A Fuzzy Controller Based on Self-Tuning Rules for the Nuclear Steam Generator Water Level

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It was demonstrated that the fuzzy control method could be applied successfully to control and regulate the nuclear steam generator water level through previous works. However, this method has some limitations from the fact that its performance largely depends on the tuning method and how to settle the rule base. In this work, a fuzzy control algorithm based on self-tuning rules is investigated to find the optimal tuning point and to generate the control rule automatically. It adopts an on-line iterative method and the objective error function which contains the variation errors of all time-steps. The triangular membership functions based on the mass flow rate and water level errors are applied. And also, a forgetting factor is used to account for an exponential decay of the past data in tracking the slow drift in system parameters. Thus it controls the steam generator water level from low power to full power with a little transients. This control algorithm is validated by computer simulations.

Key Words : Fuzzy Control, Membership Function, Self-Tuning Rule

1. Introduction

The proper control of the water level of a nuclear steam generator is of much importance in order to secure the sufficient cooling source of the nuclear reactor and the good performance of the steam separator and dryer, and to prevent the damage of turbine blades. The steam generator level control has been a main culprit of unexpected shutdown of nuclear power plants. The non-minimum phase effects are significantly greater at low power, which makes more perilous the use of a high gain of the control loop at the reduced power level.

Main objective of this work is to design a controller that not only makes the feed water mass flow rate track the steam mass flow rate as soon as possible but also constrains excessive control action and keeps the water level at a setpoint value.

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It is well-known that the conventional P-I control scheme does not offer the automatic water level control satisfactorily. This inadequate and insufficient performance of the conventional controller has often resulted in reactor trip (shutdown) and coerced operators to hang on manual operation at low power. Even to a skilled operator, however, it is hard to react effectively in response to the reverse dynamics (swell and shrink phenomena) of the water level which is induced by the non-minimum phase effects. According to EPRI report, the condensate and feed water system accounts for about 30 % of plant shutdown during 1985~1993.

Therefore, many advanced control logics which include an adaptive controller (Na and No, 1992), an optimal controller (Lee, 1994), and a fuzzy logic controller (Lee and No, 1994; Park and Seong, 1995) have been suggested to improve this chronic and cumbersome steam generator level control. In spite of many advanced control methods proposed for the stable and optimum control of the nuclear steam generator water level including the model-free fuzzy logic controller which has been regarded as the user-friendly and predictive controller, operators are still experiencing difficulties in controlling the steam generator level control at especially low power. During the startup period, manual operation is performed by well-trained and experienced operators for about 7 hours. Furthermore, 7 elements to be controlled are hardly able to be handled by one operator. Among many controllers proposed to replace the manual operations, the fuzzy logic control (FLC) algorithm is generally regarded as a suitable controller due to its human-like characteristics.

It was demonstrated that FLC could be applied successfully to control and regulate the nuclear steam generator water level through previous works (Lee and No, 1994; Park and Seong, 1995). However, some limitations in tuning methods and rule generations with the conventional methods that used expert's knowledge and experiences, were pointed out. Therefore, it is required that the fuzzy controller have learning function to create the control rules and modify them automatically according to environment variations.

It is desired to develop a new method to design the fuzzy controller with which control rules are generated and tuned automatically by the gradient descent method (Guely and Siarry, 1993) introducing a forgetting factor and an on-line iterative method.

2. Water Level Control Using the Fuzzy Logic

A fuzzy controller has the characteristics of the heuristic and non-linear tuning of all variables involved to obtain good performance, which is very difficult. Therefore, a simplified and compact-type rule base is required. A fuzzy control action consists of situation and action pairs. Conditional rules described in IF and THEN statements are generally used. The IF portion is the ANTECEDENT and the THEN portion is the CONSEQUENT.

The applied control rule is described in this study as follows (Takagi and Sugeno, 1985):

$$\text{IF } x_1 \text{ is } A_{i,1} \text{ and } x_2 \text{ is } A_{j,2}, \text{ THEN } u \text{ is } w_{ij} \; [\text{for } i=1,\cdots,m \text{ and } j=1,\cdots,m] \tag{1}$$

where

x_k: input variables [$k=1$ (water level error), 2 (mass flow error = steam mass flow rate - feed water mass flow rate)],

$A_{i,1}$ or $A_{j,2}$: membership functions for rule[i, j] of each input variable,

u: controller output for rule[i, j] which means the feedwater mass flowrate into a steam generator,

w_{ij}: real value of the consequent part for rule [i, j],

m: the number of membership functions for each input variable.

