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Fuzzy Gain Scheduling of Velocity PI Controller with Intelligent Learning Algorithm for Reactor Control

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Abstract

In this study, we proposed a fuzzy gain scheduler with intelligent learning algorithm for a reactor control. In the proposed algorithm, we used the gradient descent method to learn the rule bases of a fuzzy algorithm. These rule bases are learned toward minimizing an objective function, which is called a performance cost function. The objective of fuzzy gain scheduler with intelligent learning algorithm is the generation of adequate gains, which minimize the error of system.

The condition of every plant is generally changed as time gose. That is, the initial gains obtained through the analysis of system are no longer suitable for the changed plant. And we need to set new gains, which minimize the error stemmed from changing the condition of a plant. In this paper, we applied this strategy for reactor control of nuclear power plant (NPP), and the results were compared with those of a simple PI controller,which has fixed gains. As a result, it was shown that the proposed algorithm was superior to the simple PI controller.

1. Introduction

The best-known controllers used in industrial control processes are proportional-integral-derivative(PID) controllers because of their simple structure and robust performance in a wide range of operating conditions. Also a field engineer is very familiar of PID controller. The design of such a controller requires specification of three parameters: proportional gain, integral time constant, and derivative time constant[4]. So far, great efforts has been devoted to develop methods to reduce the time spent on optimizing the choice of controller parameters[4].

The condition of every plant is generally changed as time goes. That is, the initial gains obtained through the analysis of system are no longer suitable for the changed plant. And we may need frequent on-line tuning because of this change in system condition. Here, fuzzy gain scheduling of PI controllers with a learning algorithm of rule bases is proposed for reactor control of nuclear power plant. The new scheme utilizes fuzzy rules and reasoning to determine the controller parameters, and the PI controller generates the control signal.

2. Description of Control System

2.1 Mathematical Model of Pressurized Water Reactor

To apply the control method described in the following sections, a simplified pressurized water reactor

(PWR) model is developed based on the following assumption[2]:

1) The primary loop and steam generator of a PWR are modeled.
2) A lumped parameter nonlinear model of the primary loop is used.
3) Xenon and fuel depletion effects are not considered.
4) Single-phase heat transfer of the core coolant is considered.
5) Primary loop mass flow rate and pressure are constant.
6) Reactor power and core inlet-outlet temperatures are measured.

Then the plant model can be written as follows(Nomenclature)

$$\frac{dp}{dt} = \frac{1}{l}\left[\rho_0 - \beta + \alpha_f T_f + \alpha_C T_{avg} + bu\right]P + \sum_{i=1}^{6} \lambda_i C_i, \tag{1-1}$$

$$\frac{dC_i}{dt} = \frac{\beta_i}{l} P - \lambda_i C_i, \quad i = 1, \ldots\ldots, 6 \tag{1-2}$$

$$\frac{dT_f}{dt} = -\left(\frac{UA}{M_f c_{pf}}\right)\left(T_f - T_{avg}\right) + \left(\frac{J}{M_f c_{pf}}\right)P, \tag{1-3}$$

$$\frac{dT_{avg}}{dt} = \left(\frac{UA}{M_c c_{pc}}\right)\left(T_f - T_{avg}\right) - \frac{\dot{m}}{M_c}\left(T_{out} - T_{in}\right), \tag{1-4}$$

$$\frac{dT_{in}}{dt} = \frac{1}{\tau_{cl}}\left(T_{cl} - T_{in}\right), \tag{1-5}$$

$$\frac{dT_s}{dt} = -\frac{1}{\tau_s}\left(T_s - T_{hl}\right) - D_1 L_T, \tag{1-6}$$

$$\frac{dT_{hl}}{dt} = \frac{1}{\tau_{hl}}\left(T_{out} - T_{hl}\right), \tag{1-7}$$

$$T_d = D_2 T_s - D_3 T_{hl}. \tag{1-8}$$

2.2. The Basic Structure of PID Controller

Generally, we can express PID controller as follows:

$$u(k) = K_p e(k) + K_i T_s \sum_{i=1}^{n} e(k) + \frac{K_d}{T_s} \Delta e(k) \tag{2-1}$$

$$\Delta e(k) = e(k) - e(k-1)$$

where, $u(k)$: control signal
$e(k)$ = reference - process output
T_S: sampling period

The velocity PID controller can be defined as follows[1]:

$$u(k) = u(k-1) + K_p\left[e(k) - e(k-1)\right] + K_i T_s e(k) + \frac{K_d}{T_s}\left[e(k) - 2e(k-1) + e(k-2)\right] \tag{2-2}$$

2.3. The F.G.S. with Learning Algorithm by Gradient descent Method for Reactor Control

The purpose of learning algorithm is the generation of rule bases used in the fuzzy algorithm. Of course, we can generate the rule bases in the step of design. But in order to obtain the appropriate rule bases, we should know the behavior of system which we intend to design. In that case, we have to exhaust much efforts and time.

