Intelligent integrated control of combustion process of coke oven based on determination of operating state

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Abstract: This paper describes a hierarchical intelligent integrated control system with three layers: a decision layer, a temperature optimisation 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 in real time. The control strategy includes the temperature optimisation control and process control. The parameters of fuzzy controllers are tuned by a multiple-objective optimisation method with an adaptive genetic algorithm to keep the temperature in the proper range. An intelligent method that combines fuzzy and expert control keeps the gas flow rate and air suction power at the settings.

Keywords: coke oven temperature; operating state; hybrid system; fuzzy control; expert control; intelligent integrated control; two-stage decision; parameter optimisation for controller; self-adaptive genetic algorithm.

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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. It directly influences both the quality of coke and the lifetime of the oven. Too low an oven temperature results in poor-quality coke and a short oven lifetime; 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 non-linearity, 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 and Mccollum, 1984). All of these methods are based on exact mathematical models; but due to the complexity of the process, none of them provide adequate control performance.

The time delay, in particular, makes control of the oven temperature difficult. A Smith predictor is an effective way to handle a time delay, but it strongly depends on the exact mathematical model of the plant. Predictive control is also a practical method for process control, but it is sensitive to the precision of the plant model, as well. Although many studies on the Smith predictor and predictive control have been reported (e.g., José and Alexandre, 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 (Stratos et al., 2006; Yanan and Collins, 2003; Cao and Frank, 2000). One of its advantages is that, if we take the trend in the change in oven temperature into consideration, it can suppress the effects of the time delay to some extent. In actual practice, fuzzy control has already been shown to be effective in controlling the temperature of a coke oven (Gao et al., 2002, 2006a, 2006b).

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., 2005a, 2005b). However, there are usually two problems with existing methods of controlling the combustion process of a coke oven:

- Only tracking error information is utilised 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.
- The parameters of a fuzzy controller are selected based on operator experience and are not optimised.

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. Determination of the operating state is important for good decision making and proper control of the combustion process. It is also important for improving the intelligence of the control system and increasing production efficiency. A simple determination of the operating state can be made just by checking whether or not the oven is in the maintenance period (Gao et al., 2003), but this method does not permit a response to changes in the operating state arising from other situations.

A hybrid system is a dynamic system that contains continuous systems as well as discrete events (García et al., 2003; Engell et al., 2000; Romeo and Gareta, 2006; Paruchuri et al., 2005). It places great emphasis on the combined effect of time- and event-driven processes during system evolution. The combustion process can be regarded as a hybrid system because it can be divided into two layers: a physical layer described by the continuous variables of a dynamic evolution mechanism, and a layer of high-level coordination that features symbol manipulation and discrete monitoring and decisions.

In this study, the mechanism of the combustion process of a coke oven was analysed 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.

The rest of this paper is organised as follows: In Section 2, the mechanism of the combustion process is analysed on the basis of production planning and flue temperature, and a hierarchical intelligent integrated control structure is presented based on the determination of the operating state. In Section 3, a two-stage decision method based on information fusion is used to determine the operating state of the combustion process in a real-time fashion. In Section 4, a self-adaptive genetic algorithm is employed to optimise the parameters of a fuzzy controller for each of several operating states, and expert rules are established to switch among these fuzzy controllers to produce appropriate settings for gas flow rate and air suction power. In Section 5, a combination of fuzzy and expert control strategies is used to stabilise the gas flow rate and air suction power, thereby yielding good control of the oven temperature. Section 6 explains a real-world application of the method in the coking plant of an iron and steel company and presents the results of actual runs, which demonstrate the effectiveness of the method.

2 Description of combustion process and control system

This section describes the combustion process and presents the configuration of an intelligent integrated combustion process control system.

2.1 Combustion process

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 system. The coking and combustion chambers are arranged alternately in a line. Flues in the combustion chambers are used to heat the coking chambers to carbonise coal. The fuel is coke gas, blast furnace gas, or a mixture of the two. It enters the combustion chambers through flues, and burns using air drawn from a smoke flue. Heat is transferred to the coal in the coking chambers by radiation and convection. 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. The coking process employs four vehicles (coal charger, pusher, guide, quenching car). 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.

