PERGAMON

Expert Systems with Applications 16 (1999) 271–281

Expert Systems with Applications

A model-based expert control strategy using neural networks for the coal blending process in an iron and steel plant

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Abstract

Two important aspects of the control of the coal blending process in the iron and steel industry are computation of the target percentage of each type of coal to be blended and the blending of the different types in the target percentages. This paper proposes an expert control strategy to compute and track the target percentages accurately. First, neural networks, mathematical models and rule models are constructed based on statistical data and empirical knowledge on the process. Then a methodology is proposed for computing the target percentages that combines the neural networks, mathematical models and rule models and uses forward chaining and model-based reasoning. Finally, the tracking control of the target percentages is carried out by a distributed PI control scheme. The expert control strategy proposed is implemented in an expert control system that contains an expert controller and a distributed controller. The results of actual runs show that the proposed expert control strategy is an effective way to control the coal blending process. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Coal blending process; Expert systems; Neural networks; Mathematical models; Rule models; Process control

1. Introduction

Coke plays an important role in the iron and steel industry. It is used mainly as a fuel to provide the heat needed to melt iron ore and also as a source of reducing gases in a blast furnace. Coke is a solid product of the destructive distillation of coal. Coke for iron smelting is made from coal that satisfies specific quality indexes. Since raw coal does not generally meet the requirements, different types must be blended in suitable percentages to form a coal blend of the required quality (The Iron and Steel Institute of Japan, 1979; Hashimoto, 1989; ASM International Handbook Committee, 1990). Under certain distillation conditions (proper temperature, suitable time, etc.), the quality of coke is mainly determined by the quality of the coal blend. This means the quality and percentage of each type of coal to be blended are key factors influencing the quality of coke. To obtain the desired coal blend, it is imperative to rigorously control the coal blending process.

Two important aspects of the control of this process are computation of the target percentage of each type of coal and the blending of the different types in those percentages. It is especially important to compute the target percentages from the quality requirements of the coke and the quality of each type of coal by predicting the quality of the coal blend and coke. Conventional computation methods involve constructing mathematical models to predict quality based on measured data for coal blending and distillation, and then computing the target percentages using the models. The models mainly employ linear system identification techniques, such as the least-squares method (Miura et al., 1979; The Iron and Steel Institute of Japan, 1979; Shi, 1989; Wen et al., 1994). However, it is difficult to get accurate percentages by conventional methods, because the computation is based solely on mathematical models which do not describe the exact relationships among the parameters that characterize the quality of the coal blend and coke, and the quality and percentage of each type of coal. In order to achieve rigorous control over the coal blending process, we need a way to compute the target percentages with a high accuracy. This requires highly accurate quality prediction models.

Artificial intelligence techniques have been widely studied and used in engineering. Expert systems are one rapidly growing area, and are a very practical technique in the field of artificial intelligence (Hayes-Roth et al., 1983; Jackson, 1986; Liebowitz, 1988; Liebowitz and DeSalvo, 1989; Mockler and Dologite, 1992; Liebowitz, 1995). They are used for process control in the iron and steel

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PII: S0957-4174(98)00076-1

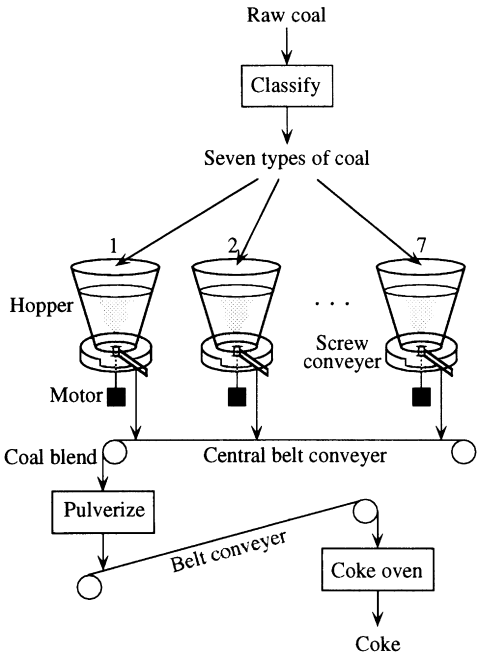

Fig. 1. Coal blending process.

industry (e.g., Tsushima et al., 1985; Yui et al., 1987; Ishiduka and Kobayashi, 1991). An expert system that is designed to emulate the expertise of experts and veteran operators in performing control activities is called an expert control system. Such a system uses empirical knowledge to solve the control problem, and is a powerful technique for controlling a complex process with nonlinearities and uncertainties (Åström et al., 1986; Efstathiou, 1989; Passion and Lunardhi, 1996; Cai et al., 1996). On the other hand, neural networks are effectively used for the modeling, identification and control of complex systems, and a large number of neural network algorithms have been developed (Rumelhart et al., 1986; Narendra and Parthasarathy, 1990; Piovoso et al., 1992; Hagan et al., 1996). Among all neural networks, the backpropagation network is the most widely used in process control applications. It can approximate large classes of continuous functions (Hornik et al., 1989; Su and McAvoy, 1997). These artificial intelligence techniques provide a way to control the coal blending process, because the relationships among the parameters in the process can be expressed through a combination of backpropagation networks, mathematical models and rule models based on the empirical knowledge of experts and veteran operators, and statistical data on coal blending and distillation. Expert systems and neural networks can be employed to construct highly accurate quality prediction models for the coal blend and coke, and to compute precise target percentages.

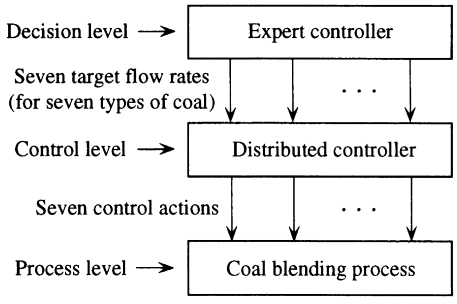

Fig. 2. Hierarchical configuration.

