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IDENTIFICATION AND ADAPTIVE CONTROL OF SUPER HEATER SYSTEM BASED ON QUASI-ARMAX MODEL

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Abstract: In this paper, a scheme to identification and control is proposed for main-steam temperature raising in a super heater system of thermal power plant. When modeling the system, a quasi-ARMAX model is effectively used by considering an appropriate treatment of external inputs in the super heater system. Then the validity of constructed model is verified through identification tests. In particular, it is found that the model validity becomes more evident for the high nonlinear case. Finally, an adaptive control system for main-steam temperature raising is designed based on a nonlinear predictor model in the framework of linear stochastic control theory

Keywords: Nonlinear system, quasi-ARMAX model, adaptive control, identification, super heater system

1. INTRODUCTION

System identification methods based on linear model have been well developed and applied in wide area of control engineering fields. However, many of dynamic systems in real world contain some sort of non-linearity, so linear approach to modeling and identification may breed modeling error. Therefore it is necessary to establish an appropriate model and its identification scheme which can deal with general nonlinear systems. To this purpose, Quasi-ARMAX modeling has been proposed for nonlinear systems (Hu,J. K.Kumamaru, K.Inoue and K.Hirasawa,1998).

The Quasi-ARMAX model has a linear structure like to ARMAX model, and in the modeling the system non-linearity is embedded into ARMAX coefficient parameters through nonlinear non-parametric models (NNMs). Thus the model can describe a wide variety of non-linearity. Furthermore, due to the linear structure, the identified Quasi-ARMAX model can easily be applied to system analysis and control synthesis in the framework of linear system theory. The effectiveness of the Quasi-ARMAX model has been confirmed through application studies on identification, fault detection and adaptive control problems (Hu,J. K.Kumamaru, K.Inoue and K.Hirasawa,1999).

So far, on these studies we have been considering mathematically described systems as the object. In this paper, in order to work toward practical use of Quasi-ARMAX model for more realistic system, we consider super heater system in a thermal power plant as the object system for identification and control. It is, however, essentially difficult to treat real working plant. Instead, we will consider a physical model of the super heater system which was constructed based on experimental knowledge of engineers engaged in the operation of thermal power plants. The physical model includes several nonlinear elements and has dynamic behavior with similar characteristics to real plant. In the temperature raising process of the super heater system, it is known that a heat unbalance is brought by valve switching in the primary and secondary super heater system's steam flow line. This causes a phenomenon that main-steam temperature temporarily drops, which is called the dip phenomenon. Besides this system is influenced by noise that produced inside plants. Then the control purpose of the super heater system is to improve the temperature raising characteristics so as to reduce the dip phenomenon. Such a control might be realized by adaptive control based on the Quasi-ARMAX modeling.

This paper is organized as follows: In section 2, a physical model of super heater system in a thermal power plant is presented. In section 3 4, it is confirmed through identification tests that the physical model can be well described by the Quasi-ARMAX model. In section 5, a method of STR-based adaptive control is applied to main steam temperature raising control and the simulation results are shown with discussions on the control performance. Finally, section 6 is devoted for conclusions.

2. SUPER HEATER SYSTEM IN A THERMAL POWER PLANT

Let us consider a boiler which supplies diurnal subsidiary power. Such a boiler is operated in a daily-start-stop method. It is necessary for such boiler to supply power effectively and promptly after the start up. But in the thermal power plant, valve switching in primary and secondary super heater systems results in a heat unbalance in the temperature raising process. This causes dip phenomenon shown in Fig.1. It prevents boiler from supplying power effectively and promptly, and it may causes thermal fatigue of turbine and danger in operation. Hence, it is very important problem that to control steam temperature according to reference output(5% $\sim$ 30% MCR: Maximum Continuous Rating), in such system. Until now, the method to solve the problem has been relied on operator's skill and experiences. But it is not so efficient. In this paper, an alternative way of adaptive control for main-steam temperature rasing is proposed in the thermal power plant operation.

