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Application of Self-Organizing Fuzzy Logic Controller to Nuclear Steam Generator Level Control

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Abstract

In this paper, the self-organizing fuzzy logic controller is developed for water level control of steam generator. In comparison with conventional fuzzy logic controllers, this controller performs control task with no control rules at initial and creates control rules as control behavior goes on, and also modifies its control structure when uncertain disturbance is suspected. Selected parameters in the fuzzy logic controller are updated on-line by the gradient descent learning algorithm based on the performance cost function. This control algorithm is applied to water level control of steam generator model developed by Lee, et al. The computer simulation results confirm good performance of this control algorithm in all power ranges. This control algorithm can be expected to be used for automatic control of feedwater control system in the nuclear power plant with digital instrumentation and control systems.

1. INTRODUCTION

Fuzzy controller as one of the intelligent controllers has shown to perform better in ill-defined or complex processes where quantitative information is not sufficient and qualitative information (such as human knowledge from operational experiences) is rich. It has the capability of converting qualitative knowledge into quantitative values and hence it can be designed in model-free fashion. Kuan, et al.[1] developed fuzzy logic controller for water level in pressurized water reactors. They constructed fuzzy rules based on purely human knowledge from operational experiences. Iijima, et al.[2] studied fuzzy control system for water level of drum type nuclear steam generator and installed the fuzzy control algorithm in feedwater control system of Fugen Prototype Reactor in Japan. And it was proved that fuzzy controller can control the water level more precisely than PI controller.

In this paper, the self-organizing fuzzy logic controller with performance cost function(SOFLC-PCF) is developed in order to provide the automatic water level control of nuclear steam generator. In this control algorithm, fuzzy rule base is constructed arbitrarily and membership functions are given uniformly so that they cover the entire input domain. This control algorithm is suited for the case that the quantitative information about steam generator is not complete and moreover, there is so few skilled operators that the satisfactory fuzzy rules and membership functions can not be obtained from the linguistic information of human operators. If the operational knowledge from experienced operators can be obtainable, their linguistic knowledge is incorporated easily into the initial fuzzy rule base.

2. DESCRIPTIONS OF SOFLC-PCF

The overall control scheme of SOFLC-PCF is depicted in Fig.1. The SOFLC-PCF has two hierarchical structures, namely, the self-organizing level and the basic level. The self-organizing level contains the learning algorithm (or, self-tuning algorithm) and the performance cost function. The learning algorithm creates and modifies the control rules of fuzzy logic controller which is included in the basic level based on the performance cost function. Then, the fuzzy logic controller performs control tasks with the updated control rules. The input and output values of controller are normalized into [-1, 1] by use of the scaling factors g_l, g_f, and g_o. Detailed descriptions of each component are presented as following subsections.

2.1. Structure of Fuzzy Logic Controller

In this paper, fuzzy logic controller is composed of the membership functions of symmetric triangular type and the rule base which has the simplified Takagi-Sugeno rule type. The simplified Takagi-Sugeno rule is presented as follows:

$$\text{If } x_1 \text{ is } MF_{i1}, \cdots, x_m \text{ is } MF_{im}, \text{ Then y is } w_i, \quad (\text{for } i = 1, \cdots, n) \tag{1}$$

where $\mathbf{x}^T = (x_1 \cdots\cdots x_m)$: input vector, MF_{ij} : membership function for j'th input of i'th rule, y : output of i'th rule, w_i : real value of consequent part, n : number of rules, and m : number of input variables.