This paper proposes an expert control strategy based on a combination of backpropagation networks, mathematical models and rule models to compute and track the target percentages accurately. The strategy was implemented in a hierarchical configuration with two controllers that does not have the drawbacks of the conventional methods. In this paper, the coal blending process and the basic idea of the expert control strategy are first described. Next, based on statistical data and empirical knowledge, highly accurate quality prediction models that consist of backpropagation networks and mathematical models are constructed, and rule models are established. Then, a methodology for computing the target percentages is proposed that combines the networks and models and uses forward chaining and model-based reasoning. Finally, an expert control system is constructed for the control of the coal blending process. It employs a distributed controller for blending in accordance with the target percentages. The results of actual runs are also presented.

2. Process description and expert control strategy

The expert control strategy proposed in this paper is used for the coal blending process in an iron and steel plant. The process can be roughly divided into two steps: first blend different types of coal in the target percentages and then pulverize the coal blend.

2.1. Process description

The coal blending process is shown in Fig. 1. Various kinds of raw coal from different mines are classified according to their properties into seven types. Each type is fed from a hopper through a screw conveyer to a central belt conveyer in the target percentage, where it is blended with the others. The coal blend is pulverized and put in a coke oven, where destructive distillation produces coke.

An important requirement of the process is to compute the target percentage of each type of coal from the quality requirements of the coke and the quality of coal to be blended. These percentages are tracked by controlling the speeds of the screw conveyers. The coke produced must satisfy the given quality requirements.

2.2. Basic idea of expert control strategy

An expert control strategy is proposed to control the coal blending process. It is based on the hierarchical configuration shown in Fig. 2, and consists of a decision level, a control level and a process level, which correspond to an

expert controller, a distributed controller and the coal blending process, respectively.

The expert controller uses a reasoning strategy based on backpropagation networks, mathematical models and rule models, and combines forward chaining and model-based reasoning to compute the target percentages from the quality requirements of the coke and the quality of each type of coal so as to obtain the desired coke. Moreover, by using the computed target percentages, the total flow rate of the coal blending process and the moisture content of each type of coal, the expert controller calculates the target flow rate of each type of coal and sends it to the distributed controller.

The distributed controller is used for blending different types of coal in accordance with the target percentages. More specifically, the distributed controller generates control actions by using a PI control algorithm to control the speeds of the screw conveyers so as to ensure that the actual flow rates track the target flow rates.

3. Quality prediction models and rule models

The quality prediction models for the coal blend and coke consist of three backpropagation networks and two mathematical models. Rule models are represented in If–Then form. This section describes these models, which are based on statistical data and empirical knowledge on coal blending and distillation.

3.1. Quality prediction models for coal blend

In the coal blending process, coal quality is characterized mainly by the caking property index, the volatile matter content, the sulfur content and the ash content (Van Krevelen, 1961). Assume that G_i, V_{bi}, S_{bi} and A_{bi} denote these properties of the ith type of coal, respectively; G, V_b, S_b and A_b are for the coal blend, respectively; and $\hat{G}$, $\hat{V}_b$, $\hat{S}_b$ and $\hat{A}_b$ are the predicted values. x_i is the percentage of the ith type of coal. The quality prediction models for the coal blend are constructed to predict its quality from the quality and percentage of each type of coal, i.e., to obtain $\hat{G}$, $\hat{V}_b$, $\hat{S}_b$ and $\hat{A}_b$ from G_i, V_{bi}, S_{bi}, A_{bi} and x_i.

Empirical knowledge and statistical data show that G, V_b, S_b and A_b for the most part depend only on x_iG_i, x_iV_{bi}, x_iS_{bi} and x_iA_{bi}, respectively. In particular, the relationship among G and x_iG_i is more complicated than the other three relationships. To predict the quality of the coal blend accurately, the following expressions are introduced:

$$\hat{G} = \sum_{i=1}^{7} a_i x_i G_i + \Delta G, \tag{1}$$

$$\hat{V}_b = \sum_{i=1}^{7} x_i V_{bi} + \Delta V_b, \tag{2a}$$

$$\hat{S}_b = \sum_{i=1}^{7} x_i S_{bi} + \Delta S_b \tag{2b}$$

and

$$\hat{A}_b = \sum_{i=1}^{7} x_i A_{bi} + \Delta A_b, \tag{2c}$$

where a_i is the correlation coefficient, and ΔG, ΔV_b, ΔS_b and ΔA_b are compensation values that are used to improve the accuracy of the prediction of coal blend quality.

In fact, Eq. (1) describes a backpropagation network with two layers for predicting G (BP2L-G) that has an input layer with seven neurons and an output layer with one neuron, while there are an input layer, several hidden layers and an output layer in a general backpropagation network (Rumelhart et al., 1986; Hagan et al., 1996). In the input layer, both the input and output of the ith neuron are x_iG_i; and in the output layer, those of the neuron are $\hat{G}$. a_i is the weight of the signal from the ith neuron of the input layer to the neuron of the output layer and ΔG is the bias of the neuron in the output layer; they are determined by training BP2L-G based on statistical data.

To determine the compensation values ΔV_b, ΔS_b and ΔA_b, Eqs. (2) are written in the following form:

$$\hat{B} = DX + \Delta B, \tag{3}$$

where

$$\hat{B} = \begin{bmatrix} \hat{V}_b \\ \hat{S}_b \\ \hat{A}_b \end{bmatrix}, \qquad D = \begin{bmatrix} V_{b1} & V_{b2} & \cdots & V_{b7} \\ S_{b1} & S_{b2} & \cdots & S_{b7} \\ A_{b1} & A_{b2} & \cdots & A_{b7} \end{bmatrix}, \tag{4a}$$

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_7 \end{bmatrix}, \qquad \Delta B = \begin{bmatrix} \Delta V_b \\ \Delta S_b \\ \Delta A_b \end{bmatrix}. \tag{4b}$$

Let B denote the measured value corresponding to $\hat{B}$. Then the compensation value $\Delta B(k)$ for the kth blending is given as the error between the last prediction, $\hat{B}(k-1)$, and the measured value, $B(k-1)$; i.e.,

$$\Delta B(k) = \hat{B}(k-1) - B(k-1). \tag{5}$$

Eqs. (3) and (5) yield the following mathematical model:

$$\hat{B}(k) = D(k)X(k) + \Delta B(k), \tag{6a}$$

$$\Delta B(k) = \sum_{j=1}^{k-1} [D(j)X(j) - B(j)] + \Delta B(1), \tag{6b}$$

where $\Delta B(1)$ is the compensation value for the first blending and is determined by the empirical data.