A physical model of super heater system is introduced instead of actual plant, because it is difficult to get real input and output data from running

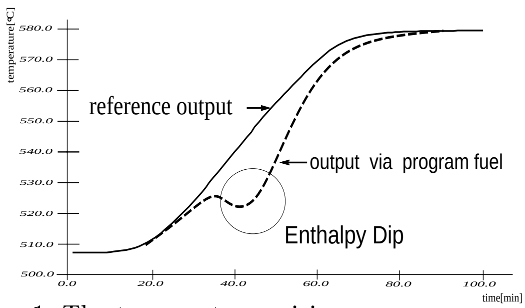

Fig. 1. The temperature raising process

one. Such the physical model is constructed by thermal power plant engineers based on their knowledge, experiences and designed parameters of actual plant. In this way, for the simulation studies, the input and output data corresponding to real plant data can be obtained from the model. In Fig.2, schematic diagram of the physical model is shown, where FF(Fuel Flow) and $Te2$(Main-Steam Temperature) are the input and the output of the system, respectively. Besides, there are other external inputs, such as SF(Steam Flow), PR(Steam Pressure), and $Entdip$(Enthalpy Dip) which are all measurable. They strongly influence on the system dynamics through the blocks consisting of nonlinear functions. The dynamics of the super heater system in Fig.2 are given as follows :

$$\begin{cases} \dot{x_1} = Hk_1(Tga_1, Tm_1) - \alpha_{ms_1} * A_s * (T_{m1} - T_{e1}) \\ \dot{x_2} = \alpha_{ms_1} * A_s * (T_{m1} - T_{e1}) + S_F * (H_{I10} - H_{e1}) \\ \dot{x_3} = Hk_2(Tga_2, Tm_2) - \alpha_{ms_2} * A_s * (T_{m2} - T_{e2}) \\ \dot{x_4} = \alpha_{ms_2} * A_s * (T_{m2} - T_{e2}) + S_F * (H_{e1} - H_{e2}) \end{cases}$$

$$Hk_j = F_h(Tga_j, Tm_j) =$$
$$Ke_j * \left\{ \left(\frac{273 + Tga_j}{100} \right)^4 - \left(\frac{273 + Tm_j}{100} \right)^4 \right\}$$
$$Ke_1 = 4.713 \quad , \quad Ke_2 = 4.792$$

$$Tga_j = F_{fgt}(FF, Tm_j) =$$
$$a_2(Tm_j) * FF^2 + a_1(Tm_j) * FF + a_0(Tm_j) \quad (1)$$
$$\begin{cases} a_2(Tm_j) = 0.000185 * Tm_j - 0.20423 \\ a_1(Tm_j) = -0.0188392 * Tm_j + 25.278 \\ a_0(Tm_j) = 0.666 * Tm_j + 257.65 \end{cases}$$

$$Tm_j = x_{2j-1}/9465 \quad (2)$$

$$Hm_j = \alpha_{ms_j} * As * (Tm_j - Te_j) \quad (3)$$

$$\alpha_{ms_j} = Kms_j * \left(\frac{SF}{90.0 * 80.83} \right)^{0.8} \quad (4)$$
$$Kms_1 = 1.97 \quad , \quad Kms_2 = 2.5$$

$$\begin{aligned} Te_j &= \theta(He_j, PR) \\ &= 1.9802 * He_j + 3.5352 * PR \\ &\quad -0.0038 * He_j * PR - 1146.0 \end{aligned} \quad (5)$$

