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적응제어알고리즘을 이용한 원자력발전소용 증기발생기 수위제어 시스템에 관한 연구

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A Study on the Microcomputer - Based Adaptive Control System of a Steam Generator

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ABSTRACT

원자력발전소의 이차계통을 모사하는 축소모형 실험장치를 만들어 Recursive Least Square estimator 와 one - step ahead controller 기능을 갖는 self - tuning regulator 를 이용한 증기발생기 수위제어계통의 성능을 평가하였다.

1. INTRODUCTION

Considerable attention has been paid to PWR steam qenerator water level control problem over the years. Loss of water level control has not only caused insufficient cooling of the reactor, but also been considered as an important cause of reactor shutdowns,especially at low load (<20%). The conventional level control qenerally takes an automatic control scheme by the P.I.D. controller above 20% load, and a manual control at low load.

Most of the earlier studies (1-4), have accepted the P.I.D. analog controller, which causes difficulties in control at low load. Recently, Feeley (5,6) investigated an estimator based on the Kalman Filter and optimal control system through numerical simulation studies. He was able to demonstrate a considerable improvement in level control. However, his work required 7 element measurements, complicated process modelling, and a computer with high speed an large capacity. Therefore, this system is not only unrealicatic to implement, but also expensive in the installment Also, from sensor failure's viewpoint, his control system depending on many sensors is inappropriate. Steam generator control system using a model reference adaptive control scheme through only numerical simulation studies has been described in Ref. (7). In Refs. (5,6,7), they recommended that the digital control system should be tested experimentally.

The MACS (Microcomputer - based Adaptive Control System of a Steam Generator) is developed to satisfy the following difficulties of level control at low load (mentioned in Refs. (3,4,5,6, 7)) :

a. Water level "swell" and "shrink" phenomena following power changes are significantly serious.
b. There exist the considerable the measurement errors and noises of the steam flow rate and feedwater flowrate in the MACS are not measured, but the water level is only measured.
c. The various disturbance inputs(e.g., sudden steam flow, primary coolant flowrate, temperature of hot log water, temperature of feedwater, and condenser pressure, etc.) cause the change of the water level.
d. The feedwater control valve is controlled by an electro - mechanical system with hysteresis. Its effects are ignored in the modelling but significant in the conventional controller with a very high gain control law.
e. The delayed response of the level to an increase in the feedwater flow, which is usually neglected, has an effect on the level control.

An adaptive control method is chosen to overcome these difficulties. An adaptive regulator can change its behavior in response to changes in the dynamics of the process and the cisturbance. A particular form of adaptive control law which combines the recursive least squares parameter estimator with the one - step ahead controller will be called self - tuning regulator. Its basic concept is to form an adaptive prediction of the system output form the input and output data, and then to determine the control input by setting the predicted output equal to the desired output.

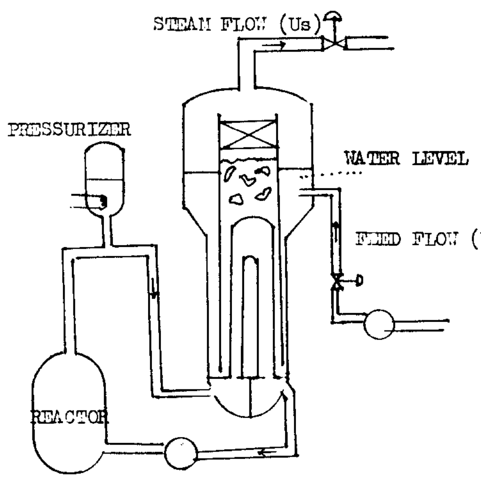


Fig 1. Steam generator in its environment

2. SELT - TUNING REGULATOR

2. 1 ARMAS

The input - output behaviour of a finite dimensional linear dynamical process can be described by an ARMAS model. It is assumed that the process is described by an ARMAS model, i.e.,

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})U(t) + C(q^{-1})W(t) \quad (2\text{-}1)$$

where d is an integer time delay and

$$A(q^{-1}) = 1+a_1q^{-1}+ \cdots\cdots + a_nq^{-n} \quad (2\text{-}2)$$

$$B(q^{-1}) = b_0+b_1q^{-1}+ \cdots\cdots + b_mq^{-m} \ ; \ b_0\neq 0 \quad (2\text{-}3)$$

$$C(q^{-1}) = 1+c_1q^{-1}+ \cdots\cdots + c\, q^{-\ell} \quad (2\text{-}4)$$

$y(t)$, $u(t)$, and $w(t)$ are sequence of outputs, inputs and white noise, respectively.