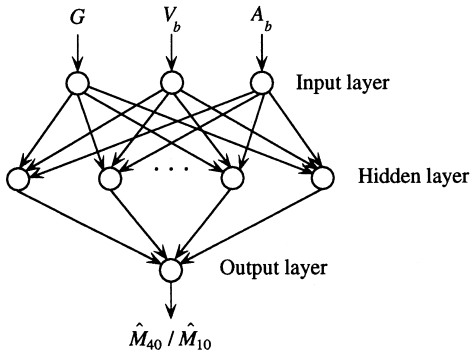

Fig. 3. Structure of BP3L-M40/BP3L-M10.

3.2. Quality prediction models for coke

The quality of coke can be characterized by the MICUM strength 40 mm index, the MICUM strength 10 mm index, the sulfur content and the ash content (The Iron and Steel Institute of Japan, 1979). Let M_{40}, M_{10}, S and A denote these properties, respectively, and $\hat{M}_{40}$, $\hat{M}_{10}$, $\hat{S}$ and $\hat{A}$ denote the corresponding predicted values. The quality prediction models for coke are constructed to predict the quality of coke from the quality of the coal blend, i.e., to obtain $\hat{M}_{40}$, $\hat{M}_{10}$, $\hat{S}$ and $\hat{A}$ from G, V_b, S_b and A_b.

M_{40} and M_{10} have been shown to depend mainly on G, V_b and A_b under certain distillation conditions. However, these relationships are nonlinear. To predict M_{40} and M_{10} from G, V_b and A_b accurately, two backpropagation networks with three layers, BP3L-M40 and BP3L-M10, are constructed, respectively.

As shown in Fig. 3, BP3L-M40 and BP3L-M10 have the same structure: an input layer with three neurons, a hidden layer with 12 neurons and an output layer with one neuron. The inputs of the three neurons of the input layer for both BP3L-M40 and BP3L-M10 are G, V_b and A_b, and their outputs are the same as the inputs. Let

$$p_1^{\mathrm{I}} = G, \qquad p_2^{\mathrm{I}} = V_b, \qquad p_3^{\mathrm{I}} = A_b. \tag{7}$$

Then the input and output of the ith neuron of the hidden layer of BP3L-M40 are defined to be

$$p_i^{\mathrm{H1}} = \sum_{j=1}^{3} w_{i,j}^{\mathrm{H1}} p_j^{\mathrm{I}} + b_i^{\mathrm{H1}} \tag{8a}$$

and

$$y_i^{\mathrm{H1}} = \mathrm{tansig}(p_i^{\mathrm{H1}}), \tag{8b}$$

respectively, and those of the neuron of the output layer of BP3L-M40 are defined to be

$$p^{\mathrm{O1}} = \sum_{j=1}^{12} w_j^{\mathrm{O1}} y_j^{\mathrm{H1}} + b^{\mathrm{O1}} \tag{9a}$$

and

$$\hat{M}_{40} = p^{\mathrm{O1}}, \tag{9b}$$

respectively, where tansig(·) denotes the tan-sigmoid transfer function, which has the form

$$\mathrm{tansig}(x) = \frac{2}{1 + \mathrm{e}^{-2x}} - 1. \tag{10}$$

The tan-sigmoid transfer function maps the input to the interval $(-1, 1)$ (Hagan et al., 1996). In Eqs. (8a) and (9a), w_{ij}^{H1} denotes the weight of the signal from the jth neuron of the input layer to the ith neuron of the hidden layer, b_i^{H1} denotes the bias of the ith neuron of the hidden layer, w_j^{O1} denotes the weight of the signal from the jth neuron of the hidden layer to the neuron of the output layer, and b^{O1} denotes the bias of the neuron of the output layer.

Eqs. (7)–(9) can be written in the following form:

$$\hat{M}_{40} = W^{\mathrm{O1}} \,\mathrm{tansig}(W^{\mathrm{H1}} P^{\mathrm{I}} + B^{\mathrm{H1}}) + b^{\mathrm{O1}}, \tag{11}$$

where

$$W^{\mathrm{H1}} = \begin{bmatrix} w_{1,1}^{\mathrm{H1}} & w_{1,2}^{\mathrm{H1}} & w_{1,3}^{\mathrm{H1}} \\ w_{2,1}^{\mathrm{H1}} & w_{2,2}^{\mathrm{H1}} & w_{2,3}^{\mathrm{H1}} \\ \vdots & \vdots & \vdots \\ w_{12,1}^{\mathrm{H1}} & w_{12,2}^{\mathrm{H1}} & w_{12,3}^{\mathrm{H1}} \end{bmatrix}, \qquad B^{\mathrm{H1}} = \begin{bmatrix} b_1^{\mathrm{H1}} \\ b_2^{\mathrm{H1}} \\ \vdots \\ b_{12}^{\mathrm{H1}} \end{bmatrix}, \tag{12a}$$

$$P^{\mathrm{I}} = \begin{bmatrix} p_1^{\mathrm{I}} \\ p_2^{\mathrm{I}} \\ p_3^{\mathrm{I}} \end{bmatrix}, \qquad W^{\mathrm{O1}} = \begin{bmatrix} w_1^{\mathrm{O1}} & w_2^{\mathrm{O1}} & \cdots & w_{12}^{\mathrm{O1}} \end{bmatrix}. \tag{12b}$$

Using the same method as for M_{40} yields

$$\hat{M}_{10} = W^{\mathrm{O2}} \,\mathrm{tansig}(W^{\mathrm{H2}} P^{\mathrm{I}} + B^{\mathrm{H2}}) + b^{\mathrm{O2}}, \tag{13}$$

where

$$W^{\mathrm{H2}} = \begin{bmatrix} w_{1,1}^{\mathrm{H2}} & w_{1,2}^{\mathrm{H2}} & w_{1,3}^{\mathrm{H2}} \\ w_{2,1}^{\mathrm{H2}} & w_{2,2}^{\mathrm{H2}} & w_{2,3}^{\mathrm{H2}} \\ \vdots & \vdots & \vdots \\ w_{12,1}^{\mathrm{H2}} & w_{12,2}^{\mathrm{H2}} & w_{12,3}^{\mathrm{H2}} \end{bmatrix}, \qquad B^{\mathrm{H2}} = \begin{bmatrix} b_1^{\mathrm{H2}} \\ b_2^{\mathrm{H2}} \\ \vdots \\ b_{12}^{\mathrm{H2}} \end{bmatrix}, \tag{14a}$$

$$W^{\mathrm{O2}} = \begin{bmatrix} w_1^{\mathrm{O2}} & w_2^{\mathrm{O2}} & \cdots & w_{12}^{\mathrm{O2}} \end{bmatrix}. \tag{14b}$$

The weight matrices W^{H1}, W^{O1}, W^{H2} and W^{O2}, and the biases B^{H1}, b^{O1}, B^{H2} and b^{O2} are determined by training BP3L-M40 and BP3L-M10 based on statistical data.