In Eq.(1), the statement in "If" part is called the antecedent part and the statement in "Then" part the consequent part. The membership function, MF_{ij}, is expressed as follows:

$$MF_{ij}(x_j) = \begin{cases} 1 - \dfrac{2|x_j - a_{ij}|}{b_{ij}} & ; \quad |x_j - a_{ij}| \le \dfrac{b_{ij}}{2} \\ 0 & ; \quad \text{otherwise} \end{cases} . \tag{2}$$

The a_{ij} and b_{ij} in Eq.(2) are the center point and the width of the symmetric triangular membership function, respectively The real value of w_i in Eq.(1) determines the content of fuzzy rule base and this value is updated by the learning algorithm. In the inference engine, AND(or t-norm) operator is defined by simple multiplication and hence, membership value for i'th rule, μ_i, is obtained such as

$$\mu_i(\mathbf{x}) = \prod_{j=1}^{m} MF_{ij}(x_j). \tag{3}$$

The basis function $\phi_i(\mathbf{x})$ is defined as follows:

$$\phi_i(\mathbf{x}) \equiv \frac{\mu_i(\mathbf{x})}{\sum_{i=1}^{n} \mu_i(\mathbf{x})}. \tag{4}$$

The control output, y, can be obtained such as

$$y = \sum_{i=1}^{n} w_i \phi_i . \tag{5}$$

As can be seen in Eq.(5), the controller output is the linear combination of control values in the consequent part of fuzzy rule base multiplied by their own basis functions.

2.3. Learning Algorithm

In order to operate the learning process, the objective function is to be constructed and this is expressed by the performance cost function, J, such as

$$J(t+d)=\frac{1}{2}e_l^N(t+d)^2+\frac{\lambda}{2}e_f^N(t)^2, \tag{6}$$

where e_l^N is the normalized level error; $e_l^N = (L_w^{set} - L_w)/g_l$, e_f^N is the normalized flow error; $e_f^N = (W_{st} - W_{fw})/g_f$, d is the system time delay of output to input, and λ is the weighting factor in [0, 1].

The updating algorithm for w_i based on the performance cost function is expressed as follows:

$$w_i(t;k+1)=w_i(t;k)-K_w\frac{\partial J(t+d)}{\partial w_i(t;k)}. \tag{7}$$

The index t and k in Eq.(7) mean the time and the number of learning iteration during the sampling period, respectively. K_w is the learning coefficient and the optimal value of learning coefficient can be obtained from the investigation of optimal range learning coefficient by Park and Seong[3]. The gradient descent of performance cost function with respect to w_i is expressed as follows:

$$-\frac{\partial J(t+d)}{\partial w_i(t;k)}=\left[(g_o/g_l)e_l^N(t+d)\frac{\partial L_w(t+d)}{\partial W_{fw}(t)}+\lambda(g_o/g_f)e_f^N(t)\right]\frac{\partial W_{fw}^N(t)}{\partial w_i(t;k)}, \tag{8}$$

where $W_{fw}^N(t) = W_{fw}(t)/g_o$. In Eq.(8), the last term, $\partial W_{fw}^N(t)/\partial w_i(t;k)$ equals to ϕ_i by replacing y in Eq.(5) by ΔW_{fw} and differentiating Eq.(5) by w_i.

We define the sensitivity factor S(t+d;t) as

$$S(t+d;t)\equiv\frac{\partial L_w(t+d)}{\partial W_{fw}(t)}. \tag{9}$$

Then, the learning algorithm for w_i can now be expressed as follows:

$$w_i(t;k+1)=w_i(t;k)+K_w\left[(g_o/g_l)e_l^N(t+d)S(t+d;t)+\lambda(g_o/g_f)e_f^N(t)\right]\phi_i. \tag{10}$$

