

## Design Of Fuzzy Controller for the Steam Temperature Process in the Coal Fired Power Plant

Shin, Sang Doo, Kim, Yi-Gon, Lee, Bong Kuk, Bae, Young Chul

Korea East-West Power Co., LTD Honam Thermal Power Plant, KOREA [sangsang@ewp.co.kr](mailto:sangsang@ewp.co.kr)

Yosu National University, KOREA [yigon@yosu.ac.kr](mailto:yigon@yosu.ac.kr)

LGIS R&D center, KOREA [bongukl@lgis.com](mailto:bongukl@lgis.com)

Yosu National University, KOREA [ycbae@yosu.ac.kr](mailto:ycbae@yosu.ac.kr)

### Abstract

In this paper, we proposed the method to design fuzzy controller using the experience of the operating expert and experimental numeric data for the robust control about the noise and disturbance instead of the traditional PID controller for the main steam temperature control of the thermal power plant. The temperature of main steam temperature process has to be controlled uniformly for the stable electric power output. The process has the problem of the hunting for the cases of various disturbances. In that case, the manual action of the operator happened to be introduced in some cases. We adopted the TSK (Takagi-Sugeno-Kang) model as the fuzzy controller and designed the fuzzy rules using the informations extracted directly from the real plant and various operating condition to solve the above problems and to apply practically. We implemented the real fuzzy controller as the Function Block module in the DCS(Distributed Control System) and evaluated the feasibility through the experimental results of the simulation.

**Key Words :** DCS(Distributed Control System), Steam temperature process, fuzzy controller, ANFIS

### I. Introduction

The proper control of the superheated steam temperature process in the thermal power plant is the important loop among the various process control loops. Because the process gives the considerable results for the life and effective operation of the plant. The superheated steam temperature control loop has the characteristics of the large time constant and mutual-interference of the various variables. Especially, there are many related process variables according to the variation of the load in the case of the sliding pressure operation in the plant. In that case, the traditional the PID controller of the analog control system had not the good performance. But the micro processor-based digital distributed control system has been applied to the power plant since the beginning of the 1980's and many kinds of the optimal algorithms have been adopted for the process. From the control system for the simple and independent process in the past, the recent control system is rapidly developed to correspond to the system. But actually, in the case of the variation of the operating points and system parameters such as the various fuels, sliding pressure operation and the response characteristics of the actuators the experiences of the operators and the methods of trial and error have been used for the tuning of the controller. In this paper, we developed the new fuzzy controller for the DCS(Distributed Control System) algorithm applied in the domestic control system that

has been replaced for the analog control system. The fuzzy controller has the characteristics of the rapid and robust responses compared to the traditional digital PID controller. We adopted the Sugeno-Takagi-Kang) model for the fuzzy controller[1][2]. We used the fuzzy clustering algorithms for the selection of the rules and the back-propagation neural network algorithm for the setting of the parameter of the rules. We implemented the fuzzy controller in the DCS system (Master P-3000, LGIS). The function block model for the controller has been developed and tested for the performances of the proposed methods. The test bed is composed of the DCS system and the simulator for the thermal power plant[3].

### II. Design of the fuzzy controller for the main steam temperature process

#### 1. The superheated steam temperature control system

The purpose of the superheated control is to maintain the steam temperature of the outlet of the superheater constant. The Fig. 1 shows the control system.

The process variable is the main steam temperature of the outlet of the superheater and the value of the set point is constant 541°C. And the attemperator spray water valves that are located in the inlet of the secondary superheater are used for the manipulating control variable. The control logic is composed of the two loops. The output of the first loop (main loop) is cascaded to the secondary attemperator control

loop(sub. loop).

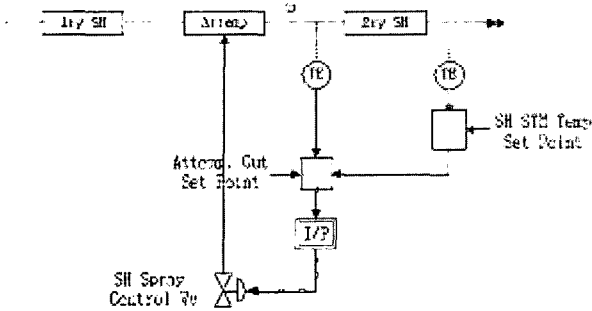


Fig.1. The SH temperature control system

**2. The fuzzy control system**

In this paper, we adopt the TSK(Takagi -Sugeno -Kang) model as the fuzzy controller for the SH steam temperature control process. The rule of TSK fuzzy system can be expressed as follows.

$$R^n: \text{If } x_1 \text{ is } C_1^n \text{ and } \dots \text{ and } x_m \text{ is } C_m^n, \\ \text{Then } y^n = a_0^n + a_1^n x_1 + \dots + a_m^n x_m \quad (1)$$

where  $C_m^n$  represents fuzzy set,  $n$  is the number of rules,  $m$  is the number of input variables,  $x$  is the input variable of the system,  $y$  is the output variable and  $a_m^n$  is the constant for the linear equation. That is, the if-part of the rule is equal to that of general if-then rules and the then-part is composed of the linear combination of the input variables. The above fuzzy system is the most popular system for the real process system. The output of the control system can be calculated as follows.

$$f(x) = \frac{\sum_{l=1}^M y^l \mu^l}{\sum_{l=1}^M \mu^l} \quad (2)$$

where, the compatibility value  $\mu^l$  can be presented by equation.

$$\mu^l = \prod_{i=1}^n u_{c_i}(x_i) \quad (3)$$

The membership function of the controller is the following symmetric gaussian type of the Fig. 2.

