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Optimal Control of Thermal Power Plants

Application of optimal control system to thermal power plants is introduced. The suggested system consists of the conventional PID controllers and the control computer. It has been successfully applied to five supercritical power plants in Kyushu Electric Power Company (Total output 2,700 MW) since 1978. In the system, system identification or state space representation of the plant is performed based on the AR (Autoregressive) model describing the system dynamics. The optimal controller is designed by the orthodox Dynamic Programming procedure under a quadratic criterion function. In the paper, the procedure of the controller design and the control performance of the system are described with some results obtained both in a power plant simulation model and in the actual plants.

Introduction

In a large capacity high-pressure high-temperature boiler for electric power generation, deviations of steam temperatures at the boiler outlet must be kept within one or two percent of their rated values in order to maintain the nominal operating efficiency and insure the safety and the maximum equipment life of the plant.

The main purpose of the boiler control is to allow the increase or decrease of steam generation as fast as possible in response to the load command from the power system's dispatch center, while satisfying the above-mentioned operating conditions.

However, since a modern thermal power plant usually includes many control loops with significant mutual interactions within the boiler process, it is not easy under the conventional PID controller to fully compensate for these interactions to satisfy the required steam conditions for large and fast changes in plant load.

To solve this problem the authors considered the use of the LQ (Linear Quadratic) regulator to the newly constructed plants.

The first difficulty encountered was how to obtain a state equation representing plant dynamics properly in a rather simple procedure.

The statistical approach using an AR (Autoregressive) model which had been proposed by Akaike [1] and successfully applied to a cement kiln control seemed appropriate for this purpose.

Experimental results using a power plant model confirmed the validity of the statistical approach. After a series of elaborate experiments using various types of power plant simulation models, an optimal control system named ADC (Advanced Digital Control) system [2] by the authors was established.

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The ADC system was first implemented at a 500 MW supercritical constant-pressure plant in Kyushu Electric Power Company in 1978. Since then it has been applied to other three supercritical constant-pressure plants and also to a supercritical variable-pressure plant.

Because of their improved performance of the steam temperature control, these plants are contributing to the LFC (Load Frequency Control) of the company's power system.

In this paper the optimal control system we adopted and the concept of system identification and controller design are introduced briefly. Then the practical procedure of the controller design is explained with some results which were obtained in a power plant simulation model or in actual plants.

Some topics such as the gain coordination between the PID controller and the computer, gain adjustment of the feedforward and feedback control loops, an approach to the gain adjustment of the optimal controller by means of spectral density function, are discussed rather in details.

Finally some field test results demonstrating the fine control performance of the proposed optimal controller are introduced.

Control of a Power Plant

The Nomenclature and Fig. 1 show principal inputs and outputs of the boiler process. When the change in load command (MWD) takes place, manipulation of the boiler input variables are made through feedforward and feedback control loops. Of these control loops, the feedforward loops work to adjust the input variables, such as the governing valve opening (Av), the flue gas damper opening (GD), fuel flow rate (FR), feedwater flow rate (FW), etc., to the values corresponding to the required load (MW).

Since the manipulation of each input variable has influence on more than one output variables in different ways, controlled variables, such as main steam pressure (TP), superheater outlet steam temperature (SHT), reheater outlet steam temperature (RHT), etc., deviate from their set-points.

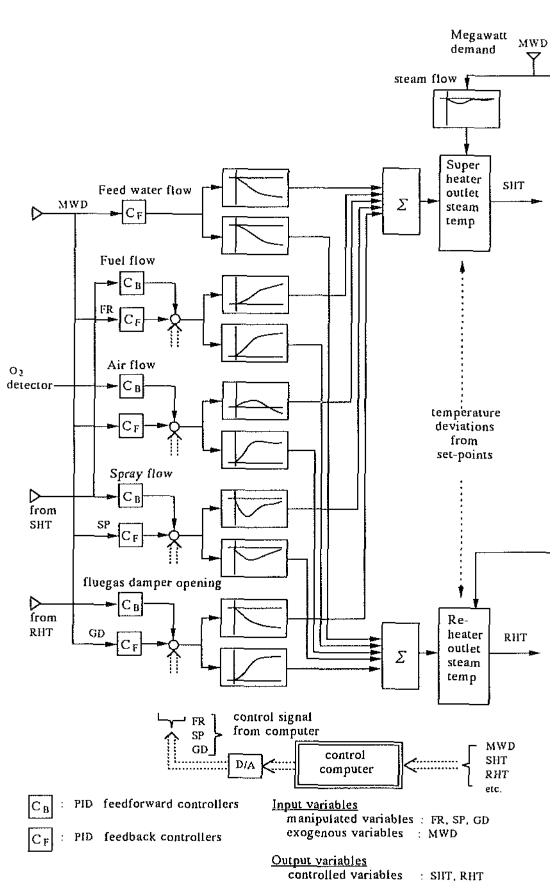


Fig. 1 Configuration of ADC system

To cancel such deviations feedback loops, connecting controlled variables with manipulated variables, adjust boiler inputs so as to achieve final thermal-hydraulic balance in the boiler process. However, as these feedback control loops interact to each other within the boiler process, they form a typical mutually interacting multivariable system. This has been the principal factor that limited load changing rate of the thermal power plants and required the suggested "Advanced Digital Control" system.

From the above discussion, it can be said that the key factor to the boiler control is how to find the optimal coordination of the feedforward and feedback loops, and at the same time how to compensate for the mutual interactions within the process as much as possible.

The Advanced Digital Control (ADC) system to be described in the following section was developed aiming at these points.

In this system the control computer is installed as shown in Fig. 1 and the control signals from the computer are added to those from the PID controller.

Optimal Control System

Figure 1 shows the configuration of the ADC (Advanced Digital Control) system proposed by the authors. As shown in the figure, the plant, consisting of the boiler-turbine process and the conventional PID controller, is regarded as the objective system of the computer control: state variables such as steam temperatures along the boiler tube, and other process variables, if necessary, are taken into the computer; control signals to the manipulated variables, such as the fuel flow rate, spray flow rate, RH fluegas-damper opening, are computed by the algorithm prepared in the computer and added via the D/A converters to the control signals from the PID controller at the summing amplifiers at every control period. It should be noted that MWD is included as a pseudo-state variable.

System Identification and Optimal Controller Design

In the ADC system, the state equation, i.e., the state-space representation of the plant including PID controllers, is derived from the AR model that describes the system dynamics. The data for AR model fitting are obtained from the system identification experiment. In this experiment we stimulate the objective system with pseudo-random test signals via the actuators of the manipulated variables and record the data of the system variables (state variables and test signals) at every equispaced sampling period. Normally five to eight hour data are used for model building.

