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Self-Tuning Predictive Control with Application to Steam Generator

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증기발생기 수위제어를 위한 자기동조 예측제어

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Abstract

An self-tuning predictive control algorithm for steam generator is presented. The control algorithm is derived by suitably modifying the generalized predictive control algorithm. The main feature of the proposed method relies on considering the measurable disturbance and a simple adaptive scheme for obtaining the controller gain when the parameters of the plant are unknown. This feature makes the proposed approach particularly appealing for water level control of steam generator when measurable disturbance is used. In order to evaluate the performance of the proposed algorithm, computer simulations are done for an PWR steam generator model. Simulation results show satisfactory performances against load variations and steam flow rate estimation errors. It can be also observed that the proposed algorithm exhibits better responses than a conventional PI controller.

요 약

증기발생기 수위제어를 위한 자기동조 예측제어기법을 제안하였다. 제어기설계시 측정 가능한 앞되먹임 신호에 대한 고려와 비선형계통이나 시변계통에 적용하기 위해 적응형으로 유도한 것이 제안된 제어기의 특징이다. 이러한 이유로 제안된 제어기는 계통의 동특성에 직접 영향을 주는 앞되먹임 신호가 존재하고, 시간이나 동작조건에 따라 계통의 계수가 변하는 계통에 적용 가능하다. 제안된 제어기의 성능을 검증하기 위해 웨스팅하우스형의 증기발생기 모델을 이용하여 모의실험을 수행하였다. 모의실험 결과 기존의 비례−적분제어기 보다 우수한 성능을 나타냄을 알 수 있었다.

1. Introduction

The steam generator, in the PWR plant, is one of major importance in order to ensure sufficient cooling of reactor and produce steam for turbine. The water level of the steam generator must not be allowed to rise too high and to fall too low in order to prevent the generation of excessive moisture carryover and uncover of the U-tubes in the secondary side. And, large water level variation can affect system power and hydrodynamic stability. Transient changes in feedwater flow not only affect plant power output but may also create a thermal shock problem. In order to minimize these adverse effects, it is desirable to hold the water level as close to a predetermined set point as possible, even during large fluctuations in steaming rate, without large changes in feedwater flow rate. But the water level control in steam generator is known to be difficult especially at low power due to several facts. First, the dynamics of the steam generator is non-minimum phase which is mainly caused by the swell and shrink phenomena. Due to thermal effects, these phenomena are more and more conspicuous as the load decreases. Secondly, there are the considerable measurement errors of the steam flow rate at low power operation. Therefore, the steam flow signal can not be used in the controller directly. Finally, the dynamics of steam generators is non-linear in nature. The task of modeling such processes is very difficult and especially so when process operating conditions change frequently. In these reasons, the conventional PI controller which has the fixed PI gains over all power range will not work efficiently and a manual control is generally used in low power operation. To solve these problems, a controller should have the stable properties for non-minimum phase system and dynamic variation caused by load change. From this viewpoint, the steam generator provides a major challenge to predictive controls.

Recently, the predictive control seems to be one of the most active topics in the field of process control engineering. As one of the predictive controls which are based on I/O models, the GPC(Generalized Predictive Control) algorithm(Clarke et al., 1987a, b) which is based on CARIMA(Controlled Auto Regressive Integrated Moving Average) models has been widely used. The CARIMA model approach is particularly motivated by both parsimony parameter estimation and offset-free performance considerations. The underlying linear quadratic control objective provides the ability to deal with those challenging control problems as non-minimum phase behavior, unknown and possibly variable time delay and plant-model mismatch. A deep stability analysis has been made in an optimal control context by Bitmead et al.(1990). The standard GPC algorithm, however, can not be used to tackle the problem of the steam generator level control since the steam generator model considered here has measurable feedforward disturbances. In addition, the steam generator model has a relatively high degree of polynomials and shows non-linear dynamics according to reactor power. Thus, the modified GPC algorithm is required.

The purpose of this paper is to develop a modified GPC algorithm, named self-tuning predictive control with feedforward, and a simple adaptive scheme for obtaining the controller gain when the parameters of the plant are unknown. In the development of the algorithm, the plant model is assumed to be described by a linear discrete-time system representing the sampled version of underlying continuous-time process but the parameters of the model are changed by operating conditions. The presence of measurable disturbance, typically the steam flow rate, primary coolant temperature, and feedwater temperature, is also considered. The algorithm is then used for the control of the water level of simulated steam generator that exhibits a significant "inverse response" of the water level, when step changes in the feedwater and steam flow rate are imposed. This paper is organized as follows. In Section 2, the GPC with feedforward is derived. Also, described is an effective adaptive scheme where the controller gain is obtained recursively from the parameters of the one-step ahead predictor which can be estimated easily using RLS algorithm. In Section 3, simulation results are shown and compared with those of a conventional PI controller. The used stream generator model is the Westinghouse 857 MWt PWR steam generator(Lee et al., 1992, 93). In doing simulation study, we use the estimated steam flow rate since the steam flow rate is not available at the low power operation. Finally, section 4 gives some concluding remarks.

2. Self-Tuning Predictive Control With Feedforward

Consider the following CARIMA model(Tuffs and Clarke 1987):

$$A(z^{-1})y(t) = z^{-d_1}B(z^{-1})u_1(t) + z^{-d_2}C(z^{-1})u_2(t) + D(z^{-1})\frac{\xi(t)}{\Delta} \quad (1)$$

where $y(t)$, $u_1(t)$, $u_2(t)$, and $\xi(t)$ are the output, the control input, the measurable disturbance, and the noise, respectively, and d_1 and d_2 are time delays and

$$A(z^{-1}) = 1 + a_1z^{-1} + a_2z^{-2} + \cdots + a_{na}z^{-na} \quad (2)$$

$$B(z^{-1}) = b_1 + b_2z^{-1} + \cdots + b_{nb}z^{-nb} \quad (3)$$

$$C(z^{-1}) = c_1 + c_2z^{-1} + \cdots + c_{nc}z^{-nc} \quad (4)$$

$$D(z^{-1}) = d_0 + d_1z^{-1} + d_2z^{-2} + \cdots + d_{nd}z^{-nd} \quad (5)$$

$$\Delta = 1 - z^{-1}. \quad (6)$$

Many industrial process can be described by this model. The noise model is capable of representing both Brownian motion and random-step-at-random-time type disturbances(Clarke et al., 1987).