The above inferential control system has the two rules, four input variables and one output variable.

The each membership function is characterized by the position of the center(c) and the standard deviation(s) of the following distribution function.

$$mf(x,s,c) = e^{-\frac{(x-c)^2}{2s^2}} \quad (4)$$

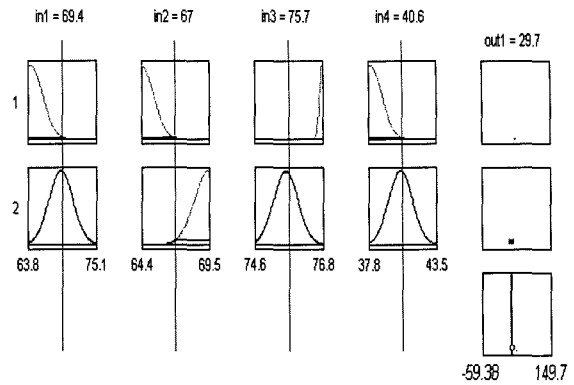


Fig. 2. The membership functions for the fuzzy inferential control system.

The following gaussian membership function shows the case that the center is 5 and the standard deviation is 2.

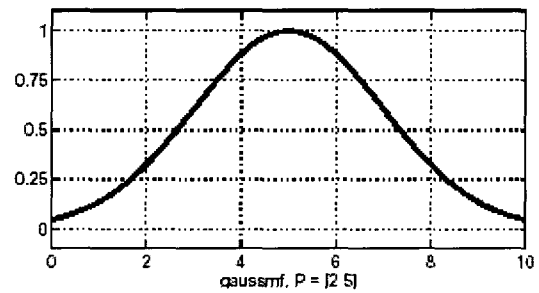


Fig 3. The symmetric gaussian membership function

We designed the fuzzy control systems for the steam temperature control system using the above fuzzy model. The Fig. 4 shows the abbreviated structure that is divided into two parts. The main part has 3 input variables of the main steam temperature(M.S.T), the steam flow(S.F), and the steam set point and one output variable of the output of  $\Sigma$ . The sub. part has 2 input variables of the output of  $\Sigma$  and the spray temperature and 2 output variables of the spray valves(V.C.S).

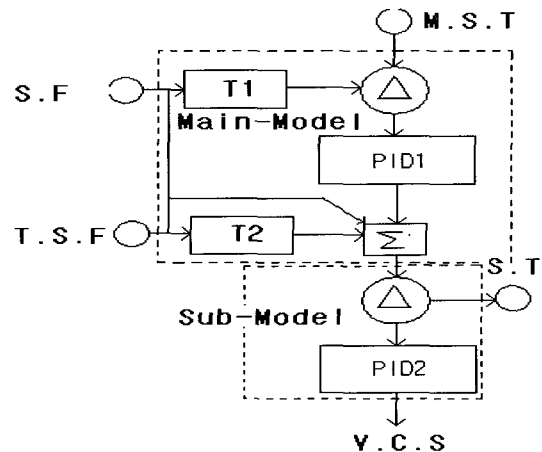


Fig. 4. The brief structure for the main steam temperature control system

The T1,T2 blocks represents the linear transducer. Each control part is replaced by the two fuzzy control system. The main part has 3 gaussian fuzzy sets and rules and the sub. part has 4 gaussian fuzzy sets and rules considering the data analysis.

### 3. The modelling of the fuzzy inference system

We construct the structure of the rules and the parameters of the fuzzy inference system using the process value automatically. The ANFIS(adaptive neuro-fuzzy inference system) algorithm is adopted for the construction.

At first, we used the fuzzy clustering algorithm to determine the number of the rules. The following objective function is used.

$$J_M(U, V) = \sum_{k=1}^N \sum_{i=1}^c (U_{ik})^m (d_{ik})^2 \quad (5)$$

$$d_{ik}^2 = PVER x_k - v_i PVER^2$$

where,  $N$  is the number of data,  $m$  is the exponential weighting value,  $|\cdot|$  means the inner product. The  $x_k$  is the  $n$ -dimensional vector of the  $N$  data. and the fuzzy partition matrix  $U$  and the center matrix  $V$  is can be defined as follows.

$$U = \begin{pmatrix} U_{11} & \cdots & U_{1k} & \cdots & U_{1N} \\ \vdots & & \vdots & & \vdots \\ U_{i1} & \cdots & U_{ik} & \cdots & U_{iN} \\ \vdots & & \vdots & & \vdots \\ U_{c1} & \cdots & U_{ck} & \cdots & U_{cN} \end{pmatrix} \quad (6)$$

$$V = v_1, v_2, \dots, v_c, v_i \in R^m$$

The  $c(2 \leq c \leq N)$  means the number of clustering group and  $u_{ik}$  is the membership degree showing that  $x_k$  is included to the  $i$ -th clustering group and  $v_i$  shows the  $n$ -dimensional center vector element.

