are used in the configuration of an intelligent integrated combustion process control system.

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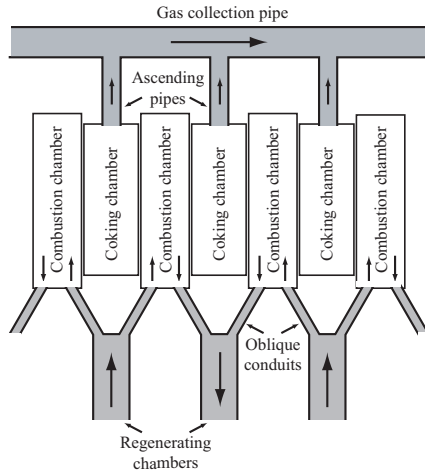


Fig. 1. Structure of coke oven.

## 2. DESCRIPTION OF COMBUSTION PROCESS AND CONTROL SYSTEM

A coke oven is the most complex furnace in the metallurgy industry. It usually has 50-100 heating units, each of which consists of a coking chamber, a combustion chamber, and a regenerating chamber. Figure 1 shows the structure of a coke oven. The coking and combustion chambers are arranged alternately in a line. The fuel is coke gas, blast furnace gas, or a mixture of the two. In the combustion process, gas and air are preheated in the regenerating chambers and fed through oblique conduits to the combustion chambers, where they burn. Waste gas is discharged into other generating chambers. Heat is transferred to the coal in the coking chambers by radiation and convection. The coal in the coking chamber is carbonized to become coke in a hermetic environment. The temperature of the oven is the key factor determining the quality of the coke, and it is kept in the proper range by regulating the gas flow rate and air suction power. In the carbonization process, raw gas from a coking chamber passes through an ascending pipe to a gas collection pipe. The temperature of the raw gas in an ascending pipe reflects the maturity of the coke in the coking chamber below.

The control system for the coking process consists mainly of a production scheduler and a coke oven temperature control system. The series of operations from coaling to discharge have a significant influence on oven temperature. Continuous combustion under favorable conditions, or in other word, an oven temperature distribution that is favorable to the formation of coke, ensures the smooth running of the coking process. The combustion process has two different kinds of variables: discrete logic variables (the command to push coke, etc.) and continuous physical variables (oven temperature, gas flow rate, etc.). So, the control of the combustion process requires both a rational schedule for the discrete logic variables and effective real-time control of the continuous physical variables.

Figure 2 shows the configuration of the hybrid hierarchical control system for the combustion process. It contains three layers: a decision layer, an optimization and control layer, and a process control layer.

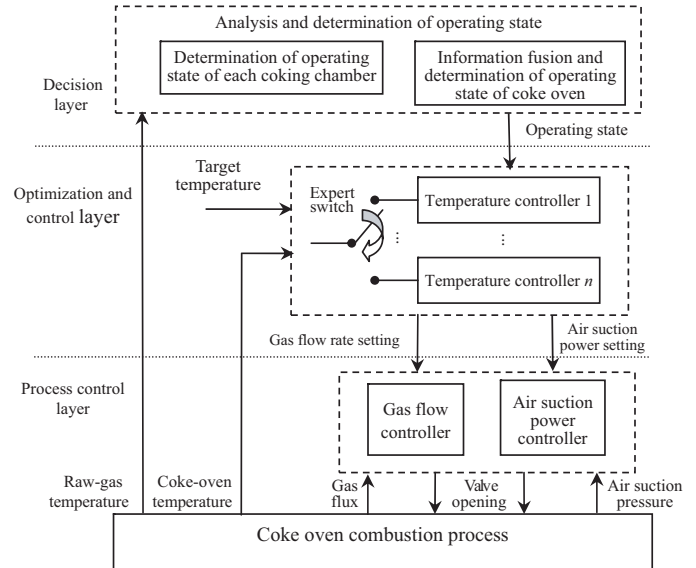


Fig. 2. Configuration of hybrid hierarchical control system of coke oven combustion process.

In this study, we defined the operating state of a coke oven to be a set of parameters that represents the process conditions in the oven. The main function of the decision layer is to determine the operating state in a real-time fashion. The total amount of heat required depends on the maturity of the coke in each of the coking chambers, and is determined by the combined needs of the coking processes in all the chambers. The measured temperatures of the raw gas in the ascending pipes, which are indicators of the maturity of the coke in the coking chambers, are used by a two-stage decision method based on information fusion to determine the operating state of the oven.

