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WAVELET-BASED IDENTIFICATION FOR CONTROL OF WATER-TUBE DRUM BOILER

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Abstract: The procedure for identifying linear time-varying systems with dead times by using the wavelet analysis has been already proposed by the authors. This paper reports an extension of the identification procedure to MIMO systems and its application to actual control systems of water-tube drum boiler in a thermal power plant. The control systems are required to supply steadily high-quality steam against disturbances due to unexpected changes in load. Therefore, it is necessary to make a model which can take the disturbances into consideration for control system design. The transfer function models identified in stationary and non-stationary states are evaluated by the prediction errors in the process outputs; steam-pressure and water-level, in comparison with an ARX model.

Keywords: Wavelet-based system identification, time-varying systems, input-dependent linear systems, MIMO systems, dead time, MSE, water-tube drum boiler, thermal power station

1. INTRODUCTON

It cannot goes without saying that the PID control is useful in practical industrial processes. But, the necessity of modeling with consideration of the non-linearity due to their operating conditions and that of designing model-based control systems are pointed out so as to realize the better control performance over a wide frequency range (Toyoda and Wada, 1999). As a practical countermeasure for building a model which covers a wide frequency range, we might better to utilize an input-dependent linear model or time-varying linear model closely related to operating conditions of the plant.

On the other hand, we proposed a method for identifying continuous-time systems with dead times by using the wavelet transform. In this paper, we apply this wavelet-based identification procedure for estimating dead times (Tabaru and Shin, 2000) and time-varying parameters (Nakano, *et al.*, 1997, 1999) to real water-tube drum boiler control systems in a power station. This boiler process is of the same type for cogeneration whose control system is for steadily supplying high-quality steam against load changes, *i.e.*, steam demands. Therefore, it is necessary to build a model with consideration of load changes and design model-based control systems.

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The proposed method is composed of two parts : one is for estimating the dead times, and the other for estimating the frequency responses. The dead time estimate is obtained from the phase component of the cross-spectrum based on the wavelet transform of the correlation function of input/output (I/O) of the process (Tabaru and Shin, 2000), and is independent of the parameter estimates in the rational parts (the transfer functions without the dead times). The frequency response estimation is based on the Blackman-Tukey method, and is calculated by using the wavelet transform, considered as a kind of Short-Time Fourier Transform (STFT), of the correlation functions of the process I/O (Nakano, *et al.*, 1997, 1999). This procedure makes it possible to identify the time-frequency characteristics of drum boiler control systems with load changes – steam-flow, etc. In this study, we extend the method for single-input/single-output (SISO) systems so as to apply to water-tube drum boiler control systems of two-input/two-output systems with feedback loops for regulating the steam-pressure and the water-level. For this purpose, we utilize M-sequence signals as the biases for fuel-flow and water-supply for exciting the systems, by which the closed-loop systems can be identified. Finally, the identified time-varying transfer functions in the boiler control systems are evaluated in terms of mean square errors (MSEs) between the actual outputs and the model-predicted outputs in comparison with an Auto-Regressive with eXogenous (ARX) model.

2. IDENTIFICATION BY USING CONTINUOUS WAVELET TRANSFORM

2.1 System Representation

The process characteristics to be identified are assumed to be of constant or slowly time-varying. In other words, the process is assumed to be stationary in a short time span. When this assumption is hold in $[t_1, t_2]$, the transfer function $G(s)$ between the input $u(t)$ and the output $x(t)$ is described by

$$G(s) = G_r(s)\exp(-Ls), \qquad T = [t_1, t_2] \quad (1)$$

where $G_r(s)$ is the rational function, and the process output $y(t)$ is measured with the noise $e(t)$ independent of the input.

2.2 Relation between Wavelet Transform and FD-STFT

Consider the following analyzing wavelet :

$$\psi(t) = h(t)\exp(j\omega_p t) \quad (2)$$

where $h(t) \in L^2(\mathbf{R})$ is the real function – a kind of window function whose center is located at the origin. If $h(t)$ is defined in a sufficiently wider domain than $|2\pi/\omega_p|$, $\psi(t)$ is approximately satisfied with the admissibility condition. Using such kind of analyzing function, the wavelet transform of $f(t)$ is written as

$$\begin{aligned}&\tilde{F}(a, b') \\ &= \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}h\left(\frac{t-b'}{a}\right)\exp\left(-j\omega_p\frac{t-b'}{a}\right)dt \\ &= \exp\left(j\omega_p\frac{b'}{a}\right)\int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}h\left(\frac{t-b'}{a}\right) \\ &\cdot\exp\left(-j\omega_p\frac{t}{a}\right)dt \quad (3)\end{aligned}$$

