A Boiler-Turbine System Control Using A Fuzzy Auto-Regressive Moving Average (FARMA) Model

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***Abstract*—This paper presents an application of an online self-organizing fuzzy logic controller to a boiler-turbine system of fossil power plant. The control rules and the membership functions of the proposed fuzzy logic controller are generated automatically without using a plant model. A boiler-turbine system is described as a multi-input multioutput (MIMO) nonlinear system in this paper. Then, three single-loop fuzzy logic controllers are designed independently. Simulation shows robust results for various kinds of electric load demand changes and parameter variations of boiler-turbine system.**

***Index Terms*—Boilers, fuzzy control, self-organizing control.**

I. Introduction

A boiler-turbine system supplies high-pressure steam to rotate the generator in thermal electric power generation. The purpose of the boiler-turbine system control is to meet the load demand of electric power while maintaining the pressure and water level in the drum within tolerance. To design a controller, the boiler-turbine system is usually modeled as a multi-input multioutput (MIMO) nonlinear system [1].

The severe nonlinearity and wide operation range to the boiler-turbine plant have resulted in many challenges of power system control engineers. Hogg and Ei-Rabaie presented an application of self-tuning generalized predictive control (GPC) to a boiler system [2]. Rovnak and Corlis presented an application of dynamic matrix control to fossil power plant [3]. Though [2] and [3] both optimize the performance on a receding horizon, the self-tuning GPC uses an online identification model, while the dynamic matrix control uses offline step-response model of the plant. Ben-Abdennour and Lee applied robust control method for a power plant [4]. They decomposed a power system to boiler, turbine, and generator, and applied the linear quadratic Gaussian with loop transfer recovery (LQG/LTR) to two subsystems, boiler, and turbine, as local controllers.

To overcome the nonlinearity of the boiler-turbine plant, many kinds of artificial intelligence techniques have also been applied. Prasad, Swidenbank, and Hogg proposed a predictive‘ control based on an NN model [5]. They used offline training of neural network to capture the nonlinearity of power plant dynamics. And the performance of receding horizon is minimized by real-time optimization. Dimeo and Lee used a genetic algorithm (GA) to enhance the wide range performance of PI controller or linear quadratic regulator (LQR) [6]. In that paper, the parameters of conventional PI controller or LQR are found by GA for wide operation range of boiler-turbine system. Alturki and Abdennour applied a neural-fuzzy control to a boiler-turbine system [7]. They trained neuro-fuzzy system with the data from five LQRs which are designed for each operating point. Cheung and Wang presented a comparison of fuzzy and PI controller for drum-boiler system [8] and concluded that the fuzzy control system has better performance than PID control system especially in setpoint tracking.

In this paper, a self-organizing fuzzy logic controller (SOFLC) proposed in [9], called fuzzy auto-regressive moving average (FARMA) controller, is applied to the boiler-turbine system. In [9], we proposed a complete design method for an online SOFLC without using the mathematical model. The FARMA fuzzy logic controller (FLC) was successfully applied to several kinds of power system stabilizer design [10], [11]. In contrast to a conventional FLC, where the rule base and membership functions are supplied by an expert or tuned offline through experiment, the FARMA FLC needs no experts in making control rules. Instead, rules are generated using the history of input-output data. The generated rules are stored in the fuzzy rule space and updated online by a self-organizing procedure.

The single-loop control scheme is applied to control the boiler-turbine system in this paper. That is, three input-output pairs of boiler-turbine system are determined. Then, three FARMA FLCs are applied independently to the three single loops. Simulation considers various kinds of electric load demand changes and parameter variations of boiler-turbine system.

II. FARMA Fuzzy Logic Controller

A. FARMA Rule

The self-organizing FARMA fuzzy logic controller is reviewed briefly [9]. A single-input single-output (SISO) system can be described with a function or a mapping of the input-output history.

$$y(k+1) = f(y(k), y(k-1), \ldots, u(k), u(k-1), \ldots) \quad (1)$$

where $y(k)$ and $u(k)$ are, respectively, the output and input variables at the k-th time step.