The optimization and control layer produces a set of optimal temperature controllers for the various operating states. The parameters of the controllers are the scaling and proportion factors of fuzzy controllers (Jung et al. [1995]); adaptive genetic algorithms optimize them off line. Expert rules are employed to switch the controllers on line to provide quick adaptation to changes in the operating state. The control system is constructed using a two-loop control strategy: the outer loop controls the oven temperature, and the inner loops adjust the gas flow rate and air suction power to reference values produced by the temperature controller. The outer loop is implemented in the optimization and control layer, and the inner loops are implemented in the process control layer.

## 3. DETERMINATION OF OPERATING STATE

The amount of heat required for coking is an important factor in the selection of a temperature controller. Since the thermal absorptivity of coal is different in the beginning, middle, and terminal stages of the coking process, even if the oven temperature is the same, the operating state is different in different stages. It is basically determined by discrete events in coking operations.

This section shows how the operating state is determined from an analysis of the maturity of the coke, which is obtained from the measured temperature of the raw gas

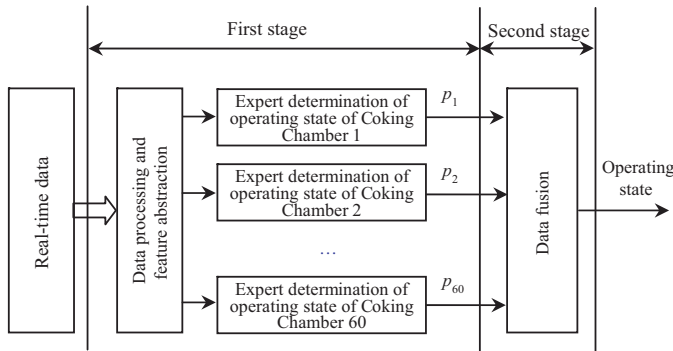


Fig. 3. Determination of operating state using two-stage decision method.

in an ascending pipe, and how critical points in the coking process are extracted.

### 3.1 Classification of Operating States

When coke is pushed out of the oven, it carries away a large amount of heat. So, a certain rhythm in pushing operations is needed to enable good control of the oven temperature. That is, when coke is pushed strictly according to the production schedule, the heat balance in the oven is maintained; but a delay in pushing causes a change in the heating level of the whole oven, resulting in a change in oven temperature.

Pushing operations are halted for two reasons. One is maintenance. There are about 6 hours of maintenance per day. This time is equally divided among the operating periods and is added at the end of each period. So, maintenance has little influence on oven temperature. The other is any kind of equipment failure that prevents mature coke from being pushed out on time. The longer it takes to fix the equipment, the larger the number of coking chambers containing mature coke there are. This changes the operating state and leads to a rapid increase in oven temperature. Furthermore, after the problem is solved and the mature coke is pushed out, the coking chambers are quickly charged with coal. This creates a situation in which a large number of coking chambers are in the beginning stage of the coking process, which changes the operating state and dramatically reduces the oven temperature.

Based on the above analysis, the operating states are classified into three types:

- $S_1$ : Normal operating state. In this state, operations (coaling, pushing, maintenance, etc.) are carried out according to the production schedule. The heat balance in the coking process is taken into consideration in the production schedule.
- $S_2$ : No pushing. This state occurs when equipment failure has caused a relatively long halt in the coking process. A large number of coking chambers contain mature coke, and the oven temperature tends to be higher than usual.
- $S_3$ : Quick pushing. After the equipment is fixed, the coking chambers must be cleared rapidly of mature coke and charged with new coal to return production to the normal operating state. Thus, a large number of coking chambers are in the beginning stage and absorb a great deal of heat. So, the oven temperature tends to be lower than usual.

Table 1. Rules for determining operating state of  $i$ -th coking chamber.

