A Learning Control of Unused Energy Power Generation

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Abstract: In recent years, the new clean energy without dependence on the fossil fuel is required. The control system of the power generation using low temperature gap is designed to keep the speed of the steam turbine in real environment. This system includes nonlinearity and the characteristics of the system change in real environment with the aged deterioration. The evaporator, the condenser, and the turbine systems are modeled, and the PID control with the ability of learning based on BP neural network is designed.

***Keywords*:** Learning control, BP Neural Network, Power generator, Low thermal gap, Evaporator, Turbine

I. INTRODUCTION

The clean energy exits in the natural world, and this energy does not emit exhaust gas when it used. The clean energy is widely used for wind energies, solar power and so on, whereas there is some clean energy that has not been used yet such as hot spring heat or exhaust heat of factories. The power generation with these unused clean energies can obtain small heat capacity from heat sources and low thermal efficiency because these power generations scatter the utilizable energies so widely. The temperature gap of unused energy is low as 20℃ to 30℃. In contrast, the temperature gap of the thermal power generation is 500℃ and the temperature gap of the nuclear power generation is 200℃. The heat efficiency is also low as well as 3% to 4%, while the thermal power generation is 40%. Moreover, these heat sources are scattered and the scale of these heat sources is small. Therefore it is necessary to establish a control method that is suitable for the power generation capacity and scale.

This paper deals with the performance improvement of the power generation using low temperature gap in the steady state. This power generation system is composed by Water/ Ammonia fluid as working fluid. This paper set up a heat exchanger model and a turbine model. The control of turbine parts is difficult, because the turbine parts include nonlinear factor. Also this paper confirms usefulness and practicability about BPNN PID-controller through simulations.

II. POWER GENERATION USING LOW TEMPERATURE GAP

The main component of the power generation system using low temperature gap with closed cycle is constructed by heat exchanger (evaporator, condenser), turbine and pump. This working fluid is liquid and carried to the evaporator by the pump. Then it is boiled and becomes steam in the evaporator by hot water. While steam of working fluid passes through the turbine, this system can generate electric power by rotating the turbine blade shaft. The working fluid that passed through the turbine is cooled with cold water in condenser, and becomes liquid again. The structure of the power generation system is illustrated in Fig.1.

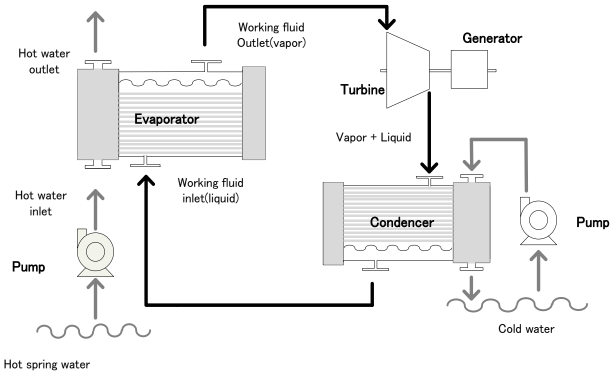

Fig.1 Closed cycle power generation system

2.1 Evaporator Model

The evaporator is shell-and-tube type is shown in Fig.2. The liquid of working fluid is carried to the evaporator tank by pump soaking the heat exchanger tube. Hot water circulates in the heat exchanger tube, and then, the working fluid is steam.

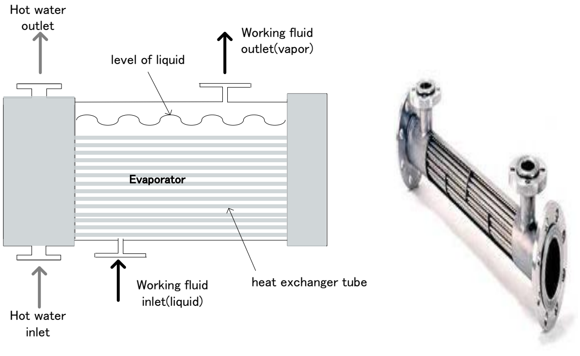

Fig.2 Structure of evaporator

Assumptions of Modeling:

- When the working fluid flows into the evaporator, it is preheated the saturation temperature to liquid phase state.
- The heat exchanger tubes are soaked by the working fluid.
- No consider radiation heat on the entire evaporator.