The objective of the control problem is to find a control input sequence which will drive the system to an arbitrary reference set point y_{ref}. Rearranging (1) for control purposes, the value of

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the input u at the k-th step that is required to yield the reference output y_{ref} can be written as follows:

$$u(k) = g\left(y_{ref}, y(k), y(k-1), \ldots, u(k-1), u(k-2), \ldots\right) \tag{2}$$

which is viewed as an inverse mapping of (1) for the setpoint.

The system (1) yields the last output value $y(k+1)$ when the output and input values $y(k), y(k-1), y(k-2), \ldots, u(k), u(k-1), u(k-2), \ldots$ are given. This implies that $u(k)$ is the input to be applied when the desired output is y_{ref} as indicated explicitly in (2). Therefore, a FARMA rule with the input and output history is defined as follows:

$$\begin{aligned}&IF\ y_{ref} \text{ is } A_{1i}, y(k) \text{ is } A_{2i},\\ &\quad y(k-1) \text{ is } A_{3i}, \ldots, y(k-n+1) \text{ is } A_{(n+1)i},\\ &AND\ u(k-1) \text{ is } B_{1i},\\ &\quad u(k-2) \text{ is } B_{2i}, \ldots, u(k-m) \text{ is } B_{mi},\\ &THEN\ u(k) \text{ is } C_i,\ (\text{for the } i\text{-th rule})\end{aligned} \tag{3}$$

where

n, m number of output and input variables;
A_{ij}, B_{ij} antecedent linguistic values for the i-th rule;
C_i consequence linguistic value for the i-th rule.

Unlike a conventional FLC, where an expert gives the linguistic values A_{ij}, B_{ij}, and C_i, and makes rules, these linguistic values are determined from the crisp values of the input and output history at each sampling time. Therefore, the assigned $u(k)$ may not be a good control initially. However, the rule base is updated each time using the self-organizing procedure and better controls are applied as time progresses.

The linguistic values A_{ij}, B_{ij}, and C_i are obtained by fuzzifying the corresponding crisp values of y and u. The fuzzification is done for a crisp value on a reasonably assumed input or output range. When an assumed input or output range is $[a, b]$, the membership function for a crisp value x_1 is defined in a triangular shape as follows:

$$\mu_{A_1} = \begin{cases} 1 + \frac{(x-x_1)}{(b-a)}, & if\ a \le x < x_1,\\ 1 - \frac{(x-x_1)}{(b-a)}, & if\ x_1 \le x < b,\\ 0 & \text{else}. \end{cases} \tag{4}$$

The above fuzzification procedure generates a FARMA rule at each sampling step and stores in a rule base. This means that every experience is regarded initially as a fuzzy logic control rule. As the run continues, the knowledge will be accumulated and the FARMA rule is updated in the rule space.

B. Inference and Defuzzification

When a new set of input and output data is sampled, its "truth value" is determined with respect to each rule and the net linguistic control action C_n is deduced with the φ-operation [12] as follows:

$$C_n = \cap_i \left(\omega_i\ \varphi\ \mu_{C_i}\right) \tag{5}$$

$$\omega_i\ \varphi\ \mu_{C_i} = \begin{cases} 1 & if\ \omega_i \le \mu_{C_i}\\ \mu_{C_i} & if\ \omega_i > \mu_{C_i} \end{cases} \tag{6}$$

where

C_n net linguistic control action;
ω_i truth value of the i-th rule;
μ_{Ci} membership degree of the consequence linguistic value C_i in the i-th rule.

By taking the α-cut of the C_n where $\alpha = \max \mu(C_n)$, the net control range (NCR) is determined as the subset $[p, q]$ of $[a, b]$ with the constant membership value α as the highest possibility.

Defuzzification is performed to determine a crisp value from the NCR resulting from the inference. First, the NCR is modified by using a prediction or "trend" of the output response. For example, the series of the last outputs can be extrapolated in time domain to estimate $y(k+1)$ using the Newton backward-difference formula.

Defuzzification is performed by comparing the two values, the estimate $\hat{y}(k+1)$ and the reference output y_{ref}, or the temporary target $y_r(k+1)$ generated by

$$y_r(k+1) = y(k) + \beta\left(y_{ref} - y(k)\right) \tag{7}$$

where β is the target ratio constant $(0 < \beta \le 1)$. The value of β describes the rate with which the present output $y(k)$ approaches the reference output value, and thus, has a positive value between 0 and 1. The value of β is chosen by the user to obtain a desirable response.