2. 2 ARMAS predictor

If the ARMAS as the model for the evolution of the time series is known, then it is possible to construct a suitable predictor from the model. An ARMAS model can be expressed in the optimal d - step ahead predictor.

For the process Eg. (2-1), provided $c(q^{-1})$ is asymtotically stable, then the optimal d - step ahead predictor satisfies

$$C(q^{-1})y^0(t+d|t) = \alpha(q^{-1})y(t) + \beta(q^{-1})U(t) \quad (2\text{-}7)$$

where

$$y^0(t+d|t) \triangleq E\{y(t+d)|F_t\} = y(t+d) - F(q^{-1})W(t+d) \quad (2\text{-}8)$$

$$\alpha(q^{-1}) = G(q^{-1}) \quad (2\text{-}9)$$

$$\beta(q^{-1}) = F(q^{-1})B(q^{-1}) \quad (2\text{-}10)$$

and $F(q^{-1})$ $G(q^{-1})$ are the unique polynomials satisfying

$$C(q^{-1}) = F(q^{-1})A(q^{-1}) + q^{-d}G(q^{-1}) \quad (2\text{-}11)$$

$$F(q^{-1}) = 1+f_1q^{-1}+ \cdots\cdots +f_{d-1}q^{-d+1} \quad (2\text{-}12)$$

$$G(q^{-1}) = g_0+ g\cdot q^{-1}+ \cdots\cdots + g_{n-1}q^{-n+1} \quad (2\text{-}13)$$

Also

$$E\{[y(t+d)-y^0(t+ d|t]^2\} = E\{E\{[F(q^{-1})W(t)]^2|F_t\}\} = \sum_{j=0}^{d-1} f_i^2\sigma^2 \quad (2\text{-}14)$$

Now, the ARMAS predictor is regarded as the model for the process.

2. 3 Parameter estimator

Let us discuss the recursive least squares parameter estimator for estimating the parameters of the predictor in Eg. (2-7) to minimize the square error between the measured output and a - posterior, predicted output.

If only the input $u(t)$ and the output $y(t)$ sequences are directly available, then the parameters can be estimated.

$d \geq 1$

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \frac{p(t-2)\phi(t-d)}{1+\phi(t-d)^T p(t-2)\phi(t-d)} \; y(t)-\phi(t-d)\hat{\theta}(t-1) \quad (2\text{-}15)$$

$$p(t-1) = p(t-2) - \frac{p(t-2)\phi(t-d)\phi(t-d)^T p(t-2)}{1+\phi(t-d)^T p(t-2)\phi(t-d)} \quad (2\text{-}16)$$

with $\hat{\theta}(0)$ given and $p(-1) > 0$ (mentioned in Refs. (16,17))

where

$$\phi(t)^T = [y(t), \cdots, y(t-n+1), U(t), \cdots, U(t-m-d+1), -\hat{y}(t+d-1), \cdots\cdot, -\hat{y}(t+d-\ell)] \quad (2\text{-}17)$$

and $\hat{y}(t)$ is the a - posteriori predicted output given by

$$\hat{y}(t) = \phi(t-d)^T\hat{\theta}(t-d) \quad (2\text{-}18)$$

and

$$\hat{\theta}(t) = \text{parameter estimate}$$
$$= (\hat{a}_1(t), \cdots, \hat{a}_n(t), \hat{\beta}_0(t)\cdots\hat{\beta}_m(t), \hat{c}_1(t)\cdots\hat{c}_\ell(t)) \qquad (2\text{-}19)$$

