Multivariable Intelligent Decoupling Control System and its Application[1)]

Tian-You CHAI Heng YUE

(*National Engineering and Technology Research Center for Metallurgic Industry Automation, Northeastern University, Shenyang* 110004 *P.R.China*)

(E-mail: tychai@mail.neu.edu.cn)

Abstract Many industrial processes have compositive complexities including multivariable, strong coupling, nonlinearity, time-variant and operating condition variations. Combining multivariable adaptive decoupling control with neural networks, this paper presents a multivariable neural network-based decoupling control algorithm. This control algorithm is integrated with distributed control technique and intelligent control technique, and a three-leveled intelligent decoupling control system consisting of basic control level, coordinating control level, and management and decision level is developed. The configuration and function of the control system are discussed in detail. This system has been successfully applied in ball mill pulverizing systems of 200MW power units, and remarkable benefits have been obtained.

Key words Neural network decoupling control, intelligent decoupling control system, coal-pulverizing systems

1 Introduction

In many complex industrial processes, the coupling among control loops often invalidates conventional single-loop controllers. How to achieve decoupling control of such processes has become a topic of considerable importance in the field of control engineering. Decoupling control was initially developed for deterministic linear systems. Typical approaches include design of pre-compensator that transforms the controlled transfer function matrix into a diagonal matrix or diagonal dominance[1], design of state feedback to reach decoupling of state equation[2], decoupling in frequency domain through inverse Nyquist array[3], and decoupling method of Bristol-Shinskey[4].

These approaches separate the controlled multivariable system into several SISO subsystems through a suitable decoupler that depends on accurate process model before controller design. So they are difficult to reach adaptive decoupling control of complex industrial processes that are multivariable, strongly coupled, with unknown or slow time-variant parameters. In [5] and [6], multivariable adaptive decoupling controllers were presented which combined decoupling design with self-tuning control. Adaptive decoupling control algorithm based on zero and pole placement was developed in [7]. In the approaches of [8∼16], the coupling effects among control loops were viewed as measurable disturbances so that they can be eliminated through feedforward compensation, and decoupling is achieved. In [14, 15, 17], multivariable adaptive decoupling control techniques were reported being successfully applied in a metallurgic furnace, a binary distillation column, and a vertical loop of continuous bar mill.

Recently, control engineers and scientists have paid more attention to the problem of how to reach decoupling control of complex processes that are multivariable, strongly coupled, strong nonlinear, and time-variant. Direct and indirect decoupling control algorithms were developed through fuzzy approaches in [18∼20], while decoupling control algorithms based on neural networks were discussed in [21, 22]. Such algorithms are complicated, and difficult to realize in engineering practice. Distributed Control Systems (DCS) become more and more popular in industrial process control because of their strong reliability. In such cases, multivariable industrial processes are often partitioned into many SISO subsystems by control engineers so that standard control modules in DCS can be used. But inherent strong coupling effects usually result in bad performances of such controllers or even controllers unusable. It is vitally important to develop intelligent decoupling control systems that are applicable in DCS.

1) Supported by National Basic Research Program of P.R.China (2002CB312201) and National High-Tech Research and Development Program of P.R.China (2004AA412030)

Received April 2, 2004; in revised form September 15, 2004

This paper combines the decoupling algorithm in [10] with neural networks and develops a neural network-based multivariable decoupling control algorithm and a three-leveled intelligent decoupling control system. The latter has been successfully applied in ball mill pulverizing systems of 200MW power units, and remarkable benefits have been obtained.

2 Multivariable neural network-based decoupling control algorithm

The process to be controlled is assumed to be a general k-input-k-output nonlinear multivariable system described by

$$\boldsymbol{y}(t+1)=\boldsymbol{f}[\boldsymbol{y}(t-n+1),\cdots,\boldsymbol{y}(t),\boldsymbol{u}(t-m),\boldsymbol{u}(t)] \tag{1}$$

where $\boldsymbol{y}(t)=[y_1(t),\cdots,y_k(t)]^{\mathrm{T}}\in R^k$, $\boldsymbol{u}(t)=[u_1(t),\cdots,u_k(t)]^{\mathrm{T}}\in R^k$ are the process output and input vectors, respectively; n and m are the system's orders; $\boldsymbol{f}[\cdot]=[f^1[\cdot],\cdots,f^k[\cdot]]^{\mathrm{T}}$ is a nonlinear vector function which is continuously differentiable and Lipshitz.