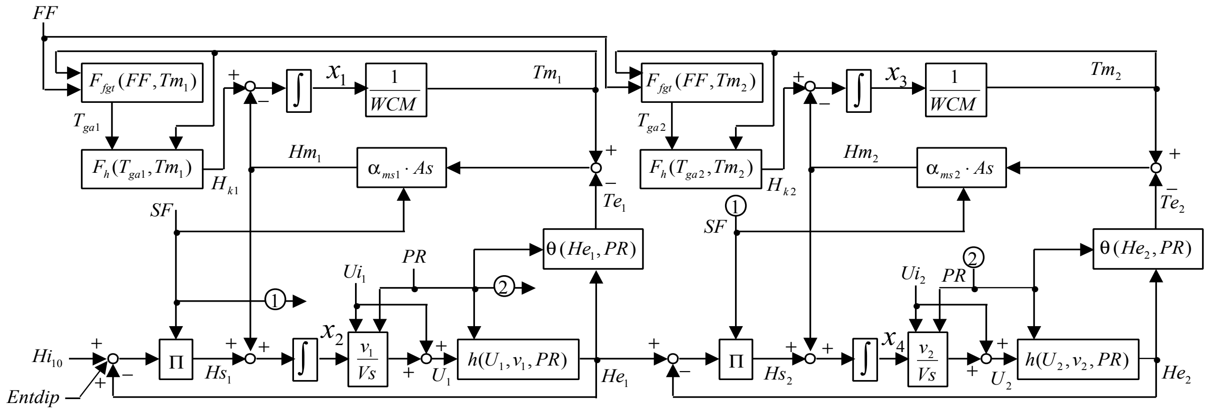

Fig. 2. Physical model of super heater system

$$He_j = h(U_j, v_j, PR) = U_j + 23.4192 * v_j * PR \quad (6)$$

$$U_j = 720.534 + \frac{v_j}{6.48} * x_{2j} \quad (7)$$

$$v_j = \frac{8.8073}{PR - 0.01232 * (x_{2j}/6.48)} \quad (8)$$

$$Hs_j = SF * (He_{j-1} - He_j) \quad (9)$$
$$He_0 = Hi_{10}$$

Table 1. Signals in Fig2

signal(unit)	contents of a signal
$FF(Kg/min)$	Fuel Flow
$SF(Kg/min)$	Steam Flow
$PR(Kg/cm^2)$	Steam Pressure
$Entdip(Kcal/Kg)$	Enthalpy Dip
$Hi_{10}(Kcal/Kg)$	SH inlet Enthalpy
$Te_j(^oC)$	Main-Steam Temperature
$Tm_j(^oC)$	Metal Temperature
$Tga_j(^oC)$	C.G Temperature
$Hk_j(Kcal/min)$	H.R.T from C.G to Steam
$Hm_j(Kcal/min)$	H.R.T from Metal to Steam
$Hs_1(Kcal/min)$	H.R.T from 1SH to 2SH
$Hs_2(Kcal/min)$	H.R.T from 2SH to Turbin
$He_j(Kcal/Kg)$	SH outlet Enthalpy
$WCM(^oC/Kcal)$	Thermal Capacity of SH Tybe
$\alpha_{ms_j}(Kcal/Kg \cdot m^2)$	Heat Conductivity
$A_S(m^2)$	Heat Conduction Surface
$v_j(m^3/Kg)$	Specific Volume
$Vs(m^3)$	Volime of SH tube
$Ui_j(Kcal/Kg)$	Internal Energy of Steam
x_1, x_2, x_3, x_4 $(Kcal)$	Heat Flow (State Variables)

H.R.T : Heat Flow Rate
C.G : Combustion Gas

Table 2. Intial, final and rated values

	FF	SF	PR	$Te2$
5%	0.5732	484.98	52.0	486
30%	29.0	2424.9	160.0	580
100%(rated value)	—	8083.0	160.0	580

Table 2 shows initial values and final values in the temperature raising process (5%∼30%) and shows rated values. Input data (programmed FF, SF, PR) are varied linearly by adjusting valves, like the broken line in Fig.6

3. QUASI-ARMAX MODELING OF SUPER HEATER SYSTEM

Quasi-ARMAX model of SISO is described as follows:

$$\begin{aligned} \bar{A}(q^{-1}, \phi(t))y(t) &= q^{-d}\bar{B}(q^{-1}, \phi(t))u(t) \\ &+ C(q^{-1})e(t) \end{aligned} \quad (10)$$
$$\begin{aligned} \phi(t) = [&y(t-1)\cdots y(t-n) \\ &u(t-d)\cdots u(t-d-m)] \end{aligned}$$

$$\bar{A}(q^{-1}, \phi(t)) = 1 + \bar{a}_1 q^{-1} + \cdots + \bar{a}_n q^{-n}$$
$$\bar{B}(q^{-1}, \phi(t)) = \bar{b}_0 + \bar{b}_1 q^{-1} + \cdots + \bar{b}_m q^{-m}$$
$$C(q^{-1}) = 1 + c_1 q^{-1} + \cdots + c_l q^{-l}$$

