PERGAMON

Control Engineering Practice 7 (1999) 469–481

A neuro-fuzzy controller for a stoker-fired boiler, based on behavior modeling

Wei Li*, Xiaoguang Chang

Department of Computer Science and Technology Tsinghua University, Beijing 100084, Peoples Republic of China

Received 29 August 1997; accepted 22 October 1998

Abstract

A key issue in an industrial stoker-fired boiler is the design of an efficient and robust controller for its combustion system, so that the boiler can provide a continuous supply of steam at the desired pressure conditions. However, it is difficult to achieve this objective by using a model-based approach because of the high nonlinearity and uncertainty of boiler systems. In addition, the control performance may also suffer as a result of strong load changes, large disturbances, large time lags, and so forth. This paper presents a behavior-modeling-based approach to the design of a neuro-fuzzy controller for the combustion control of a stoker-fired boiler. In this approach, boiler combustion processes with unknown structure are modeled by defining three dynamic behaviors. According to these behavior 'templates', their corresponding fuzzy-logic controllers can be optimized off-line. During boiler system operation, the appropriate fuzzy-logic controller is fired, based on an on-line assessment of its dynamic behavior. The application results obtained demonstrate the effectiveness and the robustness of the proposed controller. © *1999 Elsevier Science Ltd. All rights reserved.*

Keywords: Boiler control; Behavior modeling; Industrial control; Fuzzy-logic control

1. Introduction

Boilers, be they in power stations, breweries, schools, or dwellings, are accepted equipment of everyday life. One of the objectives of a boiler is to provide a continuous supply of steam at the desired pressure condition by means of combustion control, as shown in Fig. 1. The design of controllers for such units has until now been based almost entirely on the skill and intuition of experienced utility boiler-control application engineers. The use of what are known as 'model-based control' methods to solve the complex and interactive control problems of boiler systems has not been seen to any significant extent, because of the high nonlinearity and uncertainty of boiler systems (Dukelow, 1991; Gunn et al., 1989).

In China, industrial stoker-fired boilers are very widely used in many enterprises, under very poor conditions, and the fuel involved is solid fuel, mostly coal. Furthermore, most of these boilers are controlled by tedious manual operation. Only few of them are controlled by PID-type controllers. However, such a control strategy cannot ensure a good control performance.

Over the last twenty years, many researchers have reported that fuzzy-logic controllers are very suitable for controlling objects with nonlinearity and even with unknown structure. However, one of the design methods widely used for fuzzy controllers is the definition of membership functions for linguistic variables, and then the formulation of fuzzy rules by control engineers (Braae and Rutherford, 1979; Tzafestas and Papanikolopoulos, 1990; Li, 1993). Unfortunately, such a fuzzy-logic controller cannot provide the desired control performance for a boiler combustion system, due to its uncertainties and large disturbances. Besides, it is very time-consuming to find the necessary fuzzy rules and membership functions by adjusting a real boiler system on-line, because stoker-fired boilers that use solid fuel have large time lags. Another approach is to adapt a rule base or/and membership functions by means of self-organizing algorithms or a neural network, based on previous responses, until the desired control performance is achieved (Procyk and Mamdani, 1979; Scharf and Mandic, 1985; Berenji

* Corresponding author. Tel.: + 86 10 6278 4895; Fax: + 86 10 62771138; e-mail: liwei@mail:tsinghua.edu.ca.

PII: S0967-0661(98)00204-4

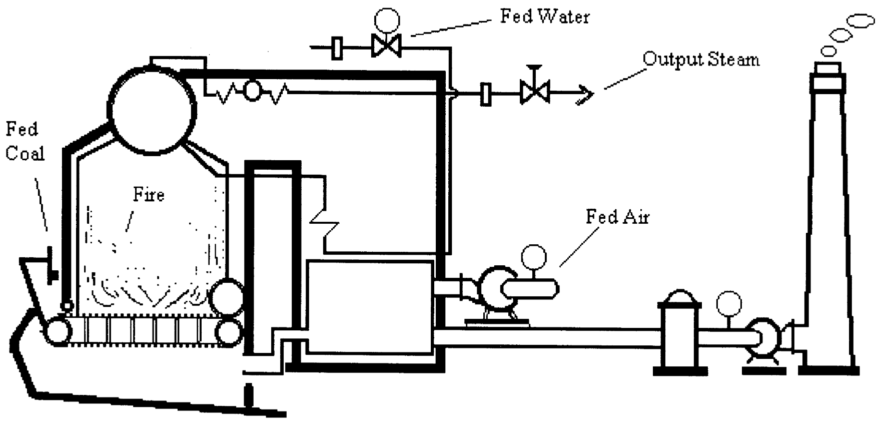


Fig. 1. An industrial stoker-fired boiler.

and Khedkar, 1992; Jang, 1992, Li, 1994). However, such adaptive strategies have not been used for the combustion control of stoker-fired boilers in practice, due to their convergence problems, which may send a boiler system out of control.

This paper describes a behavior modeling approach, proposed by Li (1997), to design a fuzzy-logic controller for the boiler combustion system (Li et al., 1997). It is known that the control signals obtained from a fuzzy-logic controller are determined by the response behavior of the controlled object, rather than by analytical models. That means that, for two plants with similar dynamic behavior, a fuzzy-logic controller can yield a similar control response, although these two plants have different mathematical equations. This idea leads to a way of describing a boiler combustion process with unknown structure by defining three types of dynamic behavior: 'smooth operation', 'violent change', and 'start'. On the basis of behavior modeling, a neuro-fuzzy controller for the boiler combustion system can be designed in two stages: First, the dynamic behaviors are modeled according to recorded historical data, and then these are used as 'templates' to optimize their fuzzy-logic controllers off-line. Second, during boiler operation, when a particular dynamic behavior is observed, its corresponding fuzzy-logic controller is fired by a neural network. This control system has been applied to several industrial stoker-fired boilers in different enterprises. Practical operating results show its many advantages, such as smooth steam pressure control in the face of strong steam-flow changes, automatic recovery of the control process after an accidental electric power shutdown, and so forth.

2. Behavior modeling of a boiler combustion system

The principle of designing a fuzzy-logic controller is to integrate empirical knowledge and operator experience into controllers by using fuzzy sets and fuzzy rules. In order to obtain such knowledge, the responses of the controlled object must be observed, and the necessary decisions and control strategy are expressed using fuzzy logic. Since this design strategy depends only on response behavior, a fuzzy-logic controller can yield similar control results for a set of plants with similar dynamic behavior, regardless of their mathematical models. According to this idea, if a cluster of systems have similar dynamic behavior, all these systems can be modelled by choosing one system with simple dynamics. Moreover, based on this system, a fuzzy-logic controller can be designed for this cluster of systems.