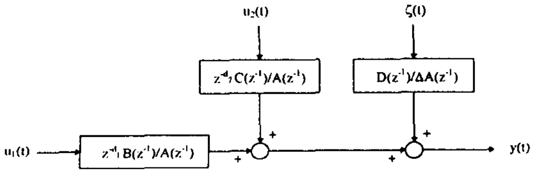

Fig. 1. Assumed Plant Model

2.1. The Control Law

In order to derive a j-step ahead predictor based on (1), consider the diophantine equation:

$$1 = H_j(z^{-1})A(z^{-1})\Delta + z^{-j}F_j(z^{-1}) \quad (7)$$

where H_j and F_j are polynomials uniquely defined from $A(z^{-1})$ and the prediction interval j(Clarke et al., 1987). From (1) and (7), the j-step ahead predictor can be shown to be represented as follows:

$$\begin{aligned}\hat{y}(t+j:t) = {} & G_j(z^{-1})\Delta u_1(t+j-d_1) \\ & + G_j^p(z^{-1})\Delta u_1(t-1) + M_j(z^{-1})\Delta u_2(t+j-d_2) \\ & + M_j^p(z^{-1})\Delta u_2(t-1) + F_j(z^{-1})y(t) \\ & + L_j(z^{-1})\xi(t+j)\end{aligned} \quad (8)$$

where

$G_j(z^{-1})\Delta u_1(t+j-d_1)$: depending on future control actions yet to be determined

$G_j^P(z^{-1})\Delta u_1(t-1)$: depending on past known control actions

$M_j(z^{-1})\Delta u_2(t+j-d_2)$: depending on future feedforward signals

$M_j^P(z^{-1})\Delta u_2(t-1)$: depending on past measured feed forward signals

$F_j(z^{-1})y(t)$: depending on measured plant output at time t

$L_j(z^{-1})\zeta(t+j)$: depending on future noise signals.

In (8), the gain polynomials G_j, G_j^p, M_j, M_j^p, F_j, and L_j are calculated recursively from given plant parameters($A(z^{-1})$, $B(z^{-1})$, $C(z^{-1})$, and $D(z^{-1})$) and diophantine equation(see Sec. 2.2).

Consider the GPC cost function of the form:

$$J(N_1, N_2, NU) = \sum_{j=N_1}^{N_2} \hat{e}^2(t+j:t) + \lambda\sum_{j=1}^{NU} \Delta u_1^2(t+j-d_1), \quad (9)$$

where the future predicted tracking error is defined as

$$\hat{e}(t+j|t) \cong r(t+j) - \hat{y}(t+j|t), \quad (10)$$

respectively, with the future reference signal, r(t+j), known in advance. And N_2, N_1, NU are referred to as the costing, the initial costing, and control horizons, respectively, and is the control weighting. In order to calculate the control input, we can derive a vector form of the predictor running j from 1 up to the maximum costing horizon(N_2). Then the predictor can be written in the vector form :

$$\overline{Y}=G\overline{U_1}+\underline{f} \tag{11}$$

where G is a gain matrix consisting of the coefficients of $G_j(z^{-1})$ and

$$\overline{Y}=[\hat{y}(t+1)\ \hat{y}(t+2)\ \cdot\ \cdot\ \hat{y}(t+N_2)]^T \tag{12}$$

$$\overline{U_1}=[\Delta u_1(t)\ \Delta u_1(t+1)\ \cdot\ \cdot\ \Delta u_1(t+N_2-1)]^T \tag{13}$$

$$\underline{f}=[f(t+1)\ f(t+2)\ \cdot\ \cdot\ f(t+N_2)]^T \tag{14}$$

If we assume the future noise and the future feedforward disturbance are zero, the expectation of the cost function (9) can be written as

$$\begin{aligned} J_1 &= E\{J(1,N_2)\} \\ &= E\{(\overline{Y}-\overline{r})^T(\overline{Y}-\overline{r})+\lambda\overline{U_1}^T\overline{U_1}\} \end{aligned} \tag{15}$$

where $\overline{r}$ are given by

$$\overline{r}=[r(t+1)\ r(t+2)\ \cdot\ \cdot\ r(t+N_2)]^T \tag{16}$$

The optimal control law which minimizes the cost function is given by

$$\overline{U_1}=(G^TG-\lambda I)^{-1}G^T(\overline{r}-\underline{f}) \tag{17}$$

where

$$\underline{f}=G^p\underline{U_1}+M^p\underline{U_2}+M\overline{U_2}+F\underline{Y}, \tag{18}$$

and G^p, M^p, M, and F matrices are obtained from the coefficients of the polynomials $G_j^p(z^{-1})$, $M_j^p(z^{-1})$, $M^j(z^{-1})$, and $F_j(z^{-1})$. In (17), it is different from GPC (Clarkè et al., 1987a, b) since the feedforward signal terms in the control law is considered. It can offer better rejection of the measurable disturbance than through feedback alone. The current control input is obtained from (17) as follows

$$u_1(t)=\Delta u_1(t)+u_1(t-1) \tag{19}$$

where $\Delta u_1(t)$ is the first element of U_1.