Using the methods of [10, 22], the original plant can be transformed through Taylor's expansion at the equilibrium point into the following form of

$$A(z^{-1})\boldsymbol{y}(t+1)=B(z^{-1})\boldsymbol{u}(t)+\boldsymbol{v}(t) \tag{2}$$

where $A(\boldsymbol{z}^{-1})$ is a diagonal polynomial matrix, and $B(z^{-1})$ is a non-diagonal polynomial matrix, and $\boldsymbol{v}(t)$ represents the high order nonlinear term and unmodeled dynamics. Then $B(z^{-1})$ is separated into

$$B(z^{-1})=\bar{B}(z^{-1})+\bar{\bar{B}}(z^{-1})$$

where $\bar{B}(z^{-1})$ is a diagonal polynomial matrix, and $\bar{\bar{B}}(z^{-1})$ is a polynomial matrix with zeros on its diagonal. Thus (2) can be rewritten as

$$A(z^{-1})\boldsymbol{y}(t+1)=\bar{B}(z^{-1})\boldsymbol{u}(t)+\bar{\bar{B}}(z^{-1})\boldsymbol{u}(t)+\boldsymbol{v}(t) \tag{3}$$

Introduce the following performance index

$$J=\| P(z^{-1})\boldsymbol{y}(t+1)-R\boldsymbol{w}(t)+Q(z^{-1})\boldsymbol{u}(t)+S\boldsymbol{u}(t)+K\boldsymbol{v}(t)\|^2 \tag{4}$$

where $\boldsymbol{w}(t)\in R^k$ is the known reference signal vector, $P(z^{-1})$ and $Q(z^{-1})$ are $(k\times k)$ diagonal weighting polynomial matrices, R and K are $(k\times k)$ diagonal weighting matrices, and S is a $(k\times k)$ weighting matrix with zeros on its diagonal.

The auxiliary output vector $\phi(t+1)$ and the ideal output $\boldsymbol{y}^*(t+1)$ are defined as

$$\boldsymbol{\phi}(t+1)=P(z^{-1})\boldsymbol{y}(t+1) \tag{5}$$
$$\boldsymbol{y}^*(t+1)=R\boldsymbol{w}(t)-Q(z^{-1})\boldsymbol{u}(t)-S\boldsymbol{u}(t)-K\boldsymbol{v}(t) \tag{6}$$

Introduce the $(k\times k)$ diagonal polynomial matrices $F(z^{-1})$ and $G(z^{-1})$ satisfying

$$P(z^{-1})=F(z^{-1})A(z^{-1})+z^{-1}G(z^{-1}) \tag{7}$$

and the optimal control law minimizing (4) is given by

$$[F(z^{-1})B(z^{-1})+Q(z^{-1})+S]\boldsymbol{u}(t)=R\boldsymbol{w}(t)-G(z^{-1})\boldsymbol{y}(t)-[F(z^{-1})+K]\boldsymbol{v}(t) \tag{8}$$

The closed loop system becomes

$$\begin{aligned}&[P(z^{-1})\bar{B}(z^{-1})+Q(z^{-1})A(z^{-1})]\boldsymbol{y}(t+1)=\\&\bar{B}(z^{-1})R\boldsymbol{w}(t)+[Q(z^{-1})\bar{\bar{B}}(z^{-1})-\bar{B}(z^{-1})S]\boldsymbol{u}(t)+[Q(z^{-1})-\bar{B}(z^{-1})K]\boldsymbol{v}(t)\end{aligned} \tag{9}$$

where $P(z^{-1})$, $Q(z^{-1})$, R, S and K can be chosen satisfying

$$[P(1)\bar{B}(1)+Q(1)A(1)]=\bar{B}(1)R \tag{10}$$
$$Q(1)\bar{\bar{B}}(1)=\bar{B}(1)S \tag{11}$$
$$Q(1)=\bar{B}(1)K \tag{12}$$

$$|P(z^{-1})B(z^{-1}) + A(z^{-1})[Q(z^{-1}) + S]| \neq 0, \quad |z| > 1 \tag{13}$$

then steady tracking errors can be eliminated and static decoupling is achieved.

When the model of the process is unknown, we excite the process using small noise signals around the equilibrium point, and the input-output data are collected as the training set. So k BP neural networks with single hidden layer and linear output can be obtained to approximate the plant (1) in a neighborhood of the equilibrium point after thorough offline training. Not only can a neural network approximate arbitrary nonlinear analytic function, but also it can approximate the derivatives of that function, so we can obtain the estimated values of $A(z^{-1})$ and $B(z^{-1})$, denoted by $\hat{A}(z^{-1})$ and $\hat{B}(z^{-1})$.