Rule	Parameters			Status of coke	
	$\delta_i$	$a_i$	$C_i$	$p_i$	$M_i$
$R_1$	0-1/3	0	—	Early Stage	Immature
$R_2$	1/3-2/3	0	—	Middle Stage	Immature
$R_3$	2/3-1	1	1-1.2	Terminal Stage	Undercoked
$R_4$	2/3-1	1	1.2-1.3	Terminal Stage	Mature
$R_5$	2/3-1	1	> 1.3	Terminal Stage	Overcoked

### 3.2 Determination of Operating State

It is difficult to determine the operating state in a real-time fashion because of the structure of the oven and limitations on production conditions. Conventionally, the maturity of coke in a coking chamber is assessed from the color of the raw gas in the ascending pipe, which changes during the coking process. This method is very labor intensive for the operators; and it is also very subjective, with the results strongly depending on the experience of an operator. To solve these problems and obtain an accurate determination of the operating state, a thermocouple was installed in each ascending pipe to measure the temperature of the raw gas, and a two-stage decision method based on information fusion is used to determine the operating state (Fig. 3).

In the first stage of the decision process, the temperatures of the raw gas are measured by the thermocouples in the ascending pipes, and the data are processed to extract critical points. Then, expert rules yield the operating state of each coking chamber ( $p_1, p_2, \dots, p_{60}$ ). In the second stage, the operating state of the whole coke oven is obtained by fusion of the first-stage outputs.

In the first stage, the temperature data is processed by the method of moving averages, which smoothes the data and filters out noise. Then, critical points are extracted from the processed data. The temperature of the raw gas in an ascending pipe gradually increases after the start of the coking process and drops sharply after coking finishes. The coking process is characterized by the point at which coking finishes and the coke becomes mature. On the other hand, the coking period,  $T$ , which ranges from 18 to 24 hours, is an important parameter provided by the production scheduler. We define  $t_i$  to be the coking time of the  $i$ -th coking chamber (that is, the time since the chamber was charged with coal) and use it to define a new variable,  $\delta_i = t_i/T$ . Now, if we let  $t_C$  be the time when coking finishes, then the coking index,  $C_i$ , which is given by  $C_i = t_i/t_C$ , indicates the maturity of the coke.

So, the operating state,  $p_i$ , of the  $i$ -th coking chamber can be represented by the triplet  $(\delta_i, a_i, C_i)$ , where  $a_i$  is a flag indicating whether or not coking is finished ( $a_i = 0$  when  $t_i < t_C$  and  $a_i = 1$  when  $t_i \geq t_C$ ). The normal operating state is further classified as early, middle, or terminal stage; and the state of the coke in a coking chamber is classified as immature, mature, undercoked, or overcoked. Table 1 shows the rules for determining the operating state of the  $i$ -th coking chamber,  $M_i$ .

In the first stage of the decision process, an output space consisting of the operating states of all the coking chambers is constructed. It is then categorized to make an input space for information fusion in the second stage. Statistics

on the coking chambers in different operating states and different coking states are collected:  $cp_e$ ,  $cp_m$ , and  $cp_t$  are the numbers of coking chambers in the early, middle, and terminal stages, respectively; and  $cm_{uc}$ ,  $cp_M$ , and  $cp_{oc}$  are the numbers of coking chambers in the terminal stage for which the coke is undercoked, mature, and overcoked. Some typical rules are listed below as examples, where  $S(k)$  indicates the present (the  $k$ -th sampling period) operating state of the  $i$ -th coking chamber:

$R_{OS1}$ : **IF**  $cp_{oc} > 5$  **AND**  $cp_t \geq 25$  **THEN**  $S(k) = S_2$ ;  
 $R_{OS2}$ : **IF**  $S(k-1) = S_2$  **AND**  $cp_e \geq 20$  **THEN**  $S(k) = S_3$ .

#### 4. DESIGN OF TEMPERATURE CONTROLLER

##### 4.1 Expert Switching

Three types of gas (coke gas, blast furnace gas, a blend of the two) are used in the coking process, and different heating methods are employed for each. There are two heating methods for blended gas: fix the flow rate of coke gas and adjust the flow rate of blast furnace gas, and vice versa. The heating method should be changed when the type of gas is changed; but if the heating method remains unchanged, a change in the type of gas causes the operating state to change.

To obtain good control performance, it is necessary to employ different controllers for the various operating states. The following on-line switching rules were established based on the above classification, the determination of the operating state, and the heating method:

$R_{ESi}$ : **IF**  $s = S_i$  **THEN** switch the controller to fuzzy control  $i$ .

That is, when the operating state,  $s$ , is determined to be  $S_i$ , select fuzzy controller  $i$ .

##### 4.2 Design and Optimization of Fuzzy Controller

In fuzzy control, the experience of experts is converted into mathematical models that can be handled by a computer. Since experience is subjective to some extent, there are certain limitations on the parameters of a controller derived directly from such experience. Furthermore, the control system has multiple control objectives (high-quality coke, saving energy, etc.), which requires fine adjustment of the parameters.