We now present an adaptive scheme for the system (1) and control law (17).

2.2. The Adaptive Scheme

For obtaining an adaptive version of (17), the gain matrices should be calculated at each sampling time. In this section, we describe an effectively calculating method of gain matrices using the one-step ahead predictor. From the plant model and diophantine equation, it can be easily seen that the gain matrices in (17) have the following recursive form :

$$F=\begin{bmatrix} f_{10} & f_{11} & \cdot & f_{1na} \\ f_{20} & f_{21} & \cdot & f_{2na} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ f_{N_20} & f_{N_21} & \cdot & f_{N_2na} \end{bmatrix} \tag{20}$$

$$=\begin{bmatrix} (1-a_1)h_0 & (a_1-a_2)h_0 & \cdot & a_{na}h_0 \\ f_{11}+(1-a_1)h_1 & f_{12}+(a_1-a_2)h_1 & \cdot & a_{na}h_1 \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ f_{N_2-1\,1}+(1-a_1)h_{N_2-1} & f_{N_2-1\,2}+(a_1-a_2)h_{N_2-1} & \cdot & a_{na}h_{N_2-1} \end{bmatrix} \tag{21}$$

$$G=\begin{bmatrix} h_0b_0 & 0 & 0 & 0 \\ h_0b_1+h_1b_0 & h_0b_0 & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ h_0b_{N_2-1}+\cdots+h_{N_2-1}b_0 & h_0b_{N_2-2}+\cdots+h_{N_2-2}b_0 & \cdot & h_0b_0 \end{bmatrix} \tag{22}$$

$$G^p=\begin{bmatrix} h_0b_1 & h_0b_2 & \cdot & h_0b_{m_b} \\ h_0b_2+h_1b_1 & h_0b_3+h_1b_2 & \cdot & h_1b_{m_b} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ h_0b_{N_2}+\cdots+h_{N_2-1}b_1 & h_0b_{N_2+1}+\cdots+h_{N_2-1}b_2 & \cdot & h_{N_2-1}b_{m_b} \end{bmatrix} \tag{23}$$

$$M = \begin{bmatrix} h_0c_0 \\ h_0c_1 + h_1c_0 \\ \cdot \\ \cdot \\ h_0c_{N_2-1} + \cdots + h_{N_2-1}c_0 \end{bmatrix} \tag{24}$$

$$M^p = \begin{bmatrix} h_0c_1 & h_0c_2 & \cdot & h_0c_{nc} \\ h_0c_2 + h_1c_1 & h_0c_3 + h_1c_2 & \cdot & h_1c_{nc} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ h_0c_{N_2} + \cdots + h_{N_2-1}c_1 & h_0c_{N_2+1} + \cdots + h_{N_2-1}c_2 & \cdot & h_{N_2-1}c_{nc} \end{bmatrix} \tag{25}$$

and $h_0=1,\ h_1=f_{10},\ h_2=f_{20},\ h_3=f_{30},\ \cdot\ \cdot\ \cdot\ ,\ h_{N_2}=f_{N_2-1\,0}$.

It can be seen that these matrices have an interesting structure, that is, the parameters of the j-step ahead predictor, i.e. j-th row of these matrices, can be obtained from the one-step ahead predictor which appear in the first row of these matrices. Using this property, we can derive an adaptive algorithm which consists of GPC and an estimating algorithm for identifying the parameters of the one-step ahead predictor. The proposed adaptive algorithm consists of the following steps :

Step 1. Using the RLS algorithm, estimate the parameters of the one-step ahead predictor,

Step 2. Calculate G, G_p, M, M_p and F matrices,

Step 3. Make the control input and feed it to the system.

The adaptive structure for steam generator is shown in Fig. 7. The stability of proposed scheme can be proved from the convergence property of the RLS algorithm(Goodwin et al., 1984) and the RHTC stability properties(Kwon et al., 1989).

3. Simulation Studies

3.1. Modeling of the Steam Generator

The dynamics of steam generators is time-varying and non-linear in nature. The task of modeling such processes is very difficult and especially so when process operating conditions change frequently. Based on the step response of the steam generator water level for step changes of the feedwater flow rate and steam flow rate, Irving et al.(1979) obtained an 4th-order transfer function that was expressed in terms of the water level, the feedwater flow rate, and the steam flow rate. This model assumes the effect of reverse dynamics due to the feedwater flow rate change to be the same as that due to the steam flow rate change. In actual situations, however, they are quite different. Also, It does not consider the dynamics due to the feedwater temperature. Actually, the water level may present an increase in the reverse dynamics effect when the feedwater temperature decreases. In these reasons, we adopts a simplified linear four-input single-output model which is made employing the thermal hydraulic model of a 857MWt Westinghouse F-type steam generator(Lee et al., 1992, 1993). The transfer function of this model is given as follows :

$$\delta L(s) = [G_1(s)\ G_2(s)\ G_3(s)\ G_4(s)] \begin{bmatrix} \delta W_f(s) \\ \delta W_s(s) \\ \delta T_p(s) \\ \delta T_f(s) \end{bmatrix} \tag{26}$$

where

$$G_1(s) = \frac{k_1}{s} + \frac{k_2 w_{n1}^2}{s^2 + 2\zeta_1 w_{n1} s + w_{n1}^2} \tag{27}$$

$$G_2(s) = -\frac{k_1}{s} + \frac{0.05k_3}{s + 0.05} \tag{28}$$

$$G_3(s) = \left[\frac{k_4(a_3 - b_3)s}{(s + a3)(s + b_{3)}} + \frac{c_3k_5}{s + c_3}\right] e^{-d_3 s} \tag{29}$$