Then we use another k neural networks to approximate $\boldsymbol{v}(t)$ on-line, which represents the high order nonlinear term and unmodeled dynamics,

$$\hat{v}_i(t) = NN_i[W_i, \boldsymbol{x}(t)] \quad \text{for} \quad i = 1, \dots, k \tag{14}$$

where W_i denotes the weighting matrix of neural network NN_i, $\boldsymbol{x}(t)$ is the input vector. The neural network-based decoupling control algorithm employing the optimal control law of (7) and (8) can be summarized as follows:

Step 1. Substitute $\hat{A}(z^{-1})$ and $\hat{B}(z^{-1})$ for $A(z^{-1})$ and $B(z^{-1})$, chose proper $P(z^{-1})$, $Q(z^{-1})$, R, S, and K so that (10)∼(13) are satisfied;

Step 2. Read input-output data to construct $\boldsymbol{x}(t)$;

Step 3. Estimate the term of $\hat{v}_i(t)$ using neural network NN_i;

Step 4. Calculate the control input $\boldsymbol{u}(t)$ using (8), and impose it on the process;

Step 5. Get the new output of the process, $\boldsymbol{y}(t+1)$;

Step 6. Obtain the tutorial signal about $\boldsymbol{v}(t)$ from calculation with $\boldsymbol{y}(t+1)$, and then train NN_i once, for $i = 1, \dots, k$;

Step 7. Let $t = t + 1$, and go to step 2.

When the process is slowly time-variant, we can identify $A(z^{-1})$ and $B(z^{-1})$, chose $P(z^{-1})$, $Q(z^{-1})$, R, S, and K online, estimate $\boldsymbol{v}(t)$, and calculate the control input through (7) and (8), so that adaptive decoupling control is achieved.

3 Multivariable intelligent decoupling control system

Modern industrial processes usually have compositive complexities including multivariable, strong coupling, strong nonlinearity, time-variant, with large time delay, and large variations of operating conditions. Academic control algorithms are often proposed for single complexity. Only integration of related control algorithms can effectively solve the automatic control problems of industrial processes with compositive complexities. Thus, studying on the architecture of decoupling control system becomes vitally important.

With DCS as its hardware platform, an intelligent decoupling control system consisting of basic control level/coordinating control level/management and decision level is developed. Its structure is shown in Fig. 1.

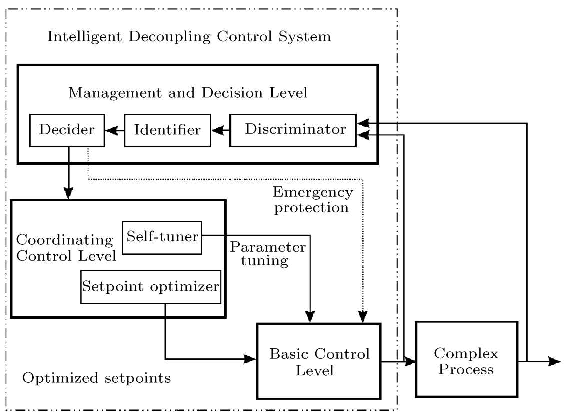

Fig. 1 Architecture of multivariable decoupling control system

3.1 Basic control level

The basic control level is at the lowest level in the control system architecture. It consists of loop controllers and an intelligent decoupling compensator and is responsible for decoupling and loop control. From (9) it can be known that decoupling control can be achieved through the compensation of coupling terms, high order nonlinear terms and unmodeled dynamics. Equivalently, one can realize decoupling control through adding the compensation signal on the relevant control input as shown in

Fig. 2. This is the base of implementation decoupling control with DCS configuration software. First, the multivariable process is partitioned into n SISO loops properly, and relevant loop controllers using DCS configuration software are designed. Then, above mentioned intelligent decoupling compensator using the neural network-based decoupling algorithm are designed.