$$\begin{cases} \bar{a}_{i,t} = a_i + \Delta a_{i,t} & (i = 1, \cdots, n) \\ \bar{b}_{i,t} = b_i + \Delta b_{i,t} & (i = 0, \cdots, m) \end{cases}$$

where $u(t)$, $y(t)$, and d are the input, the output at time t=1,2,... and the delay time, respectively. $e(t)$ is the white noise. $\bar{A}(q^{-1}, \phi(t))$ and $\bar{B}(q^{-1}, \phi(t))$ are the polynomials of q^{-1}, the backward shift operator. a_i, b_i and $\Delta a_{i,t}, \Delta b_{i,t}$ are the constant and the nonlinear terms of coefficient parameters, respectively. The non-linear terms are expressed by the following non-linear non-parametric models (NNM's) based on the adaptive fuzzy system

$$\begin{cases} \Delta a_{i,t} = f_i(\phi(t)) & (i = 1, \cdots, n) \\ \Delta b_{j,t} = f_{j+n}(\phi(t)) & (j = 1, \cdots, m+1) \end{cases}$$

$$f_i(\phi(t)) = \sum_{j=1}^{M} \omega_{ij} N_f(p_j, \phi(t)) \quad (11)$$
$$(i = 1, 2, \cdots n + m + 1)$$
$$N_f(p_j, \phi(t)) = \frac{\wedge_{k=1}^{r} \mu_{A_k^j}(x_k(t))}{\sum_{j=1}^{M}(\wedge_{k=1}^{r} \mu_{A_k^j}(x_k(t)))}$$

where $N_f(p_j, \phi(t))$'s are the "basic functions", ω_{ij}'s are the coordinate parameters to be estimated, p_j's are the scale and position parameters specifying the basis functions that are to be pre-assigned based on available information about the system dynamics. And $\wedge$ is the minimum operator, M is the number of rule, $x_k(t)$ are the elements of $\phi(t)$, and $\mu_{A_k^j}$ is the membership function of fuzzy set A_k^j. As the identification algorithm to estimate the model parameters which consist of the constant parameters a_i, b_i, c_i and the coefficients ω_{ij} of NNMs, the existing method, e.g., the Prediction Error Method is used. For more details of the Quasi-ARMAX modeling and identification, refer (J.Hu, K.Kumamaru, K.Inoue and K.Hirasawa,1999)

When modeling the super heater system via the Quasi-ARMAX model, the measurement of main steam temperature Te_2 is described with y, and the fuel flow FF is treated as the control input $u(t)$. Besides, it is important issue how to treat the external inputs, SF, PR, and $Entdip$ in the modeling. As is described in Section 2, these inputs might directly influence on non-linearity of system dynamics. Therefore, in Quasi-ARMAX modeling, the external inputs should be effectively embedded into the nonlinear terms of coefficients to describe system non-linearity in detail. Based on these considerations, the following Quasi-ARMAX model is considered to model the super heater system

$$\begin{aligned} \bar{A}(q^{-1}, \phi_x(t))y(t) &= q^{-d}\bar{B}(q^{-1}, \phi_x(t))FF(t) \\ &\quad + C(q^{-1})e(t) \end{aligned} \tag{12}$$

where the regression vector is defined by

$$\begin{aligned} \phi_x(t) = [&y(t-1)\cdots y(t-n) \\ &FF(t-d)\cdots FF(t-d-m) \\ &SF(t-d)\cdots SF(t-d-n_1+1) \\ &PR(t-d)\cdots PR(t-d-n_1+1) \\ &Entdip(t-d)\cdots Entdip(t-d-n_1+1) \quad]^T \end{aligned} \tag{13}$$

4. IDENTIFICATION OF SUPER HEATER SYSTEM

First, identification of super heater system based on ARMAX model is tried under the constant load in order to investigate non-linearity of the system. These loads are set to 6 stages (5%, 10%, 15%, 20%, 25%, 30% MCR). Identification results are shown in Fig.3. This figure shows that MSE is small in higher load than in lower load. MSE is calculated with (14). $y(t)$ and $\hat{y}(t)$ are the output and one-step-ahead predicted value. These phenomenon suggests that non-linearity of the system is stronger in lower load than in higher load.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\{y(t) - \hat{y}(t)\}^2 \tag{14}$$