When the estimate exceeds the reference or the target output, the control has to slow down. Otherwise, the control should speed up. To modify the control range, the sign of $\Delta u(k)(= u(k) - u(k-1))$ is assumed to be the same as the sign of $(y_r(k+1) - \hat{y}(k+1))$ without the loss of generality. Thus, when $y_r(k+1) > \hat{y}(k+1)$, hence the sign of $\Delta u(k)$ is positive, $u(k)$ has to be increased from the previous input $u(k-1)$. On the other hand, when the sign of $\Delta u(k)$ is negative, $u(k)$ has to be decreased from the previous input $u(k-1)$. This limits the range of control and modifies the NCR. The final crisp control value $u(k)$ is then selected as one of the midpoints of the modified NCR as follows:

$$u(k) = \begin{cases} \frac{(u(k-1)+q)}{2}, & for\ y_r(k+1) > \hat{y}(k+1)\\ \frac{(p+u(k-1))}{2}, & for\ y_r(k+1) < \hat{y}(k+1) \end{cases} \tag{8}$$

where p and q are the respective lower and upper limits of the NCR.

C. Self-Organization of the Rule Base

The FARMA rule defined in Section II-A is generated at every sampling time. Each rule can be represented as a point in the $(n+m+1)$-dimensional rule space [i.e., $(x_{1i}, x_{2i}, \ldots, x_{(n+m+1)i})$]. To update the rule base, the following performance index is defined

$$J = |y_r(k+1) - y(k+1)| \tag{9}$$

where $y(k+1)$ is the real plant output and $y_r(k+1)$ is the reference output. Therefore, at the $(k+1)$-th step, the performance index J is calculated with the real plant output $y(k+1)$, resulting from the k-th step control.

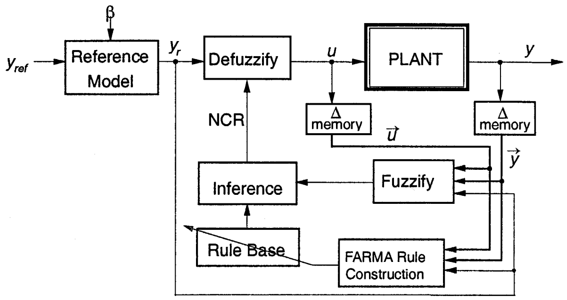

Fig. 1. FARMA control system architecture.

The fuzzy rule space is partitioned into a finite number of domains and only one rule (i.e., a point), is stored in each domain. If there is a new rule in domain with the smaller value of J, the old rule is replaced by the new one. The self-organization of the rule base, in other words "learning" of the object system, is performed at each sampling time as shown in Fig. 1.

III. Boiler-Turbine System Control

A. Boiler-Turbine System Model

The model of Bell and Åström [1] is used in the simulation for the nonlinear boiler-turbine system. It was developed for a 160-MW oil–fired drum-type boiler-turbine-generator system for overall wide-range simulation. The model is a third-order MIMO nonlinear system described as follows [1]:

$$\dot{x}_1 = -0.0018u_2x_1^{9/8} + 0.9u_1 - 0.15u_3 \tag{10}$$

$$\dot{x}_2 = \frac{\left[(0.73u_2 - 0.16)x_1^{9/8} - x_2\right]}{10} \tag{11}$$

$$\dot{x}_3 = \frac{[141u_3 - (1.1u_2 - 0.19)\,x_1]}{85} \tag{12}$$

$$y_1 = x_1 \tag{13}$$

$$y_2 = x_2 \tag{14}$$

$$y_3 = 0.05\left(0.130\,73x_3 + 100a_{cs} + \frac{q_e}{9 - 67.975}\right) \tag{15}$$

where

$$\alpha_{cs} = \frac{(1 - 0.001\,538x_3)\,(0.8x_1 - 25.6)}{x_3\,(1.0394 - 0.001\,230\,4x_1)} \tag{16}$$

$$q_e = (0.854u_2 - 0.147)\,x_1 + 45.59u_1 - 2.514u_3 - 2.096. \tag{17}$$

The three state variables x_1, x_2, and x_3 are drum steam pressure (P in kg/cm^2), electric power (E in MW), and steam-water fluid density in the drum (ρ_f in kg/m^2), respectively. The three outputs y_1, y_2, and y_3 are drum steam pressure (x_1), electric power (x_2), and drum water level deviation (L in m), respectively. The y_3, drum water level L, is calculated using two algebraic calculations α_{cs} and q_e which are the steam quality (mass ratio) and the evaporation rate (kg/s), respectively.