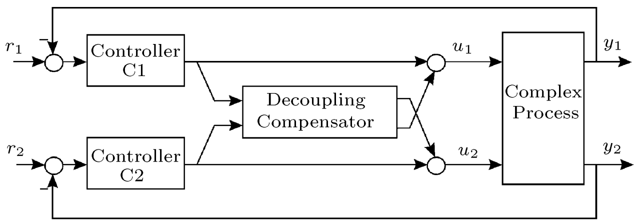

Fig. 2 The structure of the decoupling controller in the basic control level

3.2 The coordinating control level

The coordinating control level is at the middle level in the control system architecture. It consists of a setpoint optimizer and a self-tuner. It is responsible for adaptation to process uncertainty to realize optimizing control of the process. The setpoint optimizer in the coordinating control level gives optimal setpoints to the basic control level to reach optimization of integrated production index of the controlled process according to variations of operating conditions and boundary conditions. The optimization of setpoints of loop controllers has tight relationship with raw material consumption, energy consumption and production quality. For the process operation, the optimizing control of loop controllers' setpoints aiming at optimization of integrated production index is more significant than conventional optimal control aiming at controller performance. Besides, sometimes variations of operating condition might result in some control variables in saturation status, so the number of available control inputs becomes less than normal condition. By modifying these setpoints online in certain ranges, the relevant loop controllers may be coordinated so that the whole process can be stabilized using less control inputs. Thus the control system may have certain adaptability.

The other task of the coordinating control level is to modify the parameters of controllers or decouplers in the basic control level using the self-tuner after the uncertainty of time-variant parameters of the process is detected.

3.3 The management and decision level

The management and decision level is at the highest level in the control system architecture. It consists of such modules as discriminator, identifier and decider. It identifies the operating conditions through case-based reasoning, makes adequate decision about current control target according to current operating condition and tuning ability, and chooses proper control strategy.

The discriminator makes judgments about current situation of control system according to current process data , suck as process outputs, control inputs, setpoints, tracing errors and their variance ratio, etc.

The identifier is used to identify the operating conditions directly through case-based reasoning. Using the information from the discriminator, this identifier can judge what status the process is in.

The decider makes the final decision about control strategy according to the conclusions about the operating conditions drawn by the identifier. Three decision criteria with different priorities from highest to lowest are safety, quality and efficiency. As soon as higher criterion is activated, *i.e.* the current operating condition cannot satisfy the higher criterion, all lower criteria will not be under consideration temporarily. After adequate control actions have been imposed on the process and the results satisfy the higher criterion, the decider begins to consider the lower adjacent criterion.

Safety criterion is the most important criterion to guarantee the security of the controlled process. The management and decision level examines at any moment precursors about actuator failures, invalidation of control strategy and abnormal operating conditions. When such precursors appear, a series of actions must be taken as follows: the current control algorithm must be suppended, the emergency handling module is activated to protect the process and the operating support system is activated so that human operators can be indicated properly. Quality criterion is designed to guarantee quality of product and stability of process. It requires that all the outputs of the process must be kept in certain ranges respectively which are specified by technical specifications. When the above two criteria are both satisfied, the efficiency criterion is then activated to reach optimization of integrated production index, the setpoints of basic loop controller are optimized through the coordinating control level.

4 Application of intelligent decoupling control system in ball mill pulverizing systems

4.1 Process description and its model

Ball mill pulverizing systems are important heat-power equipment in fossil-fired power plants. They are used to pulverize coal to fine powder and dry them so that coal powder can be sent into boiler for burning. The flow chart of this system is shown in Fig. 3. The three inputs of this plant are the feeder speed, the hot air damper and the warm air damper. The three outputs of the plant are the outlet temperature of the mill, the inlet pressure of the mill, and differential pressure between the inlet and outlet of the mill, which representing the mill load. Such a system is a strongly coupled, multivariable, nonlinear process with large time delay and lots of uncertain disturbances; the conventional SISO automatic control system without decoupling design cannot work. Under manual operation, to prevent accidents such as mill-blockage, over-temperature, and emission of coal powder, these systems are usually operated in uneconomical status far from optimal pulverizing efficiency so that much useful power has been wasted. How to achieve the automatic control of ball mill pulverizing systems is always a desiderated problem to be solved in fossil-fired power plants.

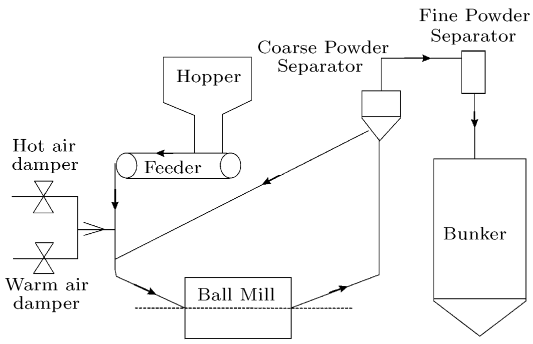

Fig. 3 The flow chart of a ball mill pulverizing system in power plants

We have established a dynamic model of a ball mill pulverizing system of a 200MW power unit in a power plant[23,24], consisting of the following equations:
the equation of conversation of energy in the ball mill