From statistical data and empirical knowledge, the predicted values of S and A can be computed from:

$$\hat{S} = \frac{\eta_s}{\eta_c} S_b + \Delta S \tag{15a}$$

and

$$\hat{A} = \frac{1}{\eta_c} A_b + \Delta A, \tag{15b}$$

Table 1
Some typical rule models for coal blending and distillation

Number	Condition	Action
R^1	G_i increases	G increases
R^2	V_{bi} increases	V_b increases
R^3	S_{bi} increases	S_b increases
R^4	A_{bi} increases	A_b increases
R^5	G increases or V_b decreases or A_b decreases	M_{40} increases and M_{10} decreases
R^6	G decreases or V_b increases or A_b increases	M_{40} decreases and M_{10} increases
R^7	S_b increases	S increases
R^8	A_b increases	A increases

where η_c is the coking coefficient of the coal blend and η_s is the residual coefficient of the sulfur content of the coal blend. Usually, $\eta_c = 0.75–0.80$ and $\eta_s = 0.65–0.75$. The compensation values ΔS and ΔA improve the prediction accuracy. The following mathematical model for predicting the sulfur content and ash content of coke in the kth blending is obtained by a process similar to that for Eqs. (6):

$$\hat{S}(k) = \frac{\eta_s(k)}{\eta_c(k)} S_b(k) + \Delta S(k), \tag{16a}$$

$$\hat{A}(k) = \frac{1}{\eta_c(k)} A_b(k) + \Delta A(k), \tag{16b}$$

$$\Delta S(k) = \sum_{i=1}^{k-1} \left[\frac{\eta_s(i)}{\eta_c(i)} S_b(i) - S(i) \right] + \Delta S(1) \tag{16c}$$

and

$$\Delta A(k) = \sum_{i=1}^{k-1} \left[\frac{1}{\eta_c(i)} A_b(i) - A(i) \right] + \Delta A(1), \tag{16d}$$

where $\Delta S(1)$ and $\Delta A(1)$ are the compensation values in the first blending, which are determined from empirical data.

3.3. Training of neural networks

BP2L-G, BP3L-M40 and BP3L-M10 are trained based on statistical data to accurately predict G, M_{40} and M_{10}. The training process requires a set of network inputs and target outputs culled from measured statistical values for the coal blending and distillation. More specifically, the network inputs of BP2L-G are $x_1G_1, x_2G_2, \ldots, x_7G_7$ and the target output is G. The network inputs of both BP3L-M40 and BP3L-M10 are G, V_b and A_b, and the target output is M_{40} for BP3L-M40 and M_{10} for BP3L-M10. The network performance functions of BP2L-G, BP3L-M40 and BP3L-M10 are the average squared errors between the network outputs and the target outputs. For example, the network performance function of BP3L-M40 is defined to be

$$J = \frac{1}{N} \sum_{k=1}^{N} [M_{40}(k) - \hat{M}_{40}(k)]^2, \tag{17}$$

where N is the total number of M_{40} values used in training, and k indicates the order of the data. The weights and biases of BP2L-G, BP3L-M40 and BP3L-M10 are iteratively adjusted to minimize the associated network performance function during training.

In our scheme, a basic backpropagation training algorithm (Rumelhart et al., 1986; Hagan et al., 1996) determines the weights and biases of BP2L-G, BP3L-M40 and BP3L-M10. It employs the gradient of the network performance function to adjust the weights and biases and minimize that function. The gradient is determined by the backpropagation technique, which involves performing computations backwards through the network using the chain rule of calculus. In the basic backpropagation training algorithm, the weights and biases are moved in the direction of the negative gradient, and the performance function decreases very rapidly. Let $x_{wb}(k)$ be the vector of current weights and biases, $g_{wb}(k)$ be the current gradient, $\eta_{wb}(k)$ be the current learning rate, and J be the associated network performance function. Then the training algorithm can be written as

$$x_{wb}(k+1) = x_{wb}(k) - \eta_{wb}(k) g_{wb}(k), \tag{18a}$$

$$g_{wb}(k) = \frac{\partial J}{\partial x_{wb}}(k), \tag{18b}$$

where k is the number of iterations. A batch training method is used to implement the above gradient descent algorithm. In this training, the weights and biases of the network are updated only after all the training data have been fed to the network. The gradients calculated during each training session are added together to determine the changes in the weights and biases.

The initial weights and biases of BP2L-G, BP3L-M40 and BP3L-M10 are based on statistical data for the last two years. When new statistical data are collected, the weights and biases are updated based on the previous weights and biases, and the new data.

3.4. Rule models

In coal blending and distillation, there may exist several sets of percentages of coal to be blended that satisfy the same quality requirements for coke. It is important to efficiently determine a practical percentage for each type of coal. On the other hand, there are some relationships that cannot be described by backpropagation networks and mathematical models; but these relationships influence the quality prediction accuracy and the computational accuracy of the target percentages. In addition, how suitable compensation values are selected in mathematical models (6) and (16) is also an important aspect for improving the quality

Table 2
Main operational states of the process

Number	States
S^1	M_{40} is smaller than M_{40g}
S^2	M_{40} is much larger than M_{40g}
S^3	M_{10} is larger than M_{10g}
S^4	M_{10} is much smaller than M_{10g}
S^5	S is larger than S_g
S^6	A is larger than A_g
S^7	G is smaller than G_g
S^8	V_b is larger than V_{bg}
S^9	S_b is larger than S_{bg}
S^{10}	A_b is larger than A_{bg}
S^{11}	G_i is larger than G_g
S^{12}	G_i is smaller than G_g
S^{13}	V_{bi} is larger than V_{bg}
S^{14}	V_{bi} is smaller than V_{bg}
S^{15}	S_{bi} is larger than S_{bg}
S^{16}	S_{bi} is smaller than S_{bg}
S^{17}	A_{bi} is larger than A_{bg}
S^{18}	A_{bi} is smaller than A_{bg}

prediction accuracy. To meet these requirements, we need to construct rule models based on the empirical knowledge of experts and veteran operators.