Then, we fit a multivariate AR model to the vector data series $X(n)$ $(n=1, 2, \ldots, N)$ to obtain

$$X(n) = \sum_{m=1}^{M} A(m)X(n-m) + U(n) \qquad (1)$$

where M denotes the model order determined by AIC (Akaike's Information Criterion) [3].

Here the actual magnitudes M relate to the sampling period, the data length and number of the variables to be used in the AR model building. Their specific values will be given in the later section.

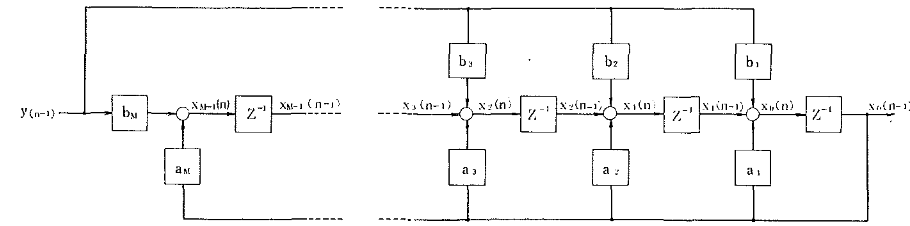
Neglecting the innovation in equation (1) and deviding $X(n)$ into two subvectors, i.e., an r-dimensional state-variable vector $x(n)$ and an l-dimensional manipulated-variable vector

Nomenclature

Av = sectional area of the governor valve
FR = fuel flow rate
FW = feedwater flow rate
GD = opening of the reheater fluegas damper in the rear path of the boiler shell
GM = rpm of the gas-mixing fan
MWC = megawatt command or load command issued from the system's dispatch center to the plant
MWD = megawatt command or load command obtained at the load changing rate setter outlet
SP = flow rate of the superheater spray water
SP1 = primary spray attemperator
SP2 = secondary spray attemperator

Output variables:

MW = generator output power
RHT = reheater outlet steam temperature (deviation from the set-point value)
SHT = superheater outlet steam temperature (deviation from the set-point value)
TP = main steam pressure (deviation from the set-point value)
TPL = platen superheater outlet steam temperature (deviation from the set-point value)
WWT = waterwall outlet fluid temperature (transient deviation from the exponentially smoothed value)



$$\begin{bmatrix} x_0(n) \\ x_1(n) \\ x_2(n) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_{M-1}(n) \end{bmatrix} = \begin{bmatrix} a_1 & I & 0 & 0 & \cdots & 0 \\ a_2 & 0 & I & 0 & & 0 \\ a_3 & 0 & 0 & I & & 0 \\ \cdot & \cdot & \cdot & 0 & \cdot & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \\ \cdot & \cdot & \cdot & \cdot & & I \\ a_M & 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} x_0(n-1) \\ x_1(n-1) \\ x_2(n-1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_{M-1}(n-1) \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ b_M \end{bmatrix} y_{(n-1)} \quad (5)$$

$$x_n = \Phi \cdot x_{(n-1)} + \Gamma y_{(n-1)}$$

Fig. 2 State equation of observable companion form

$y(n)$, we obtain

$$\begin{bmatrix} x(n) \\ y(n) \end{bmatrix} = \sum_{m=1}^{M} \begin{bmatrix} a_m & b_m \\ * & * \end{bmatrix} \begin{bmatrix} x(n-m) \\ y(n-m) \end{bmatrix} \quad (2)$$

where the symbol * expresses submatrix of $A(m)$ irrelevant to the state-variable vector $x(n)$.

From equation (2) we obtain

$$x(n) = a_1 x(n-1) + \ldots + a_M x(n-M) + b_1 y(n-1) + \ldots + b_M y(n-M) \quad (3)$$

then,

$$(I - a_1 Z^{-1} - \ldots - a_M Z^{-M}) x(n) = (b_1 Z^{-1} + \ldots + b_M Z^{-M}) y(n) \quad (4)$$

where Z^{-i} $(i=1, \ldots, M)$ denotes operators that provide the time-delay $i\Delta t$ (Δt is the sampling period). equation (4) leads to equation (5), a state equation shown in Fig. 2, which is commonly called "observable companion form." In equation (5) $x_0(n), x_1(n), \ldots, x_{M-1}(n)$ are state variables shown in Fig. 2.

According to the result obtained at a 600 MW plant, the value of the model order M was ten for seven variable system, sampling interval $\Delta t = 30$ s, maximum data number $N = 840$: for other supercritical once-through plants approximately the same values were obtained.

Once the state equation is obtained in the form of equation (5), then the optimal state-feedback gain matrix is determined by orthodox descrete type Dynamic Programming procedure using equation (5) and the quadratic criterion function defined below [4],

$$J = E \sum_{i=1}^{K} (X'(i)\, Q\, X(i) + Y'(i-1)\, R\, Y(i-1)) \quad (6)$$

where E denotes the statistical expectation, $X(n) = [x_0(n), x_1(n), \ldots, x_{M-1}(n)]'$, Q is a non-negative definite weighting matrix and R is a positive definite weighting matrix.

Preliminary Experiment

System Variables. Selection of proper system variables is important to obtain a suitable state equation. It should be avoided to include in the model more than one state variable that shows similar responses to the change in a certain manipulated variable, because such variables can cause an ill-conditioned property of coefficient matrices in the computation of AR model fitting. In determining the state variable, or in omitting unnecessary state variables relative noise contribution analysis to be described in the later section is helpful. By means of the relative noise contribution analysis minimum number of the state variables that assure controllability are chosen: the appropriateness of the state variables thus chosen is also reviewed by the digital simulation to be described later in which the dynamic characteristics of the state equation composed of such state variables is examined by comparing it with the dynamics of the actual plant.

The fundamental policy for the determination of system variables is as follows:

State Variables. Choose controlled variables such as SHT, RHT, etc., together with other process variables. For the selection of proper state variables by means of noise contribution analysis, many process variables which seem relevant to the dynamics of the control variables, SHT and RHT, are recorded in the computer in the system identification experiment.

Manipulated Variables. Process-input variables, such as FR, SP, GD, GM (control signals from the computer), and other input variables, which affect the controlled variables and are available for the control purpose, are chosen.

In addition to these variables, we usually include MWD in the state variable vector as a pseudo-state variable, in order to use the information of MWD changes that are the largest measurable disturbances to the plant.