As an example, we use the temperature fuzzy controller for blended gas, which calculates optimal settings for the gas flow rate, to explain how a fuzzy controller is designed and how its parameters are optimized. Assume that the heating method is to fix the flow rate of coke gas and adjust the flow rate of blast furnace gas. The inputs of the temperature fuzzy controller are the temperature error,  $e$ , and its rate of change,  $ec$ ; and the output is the change in the flow rate of blast furnace gas,  $u_b$ . The corresponding fuzzy sets are  $E$ ,  $EC$ , and  $U_b$ ; and their linguistic states are {NL (negative large), NM (negative medium), NS (negative small), ZO (zero), PS (positive small), PM (positive medium), PL (positive large)}, {NL, NM, ZO, PS, PM, PL}, and {NL, NM, ZO, PM, PL}, respectively. The ranges of the variables are  $[-20, 20]$  for  $e$ ,  $[-15, 15]$  for  $ec$ , and  $[-200, 200]$  for  $u_b$ . The membership

functions of  $E$ ,  $EC$  and  $U_b$  are all chosen to be trapezoidal. The Mamdani method is used for fuzzy inference, and the centroid method is used for defuzzification.

Since the scaling and proportion factors  $K_e$ ,  $K_{ec}$ , and  $K_{\Delta u}$  can be used to tune the dynamic characteristics of the closed-loop system, these parameters are determined based on trade-offs among response time, stability, and robustness. However, optimization under these conditions is almost impossible when only the experience of experts is used. Thus, in this study a multiple-objective optimization method was combined with a self-adaptive genetic algorithm to optimize the parameters of a fuzzy controller. The optimization targets for the temperature fuzzy controller are to stabilize the oven temperature, to ensure the quality of the coke, to reduce the consumption of gas, and to extend the lifetime of the oven. These considerations yield the following fitness function:

$$F = 1/(w_1 J_1 + w_2 J_2 + w_3 J_3), \quad (1)$$

where  $w_i$  ( $i = 1, 2, 3$ ) is a weight and  $J_1$ ,  $J_2$ , and  $J_3$  are the performance indices for flue temperature, gas consumption, and response time, respectively. They are given by

$$J_1 = |e|, \quad (2)$$

$$J_2 = \sum_{k=0}^M u_b(k), \quad (3)$$

$$J_3 = \sum_{k=0}^N t_s(k). \quad (4)$$

In (3),  $u_b(k)$  is the consumption of blast furnace gas during a sampling period and  $M$  is the number of control steps. In (4),  $t_s(k)$  is the regulation time and  $N$  is the number of steps in the transient response. The constraints are

$$0 \leq \Delta u_b(k) \leq \Delta U_{b \max}, \quad (5)$$

$$0 \leq e(k) \leq e_{\max}, \quad (6)$$

where  $\Delta U_{b \max}$  is the maximum allowable change in gas flow rate and  $e_{\max}$  is the maximum value of  $e$ .

A genetic algorithm is employed to optimize  $K_e$ ,  $K_{ec}$ , and  $K_{\Delta u}$  so as to yield the maximum  $F$ .  $K_e$ ,  $K_{ec}$ , and  $K_{\Delta u}$  are encoded as real numbers; the  $n$ -th chromosome of the  $i$ -th generation is  $P_n^i = [p_{k_e}^n, p_{k_{ec}}^n, p_{k_{\Delta u}}^n]$ .

The elitist strategy (Mashohor et al. [2005]) and the roulette wheel algorithm (Mahapatra et al. [2005]) are used for selection. When a set of individuals constitutes a larger percentage of the population than a given value, some are selected using the roulette wheel algorithm to maintain the diversity of population; and others are selected using the elitist strategy to preserve the individuals with the best fitness.