$$G_4(s) = \frac{k_6 w_{n4}^2}{s^2 + 2\zeta_4 w_{n4} + w_{n4}^2} \tag{30}$$

δ = current value-steady state value at an operation point (i.e., $\delta L(t) = L(t) - L(t)|_{\text{steady state value}}$) (31)

and δL, δW_f, δW_s, δT_p and δT_f denote the water level[%], the feedwater flow rate[kg/sec], the steam flow rate[kg/sec], the primary coolant temperature[°K] and the feedwater temperatures[°K], respectively. In (26), the steam flow rate, the primary coolant temperatrue, and the feedwater temperature can be considered as feedforward terms which affect the water level directly. The values of the parameters in (27)~(30) depend on the reactor power and are given as follows:

$$k_1 = 1.1 \times 10^{-4} \tag{32}$$

$$k_2 = -0.012097e^{-0.09067p} - 0.001 \tag{33}$$

$$t_{p1} = 196.37\ e^{-0.1245p} + 30 \tag{34}$$

$$\zeta_1 = 0.1985\ e^{0.03p} \tag{35}$$

$$w_{n1} = \frac{3.141592}{t_{p1}\sqrt{1-\zeta_1^2}} \tag{36}$$

$$k_3 = 0.0196e^{-0.0735p} + 0.007 \tag{37}$$

$$k_4 = \begin{cases} 1.17\times10^{-5}p^3 - 6\times10^{-4}p^2 + 0.01p + 0.0223, & p \le 25 \\ 0.0801 - 0.0004(p-25), & p > 25 \end{cases} \tag{38}$$

$$k_5 = \begin{cases} -2\times10^{-7}p + 1.1\times10^{-5}p^2 + 2.7\times10^{-4}p + 0.0041, & p \le 50 \\ 2.58\times10^{-4}(p-50) + 0.0201, & p > 50 \end{cases} \tag{39}$$

$$a_3 = \begin{cases} 0.0195p + 0.0846 & , \quad p \le 10 \\ 0.0107p + 0.1725 & , 10 < p \le 15 \\ 0.0082p + 0.21 & , 15 < p \le 20 \\ 0.0125p + 0.124 & , 20 < p \end{cases} \tag{40}$$

$$b_3 = \frac{a_3}{10} \tag{41}$$

$$c_3 = \begin{cases} 0.001p, & p \le 5 \\ 0.399p - 1.99, & 5 < p \le 10 \\ 2.0, & 10 < p \end{cases} \tag{42}$$

$$d_3 = 2 \tag{43}$$

$$k_6 = 4.43\times10^{-4}\ e^{0.0348p} \tag{44}$$

$$t_{p4} = 195e^{-0.16p} + 22 \tag{45}$$

$$\zeta_4 = \begin{cases} 0.535\ e^{-0.16p} & , p \le 15 \\ 0.172 & , p > 15 \end{cases} \tag{46}$$

$$w_{n4} = \frac{3.141592}{t_{p4}\sqrt{1-\zeta_4^2}} \tag{47}$$

where the p dentotes the reactor power(%).

3.2. Controller Design

In order to design the adaptive GPC with feedforward, the steam generator model in (27)~(30) is discretized to the following CARIMA model:

$$\begin{aligned} A(z^{-1})\delta L(t) &= z^{-d_1}B(z^{-1})\delta W_f(t) \\ &+ z^{-d_2}C(z^{-1})\delta W_s(t) + z^{-d_3}D(z^{-1})\delta T_f(t) \\ &+ z^{-d_4}E(z^{-1})\delta T_p(t) + \frac{\zeta(t)}{\Delta} \end{aligned} \tag{48}$$

where δW_f is the control input, and δW_s, δT_f and δT_p are measurable feedforward signals, and $\xi(t)$ is an uncorrelated random sequence.

The j-step ahead predictor is given by

$$\begin{aligned} \delta\hat{L}(t+j;t) &= G_j\Delta\delta W_f(t+j-d_1) + G_j^p\Delta\delta W_f(t-1) \\ &+ M_j\Delta\delta W_s(t+j-d_2) + M_j^p\Delta\delta W_s(t-1) \\ &+ P_j\Delta\delta T_f(t+j-d_3) + P_j^p\Delta\delta T_f(t-1) \\ &+ Q_j\Delta\delta T_p(t+j-d_4) + Q_j^p\Delta\delta T_p(t-1) \\ &+ F_j\delta L(t) + L_j\xi(t+j), \end{aligned} \tag{49}$$

where the future noise and future feedforward signal terms may be assumed zero. From (49), we can derive a vector form of the predictor. Next, using the GPC cost function (9), the optimal control law is obtained as follows:

$$\overline{W}_f = (G^TG - \lambda I)^{-1}G^T(\overline{r} - \underline{f}) \tag{50}$$

where $\bar{r}$ is the set point vector, λ is the control weighting, and

$$\underline{f} = G^p \underline{W_f} + M^p \underline{W_s} + M\overline{W_s} + P^p \underline{T_f} + P\overline{T_f} + Q^p \underline{T_p} + Q\overline{T_p} + F\underline{L}, \tag{51}$$

where $\underline{W_s}$, $\underline{T_t}$ and $\underline{T_p}$ are all known vectors which are composed of feedforward signals at time t. And the gain matrices(i.e., G, G^p, M, M^p, P, P^p, Q, Q^p and F) are calculated from parameters of one-step ahead predictor which are estimated from RLS algorithm. Finally, the current control $\delta W_f(t)$ is obtained as

$$\delta W_f(t) \;=\; \Delta\delta W_f(t) \;+\; \delta W_f(t-1) \tag{52}$$

3.3. Simulation and Results

It is well known that the conventional PI controller cannot work efficiently in low power operation due to swell and shrink effects. In this reason, the simulation studies have been done using both the proposed scheme and a conventional PI controller for Westinghouse 857MWt steam generator from 5% to 20% power operation conditions. In this work, the set point of the water level is set to 50% that is the half of the steam generator narrow range level and the steady state values at an operating conditions are shown in Table 1.