Measurement of Plant Dynamics

It is desirable to measure the response of the controlled variables to a stepwise change in each of the manipulated variables and MWD. Such indicial reponse curves are converted into frequency response curves to estimate the approximate frequency ranges necessary for the test signals in the system identification experiment.

Data Acquisition for System Identification

Statistical Properties of the Test Signals. As described before, the vector time series data for AR model fitting are obtained in the system identification experiment. For each test signal to stimulate the system a maximum period sequence (m-sequence), a pseudo-random binary time series, produced in the computer is used after being modified by a digital shaping filter.

The fundamental period of the *m*-sequence and the parameters of the shaping filter for each test signal are determined according to the required frequency ranges which are estimated from the frequency response curves.

Figure 3 is an example illustrating the power spectra of SHT, RHT and the test signals computed from the data of the system identification experiment at a 600 MW plant. Figure 3

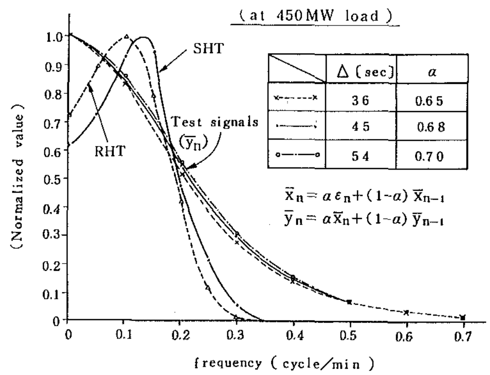


Fig. 3 Power spectra of controlled variables and test signals

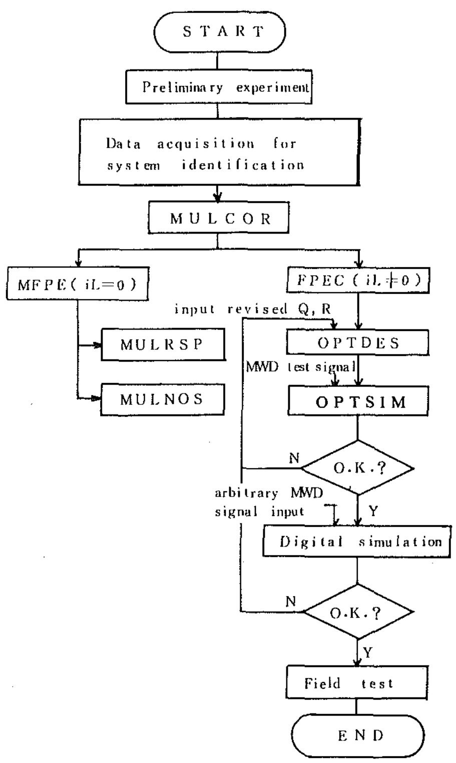


Fig. 4 Procedure for the design of ADC system

shows the results obtained by the program code MULRSP in Fig. 4. In this case a shaping filter consisting of two cascaded first-order-lag digital filters were used with the exponential smoothing factor α. As shown in the figure the values of Δ and α were chosen so that the power of the test signals is concentrated in the frequency ranges where the power of SHT and RHT is significant.

Data Acquisition

In the system identification experiment, test signals produced in the computer are simultaneously applied to the actuators of the MWD and other manipulated variables via D/A converters shown in Fig. 1.

Then, the data of system variables are recorded in the computer for several hours at every equi-spaced time interval, Δt.

The sampling period Δt and the data length differ depending upon the dynamics of the plant. Generally speaking, sampling period of 20 to 40 seconds and data length of 5 to 8 hours give satisfactory results.

Usually, system identification experiments are performed at two or three load levels for the purpose of nonlinearity compensation.

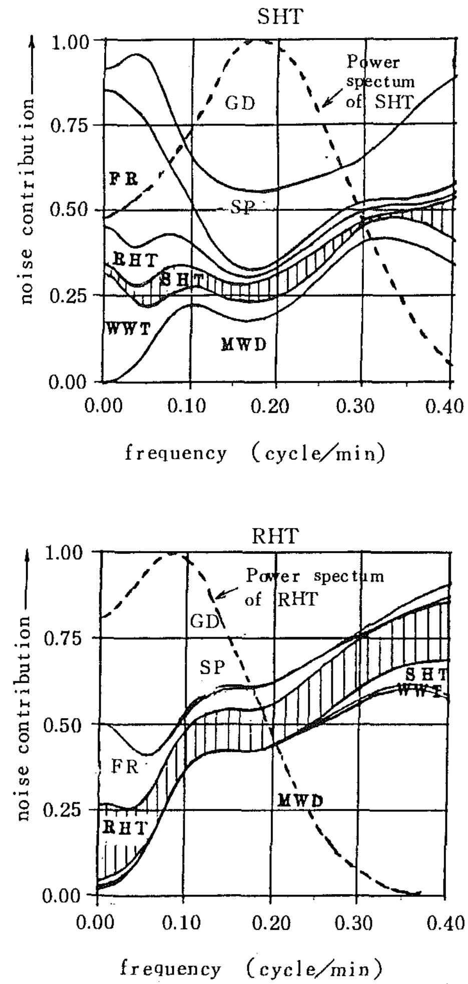


Fig. 5 An example of relative noise contribution analysis

System Analysis and Controller Design

The off-line computation programs for system analysis and controller design are prepared in the plant computer. They consist of the program package named TIMSAC [5] and some modifications or extentions of TIMSAC as shown in Fig. 4.

The functions of each block in Fig. 4 are described below: (For further details please confer the article [2], [5]).

MULCOR: This block calculates the covariance matrices of the system variables from the data obtained in the system identification experiment.

MFPE: Using the covariance matrices, this block computes the coefficient matrices of the multi-variate AR model by solving Yule-Walker equation by Levinson's algorithm [6].

MULRSP: Rational spectral density functions of the multi-variable system are computed in this block by using the coefficient matrices of the AR model and the covariance matrix of the innovation, i.e., the remainder of the AR model fitting. Power spectral density functions of the system variables and cross-spectral density functions between them are obtained.

MULNOS: Assuming the orthogonality between the elements of innovation vector $U(n)$ in equation (1), MULNOS block computes the contribution of the elements of $U(n)$ to the system variables.

Figure 5 shows an example of the relative noise contribution (solid lines) of $U(n)$ to the variance of SHT and RHT. In the figure power spectral density functions of SHT and RHT are also shown in dotted lines. The figure tells that in the variance of SHT, contribution from FR is dominant in low frequency range, while in the frequency range above 0.1 cycle/min contributions of SP, GD, and MWD are significant. It is also observed that manipulation of GD and MWD have quite a large influence on the variance of RHT.