Defining $\omega = \omega_p/a$, the above is rewritten by

$$\begin{aligned}\tilde{F}(a, b') = \exp(j\omega b')\sqrt{\frac{\omega}{\omega_p}}\int_{-\infty}^{\infty} f(t)h\left(\frac{\omega(t-b')}{\omega_p}\right) \\ \cdot\exp(-j\omega t)dt \quad (4)\end{aligned}$$

This equation is regarded as a Frequency-Dependent Short-Time Fourier Transform (FD-STFT) around b'. Defining the FD-STFT around b'

$$\hat{F}(\omega, b') = \int_{-\infty}^{\infty} f(t)h\left(\frac{\omega(t-b')}{\omega_p}\right)\exp(-j\omega t)dt,$$

we obtain the following relation :

$$\hat{F}(\omega, b') = \sqrt{\frac{\omega_p}{\omega}}\frac{\tilde{F}(a, b')}{\exp(j\omega b')} \quad (5)$$

2.3 Frequency Response Estimation

The finite-data, auto- and cross-correlation functions $\phi_{uu}(\tau; b)$ and $\phi_{uy}(\tau; b)$ around b are defined respectively as

$$\phi_{uu}(\tau; b) = \frac{1}{T}\int_{b-\frac{T}{2}}^{b+\frac{T}{2}} u(t)u(t+\tau)dt \quad (6)$$

$$\phi_{uy}(\tau; b) = \frac{1}{T}\int_{b-\frac{T}{2}}^{b+\frac{T}{2}} u(t)y(t+\tau)dt \quad (7)$$

Taking the Fourier transforms of $\phi_{uu}(\tau; b)$ and $\phi_{uy}(\tau; b)$ using the FD windows in **2.2**, we can get

$$\hat{\Phi}_{uu}(\omega, b'; b) = \int_{-\infty}^{\infty} \phi_{uu}(\tau; b)h\left(\frac{\omega(\tau-b')}{\omega_p}\right)$$

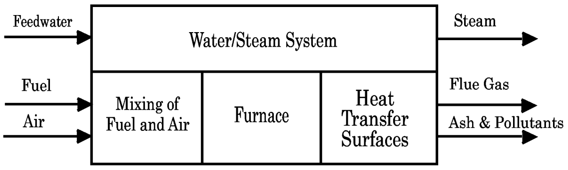


Fig. 1. Fundamental configuration of boiler systems

$$\cdot \exp(-j\omega\tau)d\tau \qquad (8)$$

$$\hat{\Phi}_{uy}(\omega, b'; b) = \int_{-\infty}^{\infty} \phi_{uy}(\tau; b) h\left(\frac{\omega(\tau - b')}{\omega_p}\right) \cdot \exp(-j\omega\tau)d\tau \qquad (9)$$

These equations correspond to the power- and cross-spectra around b using the FD window functions of $b' = 0$. The spectra are rewritten by using the relation (5) and the FD-STFT as follows :

$$\hat{\Phi}_{uu}(\omega, 0; b) = \sqrt{\frac{\omega_p}{\omega}} \tilde{\Phi}_{uu}(a, 0; b) \qquad (10)$$

$$\hat{\Phi}_{uy}(\omega, 0; b) = \sqrt{\frac{\omega_p}{\omega}} \tilde{\Phi}_{uy}(a, 0; b) \qquad (11)$$

Considering the independence of the noise $e(t)$, we have an estimate of the transfer function $G(j\omega, b)$ around b :

$$\hat{G}_r(j\omega, b) = \frac{\tilde{\Phi}_{uy}(\omega, 0; b)}{\tilde{\Phi}_{uu}(\omega, 0; b)} \qquad (12)$$

When the dead time L between u and y is already estimated (Tabaru and Shin, 2000), the estimate of the transfer function is

$$\hat{G}(j\omega, b) = \frac{\tilde{\Phi}_{uy}(\omega, 0; b + L)}{\tilde{\Phi}_{uu}(\omega, 0; b)} \qquad (13)$$

Using the analyzing wavelet located locally in $[\omega_l, \omega_h]$, $\hat{G}(j\omega; b)$ is the frequency response around ω_p, measured by the spectra from the Fourier transfroms with a FD window $[\omega_l/a, \omega_h/a]$. If the I/O relation is time-invariant, the estimate of the transfer function might be time-invariant in $b \in [0, +\infty)$. From this characteristic, the frequency response of $G(s)$ is estimated by time-averaging of $\hat{G}(j\omega; b)$ with respect to b.