It is assumed that the number of membership functions for each input variable is the same and also, the number of the input variables is two. The rule base is given in Table 1.

There is no restriction on the shape of a membership function. Generally, the triangular, bell-shaped or monotonic linear functions are usually adopted in the formula of the membership function. Typical triangular membership functions of NM_{kl}, ZO_k and PM_{kl} are adopted in this work and shown in Fig. 1. The subscript l means that there may exist several NM_k and PM_k.

Each membership function is defined as follows:

$$PB_k : A_{m,k} = \begin{cases} \dfrac{x_k - b_{k,(m-3)/2}}{b_{k,(m-1)/2} - b_{k,(m-3)/2}} & \text{for } b_{k,(m-3)/2} \le x_k < b_{k,(m-1)/2} \\ 1 & \text{for } x_k \ge b_{k,(m-1)/2} \\ 0 & \textit{otherwise} \end{cases} \tag{2}$$

$$PM_{kl} : A_{(m+1)/2+l,k} = \begin{cases} 1 - \dfrac{x_k - b_{k,l}}{b_{k,l+1} - b_{k,l}} & \text{for } b_{k,l} \le x_k < b_{k,l+1} \\ \dfrac{x_k - b_{k,l-1}}{b_{k,l} - b_{k,l-1}} & \text{for } b_{k,l-1} \le x_k < b_{k,l} \\ 0 & \textit{otherwise} \end{cases} \tag{3}$$

$$ZO_k : A_{(m+1)/2,k} = \begin{cases} 1 - \dfrac{|x_k|}{b_{k,1}} & \text{for } -b_{k,1} \le x_k \le b_{k,1} \\ 0 & \textit{otherwise} \end{cases} \tag{4}$$

Table 1 Table of rule base

NB_2	…	NM_{2l}	…	ZO_2	…	PM_{2l}	…	PB_2	FE_j / LE_l
NB $[1, m]$	…	NM_l $[1, (m+1)/2+l]$	…	NM_l $[1, (m+1)/2]$	…	NM_l $[1, (m+1)/2-l]$	…	ZO $[1, 1]$	NB_1
⋮	…	…	…	…	…	…	…	⋮	⋮
NM_l $[(m+1)/2-l, m]$	…	NM_l $[(m+1)/2-l, (m+1)/2+l]$	…	NM_l $[(m+1)/2-l, (m+1)/2]$	…	ZO $[(m+1)/2-l, (m+1)/2-l]$	…	PM_l $[(m+1)/2-l, 1]$	NM_{1l}
⋮	…	…	…	…	…	…	…	⋮	⋮
NM_l $[(m+1)/2, m]$	…	NM_l $[(m+1)/2, (m+1)/2+l]$	…	ZO $[(m+1)/2, (m+1)/2]$	…	PM_l $[(m+1)/2, (m+1)/2-l]$	…	PM_l $[(m+1)/2, 1]$	ZO_1
⋮	…	…	…	…	…	…	…	⋮	⋮
NM_l $[(m+1)/2+l, m]$	…	ZO $[(m+1)/2+l, (m+1)/2+l]$	…	PM_l $[(m+1)/2+l, (m+1)/2]$	…	PM_l $[(m+1)/2+l, (m+1)/2-l]$	…	PM_l $[(m+1)/2+l, 1]$	PM_{1l}
⋮	…	…	…	…	…	…	…	⋮	⋮
ZO $[m, m]$	…	PM_l $[m, (m+1)/2+l]$	…	PM_l $[m, (m+1)/2]$	…	PM_l $[m, (m+1)/2-l]$	…	PB $[m, 1]$	PB_1

where NB_k : negative big $[k=1, 2]$
NM_{kl} : negative medium of size l, $[l=1, \cdots, (m-3)/2]$
ZO_k : zero
PM_{kl} : positive medium of size l, $[l=1, \cdots, (m-3)/2]$
PB_k : positive big
LE_l : water level error $(\delta L = y_d - y)$
FE_j : mass flow rate error $(\delta W = W_{st} - W_j)$
Typical control action : NB, NM_l, ZO, PM_l, PB, $[l=1, \cdots, (m-3)/2]$