The next well-known characteristic of a fuzzy-logic controller is its robustness to parameter changes. In terms of this characteristic, one can define a few types of dynamic behavior to describe many response phenomena (Li, 1997). In the combustion-control system of a stoker-fired boiler, the regulated multiple variables are coal flow and air flow, and the control objective is to provide a desired steam pressure. Building on previous experience, the following three dynamic behaviors are chosen, as shown in Fig. 2. Fig. 2a shows the 'smooth operation' defined as 'dynamic behavior I'. This occurs very often during night-time operation. In this case, the requirement for steam flow is small and rather smooth, since many of the powered machines have been shut down; hence PID control is usually in operation. Fig. 2b shows a 'violent change' process, defined as 'Dynamic Behavior II'. Since in this case many power systems come into operation, the requirement for the steam flow varies widely. Consequently, PID control is often replaced here by manual control. Fig. 2c shows the 'start' process, defined as 'Dynamic Behavior III'. In this case, manual control must be in effect. These dynamic behaviors are described by using coefficients a_1, a_2, b_1, b_2, c_1 and c_2 in the following linear equation:

$$y(k) + a_1 y(k-1) + a_2 y(k-2) = b_1 u(k-1) + b_2 u(k-2) + c_1 v(k-1) + c_2 v(k-2), \quad (1)$$

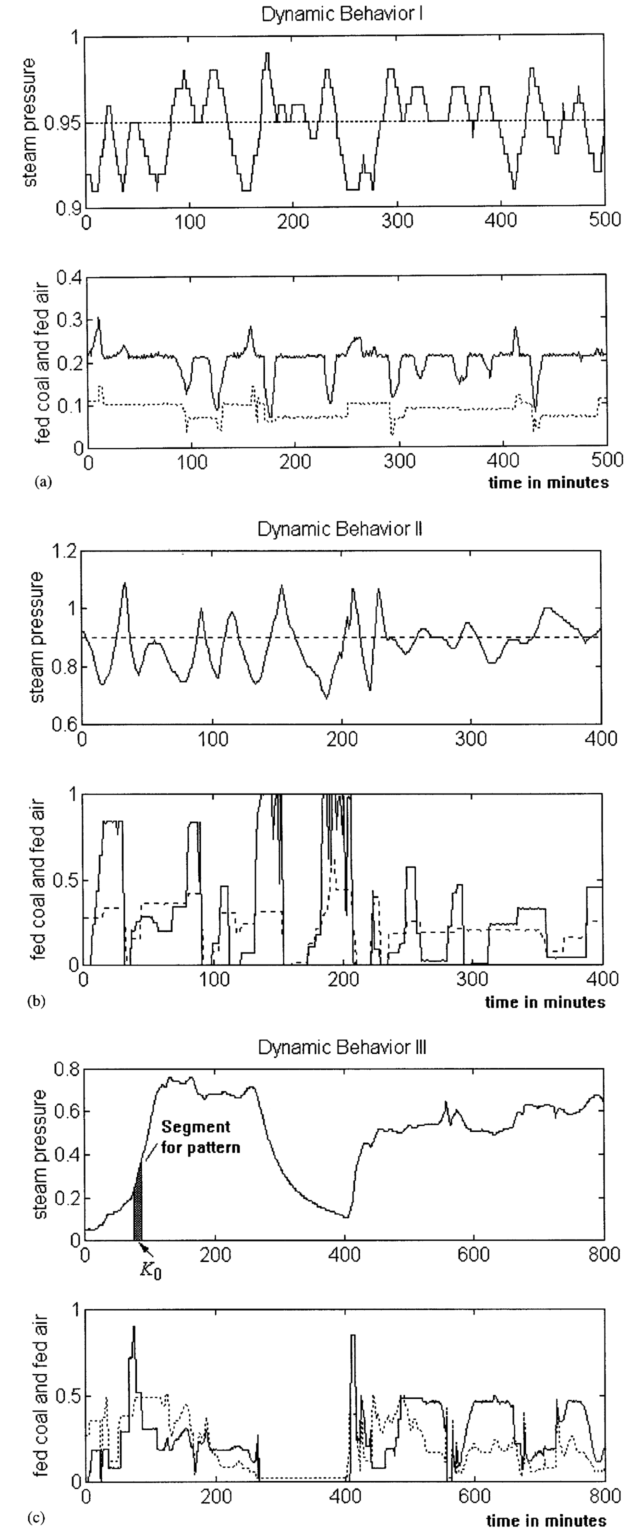


Fig. 2. Defined dynamic behaviors. (a) Smooth operation; (b) Violent change; (c) Start.

where $y(k)$ is the steam pressure, $u(k)$ is the coal flow, and $v(k)$ is the air flow. When a nonlinear plant is modeled using the coefficients a_1, a_2, b_1, b_2, c_1 and c_2, there exists an error between the linear system and the nonlinear plant, which can be expressed by

$$y(k) + a_1 y(k-1) + a_2 y(k-2) = b_1 u(k-1) + b_2 u(k-2) + c_1 v(k-1) + c_2 v(k-2) + e(k), \tag{2}$$

where $e(k)$ depends on the coefficients a_1, a_2, b_1, b_2, c_1 and c_2, and its evaluating criteria are expressed by

$$J = \sum_{k=n+1}^{N} e^2(k), \tag{3}$$

In order to do this, the vectors $\mathbf{w}$, $\mathbf{y}$, $\mathbf{e}$, $\boldsymbol{\theta}$ and a matrix $\mathbf{x}$ are defined as:

$$\mathbf{w}^T = [u(n+1), \ldots, u(N), v(n+1), \ldots, v(N)]^T, \tag{4}$$

$$\mathbf{y}^T = [y(n+1), y(n+2), \ldots, y(N)]^T, \tag{5}$$

$$\mathbf{e}^T = [e(n+1), e(n+2) \ldots e(N)]^T, \tag{6}$$

$$\boldsymbol{\theta}^T = [a_1, \ldots, a_n, b_0, \ldots, b_n, c_0, \ldots, c_n]^T, \tag{7}$$

$$\mathbf{x} = [\mathbf{y}(k-1)^T, \mathbf{y}(k-2)^T, \mathbf{w}(k-1)^T, \mathbf{w}(k-2)^T]. \tag{8}$$

In behavior modeling, it is necessary to compute the coefficient vector, $\boldsymbol{\theta}$, such that Eq. (3) can be minimized. For convenience, Eq. (2) is represented by a vector form

$$\mathbf{y} = \mathbf{x}\boldsymbol{\theta} + \mathbf{e}, \tag{9}$$

$$J = \mathbf{e}^T\mathbf{e} = (\mathbf{y} - \mathbf{x}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{x}\boldsymbol{\theta}) = \mathbf{y}^T\mathbf{y} - \boldsymbol{\theta}^T\mathbf{x}^T\mathbf{y} - \mathbf{y}^T\mathbf{x}\boldsymbol{\theta} + \boldsymbol{\theta}^T\mathbf{x}^T\mathbf{x}\boldsymbol{\theta}, \tag{10}$$

$$\frac{\partial J}{\partial \boldsymbol{\theta}} = -2\mathbf{x}^T\mathbf{y} + 2\mathbf{x}^T\mathbf{x}\boldsymbol{\theta}. \tag{11}$$