All rule models use the following production rule form (Hayes-Roth et al., 1983; Jackson, 1986; Liebowitz, 1988; Mockler and Dologite, 1992):

$$R^{\#}: \text{ If } \textit{condition} \text{ Then } \textit{action}, \tag{19}$$

where $R^{\#}$ is the number of the rule model, *condition* is the operating state of the process or a logical combination, and *action* is the conclusion or operation.

Some relationships among the parameters expressing the quality and the percentages can be represented by rule models based on statistical data and empirical knowledge. For example, some typical rule models are listed in Table 1. These rule models are also used to examine whether BP2L-G, BP3L-M40, BP3L-M10 and the mathematical models are correct or not.

The computation of the target percentages is divided into two steps: (1) determine the allowable values of the quality of the blend coal from the quality requirements of the coke; and (2) determine the target percentages from both the allowable values and the quality of each type of coal. The solution of each step is not unique. To obtain a suitable solution in each step quickly, empirical knowledge and data must be used effectively.

Table 3
Some typical rule models for computing target percentages

Number	Condition	Action
R^9	S^1 or S^2	increase G_g and decrease V_{bg}
R^{10}	S^2 or S^4	decrease G_g and increase V_{bg}
R^{11}	S^5	decrease S_{bg}
R^{12}	S^6	decrease A_{bg}
R^{13}	S^7 and S^{11}	increase x_i
R^{14}	S^7 and S^{12}	decrease x_i
R^{15}	S^8 and S^{13}	decrease x_i
R^{16}	S^8 and S^{14}	increase x_i
R^{17}	S^9 and S^{15}	decrease x_i
R^{18}	S^9 and S^{16}	increase x_i
R^{19}	S^{10} and S^{17}	decrease x_i
R^{20}	S^{10} and S^{18}	increase x_i

By using the empirical knowledge and data, rule models for computing the target percentages are constructed based on the operational states of the process. The operational states are used in the *condition* part of the rule modes. For instance, if we assume that the given quality index of coke is M_{40g}, M_{10g}, S_g and A_g, and the allowable values of the quality of the coal blend are G_g, V_{bg}, S_{bg} and A_{bg}, then some operational states, which are numbered $S^{\#}$, are listed in Table 2.

About 150 rule models for computing the allowable values of the coal blend and the target percentages were developed. Some typical ones are listed in Table 3.

4. Methodology for computing target percentages

An expert controller was designed to compute the target percentages. It uses a reasoning strategy based on the constructed backpropagation networks, mathematical models and rule models, and a combination of forward chaining and model-based reasoning. The reasoning strategy is implemented in two algorithms that compute the allowable values of the quality of the coal blend and the target percentages. The predictions of the coal blend and coke quality are repetitively performed in the two algorithms.

4.1. Computation procedure and objective

The procedure for computing the target percentages is shown in Fig. 4.

The control objective of the coal blending process is to make the quality of the coke satisfy the following quality index requirements:

$$M_{40} \geq M_{40g}, \qquad M_{10} \leq M_{10g}, \tag{20a}$$

$$S \leq S_g, \qquad A \leq A_g. \tag{20b}$$

To achieve this, the objective of the first step of the computation is to obtain the allowable values G_g, V_{bg}, S_{bg} and A_{bg} so that the predicted values $\hat{M}_{40}$, $\hat{M}_{10}$, $\hat{S}$ and $\hat{A}$ for the quality of the coke satisfy

$$M_{40g} \leq \hat{M}_{40} \leq M_{40g} + \Delta M_{40r}, \tag{21a}$$

$$M_{10g} - \Delta M_{40r} \leq \hat{M}_{10} \leq M_{10g}, \tag{21b}$$

$$\hat{S} \leq S_g, \quad \hat{A} \leq A_g. \tag{21c}$$

The objective of the second step of the computation is to obtain the target percentages x_i ($i = 1,2,\ldots,7$) so that the

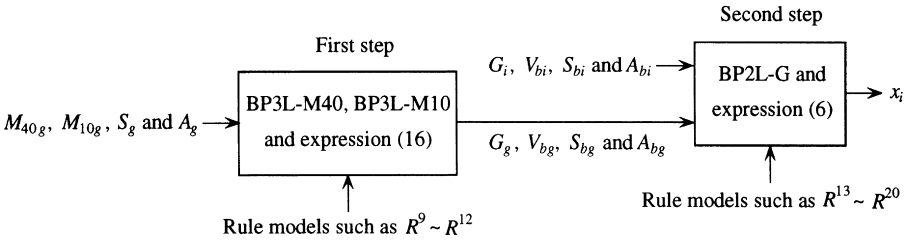

Fig. 4. Computation procedure for target percentages.

predicted values $\hat{G}$, $\hat{V}_b$, $\hat{S}_b$ and $\hat{A}_b$ for the quality of the coal blend satisfy

$$G_g \le \hat{G} \le G_g + \Delta G_r, \qquad \hat{V}_b \le V_{bg}, \tag{22a}$$

$$\hat{A}_b \le A_{bg}, \qquad \hat{S}_b \le S_{bg}. \tag{22b}$$

ΔM_{40r}, ΔM_{10r} and ΔG_r are empirically determined positive values that are used to keep the computational process from being too conservative. In general, $\Delta M_{40r} = 2–5$, $\Delta M_{10r} = 1–2$ and $\Delta G_r = 2–10$.

The introduction of ΔM_{40r}, ΔM_{10r} and ΔG_r also simplifies expressions for some states of the process. For example, the states S^2 and S^4 can be expressed as $M_{40} > M_{40g} + \Delta M_{40r}$ and $M_{10} < M_{10g} - \Delta M_{10r}$, respectively.