Therefore, we used the learning algorithm which can reduce our efforts and time. Here, Learning algorithm is obtained by gradient descent method based on the objective function, which is called a performance cost function, to be minimized and it is expressed such as follows[3]:

$$w_i(k+1) = w_i(k) - K\frac{\partial J}{\partial w_i} \tag{3-1}$$

Where, J : objective function;
K : Learning speed constant.

The performance cost function J in Eg.(3-1) can be defined as follows:

$$J = \frac{1}{2}\left\{W_T\left[T_{ref} - T_{avg}(k)\right]\right\}^2 + \frac{1}{2}\left\{W_P\left[L_T - P(k)\right]\right\}^2 \tag{3-2}$$

where, W_T, W_P: weight of cost function,
T_{ref} : programmed temperature,
T_{avg} : averaged temperature,
L_T : desired turbine load,
P : reactor power.

This performance cost function J in Eq.(3-2) is defined to represent the objectives of reactor control in the nuclear power plant and is a quadratic form of error function. Here, if we differentiate this function J in Eq.(3-2) in terms of each rule, which is each rule of a proportional gain and a integral gain. this function (3-2) can be expressed as follows:

$$-\frac{\partial J}{\partial w_{iP}(k-1)} = -\left[W_T^2 e_T(k)\frac{\partial T_{avg}(k)}{\partial U(k-1)} + W_P^2 e_P(k)\frac{\partial P(k)}{\partial U(k-1)}\right]\frac{\partial U(k-1)}{\partial K_P'(k-1)}\frac{\partial K_P'(k-1)}{\partial w_{iP}(k-1)} \tag{4-1}$$

$$-\frac{\partial J}{\partial w_{iI}(k-1)} = -\left[W_T^2 e_T(k)\frac{\partial T_{avg}(k)}{\partial U(k-1)} + W_P^2 e_P(k)\frac{\partial P(k)}{\partial U(k-1)}\right]\frac{\partial U(k-1)}{\partial K_I'(k-1)}\frac{\partial K_I'(k-1)}{\partial w_{iI}(k-1)} \tag{4-2}$$

where ,
$$\frac{\partial U(k-1)}{\partial K_P'(k-1)} = e(k-1) - e(k-2),$$
$$\frac{\partial U(k-1)}{\partial K_I'(k-1)} = T_S e(k-1),$$
$$e(k) = W_T\left[T_{ref} - T_{avg}(k)\right] + W_P\left[L_T - P(k)\right],$$
$$e_T(k) = T_{ref} - T_{avg}(k), e_p(k) = L_{ref} - P(k),$$

K_P' : value of proportional gain,
K_I' : value of derivative gain,
w_{iP} : rule of proportional gain (for i =1,....,n),
w_{iI} : rule of derivative gain(for i =1,....,n).

If we apply the above expressions in Eqs.(4-1,2) to Eq.(3-1), we can easily derive the following expressions, which make the rules tuned appropriately toward reducing the error.

$$w_{iP}(k+1) = w_{iP}(t) + K_{wP}\left[W_T^2 e_T(k)SFT + W_P^2 e_P(k)SFP\right]\frac{\partial U(k-1)}{\partial K'_P(k-1)}\frac{\partial K_P(k-1)}{\partial w_{iP}(k-1)} \tag{5-1}$$

$$w_{iI}(k+1) = w_{iI}(k) + K_{wI}\left[W_T^2 e_T(k)SFT + W_P^2 e_P(k)SFP\right]\frac{\partial U(k-1)}{\partial K'_I(k-1)}\frac{\partial K'_I(k-1)}{\partial w_{iI}(k-1)} \tag{5-2}$$

where, $$SFT = \frac{\partial T_{avg}(k)}{\partial U(k-1)} \quad ,SFP = \frac{\partial P(k)}{\partial U(k-1)} \tag{5-3}$$

K_{wP}, K_{wI} : Learning speed constant of Kp and Ki respectively

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

If x_1 is Mf_{i1}, ..., x_m is Mf_{im}, Then y is w_i (for i =1, ..., n)

where $x^T = (x_1 \ldots\ldots x_m)$: 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,
m : number of input variables.

In the inference engine, t-norm operation[5] is defined by a simple multiplication and hence, the membership value for i'th rule, μ_i, is obtained such as

$$\mu_i(x) = \prod MF_{ij}(x_j) \quad . \tag{6-1}$$

The output of fuzzy algorithm, y, can be obtained by the center average method as follows:

$$Y = \frac{\sum_{i=1}^{n} \mu_i w_i}{\sum_{i=1}^{n} \mu_i}. \tag{6-2}$$

Finally, the changing rate of output y to each rule value can be defined as follows. This expression is included in Eqs.(5-1,2).

$$\frac{\partial Y}{\partial w_i} = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i} \tag{6-3}$$

3. Simulation Results

Because the nuclear power plant is a critical safety system, we should consider this point in the step of designing controller, and we bounded the values of Kp and Ki , which are outputs of the fuzzy algorithm, in order to guarantee the stability of system. Of course, we obtained the stable range of each gain by analyzing the initial system.