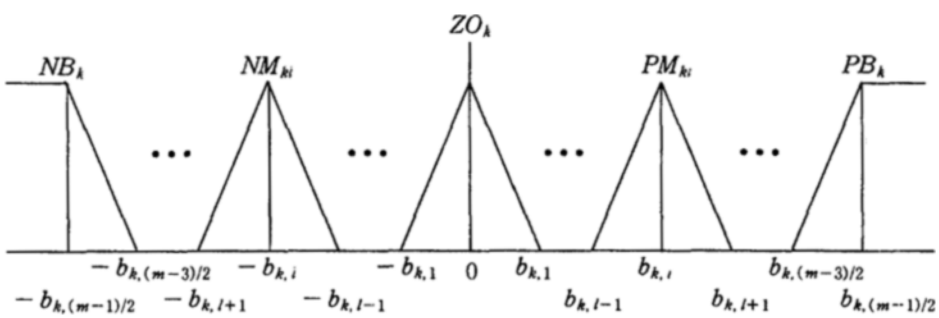


Fig. 1 Membership functions

NM_{kl} : $A_{(m+1)/2-l,k}=$

$$\begin{cases} 1-\dfrac{|x_k|-b_{k,l}}{b_{k,l+1}-b_{k,l}} & \text{for } -b_{k,l+1}<x_k<-b_{k,l} \\ \dfrac{|x_k|-b_{k,l-1}}{b_{k,l}-b_{k,l-1}} & \text{for } -b_{k,l}<x_k<-b_{k,l-1} \\ 0 & \textit{otherwise} \end{cases} \tag{5}$$

NB_k : $A_{1,k}=$

$$\begin{cases} \dfrac{|x_k|-b_{k,(m-3)/2}}{b_{k,(m-1)/2}-b_{k,(m-3)/2}} & \\ \text{for } -b_{k,(m-1)/2}<x_k<-b_{k,(m-3)/2} & \\ 1 & \text{for } x_k\leq -b_{k,(m-1)/2} \\ 0 & \textit{otherwise} \end{cases} \tag{6}$$

The membership value for rule $[i, j]$, μ_{ij}, means a compatibility grade between antecedent parts of ' if δL is a and δW is B then ...' and is expressed as follows :

$$\mu_{ij}=A_{i,1}(\delta L)\wedge A_{j,2}(\delta W)$$
$$\text{or } \mu_{ij}=A_{i,1}\cdot A_{j,2} \tag{7}$$

where $A_{i,1}$ or $A_{j,2}$ are generic terms for the fuzzy linguistic sets like NB_k, NM_{kl}, ZO_k, PM_{kl} and PB_k defined for δL and δW, respectively. The multiplicative weight ($\times$) is preferred over the minimum($\wedge$) weight because of its smoothness properties.

The output of the rule base is obtained by weighting the real value of consequent part for rule $[i, j]$ with the membership value. The control action is obtained as follows :

$$u(t)=u(t-1)+\sum_{i=1}^{m}\sum_{j=1}^{m}\mu_{ij}w_{ij} \tag{8}$$

3. The Self-Tuning of the Membership Function

The gradient descent method is used to tune the parameters of the membership function by minimizing the objective function defined as follows :

$$E=\frac{1}{2}\left\{\sum_{n=1}^{t}\lambda^{t-n}(au_n^2+[u_n-v_n]^2)\right\} \tag{9}$$

where λ is a forgetting factor, a a weighting value, u_n the feed water mass flowrate and v_n the steam mass flow rate. A forgetting factor is introduced to account for an exponential decay of the past data so that the control rules are modified fast according to the change of process dynamics. If the process dynamics is changed, the practical implementation has necessitated the employment of the forgetting factor with a value between zero and unity. The results of far previous time-steps are weighted less than those of near present ones. And also, the membership function parameters are tuned so that the excessive control effort is not called for by containing an input-squared term in the objective error function.

The parameters which minimize the above objective function, can be obtained generally by the following iterative calculation :

$$a_{ij}(t+1)=a_{ij}(t)-K\frac{\partial E}{\partial a_{ij}}\bigg|_t \tag{10}$$

where a_{ij} is the parameter which determines the shape of the membership function (what is called $b_{k,l}$ and w_{ij}), and K is called a learning coefficient, which performs the same function as the parameter adaptation gain of the least square parameter estimation algorithm. The real values of the consequent part for rule $[i, j]$, w_{ij}, are allocated so that they have reasonable values and their tuning method is simple. w_{ij} is defined as follows :

$$w_{ij}=0 \text{ for } i=j$$
$$w_{ij}=w_l \text{ for } i=j+l,\ [l=1,\cdots,m-1]$$
$$w_{ij}=-w_l \text{ for } i=j-l,\ [l=1,\cdots,m-1] \tag{11}$$