The steam pressure equations are as follows. [1]

$$H(s) = \frac{1-exp(\tau s)}{\tau s} \tag{1}$$

The steam flow of evaporator outlet response is$\Delta Q(s)$, the change in temperature of the hot water to the inlet is$\Delta\theta_h(s)$, and the change of flow for the hot water is $\Delta G_h(s)$.

$$\Delta Q(s) = \{Z_1 \quad Z_2\}\begin{Bmatrix}\Delta\theta_h(s)\\ \Delta G_h(s)\end{Bmatrix} \tag{2}$$

Here,

$$Z_1(s) = \frac{K_1(1-e^{-\tau s})}{\tau s(1+T_c s)(1+T_h s)} \tag{3}$$

$$Z_2(s) = \frac{K_2(1-e^{-\tau s})}{\tau s(1+T_c s)} \tag{4}$$

T_c, T_h are staying time constant, K_1 K_2 are constant value, τ is system constant value.

2.2 Turbine Model

The turbine is composed of the steam control valve and rotor blade, as shown in Fig.3. The steam is piped from the evaporator into the turbine blade through the steam control valve. The steam control valve adjusts steam flow to turbine blade.

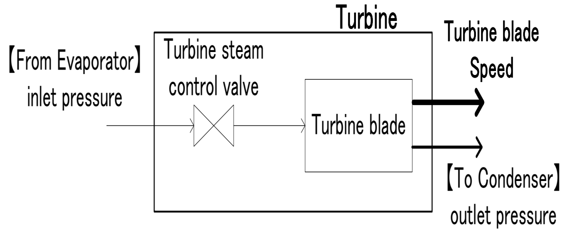

Fig.3 Turbine system

Turbine systems equations are as follows [2]:

Working fluid steam control valve:

$$\frac{dx_1}{dt} = K_3\frac{\upsilon}{\upsilon_{max}},\ 0 \le x_1 \le 1 \tag{5}$$

Working fluid steam mass rate:

$$\mu_T = \frac{x_1}{M_E}\left({\phi_E}^2 - {\phi_T}^2\right)^{1/2} \tag{6}$$

Turbine blade speed :

$$\frac{d\upsilon}{dt} = \frac{1}{\tau_T}\left[\frac{\phi_E-\phi_T}{\overline{\phi_E}-\overline{\phi_T}}\frac{\mu_T}{\upsilon\overline{\mu_T}} - (1-\varepsilon)\frac{1}{\upsilon} - \varepsilon\upsilon^2\right] \tag{7}$$

υ_{max} : max speed of turbine blade
K_3 : gain
M_E : constant
ϕ_E : evaporator outlet vapor pressure
ϕ_T : turbine outlet vapor pressure
τ_T : system constant
ε : electric load
$\bar{\ }$: desired value

III. Back Propagate Neural Network

The BPNN is a multi-layers network that consists of the input layer, the hidden layer, and the output layer. The standard structure is shown in Fig.4.

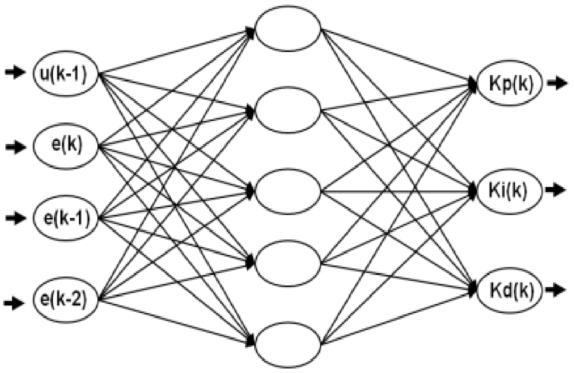

Fig.4 Structure of BP network

BP algorithm step.

Firstly, the actual output of BPNN will obtain from the actual outputs as Eq. (8). It is forward progress.

$$a^{k+1} = f^{k+1}(w^{k+1}\cdot a^k + b^k)$$
$$k = 0,1,\dots,m-1 \tag{8}$$

a: output of each layer
w: weight value
b: bias value
m: number of layer

Secondly, the error will be generated at the output layer by comparing between the actual output and the target output. The error function at output layer is defined as

$$E_p = \frac{1}{2}\sum_{k=1}^{m}(T_k - A_k)^2 \tag{9}$$

T_k : reference output
A_k : actual output

The total error function of neural network is shown in Eq. (10).