$$\frac{\mathrm{d}[(C_{gq}w_{gq}+C_m w_m)t_m]}{\mathrm{d}t} = C_{gz}G_{gz}t_{gz} + C_{lk}g_{zf}t_{lk} - \\ C_{tf}(G_{gz}+g_{zf})t_m + \frac{B_{gm}C_{gm}t_c}{3.6} - \frac{B_m C_m t_m}{3.6} + Q_0 - Q_c \tag{15}$$

the equation of conversation of mass in the ball mill

$$\frac{\mathrm{d}w_m}{\mathrm{d}t} = \frac{B_{gm}-B_m}{3.6} \tag{16}$$

the equation of inlet pressure

$$\frac{\mathrm{d}P_{in}}{\mathrm{d}t} = \frac{RT}{V_1}(G_r - \sqrt{\frac{P_{in}-\triangle P+P_o}{R1}} + G_{lf} + B_{gm}\triangle W) \tag{17}$$

the equation of differential pressure

$$\frac{\mathrm{d}\triangle P}{\mathrm{d}t} = 3(1+0.8\mu)\frac{\omega_{thr}^2}{2}(G_i - G_o)/V \tag{18}$$

where C_{gq}, C_m, C_{gz}, C_{lk}, C_{tf}, and C_{gm} are the specific heats of steel balls, coal powder, drier air, cold air, ventilation and raw coal; t_{gz}, t_{lk}, t_m, and t_c are the temperatures of drier air, cold air, mill outlet and raw coal; G_{gx}, g_{zf}, G_i and G_o are mass flow rates of drier air, air leak, air coming into the mill at the mill inlet and air leaving from the mill at the mill outlet; w_{gq} is the ball mass inside the mill; w_m is the mill load; B_m is powder yield of the mill; B_{gm} is the coal feeding rate; Q_0 is the quantity of heat generated from friction and knocking, and Q_c is the quantity of heat consumed by evaporation of water in raw coal; $\triangle W$ is quantity of water evaporation during milling; P_{in} is the inlet pressure of the mill; $\triangle P$ is the differential pressure between the inlet and outlet of the mill; P_o is the sum of outlet pressure of mill exhauster and zero position pressure; $R1$ is the sum of resistances of coarse powder separator, fine powder separator and powder elevation; V_1 is the tube volume; R is the ideal gas constant; T is the thermodynamic temperature of the inlet tube; V is the gas volume inside the mill; μ is the concentration of the coal powder inside the mill; ω_{thr} is the air speed at the mill throat.

Apparently a ball mill pulverizing system is strongly coupled, multivariable, nonlinear, and time-variant. The control requirement of such a system is to keep the outlet temperature, the inlet pressure and the differential pressure in certain ranges. If the outlet temperature is too high, there will be a risk that the coal powder in the mill might be ignited. If it is too low, the drying is not sufficient and the coal powder might cake in the bunker. The inlet pressure is related to the mill air draft and must be controlled lower than the atmospheric pressure. Otherwise, some coal powder will be released outside the mill causing environmental pollution and bodily injury. To enhance the powder production ability, the differential pressure should be kept in a high level but exorbitant differential pressure might result in mill blockage, while low differential pressure will result in low grinding efficiency.

4.2 Control system design

This proposed multivariable intelligent decoupling control system has been designed for ball mill pulverizing systems of 200 MW units in a power plant. The control configuration is shown in Fig. 4. It is realized on the I/A Series DCS of Foxboro. This multivariable intelligent decoupling control system has successfully solved the problem that ball mill pulverizing systems cannot be under automatic control. This makes the mill operation safe and reliable.

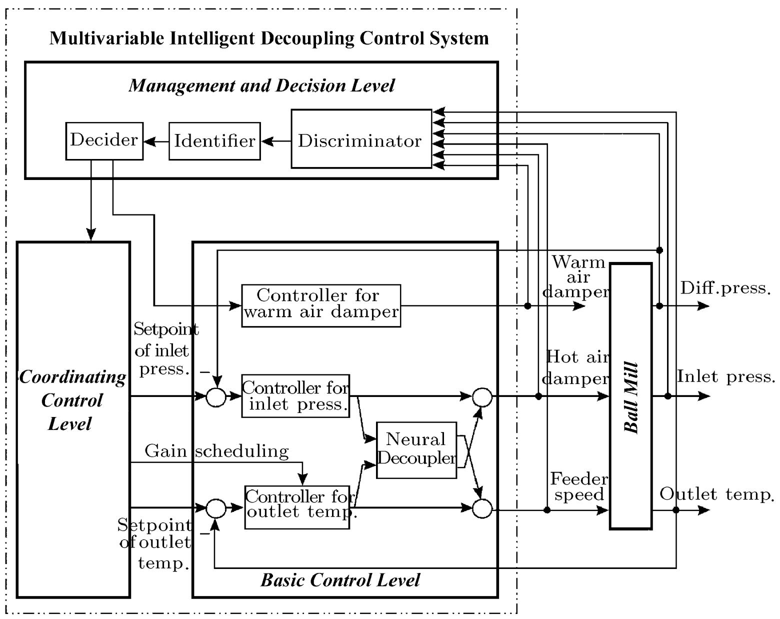

Fig. 4 The configuration of the intelligent decoupling control system for ball mill pulverizing systems