Therefore, the number of the unknowns w_{ij} becomes $m-1$. In order to apply the gradient descent method, it is required to differentiate the objective error function with respect to the parameters.

$$\frac{\partial E}{\partial b_{k,l}}=\sum_{n=1}^{t}\mu^{t-n}[(a+1)u_n-v_n]\frac{\partial u_n}{\partial b_{k,l}} \tag{12}$$

where

$$\frac{\partial u_n}{\partial b_{k,l}}=\sum_{j=1}^{m}\sum_{i=1}^{m}w_{ij}\frac{\partial \mu_{ij}}{\partial b_{k,l}}$$
$$=\sum_{j=1}^{m}\sum_{i=1}^{m}w_{ij}\frac{\partial}{\partial b_{k,l}}(A_{i,1}\cdot A_{j,2}) \tag{13}$$

$$\frac{\partial u_n}{\partial b_{k,l}}=\sum_{j=1}^{m}\sum_{i=1}^{m}w_{ij}A_{j,2}\frac{\partial A_{i,1}}{\partial b_{k,l}} \text{ for } k=1 \tag{14}$$

$$\frac{\partial u_n}{\partial b_{k,l}}=\sum_{j=1}^{m}\sum_{i=1}^{m}w_{ij}A_{i,1}\frac{\partial A_{j,2}}{\partial b_{k,l}} \text{ for } k=2 \tag{15}$$

Calculations for $\dfrac{\partial A_{i,k}}{\partial b_{k,l}}$ are derived according to $b_{k,l}$ regions as follows :

i) $b_{k,(m-1)/2}\leq |x_k|$

$$\frac{\partial A_{i,k}}{\partial b_{k,l}}=0 \text{ for all membership functions } [l=1,\cdots,(m-1)/2] \quad (16)$$

ii) $b_{k,(m-3)/2} \le |x_k| < b_{k,(m-1)/2}$

$$\frac{\partial A_{i,k}}{\partial b_{k,(m-3)/2}} \quad (17)$$

$$=\frac{-(b_{k,(m-1)/2}-b_{k,(m-3)/2})+(|x_k|-b_{k,(m-3)/2})}{(b_{k,(m-1)/2}-b_{k,(m-3)/2})^2}$$

for PB_k, NB_k, $PM_{k,(m-3)/2}$ and $NM_{k,(m-3)/2}$

$$\frac{\partial A_{i,k}}{\partial b_{k,(m-1)/2}}=\frac{-(|x_k|-b_{k,(m-3)/2})}{(b_{k,(m-1)/2}-b_{k,(m-3)/2})^2} \quad (18)$$

for PB_k, NB_k, $PM_{k,(m-3)/2}$ and $NM_{k,(m-3)/2}$

$$\frac{\partial A_{i,k}}{\partial b_{k,l}}=0 \text{ for other membership functions or other } b_{k,l}\text{'s} \quad (19)$$

iii) $b_{k,l} \le |x_k| < b_{k,l+1}$, $[l=1,\cdots,(m-5)/2]$

$$\frac{\partial A_{i,k}}{\partial b_{k,l}}=\frac{(b_{k,l+1}-b_{k,l})-(|x_k|-b_{k,l})}{(b_{k,l+1}-b_{k,l})^2}$$

for $PM_{k,l}$ and $NM_{k,l}$ (20)

$$\frac{\partial A_{i,k}}{\partial b_{k,l}}=\frac{-(b_{k,l+1}-b_{k,l})+(|x_k|-b_{k,l})}{(b_{k,l+1}-b_{k,l})^2}$$

for $PM_{k,l+1}$ and $NM_{k,l+1}$ (21)

$$\frac{\partial A_{i,k}}{\partial b_{k,l}}=0 \text{ for other membership functions or other } b_{k,l}\text{'s} \quad (22)$$

iv) $|x_k| < b_{k,1}$

$$\frac{\partial A_{i,k}}{\partial b_{k,1}}=\frac{|x_k|}{(b_{k,1})^2} \text{ for } PM_{k,1} \text{ and } NM_{k,1} \quad (23)$$

$$\frac{\partial A_{i,k}}{\partial b_{k,1}}=\frac{|x_k|}{(b_{k,1})^2} \text{ for } ZO_k \quad (24)$$

$$\frac{\partial A_{i,k}}{\partial b_{k,l}}=0 \text{ for other membership functions or other } b_{k,l}\text{'s} \quad (25)$$

And also, $\frac{\partial A_{j,k}}{\partial b_{k,l}}$ has the same form as $\frac{\partial A_{i,k}}{\partial b_{k,l}}$ except for substituting subscript j instead of subscript i.