3. IDENTIFICATION OF BOILER SYSTEMS

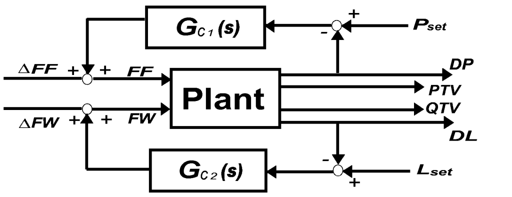
3.1 Outline of Controlled Object

Steam generators are used in both large-scaled fossil- and nuclear-fuel electric generating power plants and also used in small-scaled fossil-fuel power plants such as IPP(Independent Power Producer). A term *boiler* here is used to mean the steam generator where saturated liquid is converted to saturated or superheated steam. As shown in Fig. 1, a boiler has a furnace and heat transfer surfaces and also has steam/water system, mixing of fuel and air/flue gas system, which are independent of each other. Inputs to a boiler are feedwater, fuel and air, while outputs are steam, flue gas, ash and pollutants. Boiler control systems are normally multivariable with the control loops for fuel, air and feedwater interacting in the overall system. The boiler control system is the vehicle through which the boiler energy and mass balances are managed. All the boiler major energy inputs and mass inputs must be regulated in order to achieve the desired output conditions. In the following analysis, we used the small-scaled water-tube drum boiler systems for supplying steam as heat sources for electric generating power plant. Nowadays the boiler in study widely used for IPP, and is suitable for feasibility study. The boiler for IPP, which is used for supplying the power and high-quality process steam, should be required to follow quickly to the load demand during allowable time period based on the sales contract between the electric power company and the IPP vendor. Furthermore, when considering the optimal operation mode for minimizing fuel cost, we may alternate the existing PID controllers with the model-based controllers or the model-based controllers instead of the PID controllers.

3.2 Purpose of Identification and Representation of Control Systems

The problems to be solved in the control of water-tube drum boiler process are in the inverse response in water-level when the feedwater-flow is rapidly increasing and water-level variation due to swell and compression of fluid when the steam-pressure is rapidly changing (Shinskey, 1979 ; Åström, *et al* ., 2000). The aim of control is to regulate constant values of steam-temperature, steam-pressure and water-level against power and steam demands. As to the nonlinearity in dynamics of boiler process, the boiler dynamics is changeable due to the steam-flow, etc (Toyoda and Wada, 1999). In order to realize a model-based control applicable to a wide operation range, we consider to approximate the process dynamics by an *input-dependent linear model* for applying the linear control theory. In the construction of model-based control systems, there are two cases : one is constructed by replacing with existing PID controllers, and the other is done by equipping parallel to the existing controllers. The latter corresponds to identify closed-loop control systems. We cannot say any more which case is better. But, we chose the latter from the viewpoint of integrity of control systems.

In the systems, the steam-flow QTV and the



ΔFF : Fuel Flow Bias Signal (M Sequence)
ΔFW : Feedwater Flow Bias Signal (M Sqeuense)
FF : Fuel Flow Demand Signal
FW : Feedwater Flow Demand Signal
DP : Steam Pressure in Steam Drum
DL : Water Level in Steam Drum
QTV : Boiler Outlet Steam Flow
PTV : Boiler Outlet Steam Pressure
$Pset$: Steam Pressure Setpoint
$Lset$: Water Level Setpoint

Fig. 2. Drum-boiler distributed control systems

steam-pressure PTV are regarded as the load disturbances. and the steam-pressure DP is controlled by the fuel flow FF, the water-level DL is done by the feedwater flow FW. We intend to regulate the steam-pressure and water-level at the setpoints under various load disturbances. We consider to build a model in the linear framework with the following specifications :

(1) Precise estimation of the dead times,
(2) Countermeasure against load disturbances,
(3) Modeling in the frequency domain for control.

The control systems for the small-scaled boiler in the power station is shown as Fig. 2, where G_{c_1} and G_{c_2} are the PI controllers in the following forms :

$$G_{c_1}(s) = \frac{120s+1}{30s} \tag{14}$$

$$G_{c_2}(s) = \begin{cases} 0.3 \cdot \dfrac{120s+1}{30s} & (|DL| < 25[\mathrm{mm}]) \\ \dfrac{120s+1}{30s} & (\mathrm{otherwise}) \end{cases} \tag{15}$$

The steam-pressure is controlled by the command of fuel-valve opening, and the water-level is done by that of feedwater-valve opening through each PI controller. The steam flow is regulated by the steam control valve, and is regarded as load-variation factor in the boiler control systems.