The control system is composed of the basic control level, the coordinating control level and the management and decision level. The basic control level consists of neural decoupling compensators, inlet pressure controller, outlet temperature controller and warm air damper controller.

Based on the intelligent decoupling control technique, we have designed the inlet pressure controller, outlet temperature controller and the neural decoupling compensators that are employed to reach decoupling control of the inlet pressure loop and the outlet temperature loop. From the mill operating experiences, it is known that the warm air damper can only be used to regulate the working point instead of for direct loop regulation, so the warm air damper is governed directly by the management and decision level. Once surplus of drying ability is detected, the warm air damper will be opened larger than before. If shortage is detected, then the warm air damper will be closed to certain degree, even to be closed completely. In this case, the process degenerates to a system with two inputs, *i.e.* the hot air damper and the feeder speed, and three outputs, *i.e.* the inlet pressure, the outlet temperature and the differential pressure. The number of inputs is less than outputs, so it is impossible to keep three outputs to three certain constants when large variations of operating condition and disturbances exist. For the ball mill pulverizing systems, small variances of three outputs within certain ranges are allowable. The coordinating control level dynamically modifies the setpoints of the inlet pressure controller and the outlet temperature controller using production rules based on the instruction from the decider in the management and decision level, so that the steady relationships among the inlet pressure, the outlet temperature and the differential pressure are coordinated. It also identifies the channel gain from the feeder speed to the outlet temperature and tuning parameters of the outlet temperature controller to improve the dynamic loop performance.

The management and decision level identifies the variances of grinding ability and drying ability caused by changes of grindability and moisture content of raw coal and makes the final decision of what kind of control strategy should be used to deal with the encountered condition and gives corresponding instructions to the coordinating control level and the basic control level. For instance, when process has surplus drying ability and the coordinating control level has no further coordinating ability, then the structure of loop control is changed by the management and decision level and the warm air damper controller is put into service.

4.3 Industrial application

To compare the difference between the intelligent decoupling control strategy and conventional PID controllers, the experiment of warm air damper disturbance is made. When the feeder speed and hot air damper are under automatic status and the process is in steady state, open the warm air damper larger by 10% (shift it under manual control temperately) to introduce warm air disturbance. The experiment results of the procedures of outlet temperature and inlet pressure returning to their own original setpoints are recorded, as shown in Fig. 5 and Fig. 6. The measurement ranges of the four variables in Fig. 5 and Fig. 6 are: outlet temperature, 60°C∼ 80°C, 2°C/grid; inlet pressure, −1.0kPa∼0.0kPa, 0.1kPa/grid; feeder speed and hot air damper, 0 ∼ 100%, 10%/grid. The time unit is 3 minutes/grid.

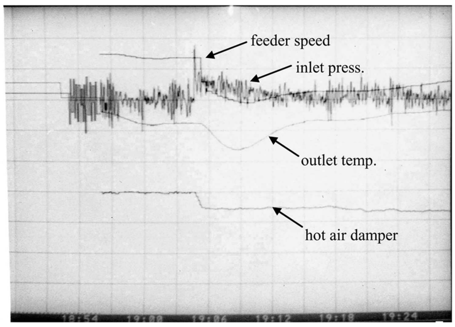

Fig. 5 Experiment result of intelligent decoupling control

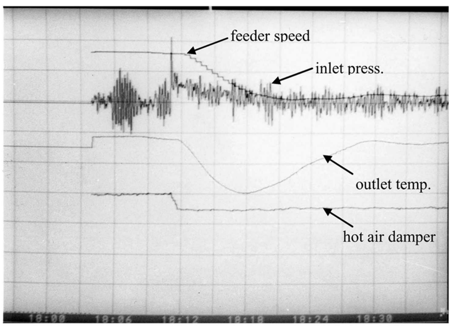

Fig. 6 Experiment result of conventional PID control

It can be seen from the experiment results that the fluctuation of outlet temperature does not exceed 2°C and the transient process is about 6 minutes when intelligent decoupling control is employed; while the fluctuation of outlet temperature is about 4°C and the transient process is more than 15 minutes when conventional PID control is employed. Apparently, the performance of the control system has been remarkably improved through decoupling design.