4.2. Structure of expert controller

An expert controller was designed to achieve the computational objective in each step. It computes the target percentages and the corresponding flow rates according to the computational procedure in Fig. 4.

The structure of the expert controller is shown in Fig. 5. It consists of a knowledge base, a database, a working memory, an inference engine, a calculation module, a control and communication interface, and a man–machine interface.

The knowledge base and database store empirical knowledge and data. When the quality requirements of the coke or the quality of the coal to be blended change, the associated states and data are sent to the working memory. The inference engine gets the empirical knowledge and data from the knowledge base and database, and uses a reasoning strategy combined with forward chaining (Hayes-Roth et al., 1983; Jackson, 1986; Liebowitz, 1988; Efstathiou, 1989; Mockler and Dologite, 1992) and model-based reasoning (Ishiduka and Kobayashi, 1991) to compute the target percentages. The intermediate results and states are stored in the working memory and employed repetitively. The computed target percentages, i.e., the reasoning results, are stored in the database and sent to the calculation module, which computes the target flow rates from the target percentages, moisture content and total flow rate of the coal to be blended. The moisture content and total flow rate come from the database. The control and communication interface is used to send the target flow rates to the distributed controller and provide process data to the database. The man–machine interface is employed to edit and modify the knowledge base and database, and display data in the database in the form of tables and graphics.

A important feature of the expert controller is that it combines the backpropagation networks, mathematical

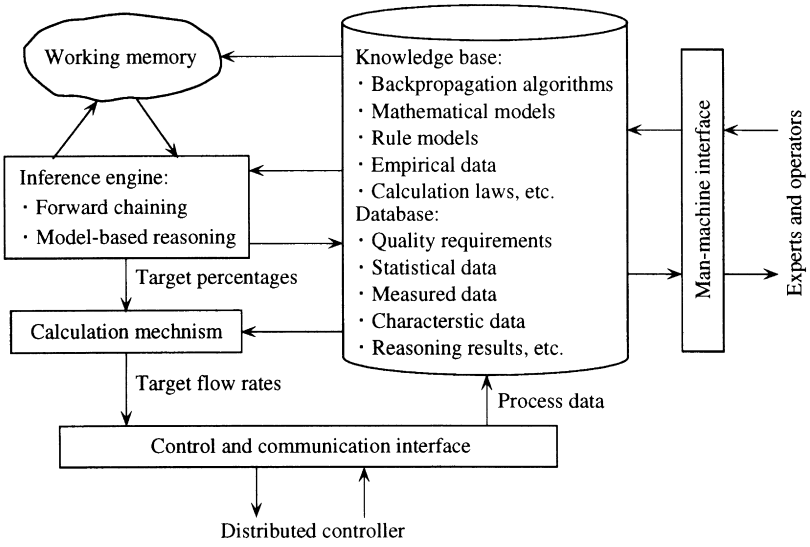

Fig. 5. Structure of expert controller.

models and rule models. The combination ensures accuracy in the computation of the target percentages.

4.3. Computation algorithms

The computation of the target percentages is implemented in two algorithms. One computes the allowable value of the coal blend quality from the quality requirements of the coke, and the other computes the target percentages from the allowable values and the quality of each type of coal.

More specifically, the allowable values S_{bg} and A_{bg} are obtained from Eqs. (15) as follows:

$$S_{bg} = \frac{\eta_c}{\eta_s}(S_g - \Delta S) \tag{23a}$$

and

$$A_{bg} = \eta_c(A_g - \Delta A). \tag{23b}$$

The allowable values G_g and V_{bg} are determined so that the predicted values $\hat{M}_{40}$ and $\hat{M}_{10}$ obtained from BP3L-M40 and BP3L-M10 satisfy inequalities (21a) and (21b), respectively. This can be achieved through an iterative computation. That is, first, select empirical initial values of G_g and V_{bg} from the knowledge base; then compute $\hat{M}_{40}$ and $\hat{M}_{10}$ from Eqs. (11) and (13), respectively, and check whether inequalities (21a) and (21b) hold or not. If not, adjust G_g and V_{bg} as follows:

$$G_g = G_g + \Delta G_g \tag{24a}$$

and

$$V_{bg} = V_{bg} + \Delta V_{bg}, \tag{24b}$$

where ΔG_g and ΔV_{bg} are determined by the errors between $\hat{M}_{40}$ and M_{40g}, and $\hat{M}_{10}$ and M_{10g}. For example, when $\hat{M}_{40} < M_{40g}$,

$$\Delta G_g = \alpha_1(M_{40g} - \hat{M}_{40}) \tag{25a}$$

and

$$\Delta V_{bg} = \alpha_2(\hat{M}_{40} - M_{40g}) \tag{25b}$$

are selected according to rule model R^9; and when $\hat{M}_{40} > M_{40g} + \Delta M_{40r}$,

$$\Delta G_g = \beta_1(M_{40g} + \Delta M_{40r} - \hat{M}_{40}) \tag{26a}$$

and

$$\Delta V_{bg} = \beta_2(\hat{M}_{40} - M_{40g} - \Delta M_{40r}) \tag{26b}$$

are selected according to rule model R^{10}, where α_1, α_2, β_1 and β_2 are empirically determined positive values that determine the convergence rate of the iterative computation.

Based on the above discussion, algorithm 1 has been developed to compute the allowable value of the coal blend quality.

Algorithm 1 (Computes Allowable Values):

Step 1. Compute the allowable values S_{bg} and A_{bg} from S_g and A_g using Eqs. (23a) and (23b), respectively.

Step 2. Select suitable empirical values of G and V_b from the knowledge base as the initial values of G_g and V_{bg}, respectively.

Step 3. Compute $\hat{M}_{40}$ and $\hat{M}_{10}$ from BP3L-M40 and BP3L-M10 by replacing G and V_b with G_g and V_{bg}, respectively.

Step 4. Check if $\hat{M}_{40}$ and $\hat{M}_{10}$ satisfy Eqs. (21a) and (21b). If not, use the rule models, such as R^9–R^{12}, and adjustment laws, such as Eqs. (24)–(26), to adjust G_g and V_{bg}, and return to step 3. If so, go to the next step.