Figure 1 Coke oven system (see online version for colours)

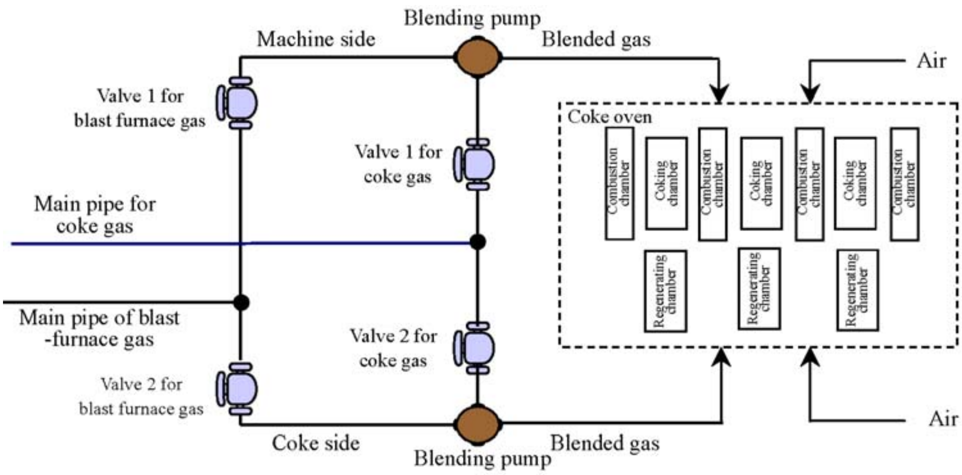


Figure 2 shows some details of the structure of the coke oven. Each coking chamber lies between two combustion chambers, which supply heat in two directions. Each combustion chamber is connected to two regenerating chambers. Each regenerating chamber is under a coking chamber, except for the ones at the ends of the oven. In the combustion process, gas is burned in the combustion chamber and the heat is transferred to the coal in the coking chamber by radiation and convection. The coal in the coking chamber is carbonised to become coke in a hermetic environment. 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. Half of the regenerating chambers draw in a mixture of gas and air for burning while the other half discharge waste gas.

In the carbonisation 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. Figure 3 shows the typical timewise change in the temperature of the raw gas. The temperature increases gradually and then drops rapidly after the point where coking is finished. Furthermore, the curve indicates when such operations as coaling and coke pushing occur.

Figure 2 Structure of coke oven

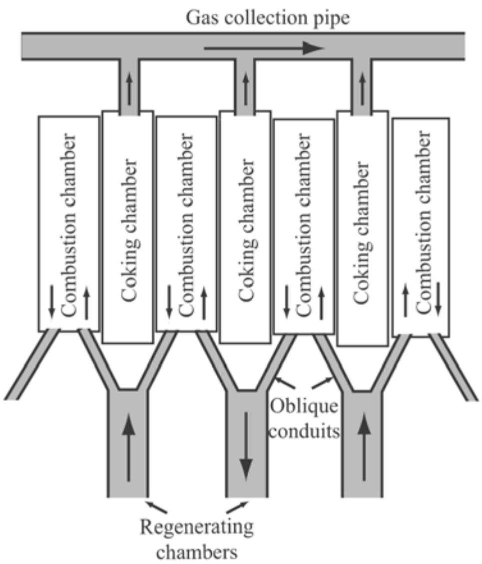
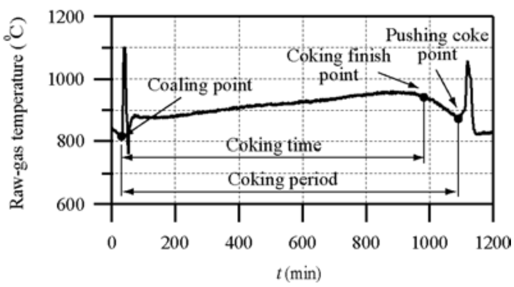


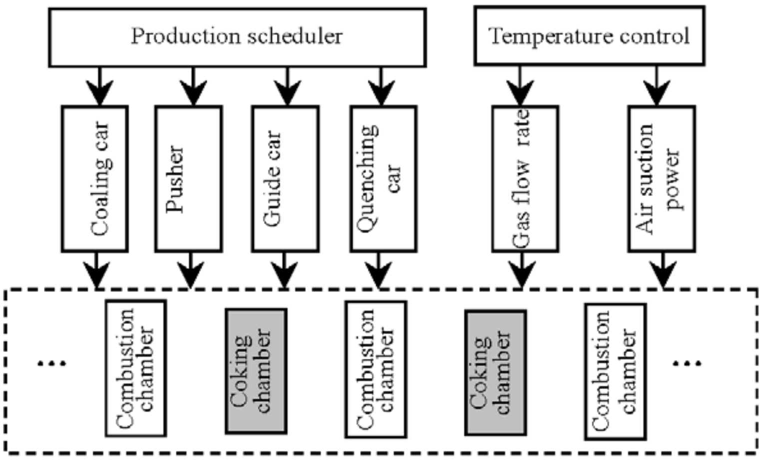
Figure 3 Timewise change in temperature of raw gas in ascending pipe during one coking period



To keep the temperature of the oven in the proper range during one coking period, it is necessary to make the temperature track a reference temperature, which is determined by the length of the coking period, the amount of coal charged into each coking chamber, and the water content of the coal. The temperature can be controlled by regulating the gas flow rate and air suction power according to the amount of heat required.