The parameter optimization algorithm which minimizes the objective function E is as follows (refer to Eq. (10)):

$$b_{kl}(t+1)=b_{kl}(t)-Kb_{kl}|y(t)-y(t-1)|\cdot \sum_{n=1}^{t}\lambda^{t-n}[(a+1)u_n-v_n]\frac{\partial u_n}{\partial b_{kl}} \text{ for } l=1,\cdots,(m-1)/2 \text{ and } k=1,2 \quad (26)$$

$$w_l(t+1)=w_l(t)-Kw_l|y(t)-y(t-1)|\cdot \sum_{n=1}^{t}\lambda^{t-n}[(a+1)u_n-v_n]\times\left(-\sum_{i=1}^{m-1}\mu_{i,i+l}+\sum_{j=1}^{m-1}\mu_{j+l,j}\right) \text{ for } l=1,\cdots,m-1 \quad (27)$$

In the above equations, $Kb_{kl}|y(t)-y(t-1)|$ and $Kw_l|y(t)-y(t-1)|$ are applied instead of Kb_{kl} and Kw_l in order to utilize the useful information of transients and it has the same effect as the gain K of Eq. (10) is increased at transient periods.

4. Stability of the Proposed Controller

The main purpose of constructing an advanced controller frequently is to obtain its robust and stable performances. Therefore, the stability of a designed controller is more important factor than any others in order to implement it in a real system.

Lyapunov's direct method (Salle and Lefschetz, 1961) of stability analysis is used to check the largest possible learning coefficient such as Kb and Kw which guarantees the convergence and stability of the controller.

A discrete-time Lyapunov function can be given by

$$V(t)=E^2(t) \quad (28)$$

where $E(t)$ represents the objective error function defined in Eq. (9).

Thus, the change of the Lyapunov function due to the training process is obtained by

$$\Delta V=V(t+1)-V(t) = E^2(t+1)-E^2(t) \quad (29)$$

$E(t+1)$ can be represented by the error difference due to the learning process as follows:

$$E(t+1)=E(t)+\Delta E(t) = E(t)+\left[\frac{\delta E(t)}{\delta a_{ij}}\right]\cdot\Delta a_{ij} \quad (30)$$

where

$$\frac{\delta E(t)}{\delta a_{ij}}=\sum_{n=1}^{t}\lambda^{t-n}[(a+1)u_n-v_n]\frac{\delta u_n}{\delta a_{ij}} \quad (31)$$

$$\Delta a_{ij}=-K|y(t)-y(t-1)|\cdot \sum_{n=1}^{t}\lambda^{t-n}[(a+1)u_n-v_n]\frac{\delta u_n}{\delta a_{ij}} \quad (32)$$

$E(t+1)$ could be rewritten as follows :

$$E(t+1) = E(t) - K\,|\,y(t) - y(t-1)\,|\,X^2 \quad (33)$$

where

$$X = \sum_{n=1}^{t} \lambda^{t-n}[(a+1)u_n - v_n]\frac{\delta u_n}{\delta a_{ij}} \quad (34)$$

Therefore,

$$E^2(t+1) = E^2(t) - 2Y\cdot E(t) + Y^2 \quad (35)$$

where

$$Y(t) = K\,|\,y(t) - y(t-1)\,|\,X^2.$$

In order to satisfy the stability of the proposed controller, it is required that the following condition be satisfied :

$$\Delta V(k) < 0 \quad (36)$$

Therefore, the following conditions must be satisfied from $Y < 2E(k)$:

$$K\,|\,y(k) - y(k-1)\,|\,X^2 < 2E(k) \quad (37)$$

Then its stability is guaranteed sufficiently if K (i.e. Kb and Kw) is selected as

$$0 < K < \frac{2\gamma_{\min}}{g_{\max}} \quad (38)$$

where

$$g_{\max} = \max\{\,|\,y(t) - y(t-1)\,|\,X^2\,\},$$
$$\gamma_{\min} = \min\{\,E(k)\,\}.$$