Table 1. The Steady State Values an on Operating Conditions

	Power (%)	$W_f = W_s$ (Kg/sec)	T_p (°K)	T_f (°K)
1	5.0	16.66	563.3	318.2
2	10.0	33.30	568.1	318.2
3	15.0	52.51	569.8	348.6
4	20.0	76.65	571.5	399.3

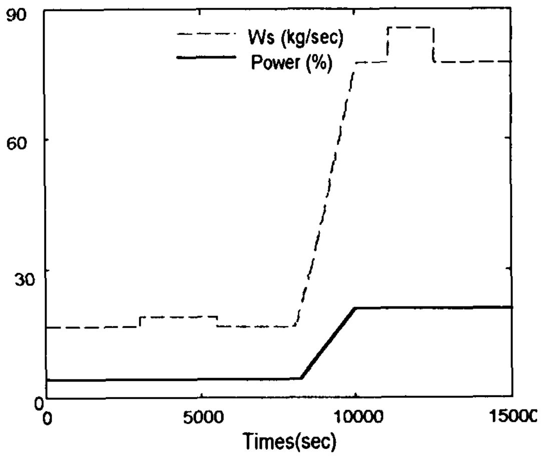

Fig. 2. The Power Operation and the Steam Perturbation

The power is taken to increase rampwise from 5% to 20% in 15,000sec. To observe the responses of water level caused by load disturbance, we assume that the steam flow rate is increased by 10% step changes of the steady state steam flow rate at a fixed power level(5% and 20% power). To prevent excessive increasing or decreasing of feedwater flow rate at a transients, the output of controller should be restricted. Thus, the feedwater valve gain is determined by using the steady state actual data of CNS(Compact Nuclear Simulator) which has been installed at KAERI(Korea Atomic Energy Research Institute) and is shown in table 2. The CNS is engineering simulator which uses as reference plants Kori 3&4 in Korea. The modeled plant is a three loop Westinghouse PWR.

Table 2. The Feedwater Valve Gains at an Operating Conditions

Power(%)	5	10	20
Valve gain (Kg/sec)	33.3	66.592	153.292

At the low power operation, the measured steam flow rate is known to be unreliable. At the steady stat e condition, however, the steam flow rate can be calculated from the following formula :

$$W_s = \frac{Q}{h_g - h_{F_w}} \tag{53}$$

where Q, h_g, h_{fw} and W_s denote the primary power level including RCP heat(BTU/hr), steam enthalpy (BTU/lbm), feedwater enthalpy(BTU/lbm) and steam flow rate(lbm/hr), respectively. If the post trip steam pressure(i.e., no load pressure) is designed to be 1170psia and the expected feedwater temperature is approximately 100deg-F, the above formula reduces to.

$$W_s = 8647130 \times P \ \ (lbm/hr), \tag{54}$$

where the P is fraction of full power.

In this reason, we assume that the steam flow rate is the estimated value at steady state conditions(Table 1), but it has an estimating errors. In doing the simulation, the assumed estimating errors are as following three cases :

- Case 1 : a random work error noise with sine wave at a time interval (Fig. 3),
- Case 2 : a random work error noise at whole range (Fig. 4),
- Case 3 : a sine wave error noise at whole range (Fig. 5).

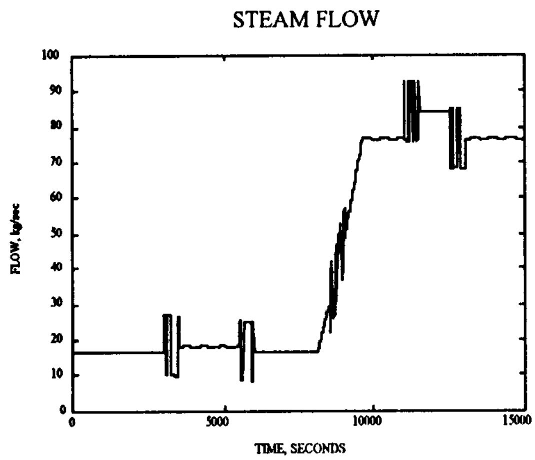

Fig. 3. Random Work Error Noise with Sine Wave at a Time Interval(Case 1)

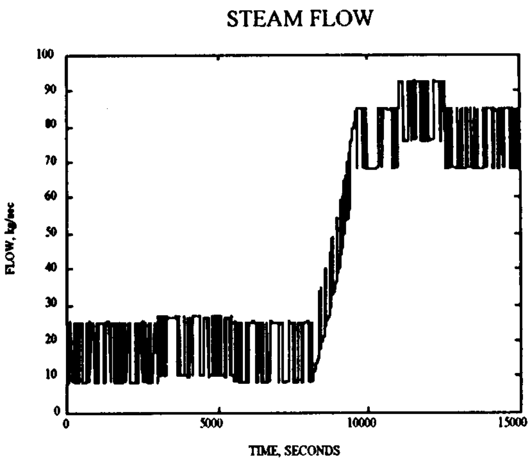

Fig. 4. Random Work Error Noise at Whole Range(Case 2)

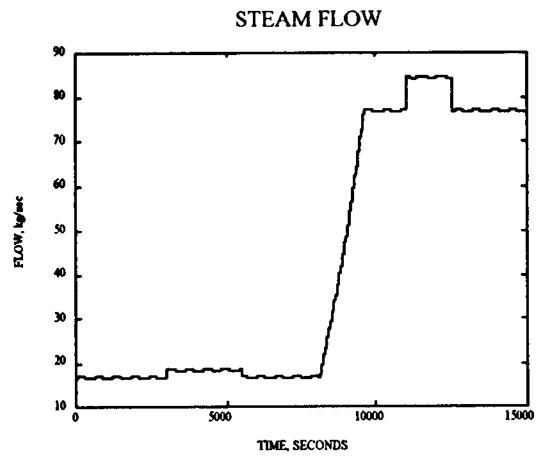

Fig. 5. Sine Wave Error Noise at Whole Range(Case 3)