Figure 4 shows the configuration of operations and temperature control for the coking process. Operations (coaling, pushing, guiding, quenching) are carried out according to the production schedule: First, a car charges the coking chambers with coal. Next, the combustion process carbonises the coal into coke. Then, pushers and guide cars transfer the coke to a quenching car. Finally, the quenching car goes into a quenching tower, where the coke is cooled. The production scheduler monitors the operations and sends commands to the equipment to ensure the smooth production of high-quality coke. It also provides sufficient time for equipment maintenance. On the other hand, the combustion process control system stabilises the oven temperature and maintains favourable conditions for the production of high-quality coke by controlling the gas flow rate and air suction power.

Figure 4 Configuration of coke oven operations and temperature control



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 favourable conditions, or in other word, an oven temperature distribution that is favourable 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.

Due to the complexity of the combustion process and the structure of a coke oven, the process has features that make control of the oven temperature difficult:

- Although gas flow rate is the main factor influencing oven temperature, there are many other factors (calorific value of gas, length of coking period, production schedule, etc.) as well. For example, even if the same heating method is used, the amount of heat produced depends on the calorific value of the gas. The relationships between these factors and oven temperature are strongly nonlinear.
- The oven temperature changes very slowly. The coke oven that is the subject of this study is about 6 metres high and 60 metres long. It has a large thermal capacity, and heating and cooling take a long time. Data from actual runs show that it takes 2–3 h for the temperature to change noticeably when coke gas is used, and about six hours when blast furnace gas is used. Moreover, the time delay of the combustion process is not constant and depends on many factors. For example, a change in the calorific value of the gas results in a change in the response speed of the oven temperature. The time delay of the process is large and time-varying.
- The operating state directly influences the oven temperature. Since most of the heat is absorbed by the coal, the state of carbonisation of the coal in the coking chambers not only influences the temperature of related combustion chambers but also changes the level of heating in the whole oven. The state of carbonisation strongly depends on the operating state.

2.2 Configuration of control system of combustion process

The following strategies are employed to control the combustion process:

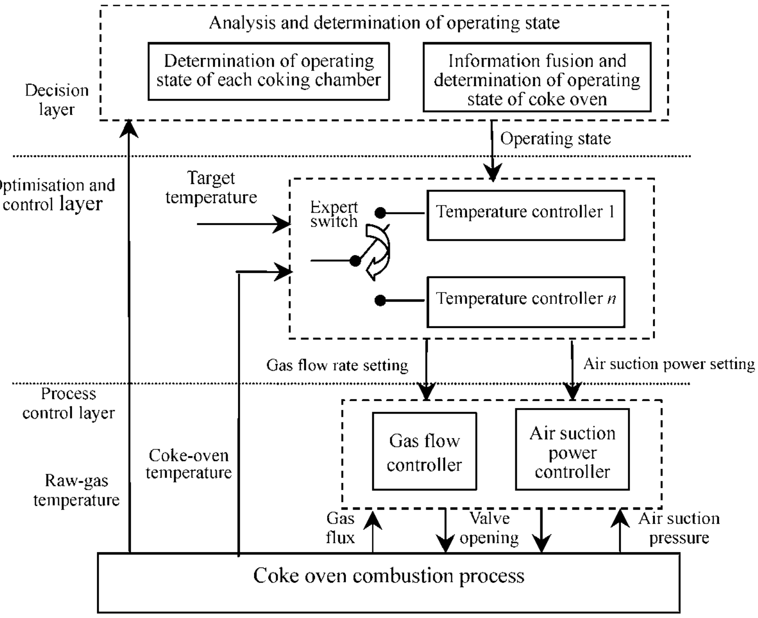
- A hybrid control system, which combines continuous control and the manipulation of discrete symbols, is constructed to control this complex process.
- Due to the complexity and large time delay of the combustion process, it is impossible to build a temperature control system with a single controller. To obtain good control performance, the operating states are classified into several types, and a controller is designed for each one.
- A two-stage decision method based on information fusion is used to determine the current operating state.
- A self-adaptive genetic algorithm optimises the parameters of the fuzzy controllers.

Figure 5 shows the configuration of the hybrid hierarchical control system for the combustion process. It contains three layers: a decision layer, an optimisation and control layer, and a process control layer.

The main function of the decision layer is to determine the operating state in a real-time fashion. In each ascending pipe, a thermocouple measures the temperature of the raw gas, which is an indicator of the maturity of the coke in the coking chambers. 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 are used by a two-stage decision method based on information fusion to determine the operating state of the oven.

The optimisation 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 optimise 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 optimisation and control layer, and the inner loops are implemented in the process control layer.