5. Application to the Nuclear Steam Generator Water Level

The block diagram of the proposed control system is shown in Fig. 2. Numerical simulations are accomplished to study the performances of the proposed algorithm. The dynamics of a steam generator is described in terms of input (feed water mass flow rate ; u), output (water level ; y) and measurable disturbance (steam mass flow rate ; v). Irving(Irving et. al., 1980) derived the following 4th order Laplace transfer function for steam generators :

$$y(s) = \frac{G_1}{s}[u(s) - v(s)] - \frac{G_2}{1+\tau_2 s}[u(s) - v(s)] + \frac{G_3 s}{\tau_1^{-2} + 4\pi^2 T^{-2} + 2\tau_1^{-1}s + s^2}u(s) \quad (39)$$

where s is a Laplace variable. The parameter values of a steam generator are given in Table 2. The dynamics of a steam generator is changed heavily according to the power levels. The sampling time is assumed to be 1 sec.

It is assumed that each of input variables has three membership functions. The initial values are given in Table 3. As shown in Table 3, the initial values of the parameters are chosen so that the parameters b_{21}, w_1 and w_2 related with mass flow rate signals increases linearly but the parameter b_{11} related with a water level signal is constant as the power level increases. That is due to the

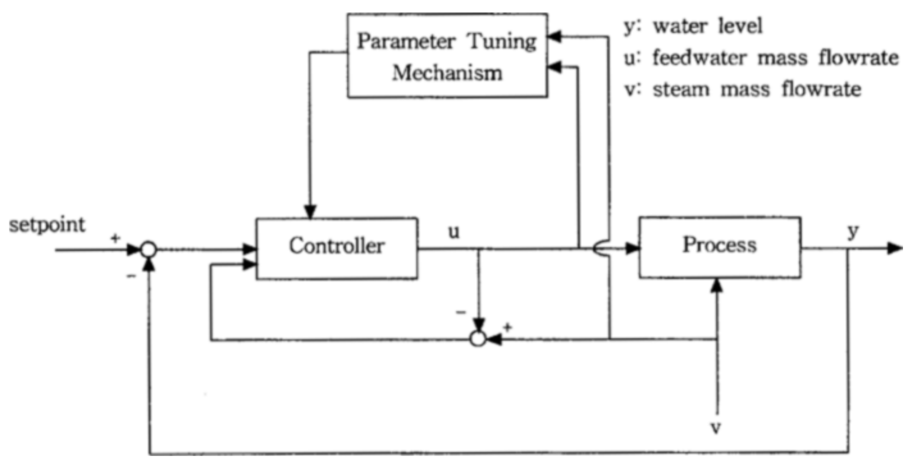


Fig. 2 Block diagram of the proposed fuzzy control system

Table 2 The parameter values of a steam generator versus power level

Power level[%] \ Parameter	G_1	G_2	G_3	τ_1	τ_2	T
5	0.058	9.63	0.181	41.9	48.4	119.6
15	0.058	4.46	0.226	26.3	21.5	60.5
30	0.058	1.83	0.310	43.4	4.5	17.7
50	0.058	1.05	0.215	34.8	3.6	14.2
100	0.058	0.47	0.105	28.6	3.4	11.7

Table 3 The initial parameter values versus power level

Parameter \ Power[%]	5	15	30	50	100	Unit
b_{11}	50	50	50	50	50	mm
b_{21}	2.5	7.8	16.6	28.7	62.5	Kg/sec
w_1	1.0	3.2	6.6	11.5	25.0	Kg/sec
w_2	4.0	12.6	26.6	46.0	100.0	Kg/sec
Kb_{11}	0.03	0.03	0.03	0.03	0.03	
Kb_{21}	0.003	0.003	0.003	0.003	0.003	
Kw_1	0.003	0.003	0.003	0.003	0.003	
Kw_2	0.003	0.003	0.003	0.003	0.003	
λ	0.7	0.7	0.7	0.7	0.7	
α	0.2	0.2	0.2	0.2	0.2	

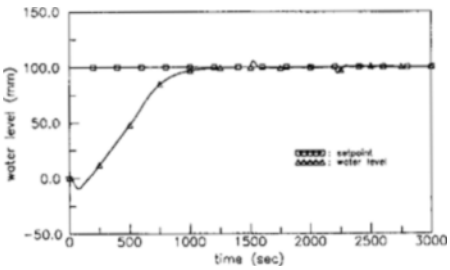
increase of the relative stability according to that of the power level (refer to Eq. (39) and Table 2).