The three inputs u_1, u_2, and u_3 are normalized positions of valve actuators that control the mass flow rates of fuel, steam to the turbine, and feedwater to the drum, respectively. Positions of valve actuators are constrained to [0.1] and their rates of change per second are limited to

$$-0.007 \leq \frac{du_1}{dt} \leq 0.007 \tag{18}$$

$$-2.0 \leq \frac{du_2}{dt} \leq 0.02 \tag{19}$$

$$-0.05 \leq \frac{du_3}{dt} \leq 0.05. \tag{20}$$

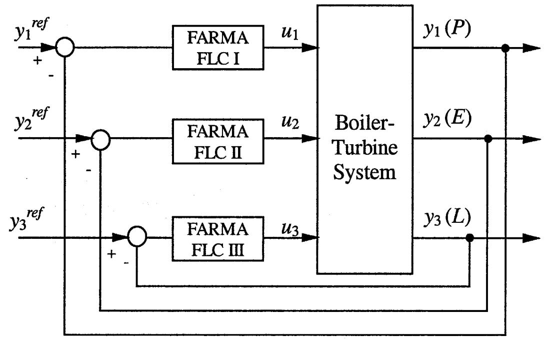

Fig. 2. Boiler-Turbine control system.

B. FARMA FLC Application to Boiler-Turbine System

In this paper, the FRAMA FLC for SISO system (1) is directly applied to the boiler-turbine system. From the input-output point of view, the boiler-turbine system (10)–(20) is a three-input and three-output system. Therefore, three single loops, which are three FARMA FLCs, are applied independently in this paper.

The dominant input-output fairs should be determined first to design the single-loop configuration. From (10), the x_1 can be controlled by u_1 and u_2. Considering that the order of x_1 is about 100 in normal operation, u_2 term is smaller than u_1 term, which means y_1 (pressure) is dominantly affected by u_1 (mass flow rates of fuel). Therefore, the first FARMA FLC loop is to control y_1 with u_1. And from (11), x_2 is affected by u_2. Therefore, the second FARMA FLC is to control y_2 (electric power) with u_2 (steam to the turbine). Finally, from the physical property of boiler-turbine system, y_3 (drum water level deviation) is controlled by u_3 (feedwater to the drum). Therefore, the third FARMA FLC is to control y_3 with u_3.

The overall structure to control the boiler-turbine system is shown in Fig. 2. In Fig. 2, FARMA FLC I, II, and III control y_1 (pressure), y_2 (electric power), and y_3 (drum water level deviation) with u_1 (mass flow rates of fuel), u_2 (steam to the turbine) and u_3 (feedwater to the drum), respectively.

The orders n and m in (3) are 3 and 1 for each FRAMA FLC. Therefore, (3) for each FRAMA FLC is as follows:

$$\begin{aligned} &IF\ y_{ref}\ is\ A_{1i}, y(k)\ is\ A_{2i}, \\ &\quad y(k-1)\ is\ A_{3i},\ AND\ u(k-1)\ is\ B_{1i} \\ &THEN\ u(k)\ is\ C_i \quad (\text{for the } i\text{-th rule}). \end{aligned} \tag{21}$$

The output ranges for (4) are [70 150] (P in kilograms/cm^2), [10 190] (E in megawatts) and [-0.5 0.5] (L in meters) for FARMA FLC I, II, and III, respectively. The input ranges are [0 1] for each FARMA FLC.

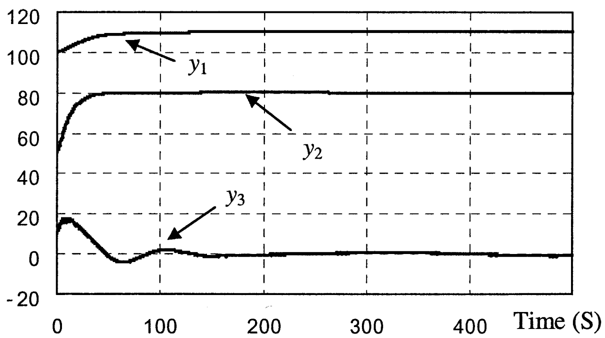

Fig. 3. Outputs of case 1.

