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Application of Fuzzy Algorithm with Learning Function to Nuclear Power Plant Steam Generator Level Control

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Abstract - A direct method of fuzzy inference and a fuzzy algorithm with learning function are applied to the steam generator level control of nuclear power plant. The fuzzy controller by use of direct inference can control the steam generator in the entire range of power level. There is a little long response time of fuzzy direct inference controller at low power level. The rule base of fuzzy controller with learning function is divided into two parts. One part of the rule base is provided to level control of steam generator at low power level (0%~30% of full power) and the other to level control at high power level (30%~100% of full power). Response time of steam generator level control at low power level with this rule base is shown to be shorter than that of fuzzy controller with direct inference.

1. Introduction

As the digital technology is introduced for the nuclear power plant control, many advanced control algorithms are being investigated for use in nuclear power plants. Fuzzy control algorithm is considered to be one of the most promising advanced control algorithms and it is known that the Fugen Prototype Reactor in Japan is currently using the fuzzy algorithm for its control[1].

Conventionally, the membership functions and the fuzzy rules for the fuzzy control have been made on the basis of the expert's experience. For this method, however, the difficulty in putting the experimental knowledge into numerical data and the difficulty in tuning the rules are the major problems. Furthermore, precise tuning of the fuzzy variables is almost impossible when there are many inputs and when the system shows nonlinearity. Therefore, it is desired to make a fuzzy controller in which rules are generated automatically and tuned by learning function. We have constructed the numerical control simulation for a linear and a nonlinear model[2,3] of steam generator in nuclear power plants and we applied a fuzzy controller with direct inference method and a fuzzy control algorithm with learning function by descent method developed by Nomura, et al.[4] into this model.

2. Fuzzy Direct Inference Controller in Steam Generator

At first, the direct inference method of fuzzy controller has been applied to the level control of steam generator. It is well known that the conventional level controller of steam generator does not work well at low power conditions and the control is generally performed by human operators in these low power situations. During the low power operation, the level control is complicated by the thermal reverse effects known as shrink and swell. Increased feedwater flow adds mass to the steam generator, which would be expected to increase the measured downcomer water level and actually increases it at high power. But at low power, the cold feedwater addition can cause a decrease in vapor content of tube bundle and a temporary decrease in level occurs. It is called shrink. Similarly, a decrease in feedwater flow can cause a temporary increase in water level, which called swell. These reverse effects are confusing for either manual or automatic operation. A typical set of the water level responses of steam generator due to a step increase of the water flow and a step increase of the steam flow are given in Fig.1 and Fig.2, respectively. To make a controller, measured variables are three elements, which are feedwater flowrate, steam flowrate, and water level. Control variable is one element- feedwater flowrate. The relation between the input variables and a control variable in fuzzy rule base are divided by three rule base groups in order to tune the fuzzy variables of the antecedent part.

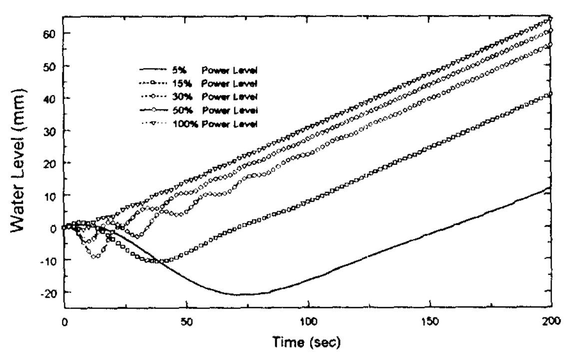


Fig. 1 Level responses of steam generator model to 5.74 kg/sec step increase of feedwater flowrate