2. 4 Weighted one - step ahead stochastic controller

It is probably a good idea to include a weighting factor in the adaptive controller since it offers a tuning parameter which can limit the amount of the control effort. in the stochastic case, the output cannot be predicted exactly. The control input is chosen so as to minimize cost function. Consider the following one - step ahead cost function.

$$J(t+d) = E\{\tfrac{1}{2}\{y(t+d)-y^*(t+d)\}^2 + \tfrac{\lambda}{2}U(t)^2 | F_t\} \qquad (2\text{-}21)$$

where,

$y^*(t+d)$ denotes the desired output sequence

Control input $u(t)$ will be chosen as a function of $y(t)$, $y(t-1)$, ..., $u(t-d)$, $u(t-d-1)$, ... so as to minimize the cost function $J(t + d)$.

Hy using Egs. (2-7), (2-8), (2-14), and (2-5), Eg. (2-21) can be written.

$$J(t+d) = \tfrac{1}{2}\sum_{j=0}^{d-1} f_i^2 b^2 + \tfrac{1}{2}\{y^0(t+d)-y^*(t+d)\}^2 + \tfrac{\lambda}{2}U(t)^2 \qquad (2\text{-}22)$$

Proceeding with the minimization leads to

$$\frac{\partial J(t+d)}{\partial U(t)} = y^0(t+d/t) - y^*(t+d) + \frac{\lambda}{\beta_0} U(t) = 0 \qquad (2\text{-}23)$$

After subtracting $C(q^{-1})[y^*(t+d) - \frac{\lambda}{\beta_0}U(t)]$ from both sides of Eg. (2-7), the d - step ahead predictor Eg. (2-7) for the system Eg. (2-1) can be rearranged into the following form :

$$\frac{\beta_0}{\beta_0^2+\lambda}C(q^{-1})[y^0(t+d/t) - y^*(t+d) + \frac{\lambda}{\beta_0}U(t)]$$
$$= U(t) + \frac{\beta_0}{\beta_0^2+\lambda}\alpha(q^{-1})y(t) + \frac{\beta_0}{\beta_0^2+\lambda}\{[\beta(q^{-1})-\beta_0] - \frac{\lambda}{\beta_0}[(q^{-1})q\}$$
$$\times U(t-1) - \frac{\beta_0}{\beta_0^2+\lambda}C(q^{-1})y^*(t+d) \qquad (2\text{-}24)$$

Finally, by using Eg. (2-23), the weighed one-step ahead optimal law could be determined from

$$U(t) = -\frac{\beta_0}{\beta_0^2+\lambda}(q^{-1})y(t)$$
$$- \frac{\beta_0}{\beta_0^2+\lambda}[\beta(q^{-1})-\beta_0] - \frac{\lambda}{\beta_0}[C(q^{-1})-1]q\, U(t-1)$$
$$+ \frac{\beta_0}{\beta_0^2+\lambda}C(q^{-1})y^*(t+d) \qquad (2\text{-}25)$$

3. COMPUTER SIMULATION

3 . 1 Simplified discrete model

Consider the continuous transfer function of a steam generator

$$y(S) = \{G_1/S - G_2/(1+\tau_2 S) + G_3 S/(\tau^2 + 4\pi^2 T^{-2} + 2\tau^{-1}S + S^2)\} \times U_F(S)$$
$$-(G_1/S - G_2/(1+\tau_2 S)U_s(S) \qquad (3\text{-}1)$$

where y : output water level
u_f : feedwater flow control input
u_s : steam flow disturbance input

In the case of feedwater flow, u_f=57.4 kg/sec, in 5% power, then
$G_1 = 0.058$, $G_2 = 9.63$, $G_3 = 0.181$,
T = 119.6 = 41.9, = 48.4

By using the Tustin's methods (16), the approximate discrete time model at a sampling time of 1 sec is obtained.