Fig. 7 and Fig. 8 show the regulation when the system works in normal situation and with surplus drying ability respectively. The measurement ranges of related variables in Fig. 7 and Fig. 8 are: outlet temperature, 50°C∼ 100°C, 5°C/grid; inlet pressure, −1.0kPa∼0.0kPa, 0.1kPa/grid; differential pressure, 0.0kPa∼5.0kPa, 0.5kPa/grid; input variables, 0∼100%, 10%/grid. The time unit is 5 minutes/grid. The abbreviation "sp." denotes setpoint. From Fig. 7 it can be seen that the difference between the outlet temperature and its setpoint is kept within less than 2.0°C. The inlet pressure and differential pressure are also kept near their setpoints. The warm air damper is completely kept closed, and process is rather smooth.

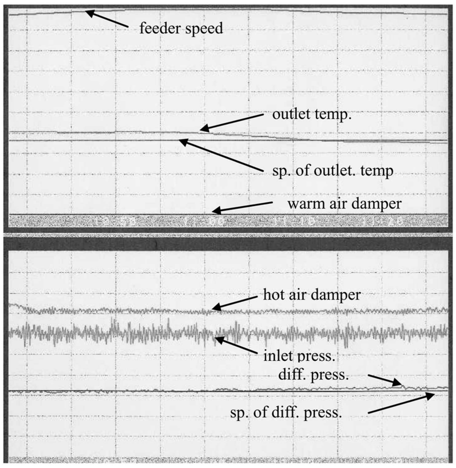

Fig. 7 Mill was controlled in normal situation

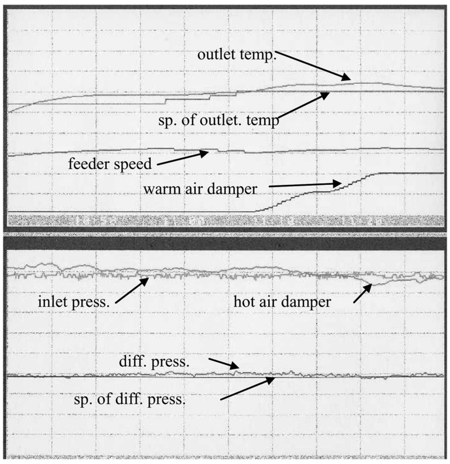

Fig. 8 Regulation strategy when the drying ability became surplus

Fig. 8 shows the control strategy when the drying ability becomes surplus. The outlet temperature and the differential pressure keep increasing. The management and decision level triggers the setpoint optimizer in the coordinating control level so that the setpoint of outlet temperature is enhanced. When the coordinating control level had no more coordinating adaptability, then the decider in the management and decision level gives instructions to open the warm air damper from zero to 20%, which results in the stoppage of outlet temperature increasing and the differential pressure returning to the normal range again. After this regulation, the process keeps stable.

The developed control system has been under strict on site testing, including steady state testing, variant operating condition testing, and emergency testing. The testing results show that this control system has strong adaptability for large variation of operating conditions. It can keep the process stable even when the character of raw coal and device changes. The control system can automatically deal with emergency conditions such as coal-break, mill-blockage and over temperature, the operating support system based on expert experience can give necessary operating instruction to avoid possible false operation of human operator. The control system keeps the coal-pulverizing systems safe, stable, reliable, and efficient. The electric power consumption for unit coal has been reduced 10.3%. Accidents like coal powder emission and mill blockage are avoided and environmental pollution has been eliminated. The economic benefits of more than 10 million RMB per year has been produced.

5 Conclusion

Combining intelligent control techniques with multivariable adaptive decoupling control algorithms, this paper proposes the multivariable neural network-based decoupling control algorithm and develops intelligent decoupling control system consisting of basic control level, coordinating control level and management and decision level, which can be implemented in DCS. The successful application of the control system in 200MW power units shows that the developed multivariable intelligent decoupling controller can effectively deal with the control problem of industrial process that has compositive complexity like multivariable, strong coupling, strong nonlinearity, with time-variant parameters and large variations of operating conditions. Its excellent control performance and possible future application prospect are also revealed.