The Fig. 6 and Fig. 7 show the structure of a PI controller and the proposed controller used in the simulation. The parameters of the PI controller were tuned by modified Ziegler-Nichols (Zhuang,1993 and Astrom, 1985) such as K1 = 3.4927, Ti1 = 200.011, Td1 = 50.0029, K2 = 0.7, and Ti2 = 200. From the closed-loop responses shown in Fig. 8, 9, and Fig. 10, it can be observed that the performances of the PI controller are satisfactory but quite sluggish.

In the case of proposed scheme, the design values N_1, N_2, NU and were set to be 1, 20, 1 and 0.2, respectively. In general, the output prediction horizon should be longer than the length of the plant "inverse response". This is a fundamental rule of thumb for achieving good control performances(Clarke, 1989). Thus, the N_2 was carefully selected, since the steam generator model is non-minimum phase system. For identifying the parameters of the one-step ahead predictor, we used the RLS algorithm with a fixed forgetting factor of 0.95, and the initial value for the parameter estimation was selected the model parameters of reactor power 20%. The closed-loop responses according to the simulation scenario are shown in Fig. 11, 12 and Fig. 13. It can be observed that the proposed control scheme exhibits much better performances than the conventional PI controller when there exist steam flow rate perturbations and power variations.

4. Conclusions

In this paper, an self-tuning predictive control algorithm for PWR steam generator level control is presented. The control algorithm is derived by suitably modifying the GPC proposed by Clarke et al.

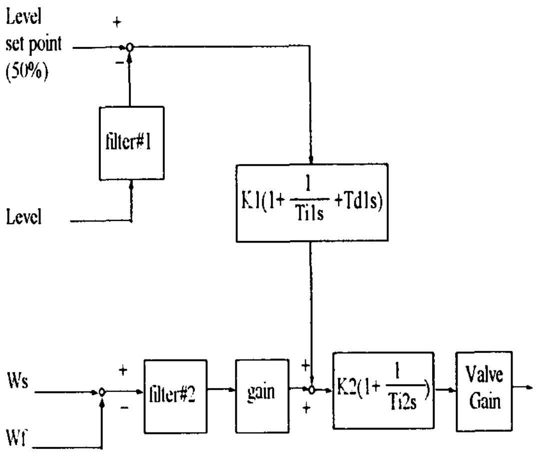

Fig. 6. The Structure of a Conventional PI Controller

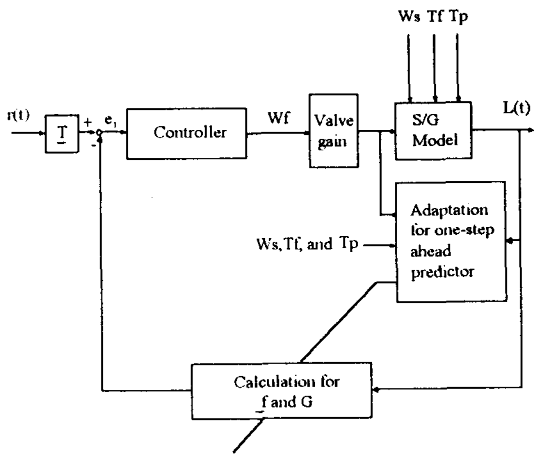

Fig. 7. The Structure of Adaptive GPC with Feedforward for S/G Level Control

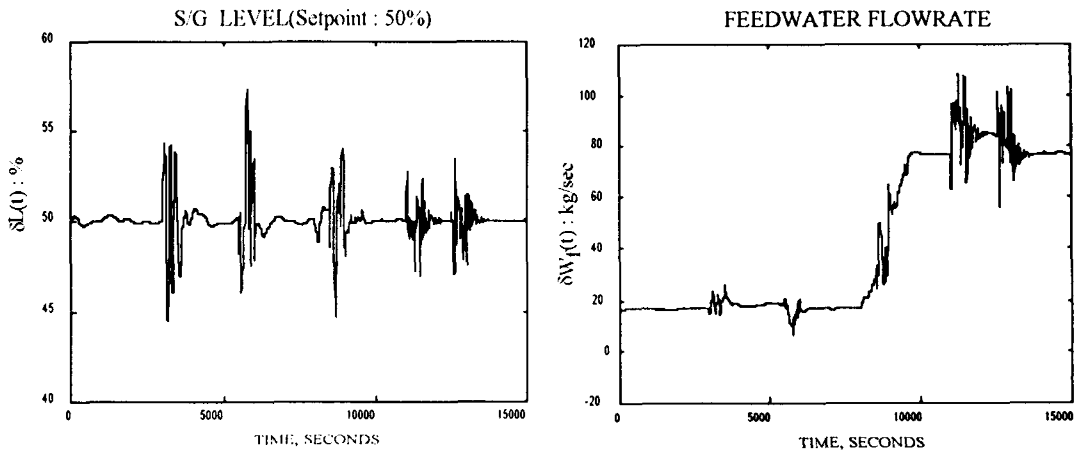

Fig. 8. Water Level Response and Feedwater Flow Rate of the PI Controller (Case 1)