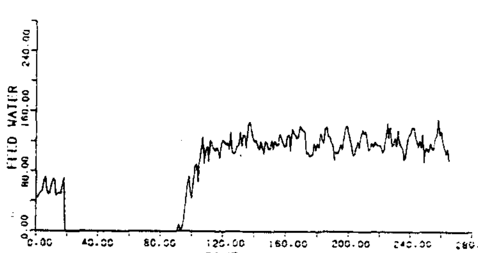
$$y(t) = (1.9796q^{-1} - 0.9796q^{-2})y(t)$$
$$+ (0.0695 - 0.000593q^{-1} - 0.07q^{-2})U_s(t)$$
$$+ q^{-1}(0.0188 + 0.000593q^{-1} - 0.0183q^{-2})U_F(t) + V(t) \qquad (3\text{-}2)$$

where V(t) represent a stochastic noise.

The result of the self - tuning regulator are presented under the conditions of n =3 1=2, m=2. The response of the closed output and control input to the zero set - point is shown in Fig. 2.

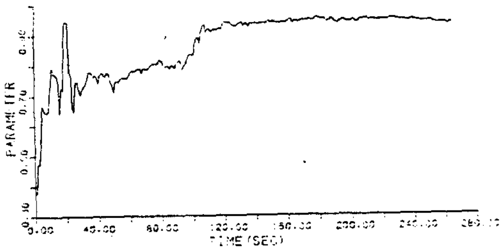
It is shown in Fig. 3 through Fig. 5 that the recursive least squares estimator provides rapid parameter estimetion and global convergence.

a) The response of water level

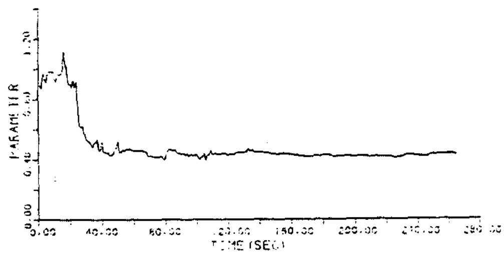


b) The response of feed water flow

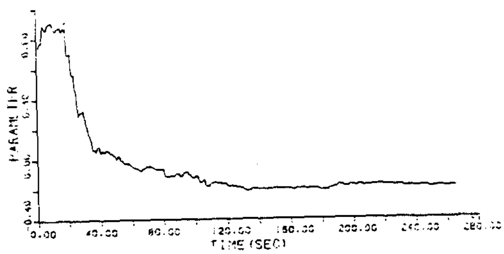
Fig. 2 A step increase in steam flow flow 5% to 10% at 5% power with self-tuning regulator under the conditions of λ = 0.0003, T = 1sec, d = 1



a) Parameter α_1

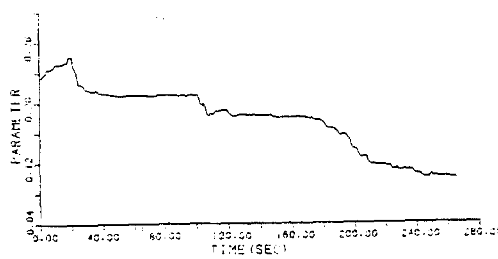


b) Parameter α_2

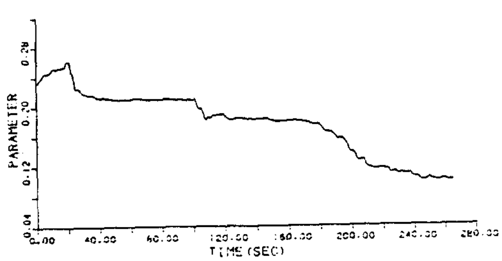


c) Parameter α_3

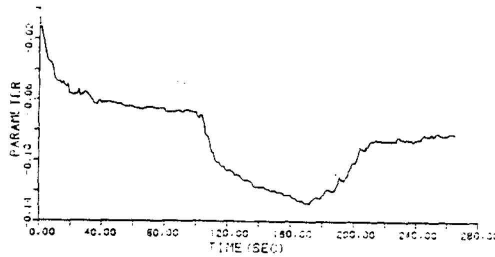
Fig. 3 Convergence of output dynamic parameters