As for state variables, it seems that including WWT in the state variable vector is desirable for the better expression of SHT in the state equation, because contribution of WWT waterwall outlet fluid temperature to SHT is clearly recognized in the lower frequency range.

FPEC: In this block, the state equation is derived through AR model fitting, where the system variables are divided into two subvectors, $x(n)$ and $y(n)$, as described in equation (2) through equation (5).

OPTDES: This block computes the optimal state-feedback gain matrix using Dynamic Programming (D.P.) under the quadratic criterion function. As a result of the D.P. computation a gain matrix with the form of Fig. 6 is obtained.

OPTSIM: In this block validity of the state equation and appropriateness of the state-feedback gain matrix are checked by the digital simulation in the following way:

Checking the state equation: If we wish to evaluate the response curves of the state variables under PID control to a specified change in MWD, we perform state transition using the state equation and replace the MWD element at each step by the specified value of the MWD while keeping the other system inputs zero. Then, the record of the state variables obtained in the state transition process represents the response of the state variables to the specified MWD change. The same procedure applies for the other manipulated variables. By comparing the simulation results with the responses of the actual plant, the validity of the state equation can be verified.

Figure 7 shows a comparison between plant dynamics (solid lines) and the digital simulations (dotted lines) which were obtained for the plant model shown in Fig. 8 in the latter section.

Estimation of control performance: The above-mentioned digital simulation is also used for the adjustment of the state-feedback gain matrix. In this case, in addition to the MWD changes the control signals from $y(n) = G\,X(n)$ in Fig. 6 are provided to the state equation at each step of state transition. The weighting matrices Q and R are adjusted by reviewing both the behavior of the state variables and the amplitudes of the control signals.

In the optimal controller design procedure, D. P. computation and digital simulation are repeatedly performed with revised Q and R at each iteration step, until several candidates of gain matrix for the field test are finally obtained.

Compensation for plant nonlinearity: In order to compensate for the significant nonlinearity of the boiler process, system identification is performed at two or three load levels. In the actual operation, the parameters in the state equation and the state-feedback gain matrix are adjusted at each control time by a linear interpolation between these pairs according to the MWD.

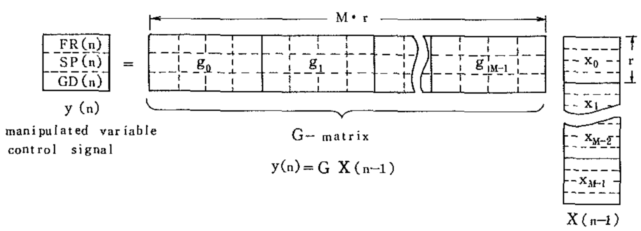


Fig. 6 State-feedback gain matrix G

Preliminary Study on a Plant Model

Prior to implementing the ADC system at an actual plant, it is advisable to have a thorough experimental investigation on

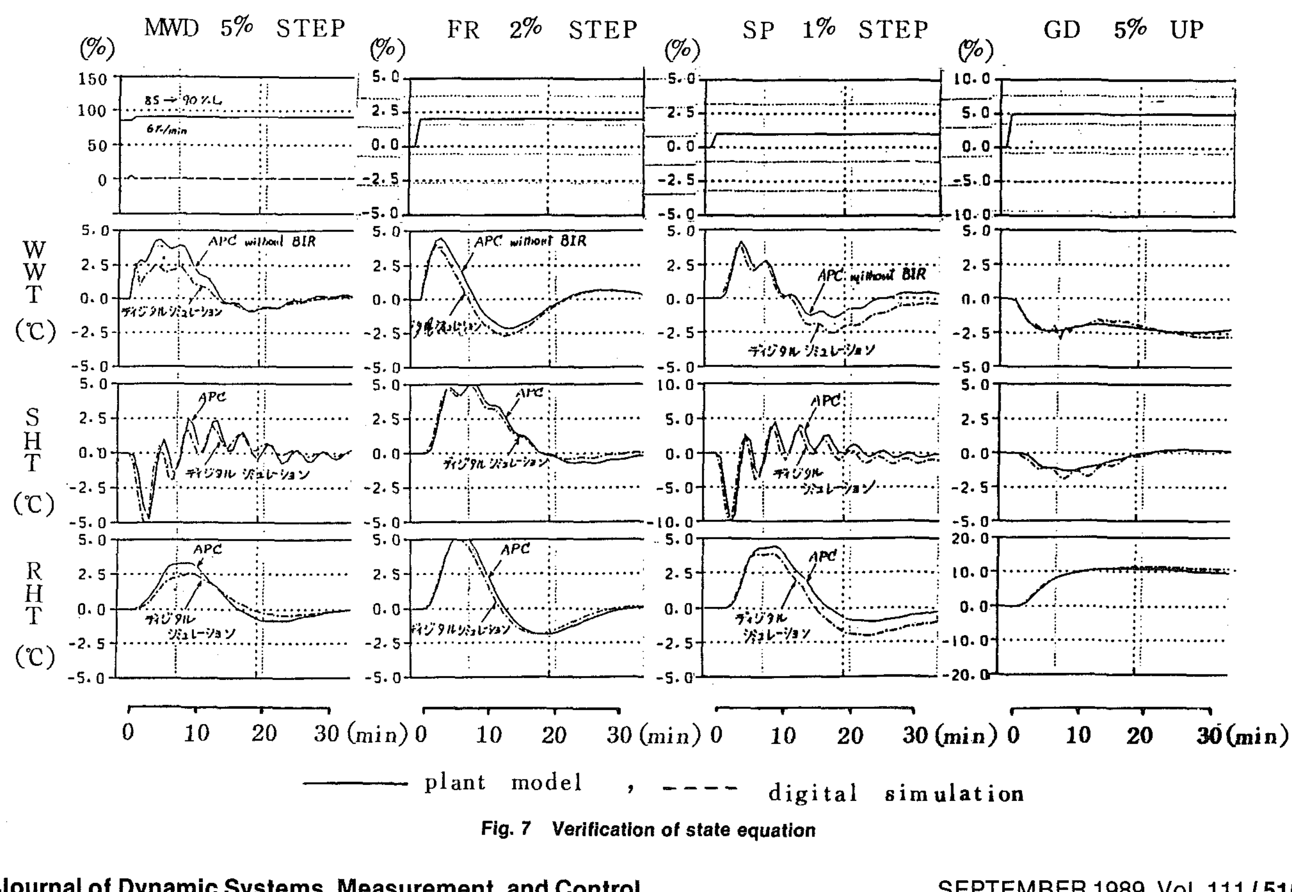


Fig. 7 Verification of state equation

a plant model having the similar dynamics to the actual plant.