Letting $\partial J/\partial \boldsymbol{\theta} = 0$,

$$\mathbf{x}^T\mathbf{x}\boldsymbol{\theta} = \mathbf{x}^T\mathbf{y}. \tag{12}$$

If matrix $\mathbf{A} = \mathbf{x}^T\mathbf{x}$ is defined, then there exists an orthogonal matrix $\mathbf{U}$ and an elementary matrix $\mathbf{V}$, $\exists\mathbf{U}, \mathbf{V}, \partial$: $\mathbf{UAV} = \mathrm{Diag}(\mathbf{D})$, and

$$\mathrm{D} = \begin{bmatrix} d_1 & 0 & \cdots & 0 \\ 0 & d_2 & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_{(N-n)} \end{bmatrix}. \tag{13}$$

Then, Eq. (12) can be transformed as

$$\mathbf{U}^T\mathbf{D}\mathbf{V}^{-1}\hat{\boldsymbol{\theta}} = \mathbf{x}^T\mathbf{y}, \tag{14}$$

$$\mathbf{D}\mathbf{V}^{-1}\hat{\boldsymbol{\theta}} = \mathbf{U}\mathbf{x}^T\mathbf{y}. \tag{15}$$

Let $\boldsymbol{\beta} = \mathbf{U}\mathbf{x}^T\mathbf{y}$, $\boldsymbol{\gamma} = \mathbf{V}^{-1}\hat{\boldsymbol{\theta}}$, and $\boldsymbol{\gamma}^T = [h_1 \cdots h_{(N-n)}]$, then $\mathbf{D}\boldsymbol{\gamma} = \boldsymbol{\beta}$. Then

$$h_i = \begin{cases} k_i/d_i & \text{if } d_i \neq 0 \\ 0 & \text{otherwise,} \end{cases} \tag{16}$$

$$\hat{\boldsymbol{\theta}} = \mathbf{V}\boldsymbol{\gamma}. \tag{17}$$

For each segment of the dynamic response of length K_0, the coefficients a_1, a_2, b_1, b_2, c_1 and c_2 can be obtained.

In order to model these dynamic behaviors more precisely, the data recorded over 5 h (Fig. 2) is used to generate the coefficients a_1, a_2, b_1, b_2, c_1 and c_2, by using a least-squares algorithm. Fig. 3 shows the open-loop transient responses of the three dynamic behaviors. It can be seen that their dynamic responses are quite different from each other. Experience has shown that it is very difficult to achieve a good control performance for these three models by using the same fuzzy-logic controller, since the boiler combustion system is not only highly nonlinear and but also uncertain.

3. Optimization of the fuzzy logic controller using a genetic algorithm

Fig. 4 shows a neuro-fuzzy control scheme based on behavior modeling, which consists of four parts:

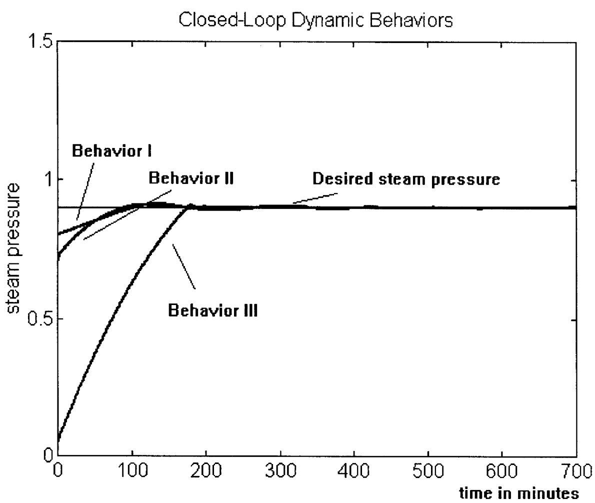


Fig. 3. Open-loop time responses.

(1) A fuzzy-P controller and a conventional integral and derivative (ID) controller. (2) An algorithm for off-line optimization of the fuzzy-logic controller. (3) A unit for behavior modeling, which consists of a set of simplified models. (4) A unit for behavior perception, which consists of the identification algorithm discussed above and a standard back-propagation neural network.

By combining the fuzzy-P and ID controllers, the static and transient behaviors of a system can be improved. The control signals $u(k)$ and $v(k)$ for a boiler are computed as follows:

$$u(k) = K_p^{coal} u_f(k) + K_i^{coal} \Delta T \sum_{j=1}^{k} e(j) + \frac{K_d^{coal}}{\Delta T}(e(k) - e(k-1)), \tag{18}$$

$$v(k) = K_p^{air} v_f(k) + K_i^{air} \Delta T \sum_{j=1}^{k} e(j) + \frac{K_d^{air}}{\Delta T}(e(k) - e(k-1)), \tag{19}$$

where ΔT is a sampling time, and $u_f(k)$ and $v_f(k)$ are the outputs of the fuzzy controllers. In Eqs. (18)–(19), only the proportional term is replaced by the fuzzy-logic controller instead of both the proportional and integral terms as in (Li, 1997), because it might be easy to tune the controller's parameters. One can understand that a fuzzy rule base represents human knowledge qualitatively, whereas membership functions change qualitative human knowledge into quantitative computations. For some problems, a fuzzy rule base can be easily obtained by using human knowledge. In such a case, a key problem is how to determine the membership functions that will realize human knowledge efficiently. For the control problem discussed in this paper, the fuzzy rule bases could be fixed, as shown in Fig. 5, since the human knowledge about the problem is clear. For each type of

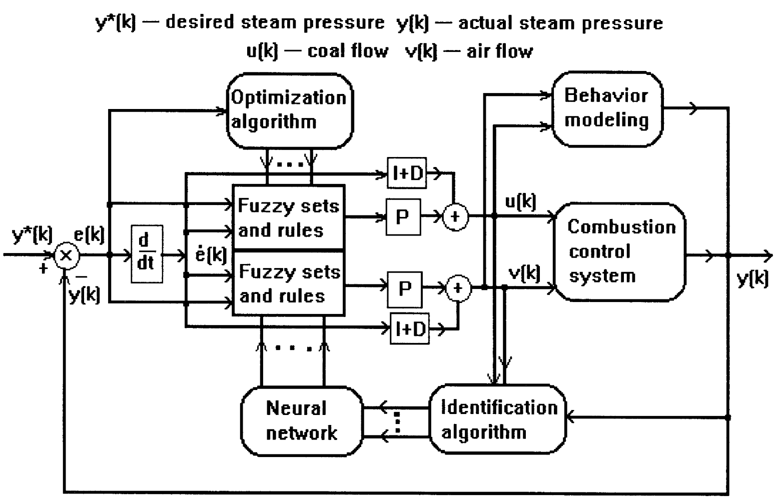


Fig. 4. A neuro-fuzzy control scheme for combustion control, based on behavior modeling.

defined behavior, one can optimize its fuzzy logic controller in advance. In doing this, the behavior models are used to replace the controlled object with unknown structure, and the parameters of the fuzzy-logic controller are optimized according to the defined dynamic behavior. In this paper, all the membership functions defined by triangular functions in Fig. 6, are optimized by using a genetic algorithm. Due to space limitations, the coding of membership functions will not be discussed here. In order to tune the controller's parameters off-line, the integral-of-time-multiplied absolute-error criterion (ITAE)

$$H = \int_0^{t_0} t|e(t)|\,\mathrm{d}t \tag{20}$$

is used to describe the control performance. If $H < \boldsymbol{\sigma}$ ($\boldsymbol{\sigma}$ is a small positive constant), the controller's parameters are tuned. For these three behavior models, the tuned controller's parameters are really different. Fig. 7 shows the time responses of the behavior models yielded by the fuzzy logic controllers.