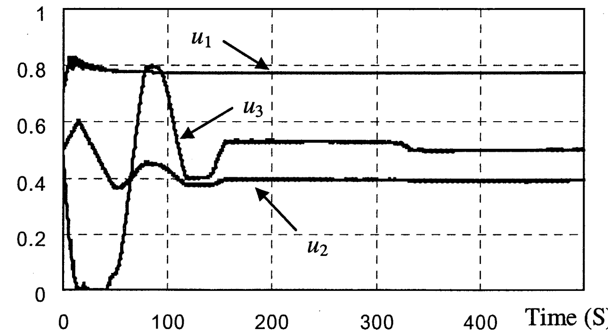

Fig. 4. Inputs of case 1.

IV. Simulation Results

The control system and process model were developed with C-language in a personal-computer environment. Sampling times for simulations are 0.5 s. Simulations presented here are to evaluate the control system performance for various kinds of electric load demand changes and parameter variations of boiler-turbine system and characteristics of single-loop controls with three FARMA FLCs. In [4], they pointed out that the pressure setpoint is increased through a functional mapping as the electric load is increased. Therefore, the pressure setpoints are also increased as electric loads increased in simulations.

With the assumption that the system is in a steady state with $X = (100, 50, 449.5)$, $Y = (100, 50, 0)$, $U = (0.271, 0.604, 0.336)$ initially, we consider the seven cases to validate the proposed control system. The first four cases are to consider various kinds of electric load demands and the second three cases are to consider the parameter variations.

A. Electric Load Demand Changes

In this case study, four cases with various kinds of electric load demand changes are considered as follows: .

Case 1) $y_1^{ref} = 110, y_2^{ref} = 80, Y_3^{ref} = 0$

Case 2) $y_1^{ref} = 120, y_2^{ref} = 100, y_3^{ref} = 0$

Case 3) $y_1^{ref} = 130, y_2^{ref} = 120, y_3^{ref} = 0$

Case 4) $$\begin{cases} y_1^{ref} = 110, y_2^{ref} = 80, y_3^{ref} = 0, & 0 \le t \le 400 \\ y_1^{ref} = 120, y_2^{ref} = 100, y_3^{ref} = 0, & 400 \le t \le 800 \\ y_1^{ref} = 130, y_2^{ref} = 120, y_3^{ref} = 0, & 800 \le t \le 1200. \end{cases}$$

Case 1 describes that the setpoints of pressure and electric load demand are increased to 110 and 80, respectively, while the drum water level is kept to zero. Cases 2 and 3 describe the cases that the setpoints of pressure and electric load demand are increased to larger values for wider-range operation. Case 4 is to demonstrate the learning ability of the FARMA FLC. The setpoints of pressure and electric load demand are increased to the values of Cases 1, 2, and 3, but successively in every 400 s while the drum water level is kept to zero. Therefore, new plant experience is added to a rule base as new setpoints are applied.

Figs. 3–10 show the simulation results for cases 1, 2, 3, and 4. In the plots, units for output variables are (kg/cm^2) for y_1, (MW) for y_2 and (cm) for y_3 and units for input variables are normalized positions of valve actuators for three inputs u_1, u_2, and u_3.

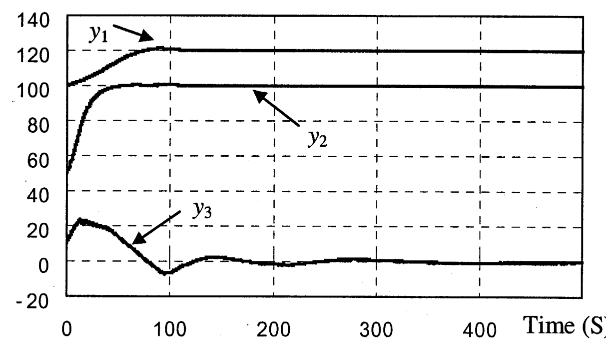

Fig. 5. Outputs of case 2.