The key factors that determine the performance of the genetic algorithm are the crossover probability,  $p_c$ , and the mutation probability,  $p_m$ . Since crossover is the primary means of producing new individuals,  $p_c$  should be relatively large. However, if it is too large, good patterns will be destroyed; and if it is too small, new individuals will be produced very slowly.  $p_m$  has a significant impact

on the optimization of the parameters: If it is too large, convergence will be slow; and if it is too small, convergence will be premature. To avoid these problems, this study employed an improved genetic algorithm (Srinival et al. 1994), in which  $p_c$  and  $p_m$  are tuned automatically in response to changes in the fitness function; and  $p_c$  and  $p_m$  are regulated as follows:

$$p_c = \begin{cases} k_1(f_{\max} - f_c)/(f_{\max} - f_{avg}), & f_c \geq f_{avg}, \\ k_2, & f_c < f_{avg}, \end{cases} \quad (7)$$

$$p_m = \begin{cases} k_3(f_{\max} - f_m)/(f_{\max} - f_{avg}), & f_m \geq f_{avg}, \\ k_4, & f_m < f_{avg}, \end{cases} \quad (8)$$

where  $0 < k_1, k_2, k_3, k_4 < 1$  and  $k_4 > k_3$ ;  $f_{\max}$  is the maximum fitness and  $f_{avg}$  is the average;  $f_c$  is the larger of the two individuals selected for crossover; and  $f_m$  is the fitness of an individual for mutation.

#### 4.3 Calculation of Air Suction Power

In the combustion process, the air suction power determines burning efficiency. It must be changed when the gas flow rate changes to ensure complete combustion. However, since there is no on-line oxygen sensor, the air-fuel ratio cannot be calculated directly. The relationship between air suction power and gas flow is (He et al. [2005])

$$u_a(k) = \alpha_0 + \alpha_1 \frac{u_b(k)}{u_b(k-1)} + \alpha_2 \frac{u_c(k)}{u_c(k-1)}, \quad (9)$$

where  $u_a(k)$  is the air suction power;  $u_b(k)$  and  $u_c(k)$  are the flow rates of blast furnace gas and coke oven gas, respectively; and  $\alpha_0$ ,  $\alpha_1$ , and  $\alpha_2$  are constants. In this study, the air suction power was calculated indirectly using the above formula.

### 5. DESIGN OF GAS FLOW RATE AND AIR SUCTION POWER CONTROLLERS

Using the settings for gas flow rate and air suction power produced by the outer-loop temperature controller, the inner loop regulates the gas flow rate and the air suction power by adjusting the openings of the corresponding valves so as to stabilize the process.

The flow rate of blast furnace gas strongly depends on the pressure in the main pipe, which fluctuates dramatically. We use a TDF controller to suppress fluctuations in the flow rate. The pressure of gas in the main pipe is measured and is fed forward as a control input for the flow rate of the blast furnace gas using expert rules. The feedback controller employs both expert and fuzzy control methods. The fuzzy controller precisely adjusts the valve opening when the magnitude of the flow tracking error for the flow rate of blast furnace gas is less than the threshold; and the expert controller quickly reduces the tracking error when the magnitude of the flow tracking error for the flow rate of blast furnace gas is greater than the threshold.

The air suction power changes only moderately and is not greatly influenced by any factors. An expert control method is used to control it. Expert rules are derived based on the experience of experts and an analysis of historical data.

### 6. SYSTEM IMPLEMENTATION AND RESULTS OF ACTUAL RUNS

The intelligent integrated optimization and control system developed in this study was used to regulate the combustion process of a coking plant in an iron and steel company. It was implemented on an industrial control computer and consists of application software and a programmable-logic-controller (PLC)-based Windows Control Center (WinCC) configuration, which includes an OPC module.

All the application software is written in Visual C++. It performs operating-state-based intelligent control with a two-stage decision method to determine the operating state. Once the operating state has been determined, appropriate inner- and outer-loop fuzzy controllers, for which the parameters are optimized off line, are chosen to control the combustion process. Then, the controllers make the gas flow rate and the air suction power track the reference values by regulating the valve openings, thereby ensuring that the oven temperature is stabilized at a given value. The values of the valve openings are sent to the PLC using OPC communication technology to drive the actuators of the valves.

The WinCC configuration software monitors and controls the combustion process, analyzes and records data in real time, produces a report, and draws historical curves. The Siemens PLC system collects the parameters of the coking process and the states of the equipment in a real-time fashion for the WinCC and controls the equipment on the production line. The OPC module carries out data communication between the application programs and the WinCC configuration software.

In the iron and steel company that is the subject of this study, the temperature of the coke oven was controlled manually before the intelligent integrated optimization and control system was installed in 2005. Some typical results of actual runs are shown in Fig. 4. It is clear that the control system reduced the variation in oven temperature from  $\pm 25^\circ\text{C}$  to  $\pm 10^\circ\text{C}$ .