$\dot{e}(k)$ \ $e(k)$ / $u(k)$ or $v(k)$	NB	NS	ZO	PS	PB
NB	PB	PS	PS	PS	ZO
NS	PS	PS	PS	ZO	NS
ZO	PS	PS	ZO	NS	NS
PS	PS	ZO	NS	NS	NS
PB	ZO	NS	NS	NS	NB

Fig. 5. Fuzzy rule-base for coal and air flows.

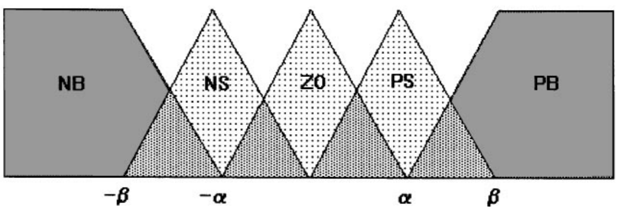


Fig. 6. Defined membership functions.

4. Neural-network training for on-line adaptation of a fuzzy controller

In order to adapt the fuzzy logic controller during system operation, a three-layer BP neural network is used to build a mapping relationship between the types of dynamic behavior, and the parameters of their corresponding fuzzy-logic controllers. A dynamic response of the combustion process can be expressed by an array of

Table 1
Examples of the input patterns of the defined dynamic behaviors

a_1	a_2	b_1	b_2	c_1	c_2
Dynamic behavior I					
−0.9205	−0.0757	−0.1140	0.1179	0.0258	−0.0002
−0.9105	−0.0792	−0.1476	0.2060	0.0047	−0.0538
−0.9011	−0.0885	−0.1216	0.1454	−0.0049	0.0572
−0.8677	−0.1217	−0.1389	0.1385	0.0801	0.0445
−0.7662	−0.2094	−0.0485	0.0891	−0.2215	0.3184
−0.7987	−0.1954	−0.1368	0.1261	0.1169	−0.0256
−0.7568	−0.1663	−0.1576	0.1370	0.4705	0.2498
Dynamic behavior II					
−1.6016	0.6211	0.0011	0.0120	0.0893	−0.0588
−1.8040	0.8074	0.0123	−0.0019	0.0722	−0.0738
−1.3336	0.3434	0.0013	0.0179	0.0816	−0.0855
−1.2702	0.2900	−0.0405	0.0147	0.1046	−0.0043
−1.1994	0.2176	−0.0088	0.0157	0.0796	−0.0175
−1.5421	0.5496	−0.0028	0.0165	0.0675	−0.0507
Dynamic behavior III					
−0.6535	−0.3391	0.0113	−0.0077	0.0012	0.0113
−1.2570	0.2732	−0.0115	0.0043	−0.0210	0.0582
−1.1215	0.1380	−0.0377	0.0726	0.0203	−0.0116
−0.3075	−0.6420	0.0439	0.0355	0.1814	0.2150
−1.2582	0.2653	0.0003	0.0120	0.0134	0.0080
1.1683	−0.1801	−0.0132	0.0040	0.0329	−0.0096

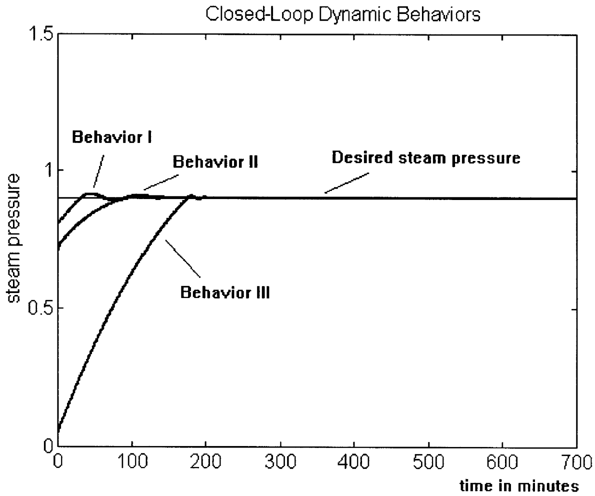
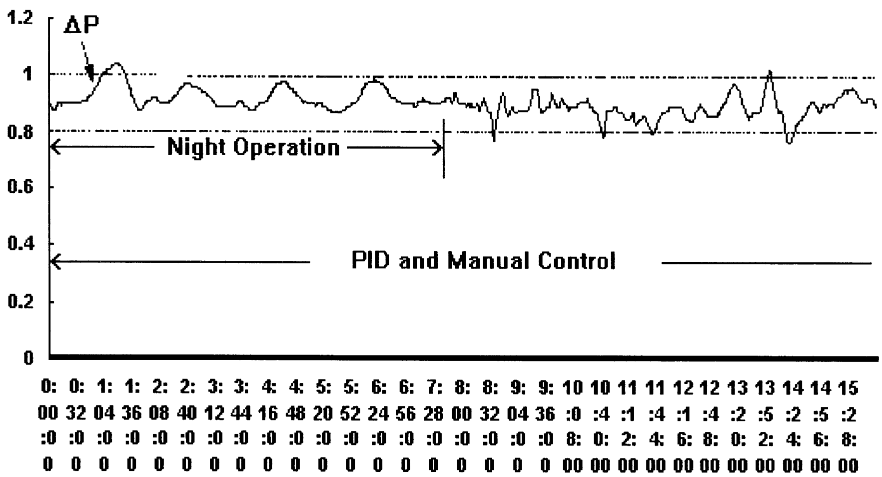


Fig. 7. Closed-loop time responses generated by the fuzzy-logic controller.

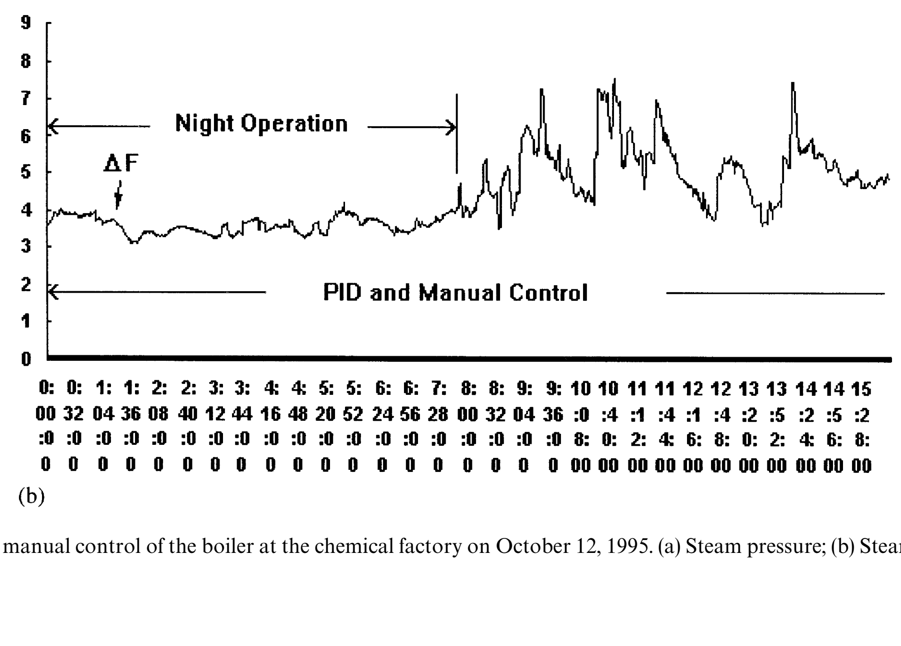
inputs and outputs with a length K_0, as shown in Fig. 2c. On the basis of the historical operating data, e.g., those in Fig. 2, the following algorithm is proposed to obtain patterns for each dynamic behavior:

Step 1: Initialize $k_0 = 0$.
Step 2: Get inputs $u(k)$ and $v(k)$ and outputs $y(k)$ $(k = k_0 + 1, \ldots, k_0 + N)$ from the test data that represent the dynamic behaviors of the controlled boiler.
Step 3: Compute coefficients, a_1, a_2, b_1, b_2, c_1 and c_2 by using Eqs. (13)–(15).
Step 4: If $k < K_0$, increase $k_0 = k_0 + N$. Go to *Step* 2.

All the parameters a_1, a_2, b_1, b_2, c_1 and c_2, which used to describe the dynamic behaviors, are considered as the input patterns to the neural network. Table 1 lists some pattern examples for the three dynamic behaviors. The output patterns from the neural network are the

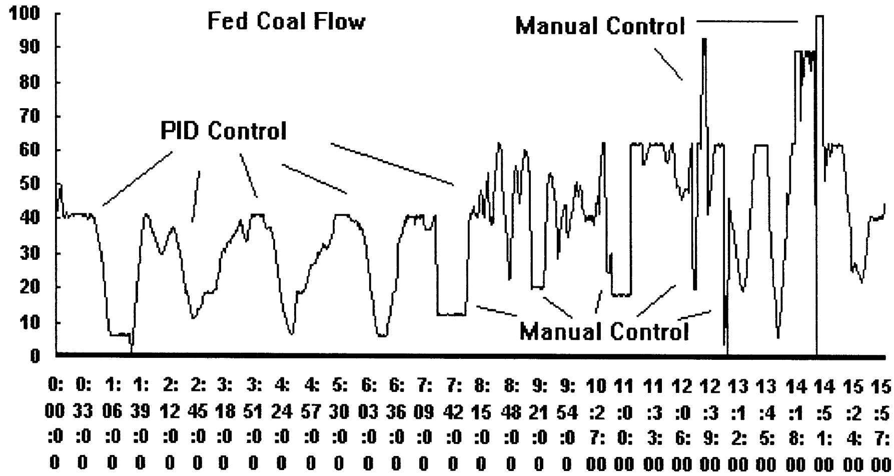


(a)

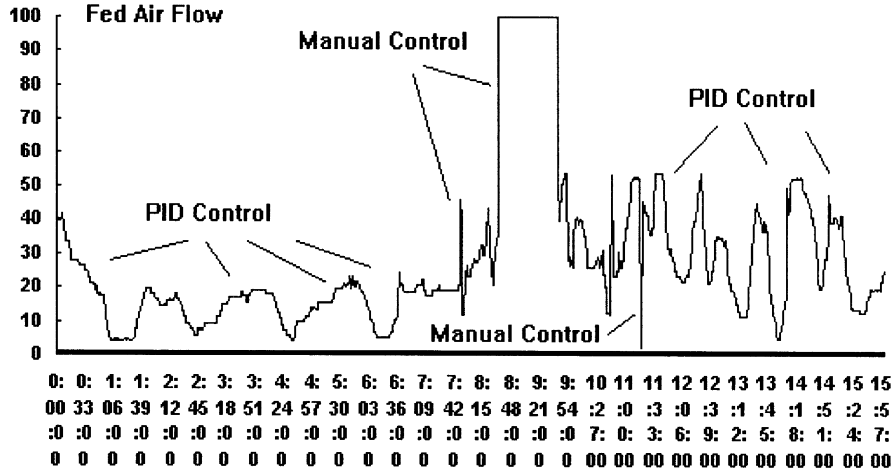


(b)

Fig. 8. PID control and manual control of the boiler at the chemical factory on October 12, 1995. (a) Steam pressure; (b) Steam flow; (c) Fed coal flow; (d) Fed air flow.



(c)



(d)

Fig. 8. (Continued).

optimized controller's parameters, corresponding to each type of dynamic behavior. The output $q_j^{[s]}$ of the jth neuron on the sth hidden layer is calculated as

$$q_j^{[s]} = f(Net_j^{[s]}) = f\left(\sum_i (w_{ji}^{[s]} * q_i^{[s-1]})\right), \tag{21}$$

where $w_{ji}^{[s]}$ is the weight on the connection joining the ith neuron in layer $(s-1)$ to the jth neuron in layer s, and $f(x)$ is a sigmoid logistic function

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{22}$$

The Widrow–Hoff $\boldsymbol{\delta}$ learning rule is used to modify the weight $w_{ji}^{[s]}$.

After the network has been trained, this hybrid control system can be operated on-line. During system operation, the unit for behavior modeling is switched off, and the identification algorithm is used to compute the coefficients, a_1, a_2, b_1, b_2, c_1 and c_2, i.e., to identify the dynamic behavior of the controlled object according to the last segment of the dynamic response, as shown in Fig. 2c. According to the type of dynamic behavior identified for the response segment, the corresponding fuzzy-logic controller is fired by the neural network.

5. Results of a real application

This control system has been applied in several industrial stoker boilers at various sites. This section reports actual control results, for two stoker-fired boilers. One of them operates at a chemical factory, and the other at a railway station. This report includes: (1) a comparison of a PID-type controller and the proposed fuzzy-logic controller; (2) automatic recovery of the control process after an electric power shutdown in a short time accidence and (3) smooth steam-pressure control under a strong steam-flow change.

5.1. Comparison of PID control and fuzzy-logic control

The boiler at the chemical factory provides the power for machines, canteens and so forth. PID-type control of the stoker-fired boiler at the chemical factory was switched off, and the proposed hybrid controller came into operation on October 13, 1995. In order to demonstrate the control performance of the fuzzy controllers, the operating record data regarding steam pressures, steam flows (loads of the steam pressures), fed coal and fed air-flows from October 12 to 14 are plotted (Figs. 8–10). Because the same situation cannot be repeated during stoker-fired boiler operation, it is difficult to provide a performance measure for the PID-type and fuzzy-logic controllers under the same conditions in real operation. However, an attemt was made to verify the effectiveness of the fuzzy-logic controller as follows.