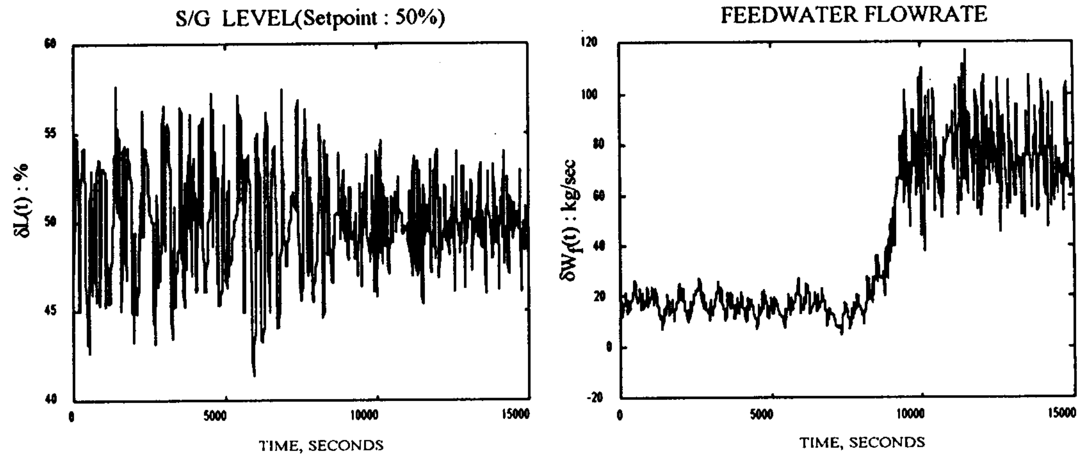

Fig. 9. Water Level Response and Feedwater Flow Rate of the PI Controller (Case 2)

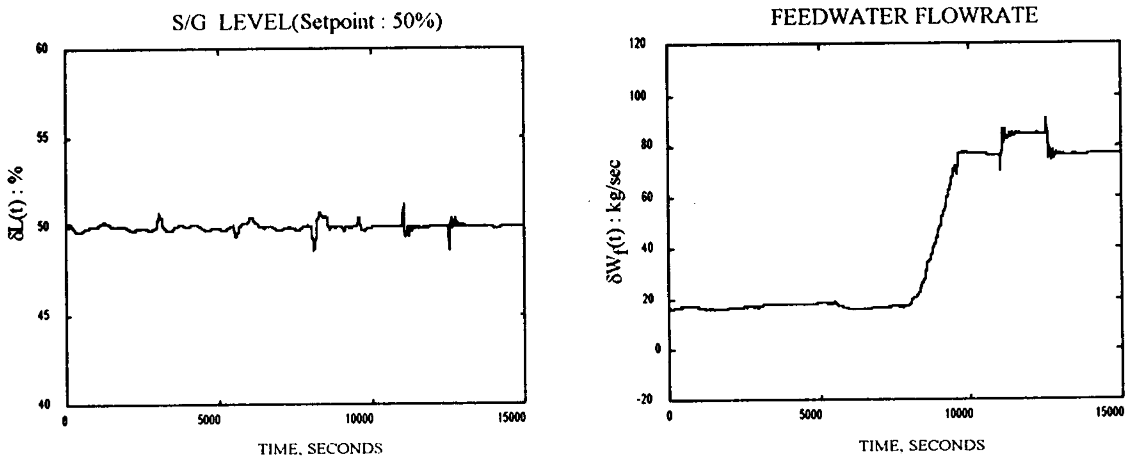

Fig. 10. Water Level Response and Feedwater Flow Rate of the PI Controller (Case 3)

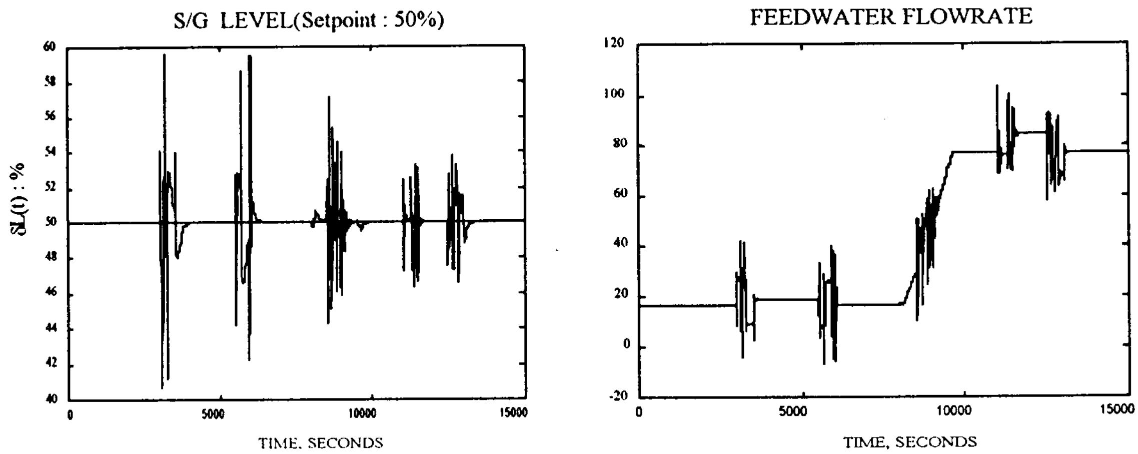

Fig. 11. Water Level Response and Feedwater Flow Rate of the Proposed Controller (Case 1)