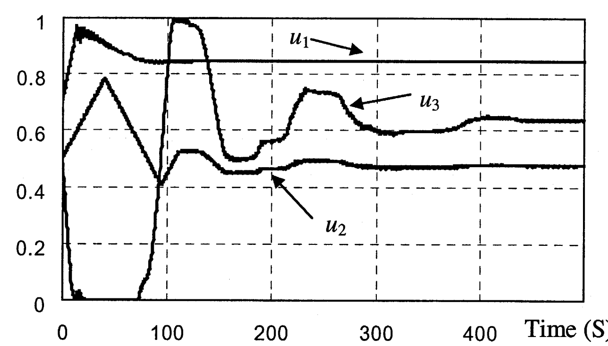

Fig. 6. Inputs of case 2.

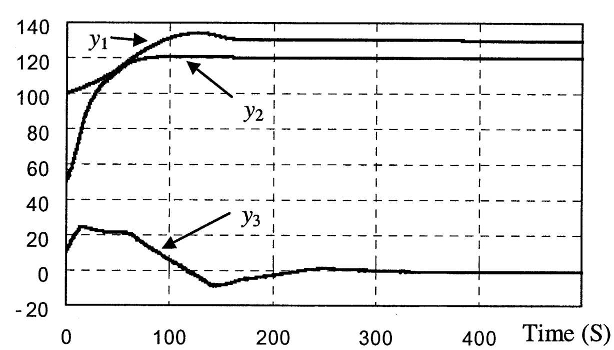

Fig. 7. Outputs of case 3.

Fig. 3 shows the outputs for case 1. The output y_1 tracks the reference 110 after 60 s and the y_2 is reached to the reference 80 in about 50 s. The drum water level is initially increased to 20, but returns to zero after 60 s. Fig. 4 shows the control actions of case 1. For larger step increases (cases 2 and 3), the outputs respond similarly, but take longer to reach the setpoint and with

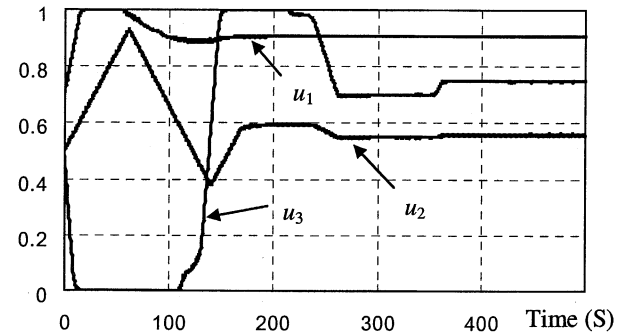

Fig. 8. Inputs of case 3.

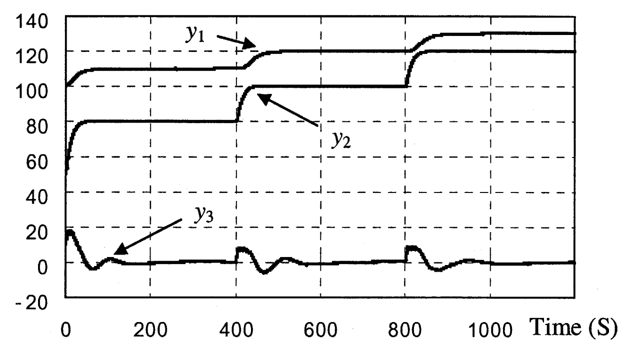

Fig. 9. Outputs of case 4.

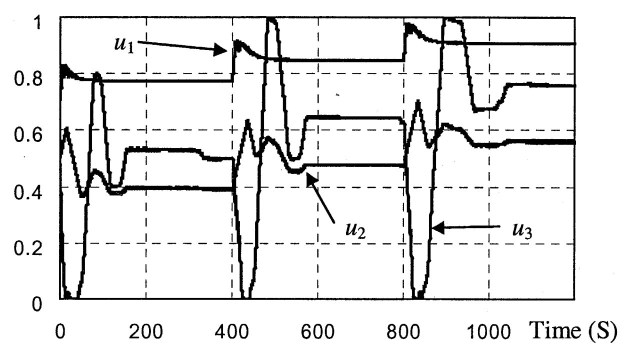

Fig. 10. Inputs of case 4.