The original control strategy is a combination of PID-type and manual control operations. If a load, i.e., a steam flow, changes greatly, the PID-type controller must be switched off, and the manual control will come into operation. Figs. 8 and 9 show that there are about 20 instances of manual control operations in the 40 h before fuzzy-control operation. Consequently, such manual control operations make the operators very nervous. However, no manual control operation is used after the fuzzy-logic control takes over. This result shows that the fuzzy-logic controller operates the combustion control system more automatically. It can be also observed that, by using PID control, the fed coal and air flow change violently.

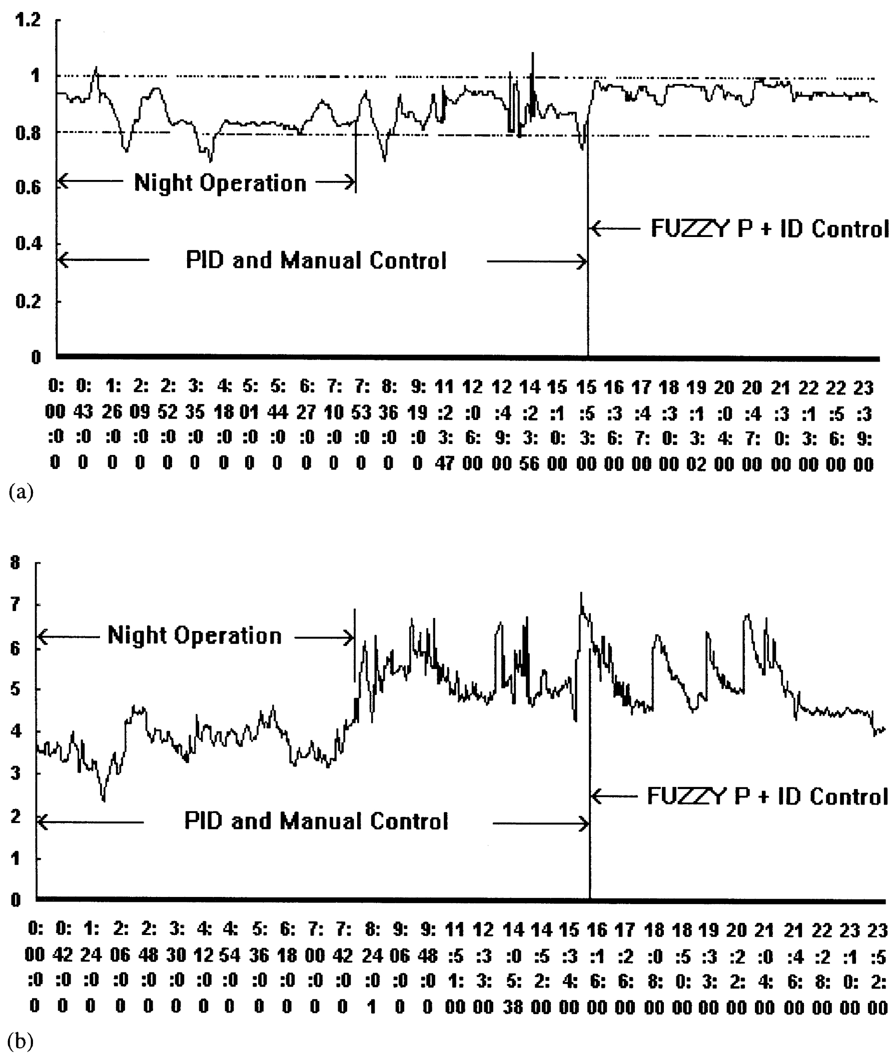
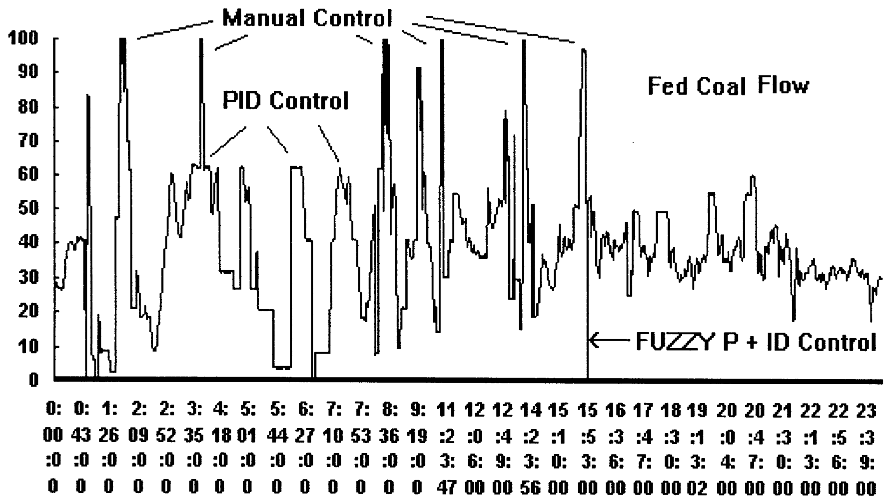
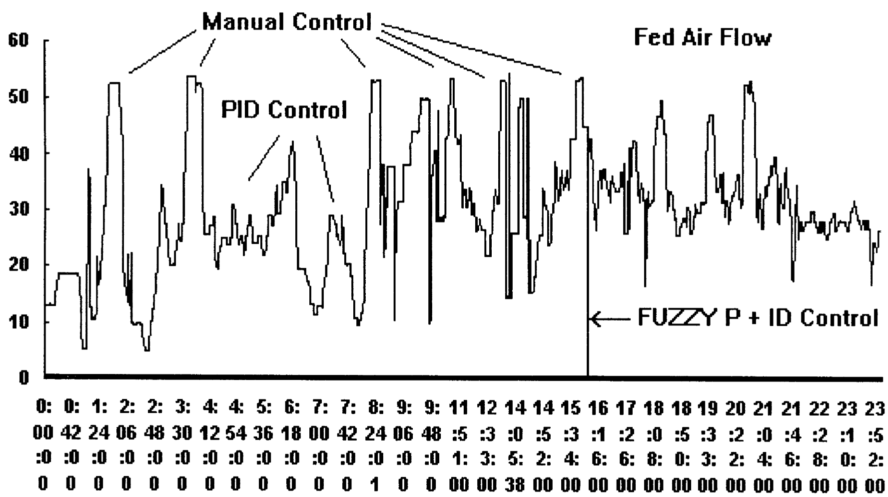


Fig. 9. PID and manual control switched off and fuzzy-logic control switched on at the chemical factory on October 13, 1995. (a) Steam pressure; (b) Steam flow; (c) Fed coal flow; (d) Fed air flow.



(c)



(d)

Fig. 9. (Continued).

5.2. Automatic recovery of control process

The next following example shows the fuzzy-logic control of the stoker-fired boiler at the railway station. On December 26, there were two examples of the electric power shutdowns due to brief accidents. Such events occur often in this boiler application. Fig. 11a and b show the recorded data of the steam pressure and the steam flow, respectively. It can be seen that when the electric power shuts down, the steam pressure and flow go down rapidly, due to the lack of fuel supply.

After the electric power recovers, the steam pressure runs to up its desired value very fast, without any overshoot, in this start process. From previous experience, it is known that the PID controller must be switched off in such cases. (Since the parameters of the PID controller are determined only in cases of small variations of the steam pressure around the desired value, i.e., dynamic behavior I, it is difficult to obtain a good dynamic response of the steam pressure in the face of large deviations). Even though manual operation comes into operation in this case, the dynamic responses of the steam pressure usually show a large overshoot.