Now, the problem is how we can obtain the sensitivity factor S(t+d;t). Because we do not have any systematic or mathematical information about the plant dynamics for output to input, the accurate value of S(t+d;t) can not be calculated for each time step. In order to circumvent this problem, instead of S(t+d;t), the approximated value of sensitivity factor, S_{app}, is calculated and used in this control algorithm through the procedure that at any operating point (operating point means power level for steam generator water level control), when the plant input(feedwater flowrate) is increased/ decreased by a magnitude in step fashion, the plant output(water level) is varied. After the transient stage is passed over, the plant output is increased/decreased in accordance with the increase/decrease of the plant input. Then, we calculate the maximum value of the variation of plant output(water level), ΔL_{max}, and the approximate sensitivity factor, S_{app}, is set to $\Delta L_{max}/\Delta W_{fw}$ for specific plant input variation(ΔW_{fw}). Above procedure is repeated for various magnitudes of plant input and the corresponding values of S_{app} are obtained for specific operating point(power level). And the above procedure is repeated again for various operating points and the values of the approximate sensitivity factor are collected. Fuzzy system with learning function proposed by Park and Seong[3] is now constructed in order to learn the sensitivity data obtained from the above procedure. After learning is completed, the trained fuzzy system can give the value of the approximate sensitivity factor for any operating point(power level) and for any variation of plant input(ΔW_{fw}).

In the steam generator, the approximate sensitivity factor is calculated after the transient effects of water level are diminished, this means that S_{app} is equivalent to the mass capacity effect which represents changes in the water level by mass influx or efflux from the volume of the particular steam generator. Therefore, S_{app} is constant for all operating points and for all variations of plant input(ΔW_{fw}). When the procedure for obtaining the S_{app} is applied to the nonlinear steam generator model developed by Lee and No[4], the values of S_{app} for five operating points are 0.00073(m/(kg/sec)) at 5% power, 0.00073 at 15% power, 0.00074 at 30% power, 0.00074 at 50% power, and 0.00074 at 100% power for all variations of feedwater flowrate. Considering the numerical calculation error, it can be thought that the S_{app} is constant for all operating points and for all input variations. Because the S_{app} is constant for steam generator, it is unnecessary to construct the fuzzy system with learning function. Calculating the S_{app} for one fixed variation of plant input at a specific operating point where flow measurements are accurate is sufficient for obtaining the approximate sensitivity factor for all operating points and for all variations of plant input.

3. APPLICATION

3.1. Implementation of Control Algorithm

In order to apply of this control algorithm to level control problem, the steam generator model developed by Lee, et al.[5] is used in the control simulation. In Lee, et al.'s S/G model, the approximate sensitivity factor of water level to feedwater flowrate is 0.00011 (m/(kg/sec)) by calculation. Time delay, d, in Fig.1 is set to 1. The values of K_w and λ are set to 1 and 0.01, respectively. The λ is a weighting factor with the range of [0,1], so that if λ is increased flow error is more significant than level error and hence, the learning algorithm is more sensitive to flow error than to level error. If λ is decreased the case is reversed.

3.2. Simulations

Fig.2 shows the results of the water level control of S/G for 5%/min ramp variations of power load from 5% to 30% as shown in Fig.3 and for step load disturbances such as 5 and 25 kg/s at 5% and 30% power loads, respectively. As can be seen in Fig.2, this controller shows good regulation performance for power ranges of 5%~30% and uncertain large load disturbances. Fig.4 shows the results of control performance of SOFLC-PCF for various values of weighting factor λ.

4. CONCLUSIONS AND FURTHER STUDY

In this paper, the SOFLC-PCF is applied to water level control of nuclear steam generator. This controller starts control task without any control information and it can create the necessary rules as time goes on and shows good control performance in all power ranges. Sensitivity value is, however, to be calculated from the operation of S/G. Because the value of approximate sensitivity factor is constant for S/G, one fixed variation of plant input at a specific power is sufficient for calculating the approximate sensitivity factor. The weighting factor, λ, can be tuned on-line in order to improve the level control performance during plant operation. The SOFLC-PCF is expected to be incorporated into the advanced control algorithm group for supporting the automatic level control of S/G and it may be used in parallel with PID controller in digital I&C system.