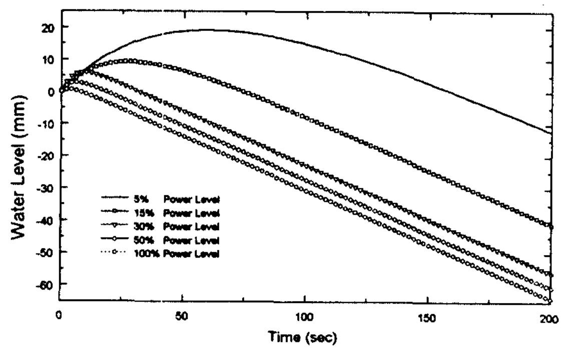


Fig. 2 Level response of steam generator model to 5.74 kg/sec step increase of steam flowrate

It is impossible to make a global tuning by use of the direct trial-and-error method on the four fuzzy variables (level error, level error change, flowrate error, swell and shrink state) which make up 4-dimensional space. The inference rules with their input fuzzy variables are as follows:

Rule Type 1 : If LE (level error) is PB and LEC (level error change) is NS, then $\Delta U1$ (feedwater flowrate) is ZO

Rule Type 2 : If FE (feedwater error) is PB, then $\Delta U2$ is NB

Rule Type 3 : If FE-ss (flow error for swell & shrink) is PB and LC (level change) is NS, then $\Delta U3$ is NB

where

LE : level(t) - level set point

LEC : $(LE(t) - LE(t-1))/\Delta t$

FE, FE-ss : (feedwater flowrate - steam flowrate)/Power

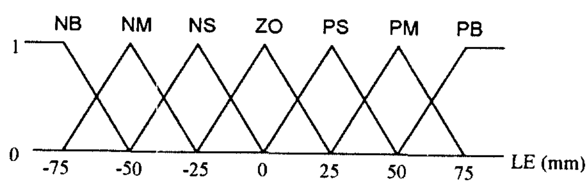
LC : $(level(t) - level(t-1))/\Delta t$.

Third inference rule base is the consideration for thermal reverse effect of the steam generator and generated on the basis of physical interpretations such as,

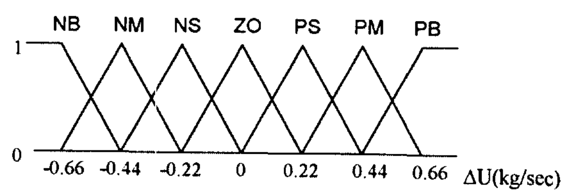
(1) FE > 0, and LC < 0 $\Rightarrow$ Shrink Phenomena $\Rightarrow$ Wfe $\downarrow$

(2) FE < 0, and LC > 0 $\Rightarrow$ Swelling Phenomena $\Rightarrow$ Wfe $\uparrow$

where Wfe is feedwater flowrate. The membership function of LE, and ΔU are shown in Fig.3 and each rule base listed above is given in Table 1.



(a) LE (level(t) - level set point)



(b) $\Delta U1$, $\Delta U2$, and $\Delta U3$ (feedwater flowrate)

Fig.3 Membership Functions of Input and Output Fuzzy Variables

LEC \ LE	NB	NM	NS	ZO	PS	PM	PB
PB	PB	PB	PB	PB	PS	ZO	NS
PS	PB	PB	PM	PS	NS	NM	NB
ZO	PB	PB	PS	ZO	NS	NB	NB
NS	PB	PM	PS	NS	NM	NB	NB
NB	PS	ZO	NS	NB	NB	NB	NB

(a) Rule Base 1

FE	NB	NM	NS	ZO	PS	PM	PB
$\Delta U2$	PB	PM	PS	ZO	NS	NM	NB

(b) Rule Base 2

LC \ FE-ss	NB	NS	ZO	PS	PB
PS	PB	PM	ZO		
ZO	ZO	PS	ZO	NS	ZO
NS			ZO	NM	NB

(c) Rule Base 3

Table 1 Rule Base of Three Types of Control

The final control value of ΔU is given by simple adding of $\Delta U1$, $\Delta U2$, and $\Delta U3$ and divided by 3. The response of water level and of feedwater/steam flowrate at 5% power with theses three rule bases are shown in Fig.4(a) and Fig.4(b)(level set point is 100mm). Level responses of steam generator at entire power range are shown in Fig.5.