5.3. Steam pressure control under a strong steam-flow change

Fig. 12a and b show the recorded data of the steam pressure and the steam flow of December 29 at the railway station, respectively. On this day, the load of the steam pressure, the steam flow, changed very violently; for example, between 7:56 a.m. and 8:07 a.m. the steam flow decreased suddenly from 10.7 units to zero. Before fuzzy control was used, manual control had to be in place. This makes for a very tense and tedious work, if the boiler operators have to watch the changes in the steam, and regulate the coal and air flows all day and night. However, using fuzzy control, the boiler provides the desired steam pressure.

6. Discussions and conclusions

This paper uses a behavior modeling approach to design a neuro-fuzzy control system for boiler combustion systems. Using behavior modeling, this problem is transformed to the off-line modeling of a controlled object, and the on-line adaptation of its controller's parameters. It is known that the operation of a fuzzy logic controller is based on the dynamic behavior of a system. If only one fuzzy-logic controller can achieve the desired control performance of a plant, a fuzzy-logic controller with fixed rules and membership functions will meet the requirements of the control objective. This implies that such a system can be described by only one type of dynamic behavior, under such a fuzzy-logic controller. However, the use of only one fuzzy-logic controller may not work very well in some cases, for example in boiler combustion control, since it is not suited to some dynamic behaviors. In order to deal with this problem, the dynamic responses may be classified into two or three dynamic behavior models. The control performance can then be improved if a particular type of dynamic behavior is controlled by its appropriate fuzzy-logic controller.

In this application, a linear model is adopted to describe the dynamic behaviors of industrial boilers, due to its simple computation and based on previous research work. In order to obtain the behavior models more precisely, recorded operating data are processed over 5 h. Firstly, this model is used off-line, to calculate the patterns of each type of dynamic behavior for the neural network. In this case, only segments of the dynamic

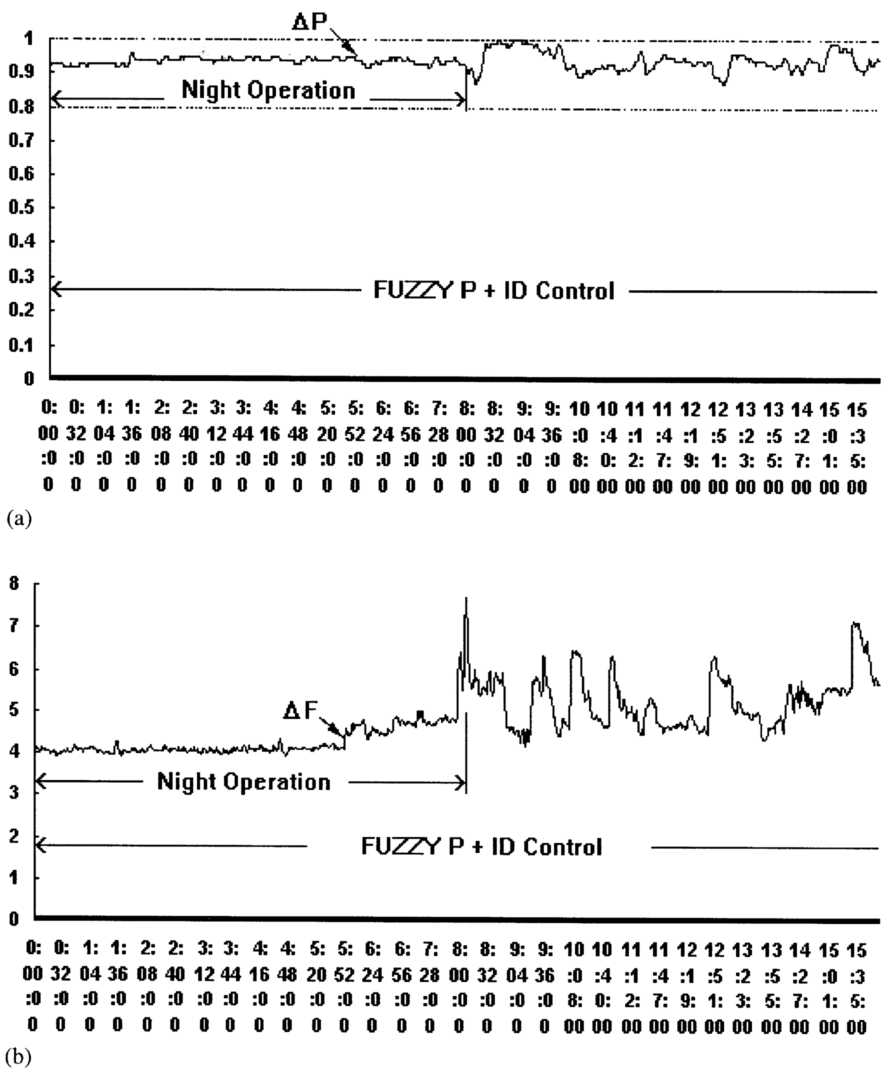
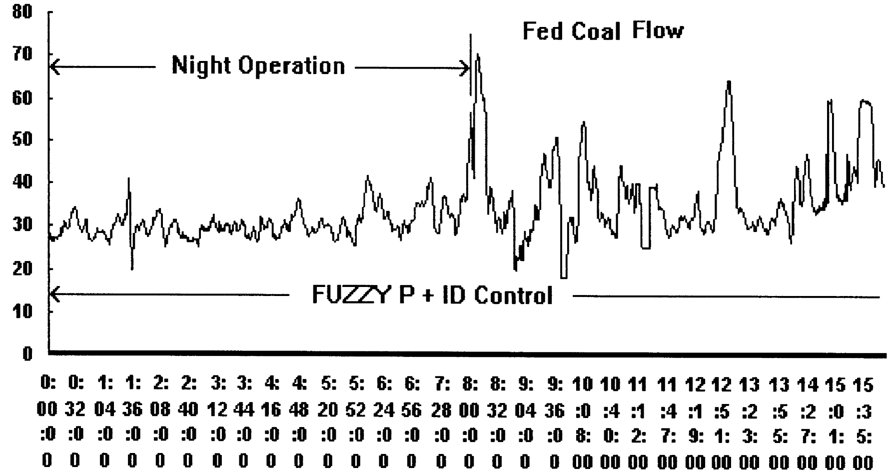
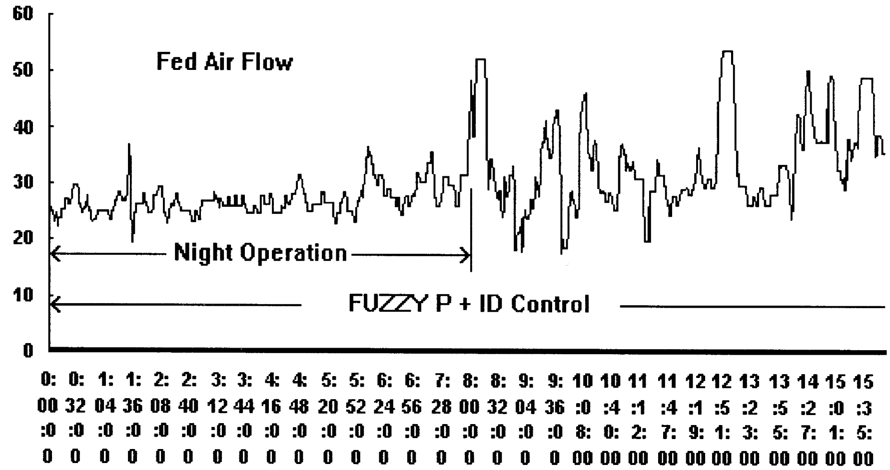


Fig. 10. Fuzzy logic control on October 14, 1995 at the chemical factory. (a) Steam pressure; (b) Steam flow; (c) Fed coal flow; (d) Fed air flow.