Figure 5 Configuration of hybrid hierarchical control system of coke oven combustion process



3 Determination of operating state

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. In this study, different controllers are used to handle this situation.

The amount of heat required for coking is an important factor in the selection of a temperature controller. 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 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 six 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:

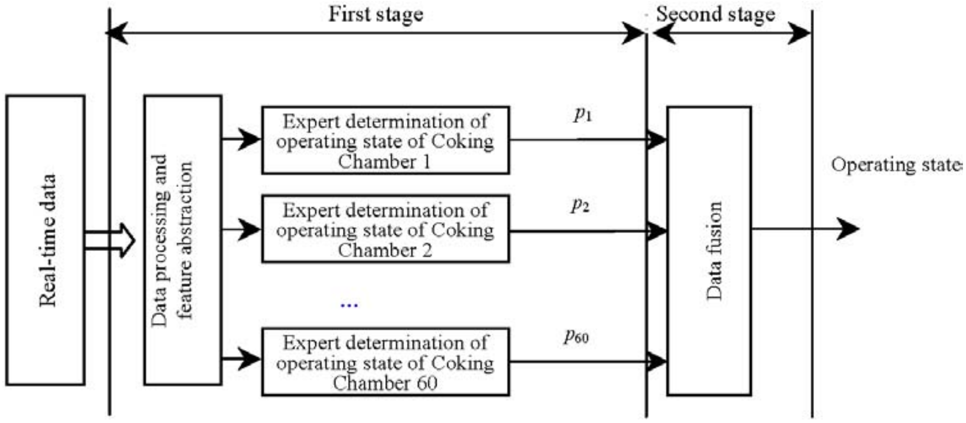
- *S_1: Normal operating state.* In this state, operations (coaling, pushing, maintenance, etc.) are carried out according to the production schedule. The heat balance in the coking process is taken into consideration in the production schedule.
- *S_2: No pushing.* This state occurs when equipment failure 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.

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 colour of the raw gas in the ascending pipe, which changes during the coking process. This method is very labour 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 was used to determine the operating state (Figure 6).

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

Figure 6 Determination of operating state using two-stage decision method



In the first stage, the temperature data were processed by the method of moving averages, which smoothes the data and filters out noise. Then, critical points were extracted from the processed data. As seen in Figure 3, 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 characterised by the point at which coking finishes and the coke becomes mature. On the other hand, the coking period, T, which ranges from 18 h to 24 h, is an important parameter provided by the production scheduler.

We define t_i to be the coking time of the ith coking chamber (that is, the time since the chamber was charged with coal) and use it to define a new variable, δ:

$$\delta = \frac{t_i}{T}.$$

Now, if let the time when coking finishes be t_C, then the coking index, C_i, given by

$$C_i = \frac{t_i}{t_C} \; (t_i \geq t_C)$$

indicates the maturity of the coke.

So, the operating state, p_i, of the ith coking chamber can be represented by the triplet (δ, 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, and overcoked. Table 1 shows the rules for determining the operating state of the ith coking chamber.

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 categorised 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 (kth sampling time) operating state of the ith coking chamber:

Rule OS1: **IF** $cp_{oc} > 5$ **AND** $cp_t \geq 25$, **THEN** $S(k) = S_2$;

Rule OS2: **IF** $S(k-1)$ = Stop **AND** $cp_e \geq 20$, **THEN** $S(k) = S_3$.

Table 1 Rules for determining operating state of ith coking chamber

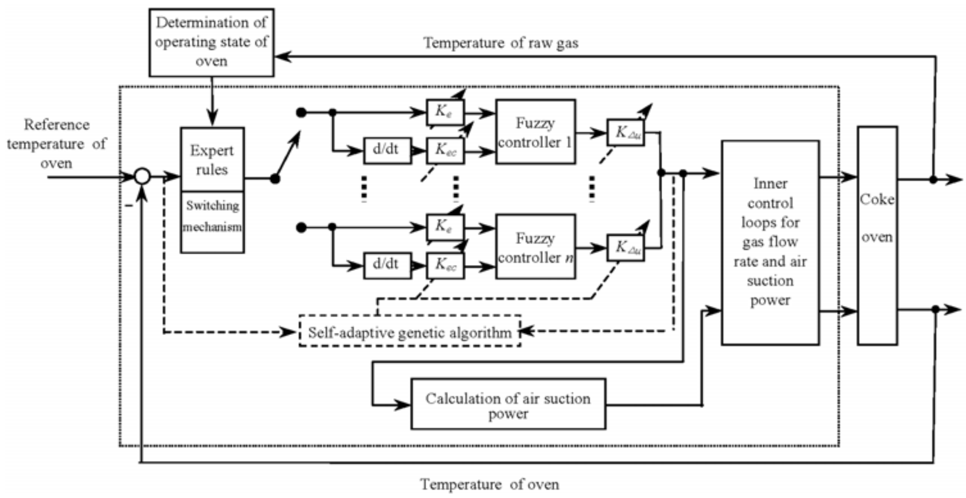
	Parameter			*Status of coke*	
Rule	δ	a_i	C_i	p_i	M_i
1	0~1/3	0	–	Early stage	Immature
2	1/3~2/3	0	–	Middle stage	Immature
3	2/3~1	1	1–1.2	Terminal stage	Undercoked
4	2/3~1	1	1.2~1.3	Terminal stage	Mature
5	2/3~1	1	>1.3	Terminal stage	Overcoked