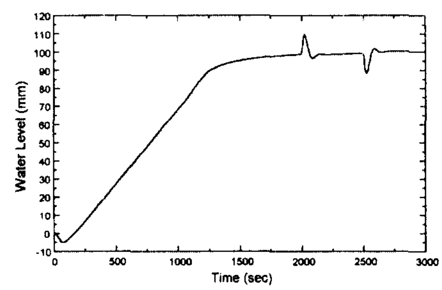


Fig.4(a) Level response of steam generator for fuzzy controller with 0.4% step increase & decrease in steam flowrate at 2000sec and 2500sec, respectively

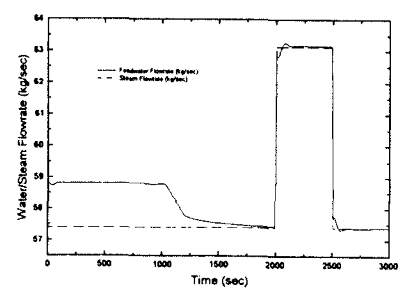


Fig 4(b) Response of feedwater flowrate of steam generator of fuzzy controller when 0.4% step disturbances of steam flowrate are applied

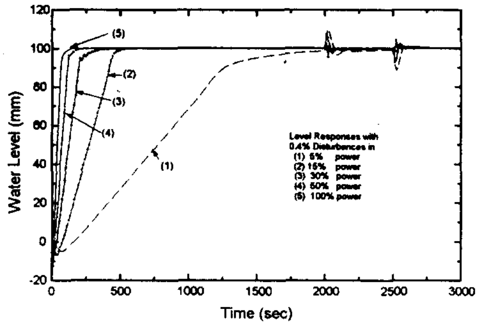


Fig.5 Level responses of steam generator with fuzzy direct inference with 0.4% disturbances in steam flowrate

From the above results, the fuzzy control algorithm is shown to be superior to the conventional control method. Even though there are delayed responses for level control at low power, it is not a critical problem in making a automatic controller for level control of steam generator in entire power range. But it takes long time to tune the membership functions and rule bases for the best optimal control. Hence we tried to make a controller with learning function to save times and works invested in tuning procedures for fuzzy direct inference.

3. Fuzzy Control Algorithm with Learning Function by Descent Method

A descent method[5] is to seek for the vector **z** which minimizes an objective function G(**z**), where **z** is a p-dimensional vector $\mathbf{z} = (z_1\ z_2, \cdots\ z_p)$. The direction that the objective function G decreases most rapidly at any point **z**(k) in abstract space is **d**(k) = -gradG where **d**(k) is a vector which represents a direction from point **z**(k). Hence a new point that has a relation G[**z**(k+1)] < G[**z**(k)] is obtained as

$$\mathbf{z}(k+1) = \mathbf{z}(k) + \lambda \mathbf{d}(k) . \tag{1}$$

Eq.(1) is rewritten as

$$z_i(k+1) = z_i(k) - \lambda \frac{\partial G(z)}{\partial z_i}, \quad (i = 1,\cdots,p) \tag{2}$$

where λ is a constant and a positive small number. Fuzzy learning algorithm by descent method is used for generating and automatically tuning the membership functions and the rule base. Fuzzy algorithm used in this method is suggested by Nomura, et al.[4]. A compositional rule of inference is expressed in terms of the input $\mathbf{x} = (x_1,\cdots,x_m)$ and the output y in learning algorithm as follows:

$$\text{If } x_1 \text{ is } A_{i1}, \cdots, x_m \text{ is } A_{im}, \text{ then y is } w_i , \quad (i = 1, \cdots,n) \tag{3}$$

where $A_{i1}, \cdots, A_{im}$ are membership functions of the antecedent part and w_i is a real number of the consequent part.

The membership function $A_{ij}(x_j)$ is formulated as

$$A_{ij}(x_j) = 1 - \frac{2|x_j - a_{ij}|}{b_{ij}}, \quad (i = 1,\cdots,n\ ;\ j = 1,\cdots,m) \tag{4}$$

where a_{ij} is a center point and b_{ij} is a width of an isosceles triangle membership function shown in Fig.6.