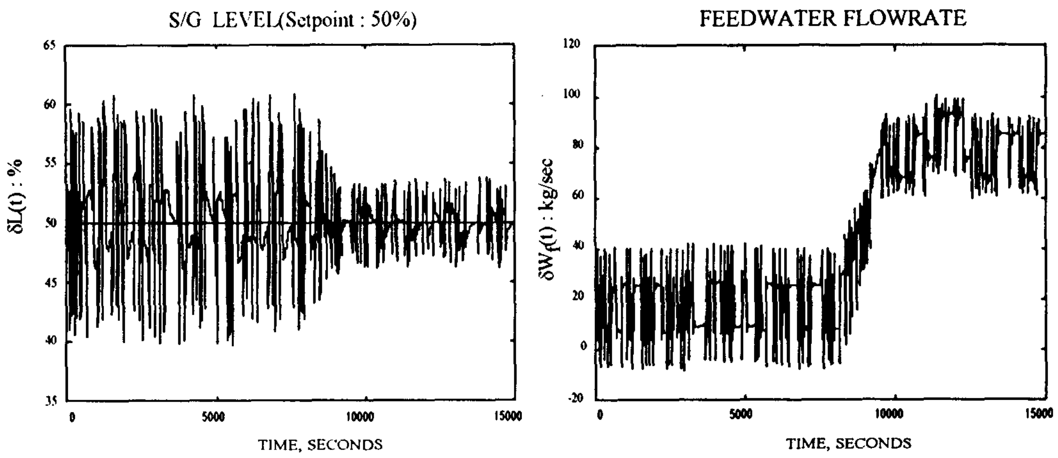

Fig. 12. Water Level Response and Feedwater Flow Rate of the Proposed Controller (Case 2)

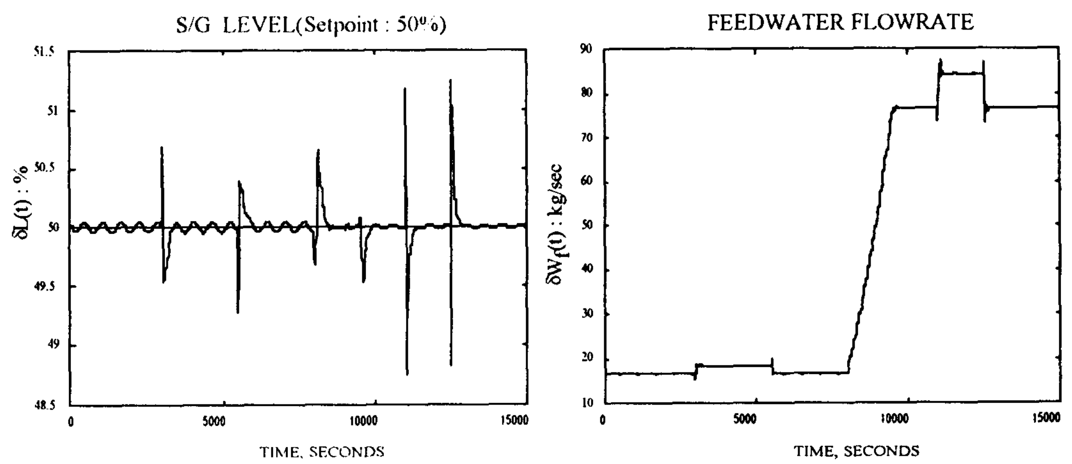

Fig. 13. Water Level Response and Feedwater Flow Rate of the Proposed Controller (Case 3)

(1987). The main feature of the proposed method relies on considering the measurable disturbance. In order to evaluate the performance of the proposed algorithm, computer simulations have been done using both the proposed control scheme and a conventional PI controller for Westinghouse 857 MWt steam generator level control in the reactor power range from 5% to 20%. Simulation results show satisfactory performances against load variations and the steam estimation errors. It can be also observed that the proposed algorithm exhibits better responses than a conventional PI controller.

References

1. D.A. Linkens and M. Mahfour, "Generalized Predictive Control with Feedforward(GPCF) for Multivariable Anesthesia," Int. J. Control, Vol. 56, No. 5, pp. 1039~1057 (1992)
2. D.W. Clarke, C. Mohtadi and P.S. Tuffs, "Generalized Predictive Control-Part I. The Basic Algorithm, Automatica, Vol. 23, No. 2, pp. 137~148 (1987)
3. D.W. Clarke, C. Mohtadi and P.S. Tuffs, "Generalized Predictive Control-Part II. Extensions

and Interpretations," Automatica, Vol. 23, No. 2, pp. 149-160 (1987)

4. D.W. Clarke and C. Mohtadi, "Properties of Generalized Predictive Control," Automatica, Vol. 25, No. 6, pp. 859~875 (1989)
5. D.W. Clarke, E. Mosca, and R. Scattolini, "Robustness of An Adaptive Predictive Controller," Proc. of the 30th Conference on Decision and Control Broghton, England (1991)
6. E. Irving, C. Miossec and J. Tassart, Proc. of the 30th Conference on Decision and Control Broghton, England (1991)
7. G.C. Goodwin et al., Adaptive Filtering Prediction and Control. Prentice-Hall: Englewood Cliffs, New Jersey (1984)
8. M. Zhuang and D.P. Atherton, "Automatic Tuning of Optimum PID Controllers," IEE Proc., Vol. 130, No. 3 (1993)
9. T.H. Lee, W.C. Lai, and K.H. Kwek, "Extended GPC incorporating Feedforward," Proceedings of the American Control Conference, pp. 2703~2708 (1990)
10. T. Hagglund and K. J. Astrom, Automatic Tuning of PID Controllers. ISA (1985)
11. Y.J. Lee, "Water Level Control of Nuclear Plant Steam Generator," Trans. on KSME J., 16, pp. 753~764 (1992)
12. Y.J. Lee and U.C. Lee, "Digitalization of the Nuclear Steam Generator Level Control System," Journal of the Korean Nuclear Society, Vol. 25, No. 1, pp. 125~135 (1993)
13. W.H. Kwon and D.G. Byun, "Receding Horizon Tracking Control as a Predictive Control and Its Stability properties," Int. J. Control, Vol. 50, No. 5, pp. 1807~1824 (1989)