4 Design of oven temperature controller

The target of the intelligent integrated optimisation and control of the combustion process is to stabilise the oven temperature in spite of disturbances by planning a rational schedule for the combustion process and properly regulating the heat supply. The key points for the optimisation and control layer (Figure 7) are

- to optimise the parameters of the controllers
- to choose a controller appropriate to the operating state in a real-time fashion and switch to it, and to use the output of the temperature controller to calculate optimal settings for the gas flow rate and air suction power.

Figure 7 Configuration of optimisation and control layer



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 online switching rules were established based on the above classification, the determination of the operating state, and the heating method:

Rule ES i: **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 optimisation 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.); this 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 optimised. 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, Δu_b. The corresponding fuzzy sets are E, EC, and ΔU_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 Δu_b. The membership functions of E, EC and ΔU_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 (Jung et al., 1995) Ke, Kec, and $K\Delta u_b$ 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, optimisation under these conditions is almost impossible when only the experience of experts is used. Thus, in this study a multiple-objective optimisation method was combined with a self-adaptive genetic algorithm to optimise the parameters of a fuzzy controller.

The optimisation targets for the temperature fuzzy controller are to stabilise 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:

$$F = \frac{1}{w_1 J_1 + w_2 J_2 + w_3 J_3} \tag{1}$$

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

$$J_1 = |e| \tag{2}$$

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

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

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

$$0 \le \Delta u_b(k) \le \Delta U_{b\max} \tag{5}$$

$$0 \le e(k) \le e_{\max} \tag{6}$$

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 optimise Ke, Kec, and $K\Delta u_b$ so as to yield the maximum F. Ke, Kec, and $K\Delta u_b$ are encoded as real numbers; the nth chromosome of the ith generation is $P_n^i = [p_{k_e}^n, p_{k_{ec}}^n, p_{k_{\Delta u_b}}^n]$ and the fuzzy parameters that need to be optimised are $p_{k_e}^n, p_{k_{ec}}^n$ and $, p_{k_{\Delta u_b}}^n$.

The elitist strategy (Fujino et al., 1997; Mashohor et al., 2005) and the roulette wheel algorithm (Koumousis and Georgiou, 1994; 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.

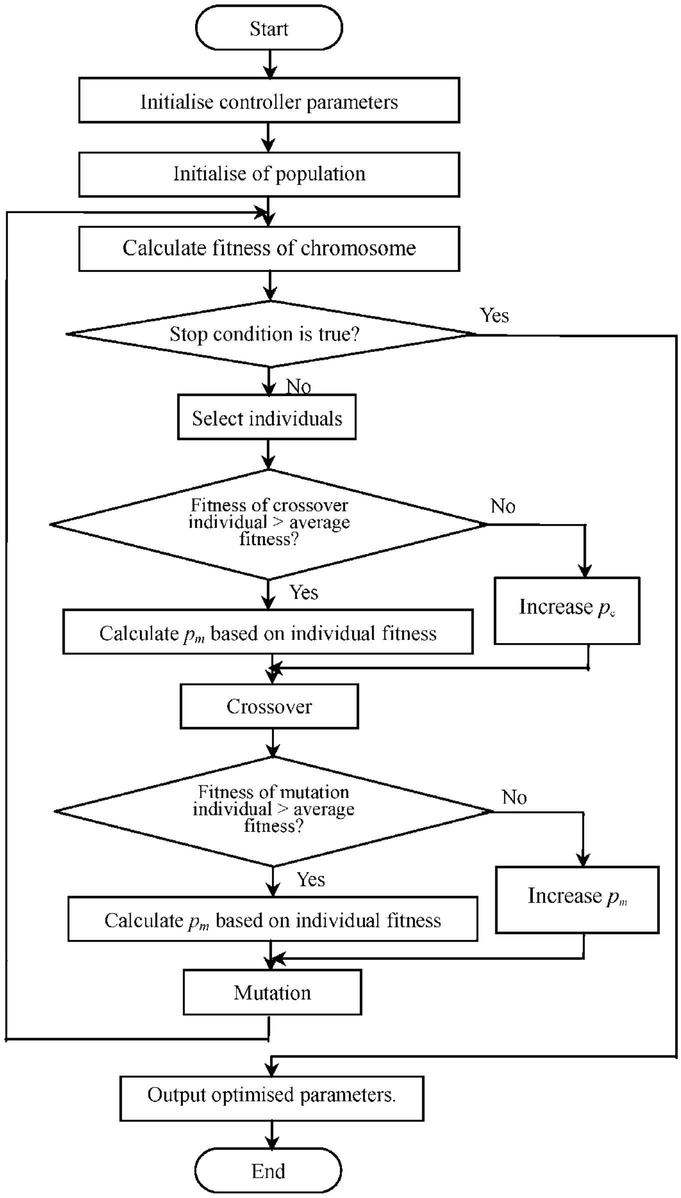
The key factors that determine the performance of the genetic algorithm are the crossover probability, p_c, and the mutation probability, p_m. Since crossover is the primary means of producing new individuals, p_c should be relatively large. However, if it is too large, good patterns will be destroyed;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