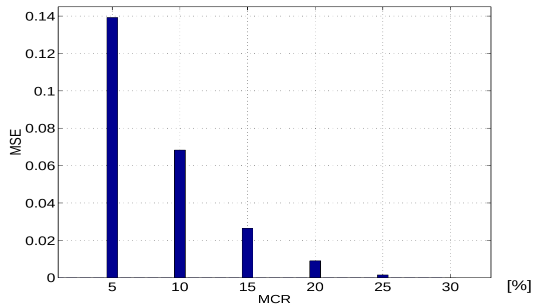

Fig. 3. MSE in identification based on ARMAX model

Next, the identification of the super heater system is executed by using the input-output data obtained during the process of temperature raising from 5%MCR to 30%MCR. Identification is carried out by using ARMAX model and Quasi-ARMAX model in order to compare to identification performance. The identification performance based on the Quasi-ARMAX modeling will strongly depend on the initial estimates of the model parameters, as well as the plant operation modes. In the identification tests, let us consider the following identification scheme.

Scheme

In the first step, perform the identification based on the linear model by using data from the temperature raising process from 5%MCR to 30%MCR. Then the estimates of linear part of parameters in Quasi-ARMAX model, a_i, b_i, c_i are obtained. In the second step, both of linear and nonlinear part of parameters in the Quasi-ARMAX model are re-estimated based on the same input-output data by using the estimation results in the first step as the initial values.

Specifications of the simulation are shown in Table 3.

Table 3. Specifications(identification)

Degree of the model	$n = 3, m = 2, l = 0, n_1 = 1$
Sampling time T(sec)	$T = 30$
The number of data(step)	$N = 200$
Delay time(step)	$d = 1$
The number of fuzzy rules	$M = 16$

Table 4. MSE in identifications

Model	MSE(Mean Square Errors)
ARMAX	2.6188
Quasi-ARMAX	8.6153×10^{-5}

Fig.4 $\sim$ Fig.5 and Table.4 shows the output of system and prediction result by using identified model. (Continuous line is predicted value of Quasi-ARMAX model and broken line is output.) The broken line does not appear in fig.5, since

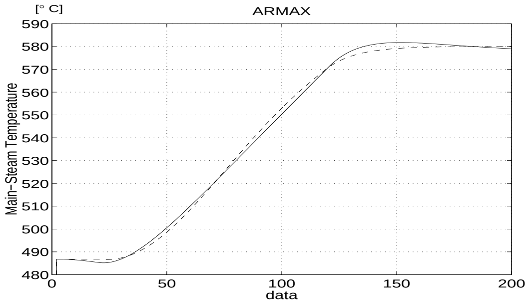

Fig. 4. Identification result based on ARMAX model

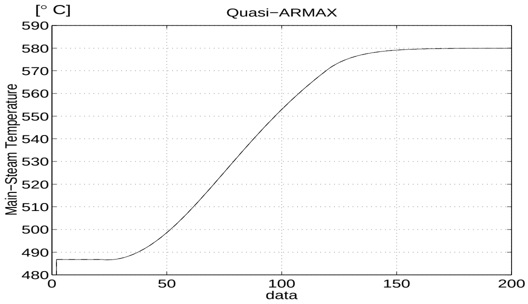

Fig. 5. Identification result based on Quasi-ARMAX model

predicted value is coincident with reference output. Table.4 shows MSE on each model. From the results, we can see that identification performance of Quasi-ARMAX model is superior to that of linear ARMAX model. This means that Quasi-ARMAX model is adapted by adjusting non-linear terms rather than linear ones.

Therefore, in next section, an adaptive control method based on Quasi-ARMAX model is considered.