a) Parameter β_0

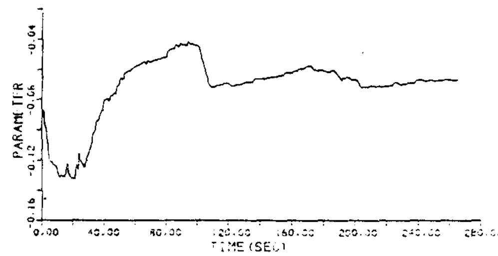


b) Parameter β_1

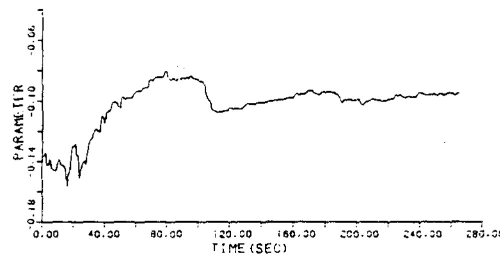


c) Parameter β_2

Fig. 4 Convergence of input dynamic parameters



a) Parameter c_1



b) Parameter c_2

Fig. 5 Convergence of noise parameters

4. Experiment

(a) Influence of random noise

The additional measurement noise to the system causes, as expected, some degradion in system performance. It is noted that the measurement noise characteristics are similar to those used in the influence of random noises, weighting factor, disturbances, and the hysteresis of valve motion on control performance will be described by referring Figs 6 and 7

In spite of a severe measurement noise, the water level is randomly distributed in the vicinity of a set - point as shown in Fig 6.

In these figures the solid and dotted lines represent the measured output and a-posteriori predicted output respectively. The measured output and a-posteriori predicted output in spite of the significant measurement noise are in excellent agreement as indicated in the computer simulation results. From the above result, it can be concluded that the recursive least squares estimator provices rapid parameter estimation and global convergence.

(b) Influence of weighting factor

In case that the weighting factor is set to zero, the water level is maintained without steady-state errors, but the feed valve motion is frequently changed as shown in Fig 6.

The feed valve motion can be reduced by increasing the feed valve input weighting factor in Fig. 7 as indicated in the numerical simulation results. The feed valve is gradually closed after the sudden close of the steam valve because the long term response of the feed valve is slow in the self - tunning regulator with the non - zero weighting factor as shown in Fig. 7. It can also be a natural result that an increase in the feed valve weighting factor increases the steady state errors because a-posterior predicted output is the desired output minus the weighted input term as indicated in Eg. (2-23).

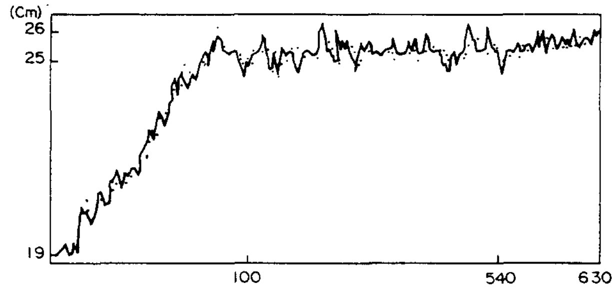
(c) Influence of disturbances

Among disturbance the steam flow disturbance input has a greatest effect on the change of the water level. It can be noted from Figs 6 and 7 that the water level is stably controller even through the disturbance input is not measured. From the above fact, it can be thought that the water level might be stably controlled against the various disturbances (primary coolant flow rate, temperature of hot leg water, and temperature of feedwater etc.) existing in the actual nuclear power plant

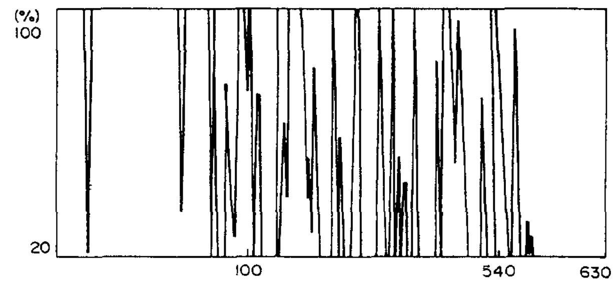
It is also interesting to observe the motion of the feed valve shown in Fig. 7 If a constant water level is maintained, then the feed water flow is simuilar to the steam flow in the steady state.