Step 5. Check if G_g and V_{bg} are in the empirical range. If so, take the G_g, V_{bg}, S_{bg} and A_{bg} obtained in steps 1–4 to be the allowable value of the coal blend quality, and stop the algorithm. If not, choose other empirical values of G and V_b as the initial values of G_g and V_{bg}, and return to step 3. If suitable G_g and V_{bg} cannot be obtained in a given number of iterations, stop the algorithm and report that the allowable values of G and V_b do not exist.

Just as in algorithm 1, the target percentages are also obtained by an iterative computation algorithm. First, select empirical percentages for the coal to be blended as the initial values of the target percentages. Next, compute the predicted values $\hat{G}$, $\hat{V}_b$, $\hat{S}_b$ and $\hat{A}_b$ from BP2L-G and mathematical model (6) based on the initial percentages. Then check if the computed $\hat{G}$, $\hat{V}_b$, $\hat{S}_b$ and $\hat{A}_b$ satisfy inequality (22). If not, adjust x_i as follows:

$$x_i = x_i + \Delta x_i, \tag{27}$$

where x_i are determined by the errors between the allowable and predicted values of the coal blend quality taking the quality of each type of coal into account. For instance, when $\hat{G} < G_g$ and $G_i > G_g$,

$$\Delta x_i = \gamma_1(G_g - \hat{G}) \tag{28}$$

is selected according to rule model R^{13}; and when $\hat{A}_b > A_{bg}$ and $A_{bi} < A_{bg}$,

$$\Delta x_i = \gamma_2(\hat{A}_g - A_{bg}) \tag{29}$$

is selected according to rule model R^{20}, where γ_1 and γ_2 are empirically determined positive values.

Algorithm 2 is obtained from the above discussion.

Algorithm 2 (Computes Target Percentages):

Step 1. Select a set of empirical percentages of coal to be blended from the knowledge base as the initial values of the target percentages x_i ($i = 1,2,\ldots,7$).

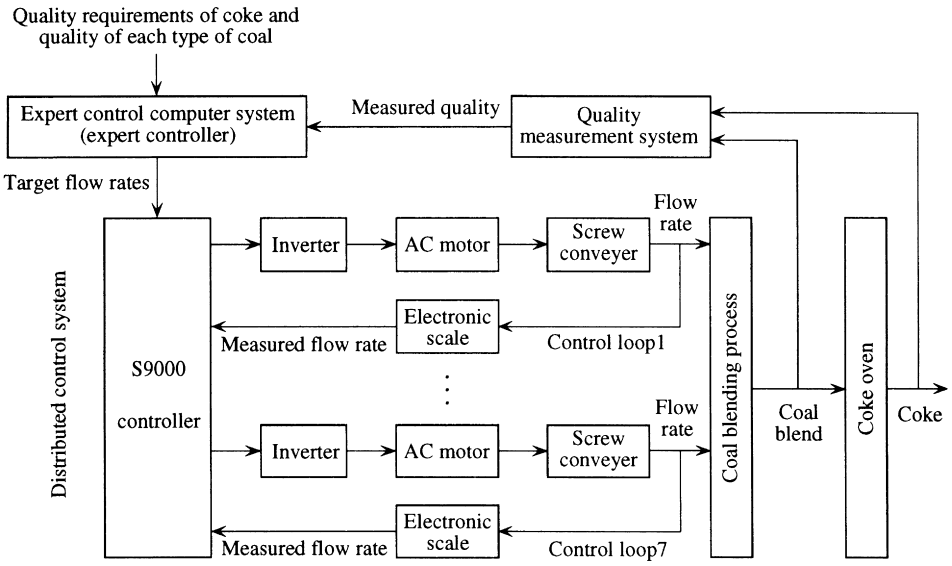

Fig. 6. Structure of the constructed expert control system.

Step 2. Predict the coal blend quality, i.e., $\hat{G}$, $\hat{V}_b$, $\hat{S}_b$ and $\hat{A}_b$, from the quality and the selected percentage of each type of coal using BP2L-G and mathematical model (6).

Step 3. Check if (22) is satisfied. If not, use adjustment laws, such as Eqs. (27)–(29), and rule models, such as R^{13}–R^{20}, to adjust x_i, and return to step 2. If so, go to the next step.

Step 4. Check if the percentages obtained in steps 1–3 are in the empirical range. If so, take the obtained percentages to be the target percentages, and stop the algorithm. If not, choose other empirical percentages from the knowledge base and return to step 2. If suitable x_i ($i = 1,2,\ldots,7$) cannot be obtained in a given number of iterations, stop the algorithm and report that useful percentages do not exist.

The target flow rate of each type of coal is determined from the following expression:

$$Q_i = \frac{x_i}{1 - b_i} Q, \tag{30}$$

where Q_i and b_i are the target flow rate and moisture content of the ith type coal, and Q is the total flow rate of the coal blend. The target flow rates are tracked by the distributed controller to obtain the desired coal blend and thus the desired coke.

5. Practical application and run results

The expert control strategy proposed was implemented in an expert control system, which carried out real-time control of the coal blending process in an iron and steel plant. The validity of this strategy has been proved by the results of actual runs.

5.1. Implementation

The expert control system has the structure shown in Fig. 6, which corresponds to Fig. 2. It consists mainly of an expert control computer system, a distributed control system and a quality measurement system. The expert control computer system uses an IPC 810 type computer, and the distributed control system uses an S9000 series controller made by the Honeywell Corporation. The expert controller was implemented in the expert control computer system. The S9000 controller is a distributed controller connected to seven control loops so as to ensure that the actual flow rate tracks the target flow rate for each type of coal.

One very important issue in the implementation of the expert controller is to determine suitable weights and biases for the backpropagation networks, and empirical values for the mathematical models. The initial weights and biases were obtained by training the backpropagation networks based on statistical data collected in 1995 and 1996, and the initial empirical values were culled from the statistical data of those two years. In addition, the rule models, such as R^1–R^8, were also used to check if the initial weights, biases and empirical values were suitable.