Defining such load disturbances as $\boldsymbol{w} = [QTV\ PTV]^T$ (T : transpose), we give the I/O relation of the systems which should be identified in the following form :

$$\begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} G_{11}(s;w) & G_{12}(s;w) \\ G_{21}(s;w) & G_{22}(s;w) \end{bmatrix} \cdot \begin{bmatrix} u_1(t) \\ u_2(t) \end{bmatrix} \tag{16}$$

where the I/O is defined as $\boldsymbol{u}=[FF\ FW]^T$ and $\boldsymbol{y}=[DP\ DL]^T$.

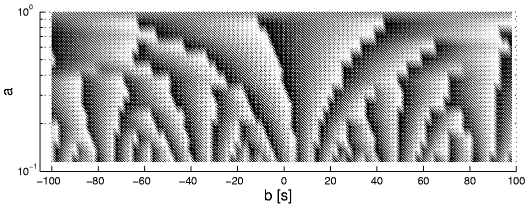


Fig. 3. Estimation of dead time ($\Delta FF - DP$)

3.3 Estimation of Dead Time and Time-Frequency Characteristics

Using the M sequence signals $\Delta FF(= m_1)$ and $\Delta FW(= m_2)$, we make the systems excited. The specs are pre-determined from the frequency characteristics of the plant and M sequences, and the identification time. For identifying G_{11} to G_{22}, the data ΔFF, $FF(= u_1)$, $DP(= y_1)$, ΔFW, $FW(= u_2)$ and $DL(= y_2)$ are collected with the sampling period 1[s]. We estimate the dead times and the dynamics (rational function) using the 9000 I/O-data length. First of all, we have to remove the noise (small variation of water-level due to swell and compression of the fluid) which exists in a high frequency band by using the FIR filter with linear phase characteristic. We carried out the pre-filtering of the data with the cut-off frequency 0.019[rad/s].

We used the following Gabor function (Tabaru and Shin, 2000) with the best locality and the minimum uncertainty in the time-frequency domain :

$$\psi(t) = \frac{1}{\pi^{\frac{1}{4}}}\sqrt{\frac{\omega_p}{\gamma}} \exp\left(-\frac{\omega_p^2}{2\gamma^2}t^2\right) \exp(j\omega_p t) \tag{17}$$

where ω_p is the central frequency, and γ is the parameter related to the locality in the time-frequency domain. The selection of these parameters ω_p and γ is made from the power spectra of output measurements. Here, the parameters in the analyzing wavelet are selected as $\omega_p = 0.1$ and $\gamma = 2\pi$, and $\omega_p = 0.0112$ and $\gamma = 2.5\pi$ in the estimations of the dead time and the rational function of $G_{11}(s)$, respectively. The estimation of the dead time between ($\Delta FF - DP$) is shown as in Fig. 3.

Fig. 3 shows the wavelet transform of the phase component of the cross-spectrum by means of the gradation method. As $a \to 0$, the contour converges to one point on the time axis. This fact shows that the dead time is about 8 [s]. Fig. 4 shows the estimate of frequency responses (gain characteristics) of $|G_{11}|$ at every b explained in *2.3*.

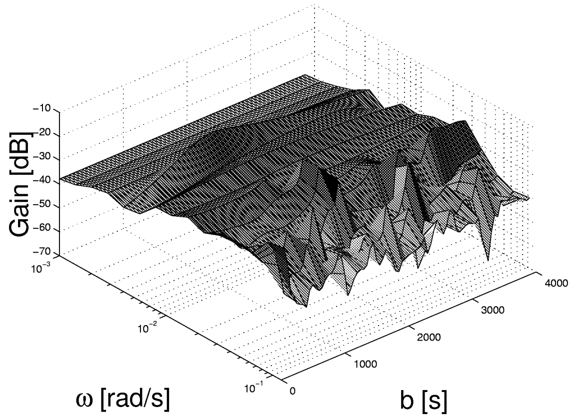


Fig. 4. Estimation of time-frequency characteristics of $|G_{11}|$

3.4 Estimation of Boiler Transfer Functions

In the feedback loop as shown in Fig. 2, considering the disturbance $\boldsymbol{w}$=$[QTV \;\; PTV]^T$ as a constant and setting $P_{set} = 0$ and $L_{set} = 0$, we get the following :

$$u_1(t) = m_1(t) - G_{c1}(s)y_1(t) \qquad (18)$$
$$u_2(t) = m_2(t) - G_{c2}(s)y_2(t) \qquad (19)$$