more overshoots (Figs. 5 and 7). However, input signals are getting larger and often saturated as in Figs. 6 and 8. Figs. 9 and 10 show the outputs and inputs for case 4, which is to demonstrate the learning ability of FARMA FLC. The outputs y_1 and y_2 track their references in every 400 s. The drum water level deviation is 20 at the first reference change, but reduced to 10 at the subsequent changes Fig. 9. On the contrary, in cases 2 and 3, the drum water level deviation is 20 and takes longer to settle down (Figs. 5 and). In case 4, however, the drum water level deviations is 10 for the same level of setpoints as cases 2 and 3 (Fig. 9). This is because there is no rule at the initial setpoint change, but the experience on the first setpoint change was accumulated in the rule space and was used for the second setpoint change. Similarly, the experience gained with the first and the second setpoint changes were accumulated and used for the third setpoint change. As the controller experiences new inputs, the knowledge base is increased and the performance of the FARMA FLC improves.

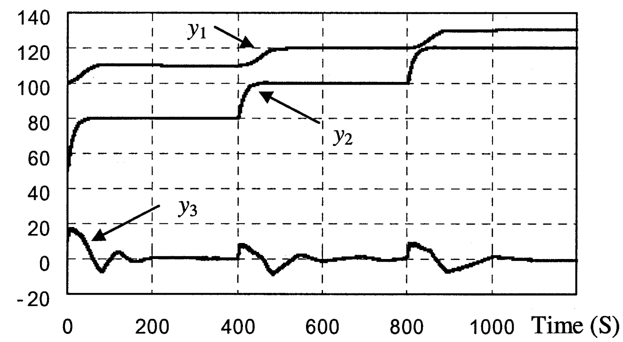

Fig. 11. Outputs of case 5.

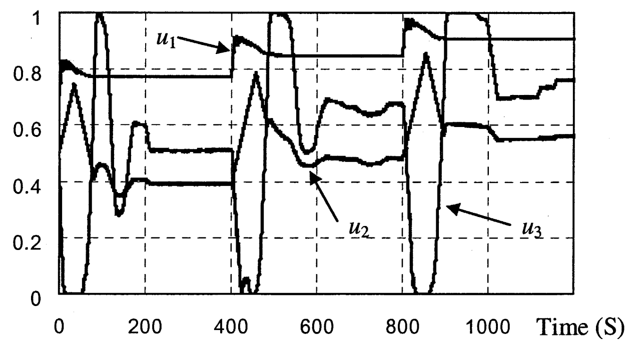

Fig. 12. Inputs of case 5.

B. Parameter Variations

Three different cases for parameter variations are considered as follows:

Case 5) 50% change in model parameters in (10);

Case 6) 50% change in model parameters in (10), (11), and (12);

Case 7) 50% change in the steam quality (mass ratio) α_{cs} in (15).

In case 5, three coefficients in (10) are reduced to 50% as follows:

$$\dot{x}_1 = -0.0009u_2 x_1^{9/8} + 0.45u_1 - 0.075u_3. \tag{22}$$

In case 6, all coefficients in the three state equations are reduced to 50% [i.e., in addition to (22)]

$$\dot{x}_2 = \frac{[(0.365u_2 - 0.08)x_1^{9/8} - 0.5x_2]}{10} \tag{23}$$

$$\dot{x}_3 = \frac{[70.5u_3 - (0.55u_2 - 0.095)\,x_1]}{170}. \tag{24}$$

In case 7, the coupling constant 100 in (15) is reduced to 50% as follows:

$$y_3 = 0.05\left(0.130\,73x_3 + 50a_{cs} + \frac{q_e}{9} - 67.975\right). \tag{25}$$

The setpoint changes of outputs for cases 5, 6, and 7 are the same as those in case 4. Figs. 11–16 show the simulation results for cases 5, 6, and 7.