(d) Influence of hysteresis of valve motion

Pneumatic valve motion is not always proportional to the pneumatic signal. The hysteresis of valve motion exist in the actual system. Also, the change of feed flow corresponding to a feed valve position is nonlinear. The hysteresis of valve is implicitly considered in calculating the control input signal.

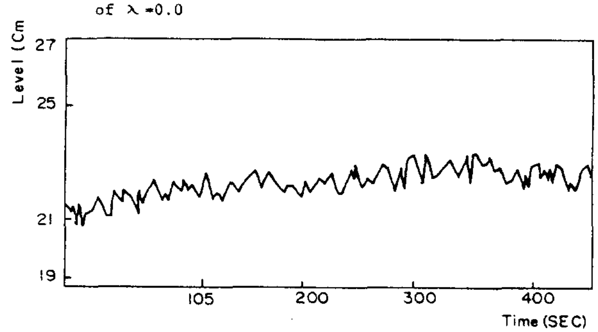


a) The Response of Water Level

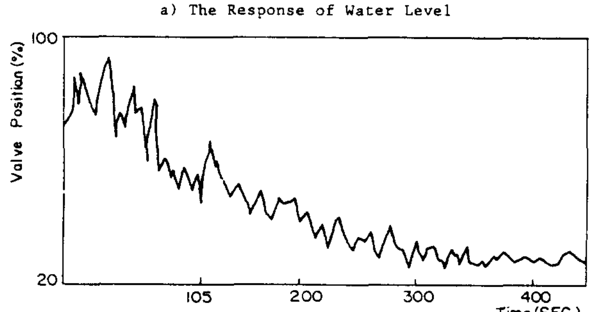


b) The Response of Feedwater Valve Position

Figure 6 A step increase in self-point from 19Cm to 25Cm with self-tuning regulator under the condition of λ =0.0



a) The Response of Water Level



b) The Response of Water Level

Figure 7 Trip from 10Kw to 30Kw at 105 Sec with self-tuning regulator under the conditions of λ =0.0001, d=1

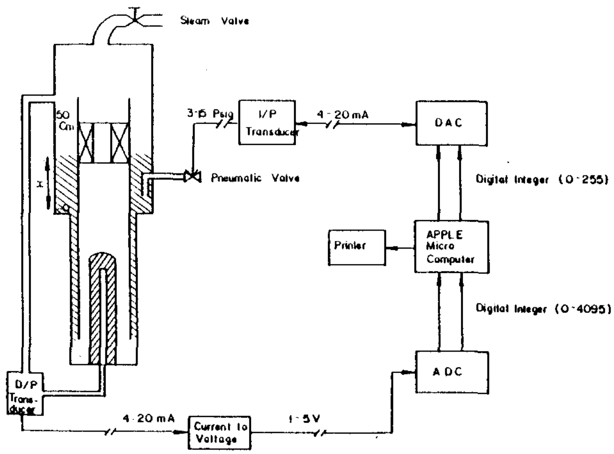


Fig. 8 Experimental apparatus

5. CONCLUSIONS

The new controller developed here, which is the facility with only one measurement, is a new concept for the level controller of the existing nuclear steam generator. A MACS (Microcomputer-based Adaptive Control System of a Steam Generator) is quite practical and efficient, and has also simple structure and higher flexibility in the installment for actual plant. A key ingredient of this system is adaptive regulator which can calculate adaptive, optimal valve position in response to changes in the dynamics of the process and the disturbances.

In spite of many difficulties in the steam generator water level control at low power, it can be concluded from the experimental and simulation results, that the MACS can provide optimal, robust steam qenerator level control from zero to full power.

The amount of the control input effort can be reduced by adjusting the weighting factor. However, the steady state water level errors are generated. To avoid the steady errors, the different adaptive algorithms should be investigated in the future. The 3 second sampling time is acceptable for this system. However, action should be taken to shorten the sampling time for better digital control.

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