The principal items usually being studied are; (1) suitable data sampling period, i.e., the control period from the computer, (2) necessary data length for system identification, (3) statistical properties required for the test signals in the system identification experiment, (4) proper adjustment of the PID controller and the proper coordination between the control signals from the PID controller and the computer, (5) suitable combination of the feedforward and feedback control loop gains of the PID controller, (6) the effect of load-adaptive parameter adjustment, (7) considerations on the nonlinearity of the equipment, such as fluegas dampers, etc.

Some examples obtained in the experiments on a boiler model will be introduced below.

Plant Model

Figure 8 shows the block diagram of the plant model used for the experiment. The simulation model built on a digital computer consists of two main parts: the model of a supercritical variable-pressure boiler-turbine process which was built on the basis of the mass and energy balance, i.e., the conservation law within the process, and the model of the PID controllers similar to those used in the actual plant. The symbol ADC in Fig. 8 shows the actuators from the control computer.

The open-loop and closed-loop dynamics of the plant are shown in Fig. 9 (*a*) and (*b*).

Supply of Feedforward Signals BIR

The heat storage in the boiler-tube metal differs depending upon the boiler load. Therefore, in increasing (decreasing) the boiler load, excessive fuel corresponding to the increment (decrement) of the heat storage in the boiler-tube metal must be added to (subtracted from) the fuel required at each load level. The excessive fuel mostly fed for SHT control has an adverse effect on the RHT control. In order to reduce the adverse effect, fluegas damper control is commonly used simultaneously.

In the steam-temperature control system of a boiler such additional transient control of the fuel and the RH fluegas dampers is performed by means of the feedforward signals called BIR (Boiler Input Rate). Accordingly, finding the proper combination of the fuel BIR and the RH gas damper BIR (FR-BIR and GD-BIR in Fig. 8) is the key factor to the steam-temperature control. Coordination of both BIRs is important especially in the variable-pressure boiler whose fuel BIR is much larger than that of the constant-pressure boiler.

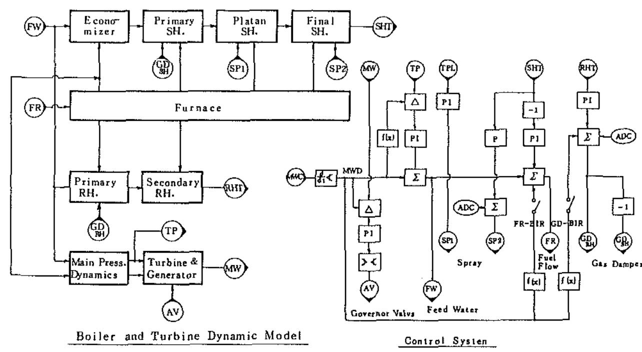
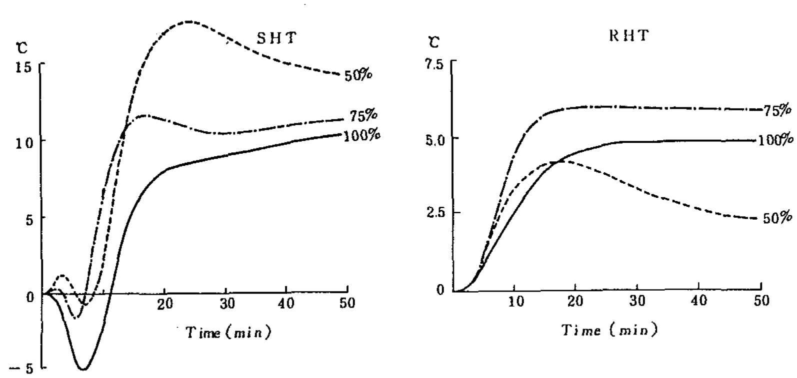
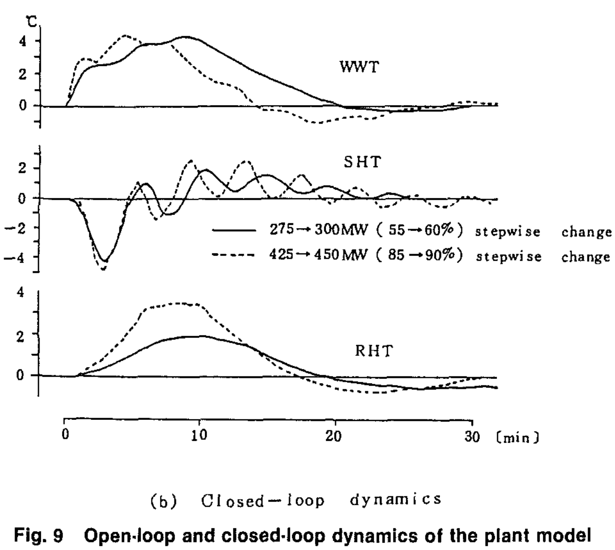