Substituting these (18) and (19) into (16), we can have the cross-correlation function $\phi_{m_1y_1}(\tau)$. Based on its wavelet transform, we have the relation

$$\tilde{\Phi}_{m_1y_1} = \hat{G}_{11}(\tilde{\Phi}_{m_1m_1} - G_{c1}\tilde{\Phi}_{m_1y_1}) + \hat{G}_{12}(\tilde{\Phi}_{m_1m_2} - G_{c2}\tilde{\Phi}_{m_1y_2}) \qquad (20)$$

As to the other cross-correlation functions $\phi_{m_1y_2}(\tau)$, $\phi_{m_2y_1}(\tau)$ and $\phi_{m_2y_2}(\tau)$, we have the same relations

$$\begin{bmatrix} \tilde{\Phi}_{m_1y_1} & \tilde{\Phi}_{m_2y_1} \\ \tilde{\Phi}_{m_1y_2} & \tilde{\Phi}_{m_2y_2} \end{bmatrix} = \begin{bmatrix} \hat{G}_{11} & \hat{G}_{12} \\ \hat{G}_{21} & \hat{G}_{22} \end{bmatrix} \cdot \begin{bmatrix} \tilde{\Phi}_{m_1m_1} - G_{c1}\tilde{\Phi}_{m_1y_1} & -G_{c1}\tilde{\Phi}_{m_2y_1} \\ -G_{c2}\tilde{\Phi}_{m_1y_2} & \tilde{\Phi}_{m_2m_2} - G_{c2}\tilde{\Phi}_{m_2y_2} \end{bmatrix}$$

with the abbreviated form

$$\tilde{\Phi}_{MY} = \hat{G}(\tilde{\Phi}_{MM} - G_c\tilde{\Phi}_{MY}) \qquad (21)$$

This leads to

$$\hat{G} = \tilde{\Phi}_{MY}(\tilde{\Phi}_{MM} - G_c\tilde{\Phi}_{MY})^{-1} \qquad (22)$$

where

$$\tilde{\Phi}_{MY} = \begin{bmatrix} \tilde{\Phi}_{m_1y_1}(\omega, b + L_{m_1y_1}) & \tilde{\Phi}_{m_2y_1}(\omega, b + L_{m_2y_1}) \\ \tilde{\Phi}_{m_1y_2}(\omega, b + L_{m_1y_2}) & \tilde{\Phi}_{m_2y_2}(\omega, b + L_{m_2y_2}) \end{bmatrix}$$

$$\tilde{\Phi}_{MM} = \begin{bmatrix} \tilde{\Phi}_{m_1m_1}(\omega, b) & 0 \\ 0 & \tilde{\Phi}_{m_2m_2}(\omega, b) \end{bmatrix}$$

$$\hat{G} = \begin{bmatrix} \hat{G}_{11} & \hat{G}_{12} \\ \hat{G}_{21} & \hat{G}_{22} \end{bmatrix} \quad G_c = \begin{bmatrix} G_{c1} & 0 \\ 0 & G_{c2} \end{bmatrix},$$

$\tilde{\Phi}_{ab}$ denotes generally the wavelet transform of the cross-correlation between signals a and b, and L_{ab} denotes the dead time beteen a and b. When L_{ab} has already estimated, the (i, j) element of $\hat{G}$ in (22) is easily estimated by the least squares method in the frequency domain (Lamaire, *et al.*, 1991) under assumption that each element is represented the in the following rational the function form :

$$\frac{b_1^{ij}(j\omega) + b_2^{ij}}{(j\omega)^2 + a_1^{ij}(j\omega) + a_2^{ij}} \quad (i, j = 1, 2) \qquad (23)$$

This makes the model-fitting possible in the frequency domain. As for the model order selection in (23), we should select an order as smaller as possible so as to cover the frequency band of our interest. Here, it is enough to select the 2nd-order system.

3.5 Estimation of Stationary Time Spans

In order to specify the non-stationary time spans of data, we divide the data into several sections and check the non-stationarity of the data from the variances of the MSEs in the outputs.

By dividing the whole 9000 data length into 8 subsequences, we obtained the MSE of outputs in each subsection.