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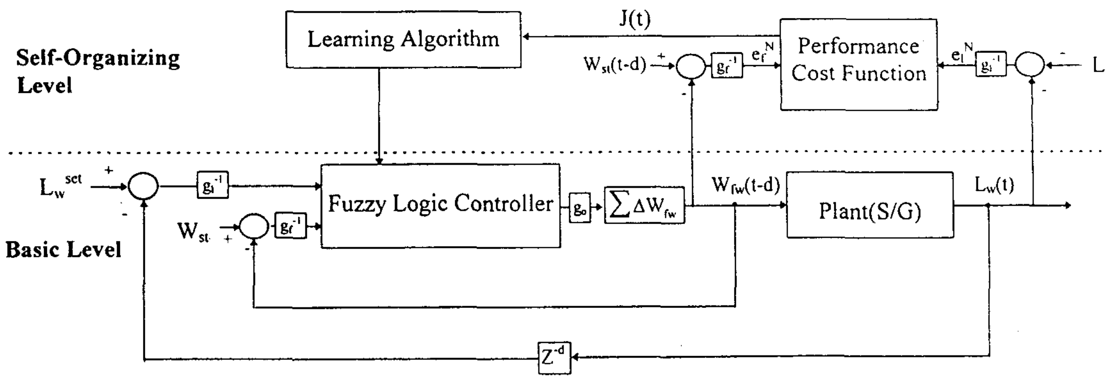

Fig.1 Schematic diagram of SOFLC with performance cost function

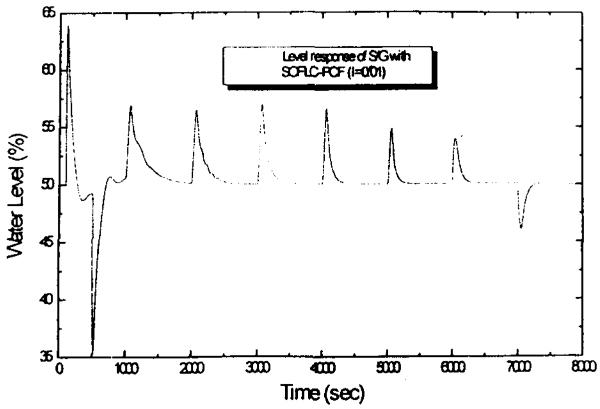

Fig.2 Level responses of S/G with SOFLC-PCF

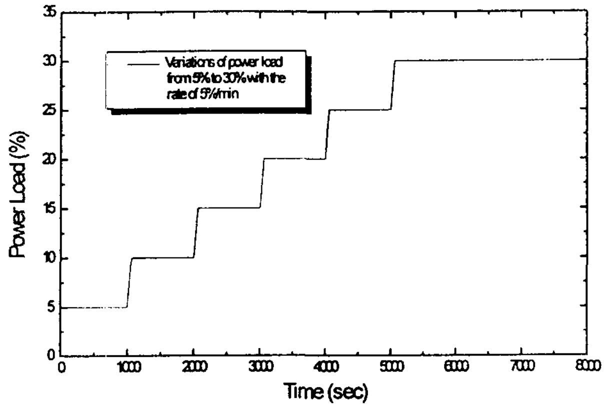

Fig.3 Variations of power load

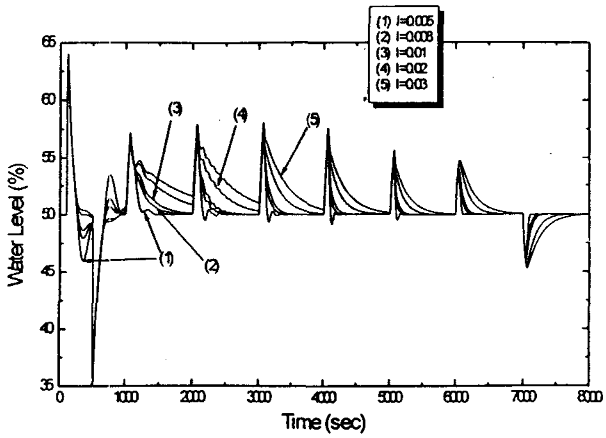

Fig.4 Level responses of S/G for various values of λ