For all simulations of the proposed controller, a steam generator has been operated at a steady state. At 0 sec, the setpoint of the water level is increased from 0 mm to 100 mm. At 1500 sec, the 5 % step increase of the power level which is being simulated occurs and at 2200 sec, the 5 % step decrease of the power level takes place. Since the nuclear steam generator level control has troubles at below 20 percent power, special importance is attached to the performances of this controller at 5 % and 15 % power levels.

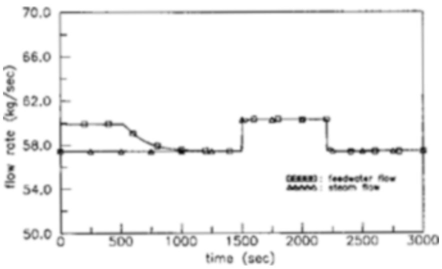
Figure 3 shows the response of the proposed controller at 5 % power level. At 0 sec, such a sudden increase of the setpoint requires more feed water, which brings a shrink phenomenon. At 1500 sec, the increase of the steam mass flow rate induces a swell phenomenon. And at 2200 sec, the sudden decrease of the steam mass flow rate induces a shrink phenomenon. From Fig. 3(b), it is known that the feed water mass flow rate tracks the steam mass flow rate in the disturbances of the steam mass flow rate at 1500 sec and 2200 sec.

Figure 4 shows the responses of the proposed controller at 15 % power level. Figure 4 is similar to Fig. 3 except that the response speed is more increased, the tuning of the membership function parameters is finished earlier and the swell and shrink phenomena are decreased as compared with the absolute steam mass flow disturbances.

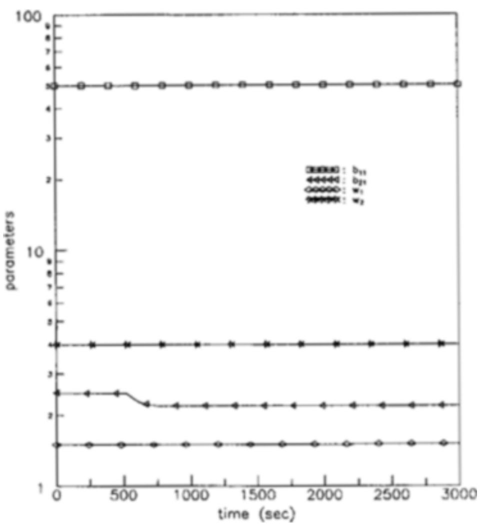
In order to examine the performances of this controller at several power levels (5 %, 15 %, 30 %, 50 % and 100 %), Fig. 5 shows the responses of the proposed controller at several power levels. As the power level increases, it is expected that the shrink and swell phenomena decrease as compared with the absolute steam mass flowrate change and the response speed increases. At 1500



(a) Water level

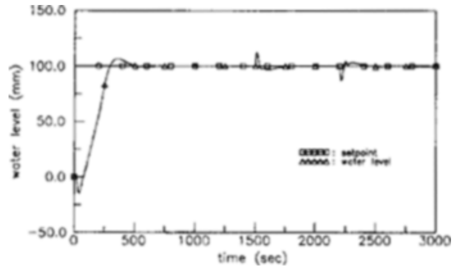


(b) Flowrate

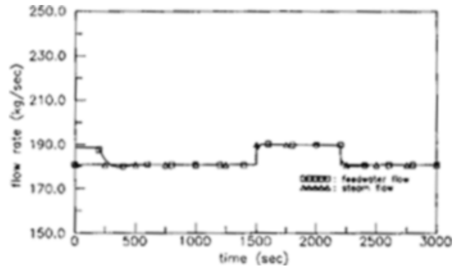


(c) The parameters of the membership functions

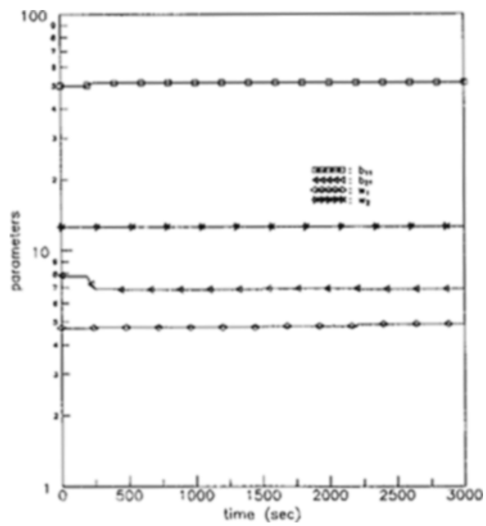
Fig. 3 Performances of the fuzzy controller at 5 % power