Compared to the base case, case 4, the output responses of cases 5 and 6 are closed to each other and the base case Figs. 11 and 13. However, control efforts are much larger (Figs. 12 and 14). Figs. 15 and 16 are for case 7. In Fig. 15, y_3 is better than

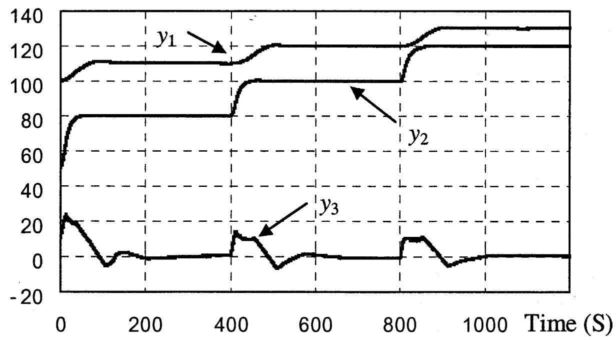

Fig. 13. Outputs of case 6.

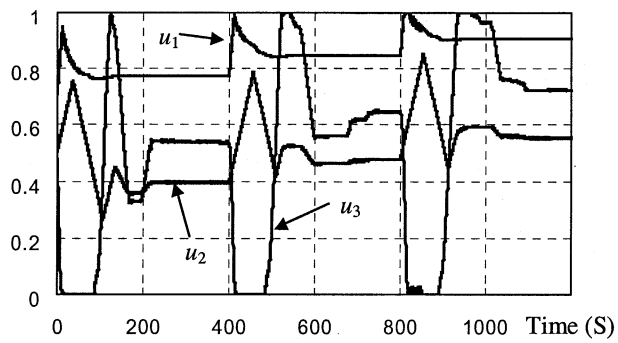

Fig. 14. Inputs of case 6.

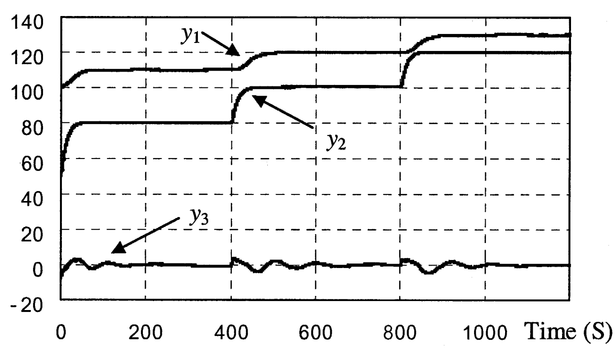

Fig. 15. Outputs of case 7.

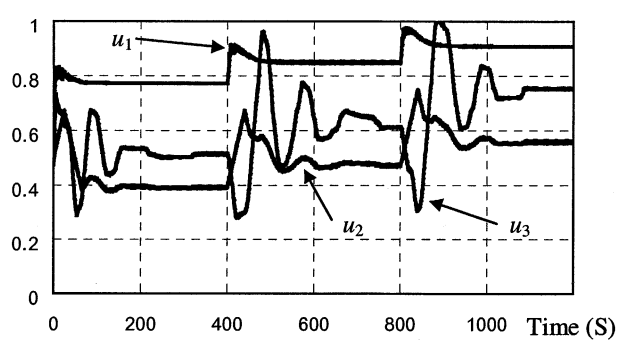

Fig. 16. Inputs of case 7.

that of case 4. This is because the effect of a_{cs} on y_3 is reduced to 50% in (25), which makes smaller response of y_3 than that of case 4.

From cases 5, 6, and 7, the proposed controller shows satisfactory performances though the plant model is changed significantly. This is because the proposed controller does not use the mathematical model of the system. Instead, the control rules are generated automatically with input-output history and the rule base is updated online to learn the behavior of the controlled plant.

The simulation results for various electric load demand changes and parameter variations show that the boiler-turbine system, which is highly complex and nonlinear, can be effectively controlled by the three single-loop FARMA FLCs.

V. Conclusion

This paper presents an application of online self-organizing fuzzy logic controller (SOFLC) to a boiler-turbine system in a fossil power plant. The control rules and the membership functions of FARMA FLC are generated automatically without using the plant model. The generated rules are stored in the fuzzy rule space and updated online by a self-organizing procedure. Three single loops are controlled with three FARMA FLCs. The boiler-turbine system considered is a highly nonlinear MIMO system. For various electric load demand changes and parameter variations, simulation results show that the MIMO nonlinear boiler-turbine system can be controlled effectively with the proposed SOFLC. Moreover, the proposed control system is shown to be adaptive and robust.

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