In the step of simulation, we need to know SFT and SFP which are called sensitivity factors. In the case of considering the characteristics of reactor control, we can assume the sensitivity factors as a constant. Therefore, we could obtain the values through the simulation. Also in order to simulate the change of condition, we made the U, the heat transfer coefficient, in Eq.(1-3,4) changed at the specific time.

As a result, when the change of condition occurs, the performance of the proposed algorithm was better than that of the fixed PI controller as shown in figure 1and 2.

4. Conclusion

There are many methods in tuning of PID controller gains. For example, the Ziegler-Nichols tuning formula is perhaps the most well known tuning method. This method is very simple, but cannot always effectively control systems with changing parameters, and may need frequent on-line tuning when the system of condition is changed, and can be used only for linear control system. Also there are other restrictions in the Ziegler-Nichols tuning method. Therefore, One can not use the Ziegler-Nichols tuning when one designs a controller of nonlinear control system.

In this research, we proposed a fuzzy gain scheduler with intelligent learning algorithm for a reactor control. In the case of a fuzzy gain scheduler without intelligent learning algorithm, we should know the behavior of system in order to obtain the appropriate rule bases. This is a big demerit of fuzzy system because we have to exhaust much efforts and time. Therefore, we proposed a fuzzy gain scheduler with intelligent learning algorithm which is obtained by gradient descent method based on the objective function, which is called a performance cost function, to be minimized.

The proposed control algorithm is very effective when the condition of system is changed as time goes. That is, this algorithm automatically generates adequate gains toward minimizing the error which is stemmed from the change in system condition. Also because this algorithm obtains information from a linguistic knowledge and reasoning to determine the controller parameters, The performance of this algorithm is more effective than that of any other tuning algorithms. we are able to know that the performance of the proposed algorithm was better than that of the fixed PI controller as shown in figure 1and 2. Also we can expect a very good performance of control in the case of linear system as well as nonlinear system when the condition of system is changed as time goes.

It is still possible to make further performance improvements by fine tuning the ranges as well as by modifying the learning speed constant. These points require further research and development.

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♣ Nomenclature

T_{in} : Core inlet temperature(^{0}C)
T_{hl} : Hot let temperature(^{0}C)
T_s : *Steam generator steam temperature*(^{0}C)
U : Convective heat transfer coefficient (MW*m^{-2}*^{0}C^{-1})
K_c : Thermal conductivity of reactor coolant(MW*m^{-2}*^{0}C^{-1})
v : Average velocity of the coolant(m*s^{-1})
c_{pc} : Coolant specific heat(MW*s*kg^{-1}*^{0}C^{-1})
J: Conversion factor
P : Core averaged neutronic power(%)
l: *Neutron generation time(s)*
β : Total effective delayed neutron fraction
α_c : Moderator temperature coefficient of reactivity
λ : Effective delayed neutron decay constant
M_c : Coolant mass(kg)
A : *Effective heat transfer area*(m^2)

T_{out} : Core outlet temperature(^{0}C)
T_{avg} : Core averaged coolant temperature(^{0}C)
L_T : *Turbine load(%steam flow to turbine)*
μ : Viscosity of the coolant(kg*m*s^{-1})
D_e : Equivalent diameter of the lattice of coolant channel(m)
ρ_c : Density of the coolant(kg*m^{-3})
C_v : A constant determined by water-fuel volume fraction of the lattice
$\dot{m}$: Core mass flow rate (kg*s^{-1})
C : Core averaged ith group precursor concentration
ρ_o : *Total core reactivity at initial state*
α_f : Fuel temperature coefficient of reactivity
λ_i : ith group delayed neutron decay constant
b : Differential control rod worth(Δρ*step^{-1})
c_{pf} : Fuel specific heat(MW*s*kg^{-1}*^{0}C^{-1})
τ_1 , τ_2 , τ_3 , τ_4 : Time constant for control model(s)

τ_{cl} , τ_{hl} , τ_s : Time constants for coolant loop and steam generator(s)
D_1 , D_2 , D_3 , D_4 : Nominal parameters for reactor and steam generator model

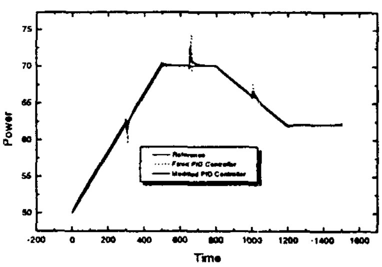

Figure. 1

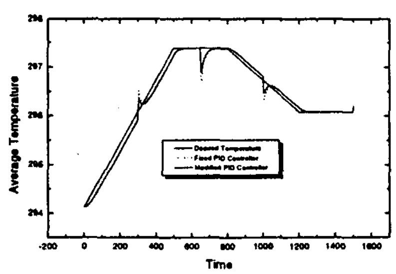

Figure. 2