References

1 Kavangh R J. Noninteracting Controls in Linear Multivariable Systems, *Transactions of the American Institute of Electronic Engineers, Part II, Applications and Industry*. 1957, **76**(5): 95∼99

2 Falb P L, Wolovich W A. Decoupling in the design and synthesis of multivariable control systems, *IEEE Transactions on Automatic Control*. 1967, **12**(6): 651∼659

3 Rosenbrock H H. Design of multivariable control systems using inverse Nyquist array, *IEE Proceedings: Control Theory and Applications*, 1969, **116**(1): 1929∼1936

4 Shinskey F G. Process Control Systems, Second Edition, McGraw-Hill Book Company, 1979

5 McDermott P E. Mellichamp D A. A decoupling pole-placement self-tuning controller for a class of multivariable process, *Optimal Control Applications and Methods*, 1986, **7**(1): 55∼79

6 Lang S J, Gu X Y, Chai T Y. A multivariable generalized self-tuning controller with decoupling design, *IEEE Transactions on Automatic Control*. 1986, **31**(5): 474∼477

7 Wittenmark B, Middleton R, Goodwin G. Adaptive Decoupling of Multivariable Systems. *International Journal of Control*, 1987, **46**(6): 1993∼2009

8 Chai T Y, Lang S J, Gu X Y. A multivariable self-tuning feedforward controller and its application, *Acta Automatica Sinica*, 1986, **12**(3): 229∼236

9 Chai T Y. Multivariable generalized self-tuning decoupling controller and application, In: Proceedings of the American Control Conference, 1986, 739∼744

10 Chai T Y. Direct adaptive decoupling control for general stochastic mulitvariable systems, *International Journal of Control*, 1990, **51**(4): 885∼909

11 Chai T Y. A multivariable implicit pole assignment self-tuning controller and its application, *Acta Automatica Sinica*, 1989, **15**(4): 332∼338

12 Chai T Y. A multivariable indirect adaptive decoupling control algorithm, *Acta Automatica Sinica*, 1991, **17**(2): 182∼190

13 Chai T Y. The global convergence analysis of a multivariable decoupling self-tuning controller, *Acta Automatica Sinica*, 1989, **15**(5): 432∼436

14 Chai T Y. A self-tuning decoupling controller for a class of multivariable systems and global convergence analysis, *IEEE Transactions on Automatic Control*, 1988, **33**(8): 767∼771

15 Chai T Y, Wang G. Globally convergent multivariable adaptive decoupling controller and its application to a binary distillation column, *International Journal of Control*, 1992, **55**(2): 415∼429

16 Zhu K Y, Qin X F, Chai T Y. A new decoupling design of self-tuning multivariable generalized predictive control, *International Journal of Adaptive Control*, 1999, **13**(3): 183∼196

17 Chai T Y, Zhang Z S. Multivariable adaptive decoupling controller for vertical loop of continuous bar mill, *Acta Automatica Sinica*, 2001, **27**(6): 744∼751

18 Xu C W, Lu Y Z. Decoupling in fuzzy systems: a cascade compensation approach, *Fuzzy Sets and Systems*, 1989, **29**(2): 177∼185

19 Gupta M M. Multivariable structure of fuzzy control systems, *IEEE Transactions on Systems, Man and Cybernetics*, 1986, **16**(5): 638∼656

20 Wang D H, Chai T Y, Zhang H G. A new composition algorithm for fuzzy inference, *Control and Decision*, 1994, **9**(1): 59∼63

21 Wu L M, Chai T Y. A neural network decoupling strategy for a class of nonlinear discrete time systems, *Acta Automatica Sinica*, 1997, **23**(2): 207∼212

22 Yue H, Chai T Y. Adaptive decoupling control of a class of multivariable nonlinear systems using neural networks, *Information and Control*, 1999, **28**(7): 607∼612

23 Chai T Y, Yue H, Bai Y. Intelligent control of coal-pulverizing systems with ball-tube mill, In: Preprints of 14th IFAC World Congress, Beijing, China, Vol. O, 1999, 97∼102

24 Tao W H, Chai T Y, Yue H. Research of dynamic mathematical model and simulation of ball coal mill system, *Journal of System Simulation*, 2004, **16**(4):778∼780

Tian-You CHAI Received his Ph.D. degree from Northeastern University in 1985. Now he is a professor in Northeastern University. He is also a member of Chinese Academy of Engineering, the director of National Engineering and Technology Research Center for Metallurgic Industry Automation of Northeastern University. His research interests include adaptive control, intelligent control and integrated automation of industrial processes.

Heng YUE Received his Ph.D. degree from Northeastern University in 1999. Now he is an associate professor in Northeastern University. His research interests include multivariable decoupling control, modeling and optimizing control of complex industrial processes.