Table 1. Parameter estimates

Time Span 1 → 2000				
Model	a_1	a_2	b_1	b_2
G_{11}	0.0136	0.0001	0.0006	0
G_{12}	0.0100	0.0001	0	0
G_{21}	0.0076	0.0001	0.0136	0
G_{22}	0.0111	0.0001	0.0115	0
Time Span 2001 → 4000				
Model	a_1	a_2	b_1	b_2
G_{11}	0.0090	0	0.0006	0.1×10^{-5}
G_{12}	0.0130	0.0001	0.0003	0
G_{21}	0.0080	0	0.0128	0
G_{22}	0.0133	0	0.0325	3.1×10^{-5}
Time Span 4001 → 9000				
Model	a_1	a_2	b_1	b_2
G_{11}	0.0810	0.0002	0.0004	0
G_{12}	0.0130	0.0001	0.0006	0.3×10^{-5}
G_{21}	0.0171	0	0.0079	0
G_{22}	0.0077	0.0001	0.0177	0

As a result, we could see that the prediction error in [2001, 4000] [s] is larger than the others, that is, non-stationarity appears outstandingly in this span. This is the reason why we met an undesirable accident that steam from the water-tube drum boiler was randomly used for another purposes while the boiler had been kept at a constant load level during the identification experiments. We result in the other sections being stationary because of small variances in the MSE. We identified the transfer function models in the stationary [1, 2000], [2001, 4000] and the non-stationary [4001, 9000]. The identified transfer function means time-average characteristics in the non-stationary [2001, 4000]. Here, we set the frequency range to be identified as [0.001, 0.02][rad/s] considering the FIR filter characteristics.

The parameter estimates of transfer functions in each time span are shown in Table 1.

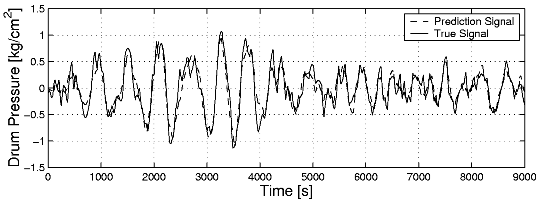


Fig. 5. Prediction of DP

3.6 Evaluation of Identified Models

We show the predicted steam-pressure $\hat{DP}$ and the corresponding actual measurements DP with the solid and broken lines, respectively, in Fig. 5.

Comparing the predicted outputs based on the time-invariant transfer functions with those based on the time-varying transfer functions with such three spans [1, 2000], [2001, 4000] and [4001, 9000] as shown in Table 1, we resulted in

- Steam-pressure system

Time-invariant model : MSE=3.097×10^{-2}
Time-varying model : MSE=2.389×10^{-2}
ARX model : MSE=3.600×10^{-2}

- Water-level system

Time-invariant model : MSE=$1.655 \times 10^{+1}$
Time-varying model : MSE=$1.405 \times 10^{+1}$
ARX model : MSE=$3.033 \times 10^{+1}$

As shown above, the estimation accuracies were improved by 16% in the steam-pressure and 22% in the water-level by specifying non-stationary spans. Finally, we compared our model with the 2-input/2-output statistical model - ARX model. The estimation accuracy is improved by 33% in the steam-pressure and 54% in the water-level, respectively. The drawbacks of such ARX modeling are in indefiniteness in physical meanings and necessity in decimation. Our modeling procedure has the following advantages : (1) the modeling is suitable for the linear control system design in the frequency domain, (2) it is based on comparatively low-order systems with consideration of temporal variations, and (3) it satisfies the specifications stated in *3.2*. The causes of the prediction errors in $\hat{DP}$ and $\hat{DL}$ are the non-stationarity of divided subsections and the non-linearity due to the PI controllers with input-dependent parameters.

4. CONCLUDING REMARKS

At present, the variable pressure operation supercritical once-through boiler is more often used than the drum boiler in thermal power stations for business. But the drum boiler is even now useful for small-scaled cogenerator. The cogenerator is required not only to satisfy the power and steam demands but also to run with consideration of both the economical operation and the environmental integrity. The bottleneck when applying a model-based control (e.g., model prediction control) to such kinds of processes, is the difficulty in building a nonlinear process model which sufficiently covers a wide frequency range closely related to its wide operating condition. In this study, a wavelet-based method for estimating dead times and time-varying parameters was applied to identification of a boiler with control systems, which is considered to be a systematic traditional procedure as *dead time + finite-dimensional system*. That is, considering the non-linearity due to load disturbances to the boiler systems, we carried out the identification experiment so as to estimate both dead times and temporal parameter variations in the framework of linear systems.

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