Fig. 8 Variable-pressure plant model used for preliminary study

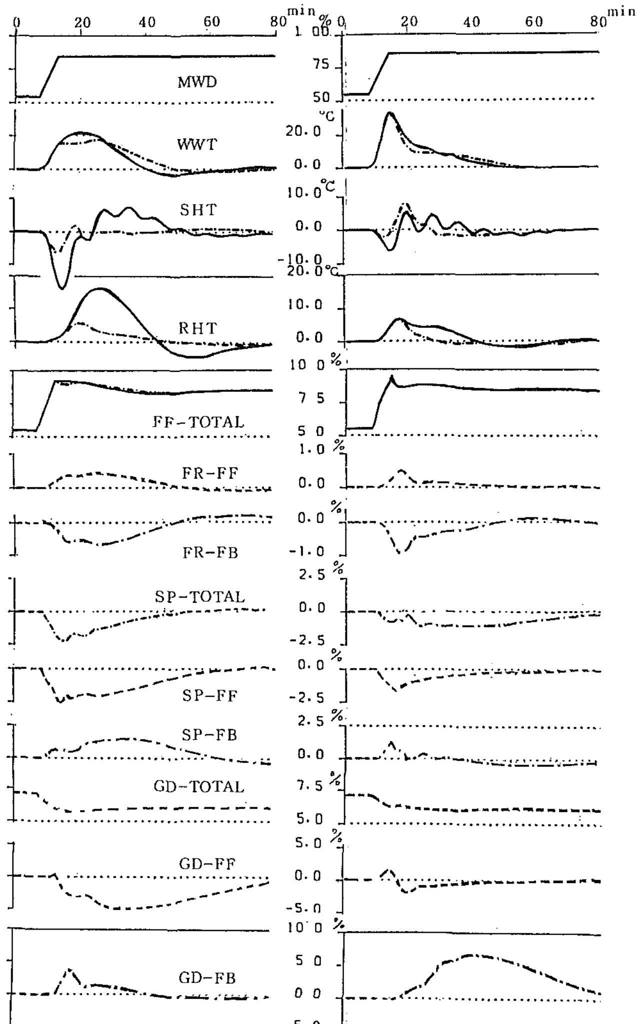


(a) Open—loop dynamics



(b) Closed—loop dynamics

Fig. 9 Open-loop and closed-loop dynamics of the plant model



(a) BIR-OFF (b) BIR-ON

Fig. 10 Comparison of the performance of four systems; PID without BIR, ADC without BIR, PID with BIR, and ADC with BIR

In the system identification and controller design of the ADC system, two ways are possible concerning the BIR; one is to identify the plant with the BIR loops on and to design the optimal controller based on it (hereafter referred to as the ADC system with BIR), and the other is to do the same procedure for the plant with the BIR loops switched-OFF (the ADC system without BIR).

Figure 10 is a result obtained in the plant model shown in Fig. 8. In Fig. 10 is given the behavior of the steam temperatures and the control signals when the plant model is subjected to a rampwise load increase from 55 to 85 percent of its rated output 500 MW.

In the figure four cases are shown, i.e., PID control without BIR, PID control with BIR, and ADC without BIR, and ADC with BIR. The solid lines in the figure show the control performance of the PID controller alone, while the dotted lines the optimal ADC.

As can be seen in Fig. 10, the amplitudes of both steam temperatures and control signals are considerably reduced by the effect of the fuel and the RH gas damper BIRs of the PID controller.

Further improvement in the control error area of the steam temperatures is realized in the ADC regardless of the systems with or without BIR.

Comparison of the ADC without BIR ((*a*) in Fig. 10) and the ADC with BIR ((*b*) in Fig. 10) reveals that the difference between them is hardly recognizable in steam temperatures except WWT. As for WWT, its transient deviation is larger in the ADC with BIR than that without BIR. This is because that in the system with BIR, feedforward signals are mainly supplied from the PID controller, while in the ADC system without BIR, feedforward signals are determined based on the predictions of the process-variables' behavior due to MWD changes.

This fact is clearly seen in the control signals in Fig. 10 (*a*) and (*b*). In the figure, are shown the feedforward signals (with suffix FF) determined from the MWD changes and the feedback signals (with suffix FB) determined from the steam-temperature deviations, together with the sum of the signals from the PID controller and the computer (with the remark, TOTAL). From this figure it is observed that in the ADC system without BIR, the feedforward signals from the computer substitute for the BIR of the PID controller at the initial stage of MWD change, then, the feedback signals work afterwards so as to compensate the effect of the BIR, thus resulting in the almost the same amount of the total control signals as the ADC with BIR. This leads to the conclusion that including MWD as a pseudo-state variable is quite important in the ADC system design. This conclusion was verified by other experiment [9].

From the above discussion, it is said that the ADC system without BIR is preferable. Further experiment revealed that to design the system without BIR and supplement it with a proper amount of BIR at the stage of control was desirable for a better performance of steam temperature control.

Gain Coordination of PID-Controller and Computer

It is advisable for a better control performance of the ADC system to choose the gains of P (Proportional) and D (Derivative) elements except I (Integral) elements in the PID controller to the values lower than those in the usual PID controller, leaving the control for higher frequency ranges to the computer. Especially, high gain of D elements in the feedback controller sometimes causes undamped oscillations within the control system itself or conflict between the control signals from the PID controller and the computer.

As regards the PID controller itself, it is desirable to adjust the gain-setting function generators to compensate as much as possible, for the process nonlinearity due to the load level, so that the plant viewed from the computer, (i.e., the system consisting of the boiler process and the PID controller has roughly linear behavior over the whole ranges of the plant load.

Such consideration not only enables the designer an easier adjustment of the system, but increases robustness of the system against the changes in the process characteristics due to the seasoning of the boiler process or deterioration of the actuators of the manipulated variables, etc.

Another benefit obtained from the proper adjustment of the PID controller is as follows:

As described before, load-adaptive parameter adjustment is adopted in the ADC system, to compensate for the system non-linearity. However, if the changes in the plant dynamics remain within some allowable extent over a wide range of plant load levels, the ADC system with fixed control parameters will work quite effectively.

Figure 11 shows some results varifying this fact. In the figure are shown the control performances for the three ADC systems with fixed control parameters in the state-transition matrices and state-feedback gain matrices, which were identified and designed at three load levels, i.e., 55, 70, and 85 percent of the rated load. The results illustrated that although the system designed for 55 percent load causes slight undamped oscillations at 85 percent load, the other two systems designed at 70 and 85 percent loads show quite a satisfactory control performance in the load range from 55 to 85 percent. This is

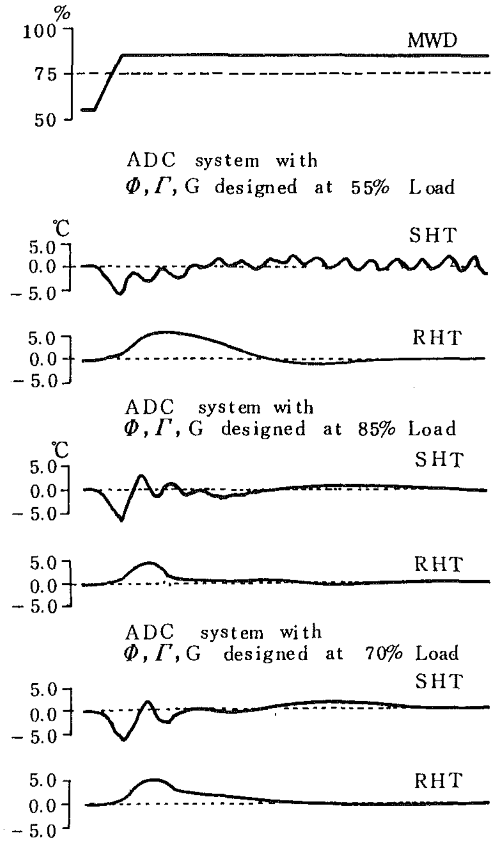


Fig. 11 Control performance of three ADC system with fixed control parameters

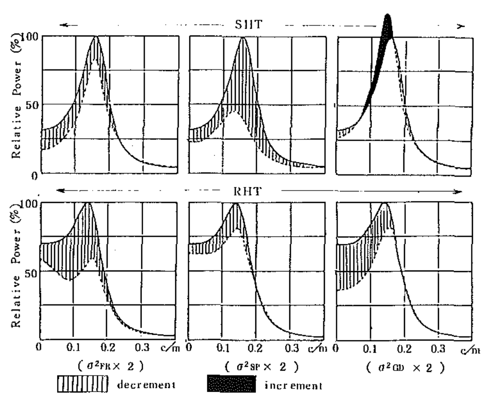


Fig. 12 Influence of each manipulated variable on the power spectra of SHT and RHT