$$E = \sum_{k=1}^{P} E_p \tag{10}$$

P: total numbers of pattern

Thirdly, the gradient descent method is utilized to calculate the weights of network and adjusts the weights of interconnections to minimize the output error. The gradient descent algorithm adopts the weights according to the gradient error, which is given by Eq. (11).

$$\Delta W_{ij} = -\eta \times \frac{\partial E}{\partial W_{ij}} \tag{11}$$

η: Learning rate

The general form of ∂E/ ∂W is expressed as following Eq. (12).

$$\frac{\partial E}{\partial W_{ij}} = -\delta_j^n \times A_i^{n-1} \tag{12}$$

A: output value of each layer
W: connective weight
δ: error signal
n: layer number of BP network

Substituting Eq. (11) into Eq. (12), the gradient error is expressed as

$$\Delta W_{ij} = \eta \times \delta_j^n \times A_i^{n-1} \tag{13}$$

ΔW adjusts the weight values between the input layer nodes the output layer nodes from output layer to the input layer. According to these adjustments, the error will decrease until the small set point.

IV. PID parameters with BP NN

BP Neural Network PID control system has structure as depicted in Fig.5. In this PID controller, the connection between the output and the input is given by Eq. (16). BPNN block in Fig.5 shows the structure of NN.

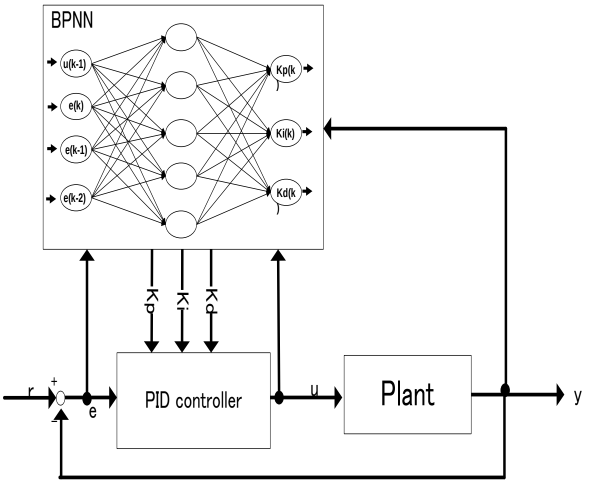

Fig.5 Structure of BP network System

Algorithm:
Step1 Initialization
Neural Network parameters, W_{kj} ,W_{kj} ,η,α.
k: outputs unit number
j : middle unit number
i :Input unit number
Step2 Load
Plant input $u(t)$, output $y(t+1)$.
Step3 Calculate Neural Network output

$$O_j = f(net_k),\ net_j = \textstyle\sum_{i-0}^{M} W_{ji}\, O_i,$$

$$f(x) = \frac{1}{1+exp\,(-x)} \tag{14}$$

$$O_k = net_k,$$

$$net_k = \textstyle\sum_{i-0}^{N} W_{kj}\, O_j \quad k = 1,2,3 \tag{15}$$

Step4 Calculate the PID parameter

$$\begin{aligned} u(n) = u(t-1) \\ +K_p\big(e(t) - e(t-1)\big) + K_i e(t) \\ +K_d\,(e(t) - 2e(t-1) + \ e(t-2)) \end{aligned} \tag{16}$$

Next, calculate *y(t+1)* from *u(t)*.
Step5 Calculate and evaluate error

$$e(t+1) = r(t+1) - y(t+1) \tag{17}$$

$$E(t+1) = \frac{1}{2} e(t+1)^2 \tag{18}$$

Step6 Calculate normalized error

$$\delta_k = e(t+1)J(n)\frac{\partial u(t)}{\partial O_k} \quad k = 1,2,3$$

$$\delta_j = \sum_{k=1}^{3} \delta_k W_{kj}\, O_j\big(1 - O_j\big)$$

$$j = 1,2,\dots,5, i = 1,2,\dots,4 \tag{19}$$

Step7 Update weight value

$$W_{ji}\,(t+1) = W_{ji}\,(t) + \eta\delta_k O_i + \alpha\Delta W_{ji}\,(t) \tag{20}$$

$$W_{kj}\,(t+1) = W_{kj}\,(t) + \eta\delta_k O_j + \alpha\Delta W_{kj}\,(t) \tag{21}$$

V. SIMULATION

BPNN has 3 layers: input layer, middle layer, output layer. There are 4 units in the input layer, 5 units in the middle layer, and 3 units in the output layer. Learning rate is α=0.25, and inertia coefficient is η=0.005.