5. DESIGN OF MAIN-STEAM TEMPERATURE CONTROL SYSTEM

5.1 Control method

Let us consider a minimum variance Self-Tuning-Regulator(STR) (Graham C.Goodwin, Kwai Sang Sin,1984), as the control design method for main-steam temperature raising. It is achieved by minimizing d-step-ahead cost function defined by

$$J(t+d) \quad (15)$$
$$= E\left[\frac{1}{2}\{y(t+d)-y^*(t+d)\}^2+\frac{\lambda}{2}FF^2(t)\right]$$

where $y^*(t+d)$ and λ are the given reference output and the weighting factor for control input $FF(t)$, respectively. The optimal control input $FF(t)$ can be obtained analytically by minimization of (15) w.r.t. $FF(t)$

$$FF(t)=\frac{\bar{\beta}_{0,t}}{\bar{\beta}^2_{0,t}+\lambda}\{y^*(t+d)-\bar{\alpha}(q^{-1},\phi_c(t+d))y(t)$$
$$-q[\bar{\beta}(q^{-1},\phi_c(t+d))-\bar{\beta}_0]FF(t-1)$$
$$+[C(q^{-1})-1]y^\circ(t+d/t)\} \quad (16)$$

In (16), $y^\circ(t+d/t)$ denotes d-step-ahead prediction of $y(t)$ and it subjects to

$$C(q^{-1})y^\circ(t+d/t)=\bar{\alpha}(q^{-1},\phi_c(t+d))y(t)$$
$$+\bar{\beta}(q^{-1},\phi_c(t+d))FF(t) \quad (17)$$

$$\begin{cases}\bar{\alpha}(q^{-1},\phi_c(t)) = \bar{\alpha}_{0,t}+\cdots+\bar{\alpha}_{n-1,t}q^{-(n-1)}\\ \bar{\beta}(q^{-1},\phi_c(t)) = \bar{\beta}_{0,t}+\cdots+\bar{\beta}_{m+d-1,t}q^{-(m+d-1)}\end{cases}$$

$$\begin{cases}\bar{\alpha}_{i,t} = \alpha_i+\Delta\alpha_i(\phi_c(t)) \quad (i=1\cdots n)\\ \bar{\beta}_{j,t} = \beta_j+\Delta\beta_j(\phi_c(t)) \quad (j=1\cdots m+d)\end{cases}$$

where $\phi_c(t+d)$ is constructed by

$$\begin{aligned}\phi_c(t+d) = [&y(t+d-1)\cdots y(t+d-n)\\ &FF(t-1)\cdots FF(t-m)\\ &SF(t)\cdots SF(t-n_1+1)\\ &PR(t)\cdots PR(t-n_1+1)\\ &Entdip(t)\cdots Entdip(t-n_1+1)\ ]^T\end{aligned} \quad (18)$$

Note here that optimal control law (16) can analytically be derived by minimizing the criterion function (15) w.r.t. $FF(t)$, since the vector $\phi_c(t+d)$ does not contain the variable $FF(t)$ in its elements. In order to synthesize adaptive control based on the direct approach, parameters of the predictor model (17), $\bar{\alpha}$, $\bar{\beta}$ are directly estimated by using Quasi-ARMAX modeling and identification. Then the adaptive control of $FF(t)$ is realized, based on the C.E(Certainly Equivalence)principle, by replacing $\bar{\alpha}$, $\bar{\beta}$ and $y^\circ(t+d/t)$ in (16) with their estimates.

5.2 Control simulations

The temperature is raised from 5%MCR to 30%MCR during 50 minutes. Specifications of the simulation are shown in Table 3. Weighting factor $\lambda = 0.001$. For estimation method of the initial values of controller, let us consider the same scheme as in section 4.

The control results are shown in Fig.6. Fig.6 shows the output of system and reference. MSE of output and reference is 0.0144. These results shows that the dip phenomenon is reduced by this method.