true for both the rampwise increase and decrease of plant load.

The plant used in this experiment has the open-loop and closed-loop dynamics as shown in Fig. 9 (*a*), and (*b*) in the previous section. As can be seen in Fig. 9 the plant having quite different open-loop dynamics (Fig. 9(*a*)) has been brought to have nearly similar closed-loop response (Fig. 9 (*b*)) to the stepwise load change both at 55 and 85 percent load levels. This is the principal reason that made the fixed parameter system effective.

Adjustment of the Weighting Matrices Q and R

The most elaborate part in the optimal controller design is the proper choice of the coefficients in the weighting matrices Q and R in equation (6). The following is an approach to this problem:

(1) The coefficient in Q corresponding to MWD is put to zero to permit the free movement of MWD, because MWD is an exogenous state variable to be treated as a pseudo-state variable which is uncontrollable at the plant.

(2) Obtain the state-feedback gain matrix by the D.P. computation with proper initial values of the elements in Q and R.

(3) Perform digital simulation of the optimal control using specified random input of MWD and record the data of the system variables.

(4) From the record of the simulation data, compute the power spectra of the controlled variables and the variance of the manipulated variables.

Figure 12 shows an example of the power spectral density function of SHT and RHT under optimal control which was obtained from the simulation record using the data of a 600 MW plant.

In the figure the solid lines show the power spectra corresponding to a prescribed set of Q and R, and the dotted lines are those corresponding to the system with one of the three manipulated variables increased from the original value by two times in variance, keeping the other two to the prescribed variances. The method [7] using the iteration of D.P. computation and digital simulation is available to find a proper pair of Q and R that provide desired variances of manipulated variables.

The results indicate that increasing FR gain is favorable for reducing the deviations of both SHT and RHT, and that increasing GD gain has a favorable effect on RHT, but an adverse effect on SHT. It is also observed that increasing SP gain is effective for SHT control especially in the lower frequency range with no adverse effect on RHT control.

Such results provide useful information for the systematic determination of the coefficients in Q and R.

Field Test Results

The ADC system can be applied to the once-through constant-pressure and the variable-pressure boilers, drum-type

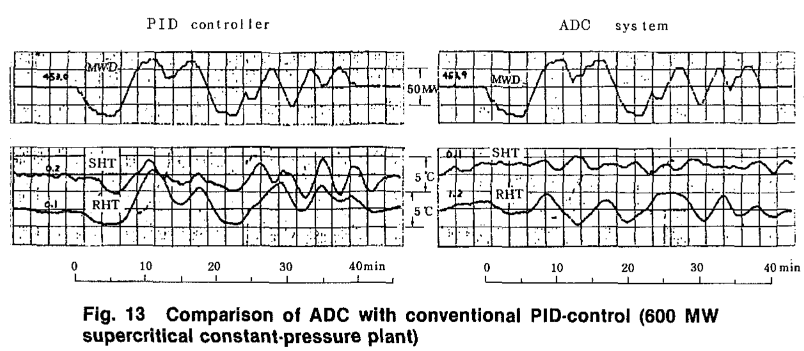


Fig. 13 Comparison of ADC with conventional PID-control (600 MW supercritical constant-pressure plant)

boilers, etc. As a rule, finer tuning of the PID controller is required for the variable-pressure boiler than for the constant-pressure boiler to compensate for the system non-linearities.

Some results obtained in the actual plants will be introduced below.

600 MW Supercritical Constant-Pressure Plant

In Fig. 13 the control performance of the ADC system is compared with that of the conventional PID controller. In this plant, significant hysteresis characteristic was recognized in the RH gasdamper (shown in Fig. 14) at the stage of PID controller tuning. The computer control was applied after the hysteresis was reduced.

In this experiment, MWD, the largest disturbance to the plant, was manipulated by the plant computer so as to provide an identical pattern of MWD change for both the PID controller and the ADC system. As can be seen in Fig. 13 the fluctuations of SHT and RHT are remarkably reduced by the adoption of ADC system.

500 MW Supercritical Constant-Pressure Plant

A new feedforward control system named ADC-ARLP system was proposed by M. Uchida and others [8], in which feedforward control signals substituting for BIRs of the PID controller are determined by the application of Linear Programming (LP). The optimal control ADC is applied to the plant operating under the PID controller and feedforward control signals composed by LP in the computer.

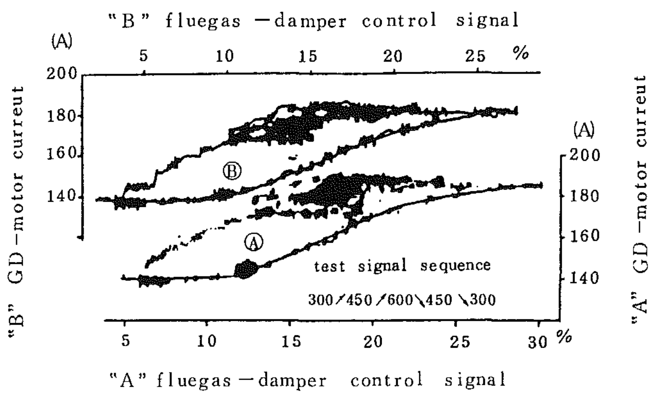


Fig. 14 Hysterisis in the fluegas damper

Figure 15 shows a record of the plant in routine operation under the load command from the power system's dispatch center. In the figure the control system is switched from the conventional PID controller to the above-mentioned ADC at the time point shown with arrows. Considerable improvement of the control performance by means of the optimal control is clearly observed in the figure.