5.1 Evaporator outlet pressure control

The block diagram of control system for the evaporator outlet pressure is illustrated in Fig.6. The manipulate variable is the hot water flow to the evaporator, and the controlled output is the outlet pressure of the evaporator. The simulate result of the outlet pressure in shown in Fig.7.

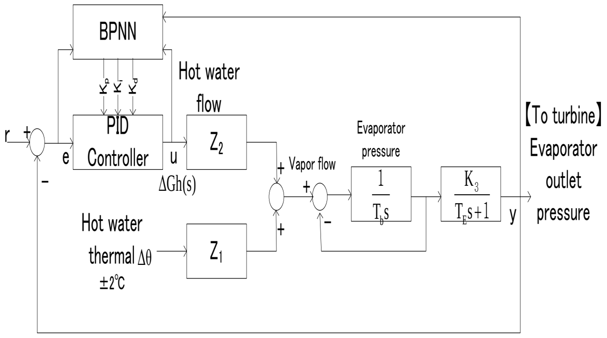

Fig.6 Evaporator block diagram

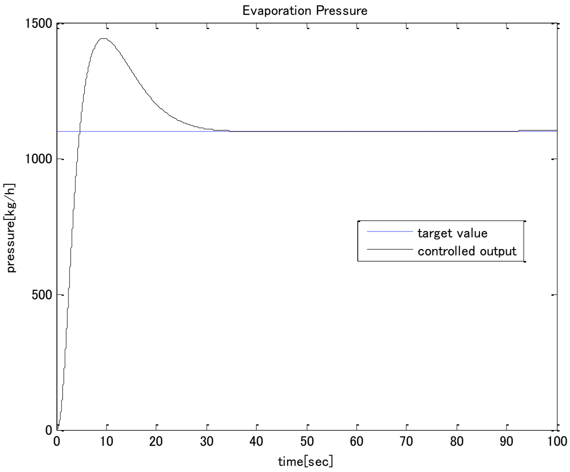

Fig.7 Result of the evaporator outlet Pressure

5.2Turbine blade speed control

The block diagram of the turbine blade speed control system is illustrated in Fig.8. The manipulated variable is the steam control valve, and the controlled output in the turbine blade speed. The simulation result is shown in Fig.9.

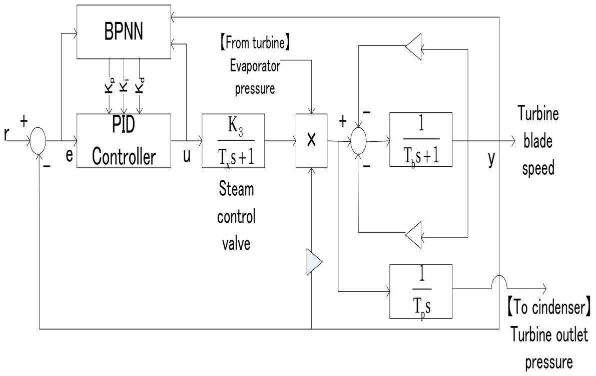

Fig.8 Turbine block diagram

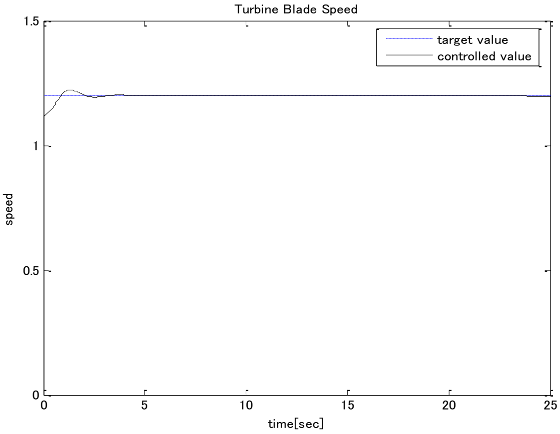

Fig.9 Control performance of
Turbine Blade Speed

The turbine has complicated nonlinear factor, however BPNN PID controller is adjusted.

VI. CONCLUSION

The control systems of the power generation using low temperature gap were designed in this paper. The models of the evaporator and the steam turbine system were deduced, and PID controller with BP Neural Network was designed to keep the turbine blade speed to be constant.

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