$$p_c = \begin{cases} \dfrac{k_1(f_{\max} - f_c)}{f_{\max} - f_{avg}}, & f_c \ge f_{avg} \\ k_2, & f_c < f_{avg} \end{cases} \tag{7}$$

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

where $0 < k_1, k_2, k_3, k_4 < 1$, $k_2 > k_1$, 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. Figure 8 shows a flow chart of parameter optimisation.

Figure 8 Flow chart of parameter optimisation for fuzzy controller



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 online oxygen sensor, the air-fuel ratio cannot be calculated directly. The relationship between air suction power and gas flow is (He et al., 2005):

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

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 α_0, α_1, and α_2 are constants. In this study, the air suction power was calculated indirectly using the above formula.

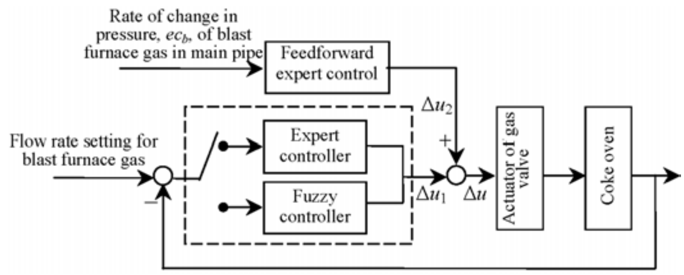
5 Design of gas flow rate and air suction power controllers

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 stabilise the process. The design of these controllers is explained below.

5.1 Control of flow rate of blast furnace gas

Taking the control of the flow rate of blast furnace gas as an example, we explain how to design an appropriate TDF controller. The flow rate of blast furnace gas strongly depends on the pressure in the main pipe, which fluctuates dramatically. The TDF control system in Figure 9 suppresses fluctuations in the flow rate. A feedforward expert controller mainly reduces the influence of the main pipe pressure, and an expert and fuzzy feedback controller stabilises the flow rate and suppresses fluctuations caused by other factors. The sampling period for the valves was set to 15 s.

Figure 9 Configuration of TDF control system for flow rate of blast furnace gas



5.1.1 Design of feedforward controller

A pressure change in the main pipe for blast furnace gas can cause a large change in the flow rate of the gas. 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 the following expert rules:

Rule 1:	**IF**	$ec_b > 500$ Pa/s,	**THEN**	$\Delta u_2 = -0.7$
Rule 2:	**IF**	250 Pa/s $< ec_b \le 500$ Pa/s,	**THEN**	$\Delta u_2 = -0.6$
Rule 3:	**IF**	150 Pa/s $< ec_b \le 250$ Pa/s,	**THEN**	$\Delta u_2 = -0.4$
Rule 4:	**IF**	50 Pa/s $< ec_b \le 150$ Pa/s,	**THEN**	$\Delta u_2 = -0.2$
Rule 5:	**IF**	-50 Pa/s $\le ec_b \le 50$ Pa/s,	**THEN**	$\Delta u_2 = 0$
Rule 6:	**IF**	-150 Pa/s $\le ec_b < -50$ Pa/s,	**THEN**	$\Delta u_2 = 0.2$
Rule 7:	**IF**	-250 Pa/s $\le ec_b < -150$ Pa/s,	**THEN**	$\Delta u_2 = 0.4$
Rule 8:	**IF**	-500 Pa/s $\le ec_b < -250$ Pa/s,	**THEN**	$\Delta u_2 = 0.6$
Rule 9:	**IF**	$ec_b < -500$ Pa/s,	**THEN**	$\Delta u_2 = 0.7$

where ec_b is the rate of change in the pressure of the blast furnace gas in the main pipe, and Δu_2 is the change in the valve opening.