(c)



(d)

Fig. 10. (Continued).

responses are processed. Secondly, it is used on-line to estimate the coefficients during system operation. In this case, these coefficients are just used to describe features of the dynamic behaviors, rather than to re-compute controller's parameters. This point differs from a model-based control strategy. In the real operation, this approach to behavior perception is very sensitive to noise (see Table 1), so that sometimes the identified parameters cannot match each of the dynamic behaviors. In this case, the controller's parameters are not adapted.

One may question why a model-based controller was not designed based on the dynamic behaviors defined in the paper. Due to the high nonlinearity, the identified parameters (see Table 1) are quite different from one segment of time responses to another. In particular, the perception of a dynamic behavior by linear model is highly uncertain. This can be clearly observed by comparing the night operations in Figs. 8a and in Fig. 10a. In both cases, the boiler combustion system exhibits dynamic behavior I – 'smooth operation'. Under fuzzy-logic control, the steam pressure is almost identical to its desired value in Fig. 10a. Using the PID-type of controller, however, the variation in the steam pressure in Fig. 8a is quite large. In the application, different fuzzy logic controllers have been implemented; for example, a fuzzy-logic controller in an incremental form, or a fuzzy PI + D controller, and all of these can work after optimization.

The selection of dynamic behaviors is based on the control performance yielded by the fuzzy-logic controller instead of on analytical models of the systems, hence one can use other methods to identify a type of dynamic behavior. For example, the neural network can be used to perceive the dynamic behavior directly, without a linear model. In this case, the patterns input to the neural network are the recorded steam pressure, steam flow, fed coal flow and fed air flow; while the output patterns from the neural network remain unchanged.

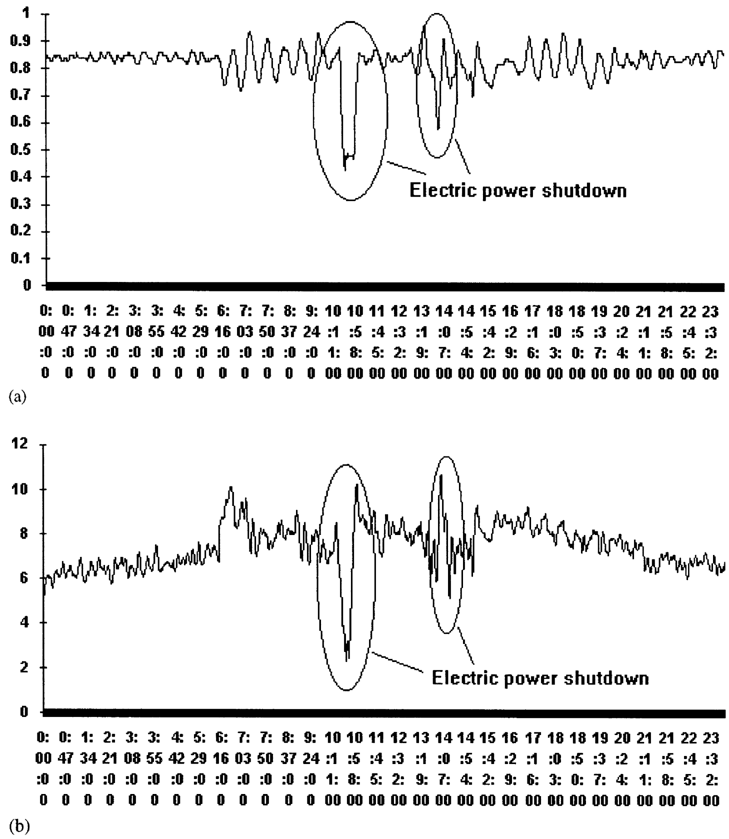


Fig. 11. Automatic recovery of combustion process after electric power shutdown at the railway station. (a) Steam pressure; (b) Steam flow.

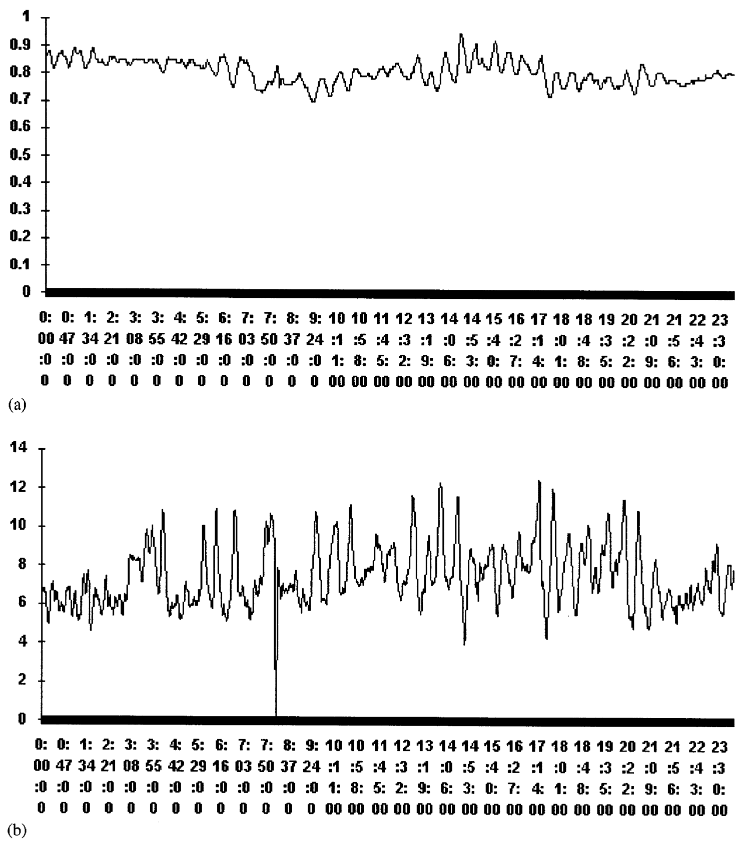


Fig. 12. Smooth steam pressure control under a strong steam flow change on December 29, 1995. (a) Steam pressure; (b) Steam flow.

Acknowledgements

This work is funded by the National Natural Science Foundation of China under grant 69585004, and by the Chinese Education Committee Foundation for Outstanding Young Teacher. The authors would also like to express their gratitude to the referees for detailed and helpful comments.

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