In order to adapt to changes in the environment and operating conditions, the backpropagation networks, mathematical models and rule models should be modified using new statistical data and empirical knowledge. This adaptation is

Table 4
Quality and computed percentages of each type of coal

i	G_i	V_{bi}	S_{bi}	A_{bi}	x_i
1	72.03	22.29	0.73	8.31	14.04
2	75.98	30.47	0.54	12.78	17.48
3	86.68	23.84	0.85	11.80	15.20
4	36.32	15.92	0.46	10.29	13.76
5	84.13	23.49	1.10	12.21	8.00
6	72.03	22.29	0.73	8.31	14.04
7	75.98	30.47	0.54	12.78	17.48

carried out by learning functions of the expert control system, which mainly

1. renew the statistical data used in the training of the backpropagation networks;
2. update the weights and biases of the backpropagation networks, and the empirical values of the mathematical models and rule models; and
3. add new rule models and delete unnecessary old rule models.

The coke and coal quality is measured every eight hours. New statistical data is culled from the measured process data by an arithmetic mean method. The number of statistical data used in training the backpropagation networks is fixed. These data are renewed and the oldest data are deleted when new data are added. The training of the backpropagation networks for determining new weights and biases is based on the renewed statistical data and the previous weights and biases.

The functions of the expert controller, which mainly computes the target percentages and the target flow rates, were implemented in a special program package written in Borland C++. The functions of the distributed controller, which mainly performs the tracking control of the target flow rates, were implemented by configuring the S9000 controller, which employs a PI control algorithm and a single-loop control technique to perform the distributed tracking control of the target flow rates.

5.2. Run results

The proposed expert control strategy was applied to the control of the coal blending process. Tables 4 and 5 show some run results. The quality index of coke and the empirical values used in computing the target percentages were

$$M_{40g} = 76.5, \qquad M_{10g} = 9, \qquad S_g = 0.7, \qquad A_g = 14.5, \tag{31a}$$

$$\Delta M_{40r} = 3, \qquad \Delta M_{10r} = 2, \qquad \Delta G_r = 8. \tag{31b}$$

The types of coal in the sixth and seventh hoppers were the same as those in the first and second hoppers, respectively. It is clear that the quality of coke produced using the computed target percentages satisfied the quality requirements described in Eqs. (20).

Table 5
Predicted and measured quality of coal blend and coke

Coal blend	G	V_b	S_b	A_b
Predicted value	74.72	24.60	0.67	10.99
Measured value	75.12	24.71	0.66	11.06

Coke	M_{40}	M_{10}	S	A
Predicted value	79.06	8.29	0.61	13.91
Measured value	79.20	8.20	0.59	13.82

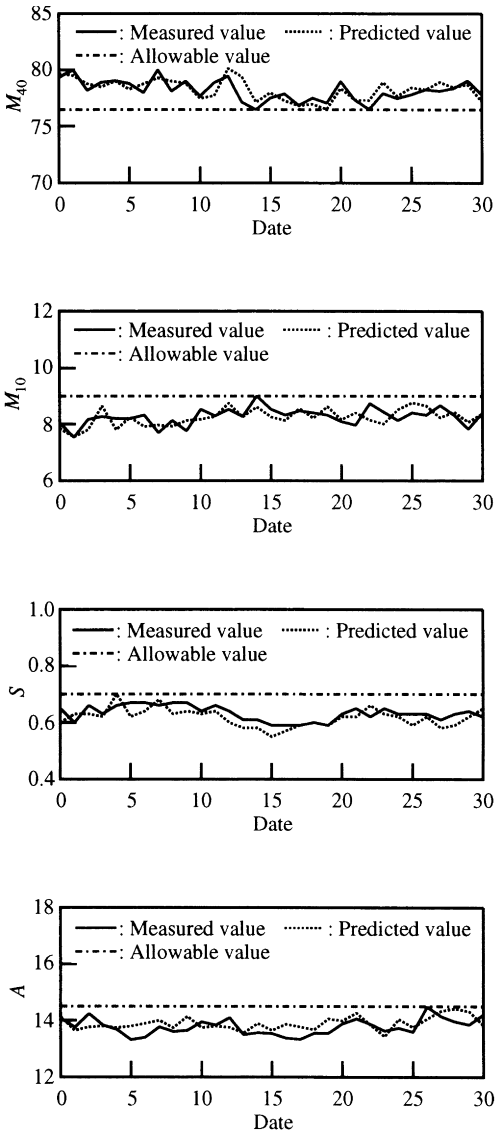

Fig. 7. Measured and predicted values of quality of coke during one month.

Fig. 7 shows the measured and predicted values of the quality of coke during one month. The quality index of coke and the empirical values in Eqs. (31) were used to compute the target percentages. The mean measured values of M_{40}, M_{10}, S and A are 78.18, 8.27, 0.63 and 13.78, and the mean

predicted values are 78.28, 8.24, 0.62 and 13.89, respectively. The results show that the measured values of coke quality satisfied the following general quality requirements:

$$M_{40} \geq 76.5, \qquad M_{10} \leq 9, \qquad S \leq 0.7, \qquad A \leq 14.5, \tag{32}$$

and the measured values approach the predicted values very closely. The run results show that the control requirements of the coal blending process are satisfied.

6. Conclusions

A model-based expert control strategy using backpropagation networks is proposed for the control of the coal blending process in an iron and steel plant. It involves the computation and tracking of the target percentage of each type of coal to be blended. The computation is implemented through two iterative algorithms that are based on a combination of backpropagation networks, mathematical models and rule models, and use forward chaining and model-based reasoning. The prediction of the coal blend and coke quality is carried out repetitively based on the backpropagation networks and mathematical models during the computation of the target percentages. The backpropagation networks, mathematical models and rule models that are used to express the relationships among the parameters of the process are constructed based on statistical data and empirical knowledge. The tracking of the target percentages is achieved by a distributed control technique employing a PI control algorithm. An expert control system designed using the proposed expert control strategy was applied to the control of the coal blending process. The run results show that the proposed strategy is an effective way to control the coal blending process.

Acknowledgements

The authors would like to thank Professor De-Yao Shen of Central South University of Technology for his helpful direction, and engineers Ke-Sheng Li, Sheng-Shu Chen, Bai-Ning He and Ke-Chun Zhou of Lianyuan Iron and Steel Corporation for their contributions to this project.

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