5.1.2 Design of feedback controller

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, e_f, is less than the threshold; and the expert controller quickly reduces the tracking error when the magnitude of e_f is greater than the threshold. Since -3000 m^3/h $< e_f < 3000$ m^3/h in practice, the threshold was chosen to be 6000 m^3/h in this study. The following expert control rules are used:

Rule 1:	**IF**	$e_f > 12000$ m^3/h,	**THEN**	$\Delta u_1 = -2.5$
Rule 2:	**IF**	6000 m^3/h $< e_f \le 12000$ m^3/h,	**THEN**	$\Delta u_1 = -2.2$
Rule 3:	**IF**	-12000 m^3/h $\le e_f < -6000$ m^3/h,	**THEN**	$\Delta u_1 = 2.2$
Rule 4:	**IF**	$e_f < -12000$ m^3/h,	**THEN**	$\Delta u_1 = 2.5$

where Δu_1 is the change in the valve opening.

The inputs of the fuzzy controller are e_f and ec_f; and the output is the change in the valve opening, Δu_1. The ranges of e_f, ec_f, and Δu_1 are chosen to be [–6000, 6000], [–2000, 2000], and [–2, 2], respectively. Accordingly, the linguistic values of the control error, E_f, its rate of change, EC_f, and the change in the valve opening, ΔU_1, are {NL, NM, NS, ZO, PS, PM, PL}, {NL, NM, ZO, PS, PM, PL}, and {NL, NM, NS, ZO, PS, PM, PL}, respectively. Trapezoidal functions were selected to be the membership functions for the linguistic values of E_f, EC_f, and ΔU_1 because they are insensitive to linguistic values. ΔU_1 is set as shown in Table 2. For example, if E is PL and EC is ZO, then the output, ΔU_1, is PL. That means that, when the flow rate of blast furnace gas is much smaller than the reference value and the rate of change in the tracking error is also very small, then the valve should be opened a great deal to quickly increase the flow of gas. The output of the fuzzy controller is obtained by defuzzification. The total change, Δu, in the valve opening is given by

$$\Delta u = \Delta u_1 + \Delta u_2.$$

Table 2 Fuzzy rules of fuzzy feedback controller in TDF control system for flow rate of blast furnace gas

EC	*E*						
	NL	*NM*	*NS*	*ZO*	*PS*	*PM*	*PL*
NL	NL	NL	NM	NS	NS	ZO	PS
NS	NL	NM	NM	NS	ZO	PS	PM
ZO	NL	NM	NS	ZO	PS	PM	PL
PS	NM	NS	ZO	PS	PM	PM	PL
PL	NS	ZO	PS	PS	PM	PL	PL

5.2 Design of air suction controller

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. e_a is the error between the setting and the actual value of the air suction power, and Δu_a is the change in the opening of the air suction valve. Some of the main rules are as follows:

Rule 1: **IF** $e_a > 25$ Pa, **THEN** $\Delta u = -2$

Rule 2: **IF** $8 \text{ Pa} < e_a \le 25$ Pa, **THEN** $\Delta u_a = -1.5$

Rule 3: **IF** $6 \text{ Pa} < e_a \le 8$ Pa, **THEN** $\Delta u_a = -1.2$

Rule 4: **IF** $4 \text{ Pa} < e_a \le 6$ Pa, **THEN** $\Delta u_a = -0.9$

Rule 5: **IF** $3 \text{ Pa} < e_a \le 4$ Pa, **THEN** $\Delta u_a = -0.6$

Rule 6: **IF** $-3 \text{ Pa} \le e_a \le 3$ Pa, **THEN** $\Delta u_a = 0$

Rule 7: **IF** $-4 \text{ Pa} \le e_a < -3$ Pa, **THEN** $\Delta u_a = 0.6$

Rule 8: **IF** $-6 \text{ Pa} \le e_a < -4$ Pa, **THEN** $\Delta u_a = 0.9$

Rule 9: **IF** $-8 \text{ Pa} \le e_a < -6$ Pa, **THEN** $\Delta u_a = 1.2$

Rule 10: **IF** $-25 \text{ Pa} \le e_a < -8$ Pa, **THEN** $\Delta u_a = 1.5$

Rule 11: **IF** $e_a < -25$ Pa, **THEN** $\Delta u_a = 2$

6 System implementation and results of actual runs

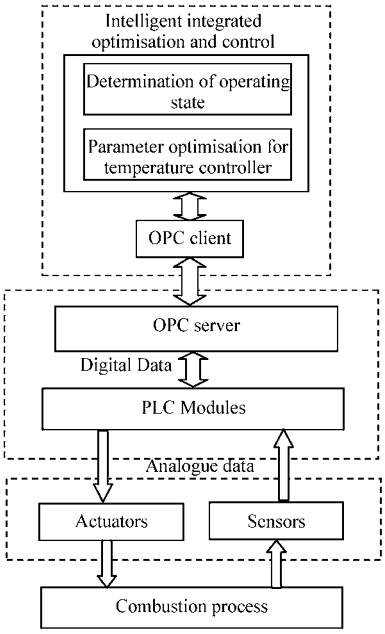
The intelligent integrated optimisation and control system developed in this study was used to regulate the combustion process of a coking plant in an iron and steel company. The results of actual runs demonstrate the validity of this method.