The output value y is calculated as follows:

$$y = \frac{\sum_{i=1}^{n} \mu_i w_i}{\sum_{i=1}^{n} \mu_i} \tag{5}$$

where $\mu_i = A_{i1}(x_1)\cdot A_{i2}(x_2)\cdots A_{im}(x_m)$. From Eq.(4) and (5), y is composed of w_i and $A_{ij}(x_j)$. $A_{ij}(x_j)$ is composed of a_{ij} and b_{ij}, i.e., a center point and a width of an isosceles triangle. Objective function G(z) is set by $G = \frac{1}{2}(y-y_d)^2$ where y_d is the acquired output data from other controller or skilled operators. Hence, Eq.(2) is a function of a_{ij}, b_{ij}, and w_i ($i = 1,\cdots,n$; $j = 1,\cdots,m$). Then a vector **z** is defined as follows:

$$\mathbf{z} = (z_1,z_2,\cdots,z_p) = (a_{11},\cdots,a_{nm};b_{11},\cdots,b_{nm};w_i,\cdots,w_n) \tag{6}$$

where p = 2nm + n. According to tuning parameters from Eq.(6), Eq.(5) is expressed for each tuning parameter, a_{ij}, b_{ij}, and w_i as follows:

$$a_{ij}(k+1) = a_{ij}(k) - \frac{\lambda_a \mu_i}{\sum_{i=1}^{n} \mu_i}(y-y_d)(w_i-y)\mathrm{sign}(x_j-a_{ij})\frac{2}{b_{ij}(k)A_{ij}(x_j)} \tag{7}$$

$$b_{ij}(k+1) = b_{ij}(k) - \frac{\lambda_b \mu_i}{\sum_{i=1}^{n} \mu_i}(y-y_d)(w_i-y)\frac{1-A_{ij}(x_j)}{b_{ij}(k)A_{ij}(x_j)} \tag{8}$$

$$w_i(k+1) = w_i(k) - \frac{\lambda_w \mu_i}{\sum_{i=1}^{n} \mu_i}(y-y_d) \tag{9}$$

where λ_a, λ_b, and λ_w are positive small numbers. Using the learning rules of the above Eqs.(7),(8) and(9), the tuning parameters of inference rules are optimized to minimize the inference error between the desired output y_d and the output of fuzzy reasoning y.

Fuzzy algorithm with learning function described previously is applied to a computer simulation for the control of water level of the steam generator in nuclear power plants. In this work, three fuzzy variables are determined. There are water level error(LE), level error change(LEC), and feedwater flowrate error(FE). Each fuzzy variable has seven fuzzy numbers and the initial triangle membership functions for LE are shown in Fig.7. The control variable is the feedwater flow rate(kg/sec) and the output measured in this simulation is the water level and water/steam flowrate of the steam generator. Values of input variables and a control variable are normalized before these are used in the fuzzy algorithm. When the set point of water level is set by 100mm, and 0.4% disturbances of steam flowrate at 2000sec and 2500sec are applied, the number of rules inputted to the rule base is 343 with these fuzzy variables.

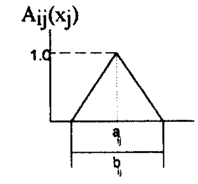


Fig. 6 Membership Function

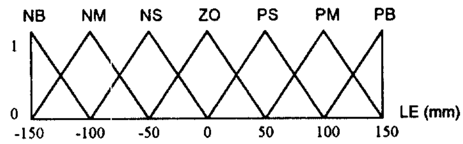


Fig.7 Membership Functions of Level Error Change

Required input and output data for learning of the fuzzy algorithm should be obtained from the control actions of skilled operators at low power(<30%) and from the control action of PID controller at high power (≥30%) for steam generator level control. Due to the lack of data, the input and the control data are obtained by use of PID controller with well-tuned gain values at 30% power level as alternatives for operator's control at low power condition. For control at high power condition, the data obtained from PID controller with 100% power level are used to construct the rule base by learning. Rule base of fuzzy inference is composed of two parts as shown in Fig.8. One part (Rule Base1) of the rule bases deals with low power range (<30% power) and the other (Rule Base2) high power range (≥30% power).