(a) Water level



(b) Flowrate



(c) The parameters of the membership functions

Fig. 4 Performances of the fuzzy controller at 15 % power

sec and 2200 sec, the reason why the swell and shrink phenomena of 100 % power are seen to be larger than those of 5 % power is that the absolute steam mass flow rate change of 100 % power is twenty times greater than that of 5 % power.

Contrary to the conventional method which has training data from other controller or operator skill during some periods, in this method, the membership function parameters b_{11}, b_{21}, w_1 and w_2 are tuned on-line with a forgetting factor and by applying an iterative method based on the gradient descent method [refer to Figs. 3(c) and 4(c)]. It can have ability to adjust inputs properly by using a forgetting factor and a weighting

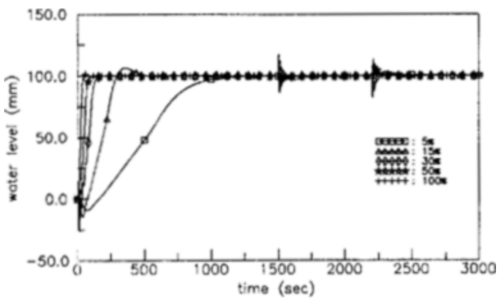


Fig. 5 Water level responses of the fuzzy controller according to power levels

value, too. Figures 3, 4 and 5 show the small overshoot and fast recovery time in the disturbances of 5 % step increase at 1500 sec and 5 % step decrease at 2200 sec.

6. Conclusions

The performance of the fuzzy control method largely depends on the tuning method and how to settle the rule base. Therefore, the fuzzy control algorithm with a learning function was investigated which could automatically construct and tune the rule base and membership functions. A forgetting factor was used to account for an exponential decay of the past data so that the control rules should be modified fast according to the change of process dynamics. The triangular membership functions were applied and also, the number of the membership functions of each input variable can be increased or decreased easily based on the given algorithm because of the generalization and simplification of the derived logic. Contrary to the conventional method which use the training data from other controller or operator skill during some periods, the proposed controller has the on-line learning function based on the gradient descent method in order to realize so-called a self-organizing fuzzy logic controller.

This controller provides satisfactory performances although it has small number of rules. The proposed controller can be applied successfully to the nuclear steam generator water level. However, Although its parameters are tuned automatically, its performance is affected a little by the assumed initial values of the parameters.

References

Guely, F. and Siarry, P., 1993, "Gradient Descent Method For Optimizing Various Fuzzy Rule Bases," *2nd IEEE Int. Conf. on Fuzzy Systems*, pp. 1241~1246.

Irving, E., et. al., 1980, "Toward Efficient Full Automatic Operation of the PWR Steam Generator with Water Level Adaptive Control," *BNES*, London, Boiler Dynamic and Control in Nuclear Power Stations, pp. 309~329.

Lee, J. Y. and No, H. C. (1993), "A 9-rule Fuzzy Logic Controller of the Nuclear Steam Generator," *J. of KNS*, Vol. 25, No. 3, pp. 371 -380.

Lee, Y. J., 1994, "Optimal Design of the Nuclear S/G Digital Water Level Control System," *J. of KNS*, Vol. 26, pp. 32~40.

Na, M. G. and No, H. C. 1992, "Design of an Adaptive Observer-Based Controller for the Water Level of Steam Generators," *Nucl. Eng. and Des.*, Vol. 135, pp. 379~394.

Park, G. Y. and Seong, P. H. 1995, "Application of a Fuzzy Learning Algorithm to Nuclear Steam Generator Level Control," *Annuals of Nuclear Energy*, Vol. 22, No. 3/4, pp. 135~146.

Salle, J. L. and Lefschetz, S., 1961, *Stability by Liapunov's Direct Method with Applications*, New York, Academic Press.

Takagi, T and Sugeno, M., 1985, "Fuzzy Identification of Systems and Its Applications to Modeling and Control," *IEEE Trans. Syst. Man. Cyber.*, Vol. SMC-15, No. 1, pp. 116~132.