Next, let us consider control problems under the mesurement additive noise. It is well known that $FF(FuelFlow)$ and $SF(SteamFlow)$ is influenced by disturbance produced in the supply process. Therefore, the control of the super heater

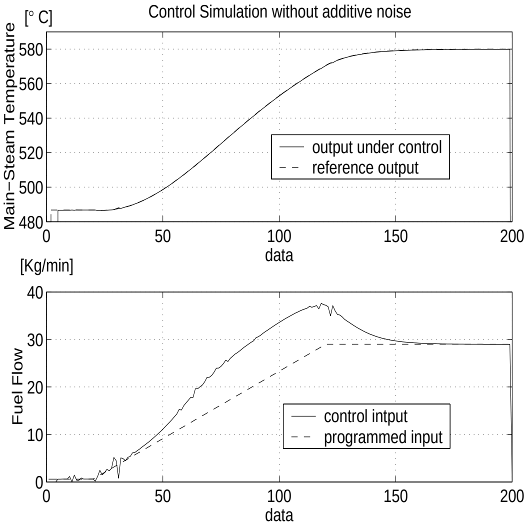

Fig. 6. Control results [upper graph:output lower graph:input]

system is tried under such a stochastic situation. Table.5 shows the noise variance and S/N ratio in the simulation.

Table 5. Specification and results of control simulation

	Specification		Result
	FF Kg/min (S/N)	SF Kg/min (S/N)	MSE
Simu. 1	1 (20)	100 (190)	0.0914
Simu. 2	1 (20)	400 (94)	0.4881
Simu. 3	1 (20)	900 (63)	3.1787

$$\frac{S}{N}\ (dB) = \frac{\sqrt{\frac{1}{N}\sum x^2}}{\sqrt{\sigma^2}} \tag{19}$$

x : signal σ^2 : noise variance

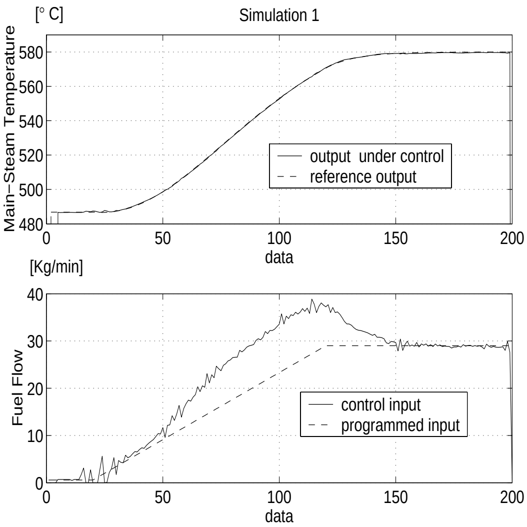

Fig. 7. Control result with additive noise (Simulation 1)

The control results are shown in Fig.7 $\sim$ Fig.8 and Table.5. Table.5 shows MSE on each scheme. These results show that the dip phenomenon is

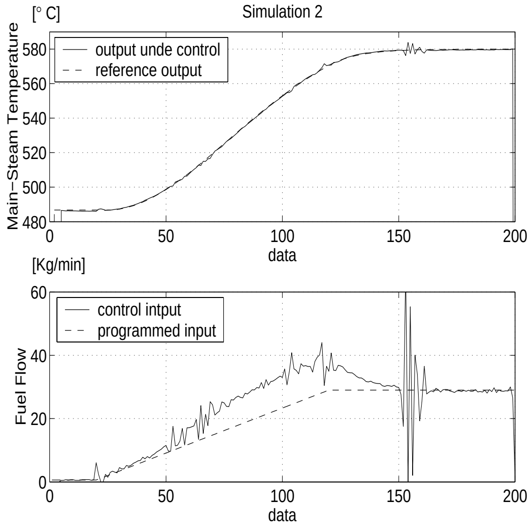

Fig. 8. Control result with additive noise (Simulation 2)

also reduced by this method. But, the control performance deteriorates when the noise variance becomes larger. And the synthesized input is more oscillatory compared with deterministic case.

6. CONCLUSIONS

An appropriate model for the super heater system was constructed based on Quasi-ARMAX model. And its identification tests were executed in order to verify the model validity. Such the modeling and identification could be applied to adaptive control for temperature raising of super heater system. Through the simulation studies, the effectiveness of our method was confirmed under the deterministic case. It was also confirmed that the method can be applied to stochastic case caused by measurement noise with small variance. For more general stochastic case with various disturbance, further investigation on adaptive control method (e.g. sliding mode control) based on Quasi-ARMAX model is under consideration.

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