The side of the oven where the pusher operates is called the machine side, and the side where the guide operates is called the coke side. The two variables  $K_S$  and  $K_A$  are defined to be

$$K_A = \frac{(M - A_{machine}) + (M - A_{coke})}{2M}, \quad (10)$$

$$K_S = \frac{2N - (A'_{machine} + A'_{coke})}{2M}, \quad (11)$$

where  $M$  is the number of combustion chambers in the coke oven;  $A_{machine}$  and  $A_{coke}$  are the numbers of combustion chambers for which the flue temperature on the machine or coke side, respectively, is outside the error range ( $\pm 7^\circ\text{C}$ );  $N$  is the number of measurements of the oven temperature;  $A'_{machine}$  is the number of times that the oven temperature error (which is the difference between the reference value and the average oven temperature) on the machine side is outside the range  $\pm 7^\circ\text{C}$ ; and  $A'_{coke}$  is the number of times that the oven temperature error on the coke side is outside the range  $\pm 7^\circ\text{C}$ .

$K_S$  and  $K_A$  indicate the stability and uniformity, respectively, of the oven temperature. Two more evaluation

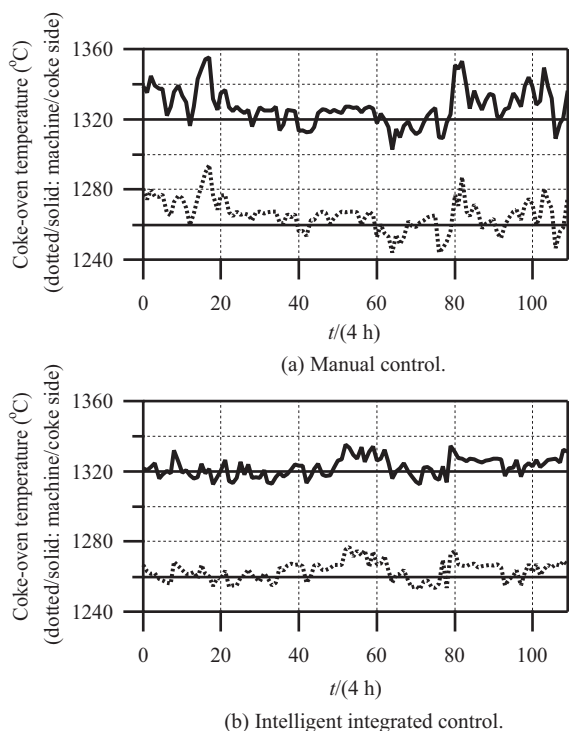


Fig. 4. Results of actual runs: Coke oven temperature.

parameters—crushing strength,  $M_{40}$ , and wear resistance,  $M_{10}$ —are also employed in the evaluation.  $M_{40}$  is the percentage by weight of coke balls with a diameter greater than 40 mm in 100 kg of coke balls, and  $M_{10}$  is the percentage by weight of coke balls with a diameter less than 10 mm in 100 kg of coke balls. A larger  $M_{40}$  and a smaller  $M_{10}$  mean better air permeability in iron making, which is desirable. Actual runs show that the intelligent integrated control method improves both  $K_S$  and  $K_A$ . Compared with manual control,  $M_{40}$  is 1.3% greater,  $M_{10}$  is 1.1% smaller, and the average energy consumption is 2.0% less. These numbers show that the intelligent integrated control method improves the quality of the coke and reduces the consumption of gas.

## 7. CONCLUSION

An intelligent integrated hybrid optimization and control system for the temperature of a coke oven has been developed based on the features of the combustion process. The framework of the control system consists of a decision layer, an optimization and control layer, and a process control layer. For the decision layer, the operating states of the combustion process were classified into several types to enable the control problem to be solved simply; and a two-stage decision method was devised to determine the operating state in real time. In the optimization and control layer, an on-line switching control strategy was employed to select a suitable controller for the current operating state.

The temperature control system contains one control loop for temperature and one for gas flow rate and air suction power. In the temperature control loop, a multiple-objective optimization method employs an adaptive genetic algorithm to optimize the controller parameters. In the other control loop, controllers for valve openings stabi-

lize the gas and air fluxes. The results of actual runs show that the system stabilizes the oven temperature, improves the quality of coke, and reduces energy consumption.

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