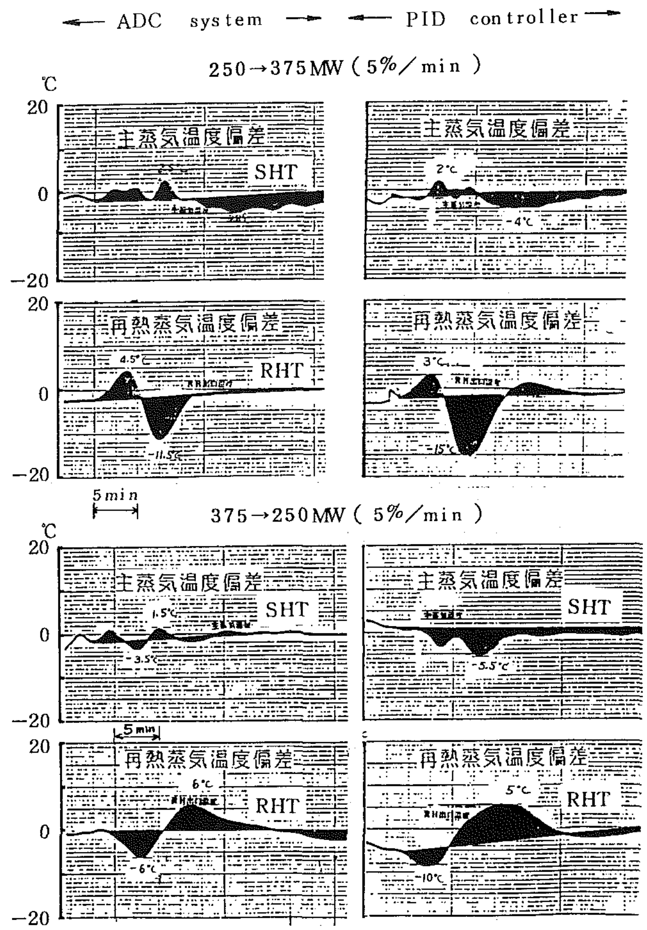


Fig. 16 Comparison of ADC with conventional PID-control (500 MW supercritical variable-pressure plant)

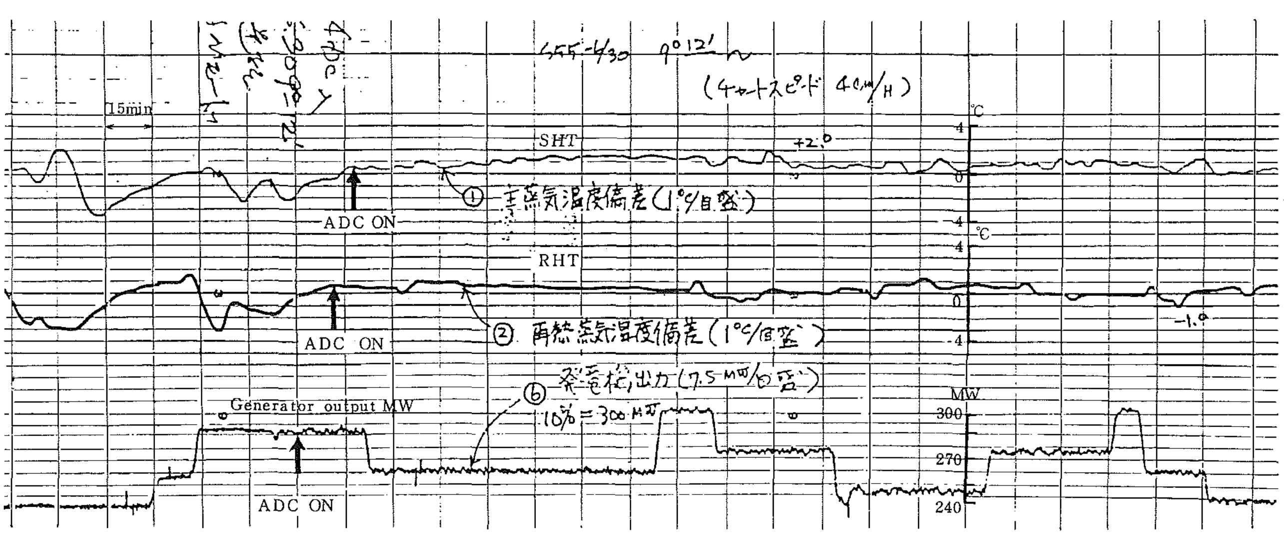


Fig. 15 Control performance of the ADC (ARLP) system (500 MW supercritical constant-pressure plant)

500 MW Supercritical Variable-Pressure Plant [9]

After a series of elaborate preliminary studies, the ADC system was applied to a 500 MW supercritical variable-pressure plant. Figure 16 shows the results obtained in the field test in which the control performance of the ADC system against a rampwise load change was compared with those of the conventional PID controller.

The effectiveness of ADC system can be proved even for the variable-pressure plant.

Conclusion

The optimal control system ADC introduced in this paper has been in routine operation since 1978. Since its first implementation at a 500 MW supercritical plant, the ADC system has experienced no trouble. Operating experiences during these several years have revealed outstanding features of the system as described below:

Stability: By the adoption of the ADC system, the resultant behavior of the plant becomes quite calm even in the LFC operation when the plant is often subjected to a large, quick, frequent load change. Such effect is realized by the substantial property of the LQ (Linear Quadratic) controller which aims to bring the deviations of the process variables back to their specified values by eliminating mutual interference beteen the process variables.

Robustness: As a rule, implementation of the ADC system is performed at the final stage of the plant construction. In spite of the gradual change in process dynamics due to the seasoning effect of the boiler, fouling and slagging of boiler tubes, the change of the fuel mixing rate, the deterioration of the actuators, etc., no plant has ever necessitated readjustment of the control parameters. This fact clearly demonstrates the robustness of the ADC system.

Another feature that should be emphasized is the simplicity of the design and maintenances of the ADC system. Since all the programs required for the system identification and controller design are stored in the plant computer, even a plant engineer, if he has some knowledge on the system, can perform the design and maintenance work with the help of the instruction manual. This is an important point to transfer the technique for generations and improve it.

Although more than twenty years have past since the completion of the optimal control theory, its application to the actual industrial processes seems to be rather small in number. According to the authors' experience the largest problem preventing the application of modern control theory is how to express the system properly in a rather simple way. As described in the paper, if we perform controller design with deliberate consideration under suitable preparation, the statistical approach will offer quite a practical means in realizing optimal control not only in the power plants but in other industrial processes.

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