6.1 System implementation

The intelligent integrated optimisation and control system was implemented on an industrial control computer. The system consists of the application software, a Programmable-Logic-Controller (PLC)-based Windows Control Center (WinCC) configuration, and object linking and embedding for process control (OPC). WinCC is a communication interface between the application software and the PLC. The application software 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 optimised 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 stabilised 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 gas flow rate, the air suction power, and the valve openings are measured and sent to the intelligent integrated optimisation and control system. Figure 10 shows the flow of information and data in the system.

All the application programs are written in Visual C++. The configuration software uses PLC-based Siemens WinCC configuration software, which includes an OPC server, OPC configuration software, and PLC modules. The OPC server carries out data communication between an OPC client and the WinCC configuration software. The WinCC configuration software monitors and controls the combustion process, analyses 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.

Figure 10 Flow of information and data in intelligent integrated optimisation and control system



6.2 Industrial application

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 optimisation and control system was installed in 2005. The results of actual runs are shown in Figure 11. It is clear that the control system reduced the variation in oven temperature from ±25°C to ±10°C.

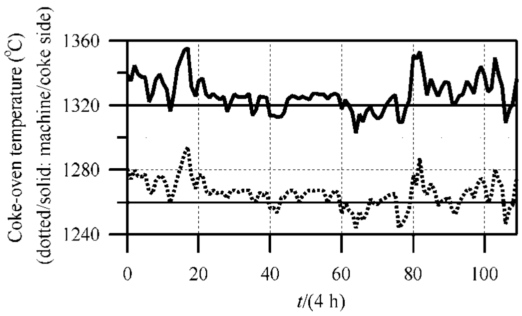
Some statistics on actual runs are shown in Table 3. The two variables K_S and K_A in the table are defined to be

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

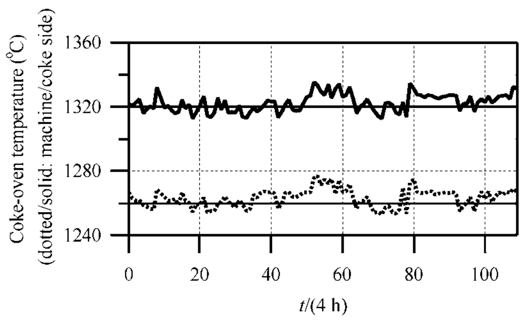
$$K_S = \frac{2N - (A'_{\text{machine}} + A'_{\text{coke}})}{2M}$$

where M is the number of combustion chambers in the coke oven; A_{machine} and A_{coke} are the numbers of combustion chambers on the machine and coke sides, respectively, with flue temperatures outside the error range (±7°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 ±7°C; and A'_{coke} is the number of times that the oven temperature error on the coke side is outside the range ±7°C.

Figure 11 Actual run results of coke oven temperature: (a) manual control and (b) intelligent integrated control



(a)



(b)

K_S indicates the stability of the oven temperature, and K_A indicates the uniformity of the oven temperature. Two more evaluation parameters–the crushing strength, M_{40}, and the wear resistance, M_{10} – are also employed in the evaluation. M_{40} is the percentage by weight of coke balls with a diameter greater then 40 mm in 100 kg of coke balls, and M_{10} is the percentage by weight of coke balls with a diameter less then 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. It is clear from Table 3 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.

Table 3 Statistics on control results

	Manual control (*Average*)	*Intelligent integrated control* (*Average*)
K_S	0.48	0.76
K_A	0.32	0.78
M_{40}	81.77%	83.10%
M_{10}	7.48%	6.34%
Avg. energy consumption	*2.316* GJ/t	*2.269* GJ/t

7 Conclusions

An intelligent integrated hybrid optimisation 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 optimisation 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 optimisation and control layer, an online 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 optimisation method employs an adaptive genetic algorithm to optimise the controller parameters. In the other control loop, controllers for valve openings were designed to stabilise the gas and air fluxes. The intelligent integrated optimisation and control system was implemented in the coking plant of an iron are steel company. The results of actual runs show that the system stabilises the oven temperature, improves the quality of coke, and reduces energy consumption.

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