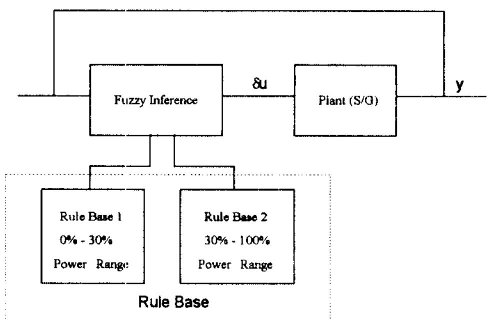


Fig.8 Rule Base of Fuzzy Inference with Learning Function

45 rules are extracted from initial 343 set of rules in rule base1 and 70 rules are extracted from 343 rules in rule base by use of PID data at 30%, 100% power, respectively. Responses of water level and of water/steam flowrate with 0.4% step disturbances in steam flowrate of steam generator at 5% power are shown in Fig.9(a), (b) and level responses at entire power range are shown in Fig.10. These results show good performance of the fuzzy controller with learning function for level control of steam generator in nuclear power plants. Response time of level control at low power is shorter than that of fuzzy controller by use of the direct inference method. There is an overshoot in level response level but rapid convergence follows from it at 15% power.

4. Conclusion and Further Study

Performances of steam generator level control in nuclear power plants by the fuzzy direct inference method and the fuzzy algorithm with learning function are superior to other controllers such as PID controller from the viewpoint of the capability of level control in entire power range which is important point in automatic control of nuclear power plant operation. Organization of learning algorithm of fuzzy reasoning to have the on-line adaptive learning function is needed and research on this subject will be carried out.

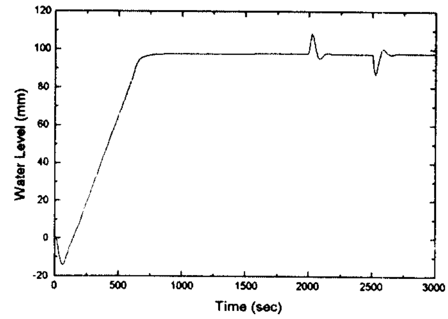


Fig 9(a) Level response of steam generator with fuzzy learining controller when 0.4% step disturbances in steam flowrate are given

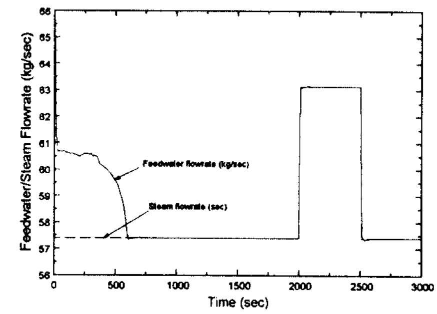


Fig.9(b) Feedwater/steam flowrate of steam generator with fuzzy controller with learning function when 0.4% step increase and decrease of steam flowrate at 2000sec and 2500sec, respectively

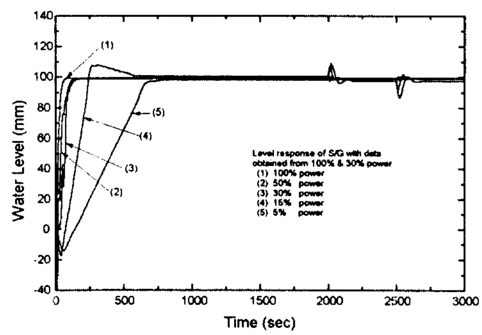


Fig.10 Level responses of steam generator in entire power range with fuzzy controller with learning function for step input and 0.4% step disturbances in steam flowrate

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