Our objective is to determine the values  $u_{ik}$ ,  $v_i$  to minimize the above objective function. That is, the values can be expressed as follows.

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left( \frac{d_{jk}}{d_{ik}} \right)^{\frac{2}{m-1}}} \quad (7)$$

$$v_{il} = \frac{\sum_{k=1}^N (u_{ik})^m x_{kl}}{\sum_{k=1}^N (u_{ik})^m}, l=1, \dots, n$$

The above values can be obtained through the iterative calculations. At last, we determine the number of the rules. At the next step, we have to decide the characteristic values of the membership function of the rules using the neural network. The neuron of the neural network can be represented as the following equation.

$$\neq t = \sum_{k=1}^N w_k \cdot x_k \quad (8)$$

$$Y = \frac{1}{1 + e^{-\neq t}}$$

where,  $w_k$  is the weighting value and  $x_k$  is the input

variables and  $Y$  is the output. We adopt the following the ANFIS model using the above the fuzzy variables and the neural network.

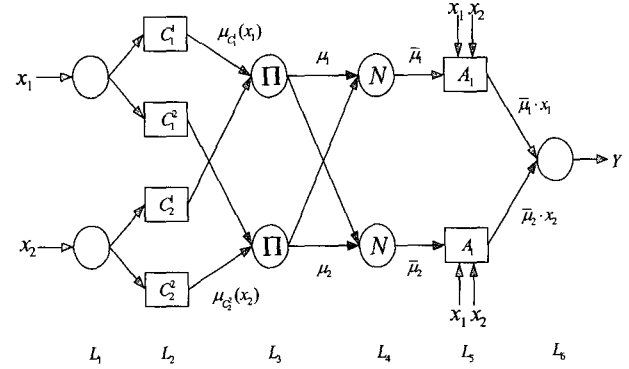


Fig.5. The ANFIS model

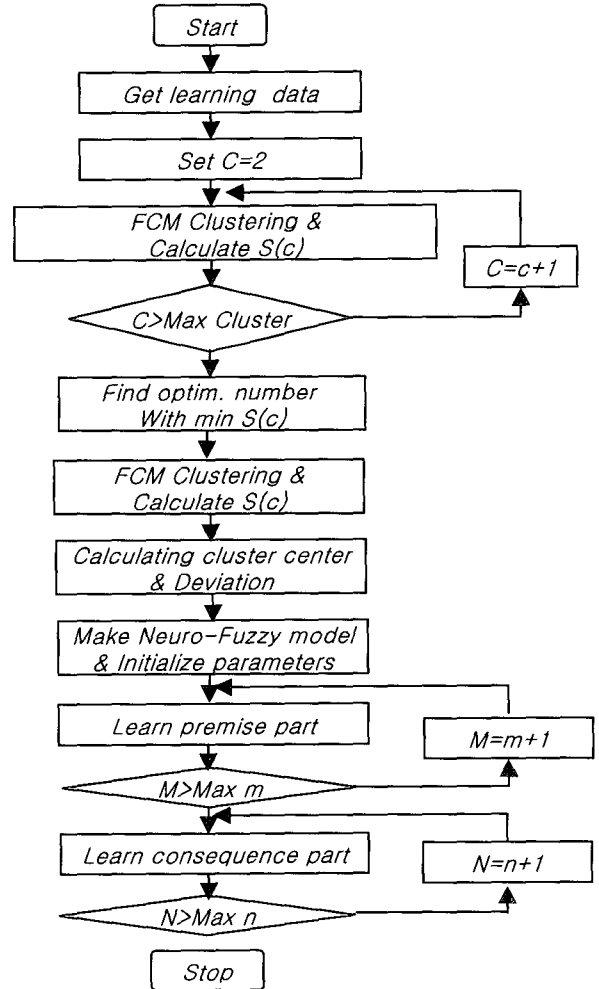


Fig. 6. The flow for the modelling for the fuzzy inference system.

The above ANFIS model shows a network-type structure similar to that of a neural network. The network maps inputs through input membership functions and various characteristic values, and then through output parameters to outputs. The

model can be used to interpret the input/output map that has the same meaning compared with the original fuzzy inference system. The overall system is composed of six levels. The first level transfers the input data to the next level. The fuzzy variable of the second level is the same as that of the premise part of the fuzzy model. That is, the characteristic values of the fuzzy variables will be learned through the iterative calculations. The nodes of the third level output the compatibility values after calculating the multiplication and addition of the previous input data. At the 4'th level, the data is normalized. The fuzzy variables of the 5'th level is the same as that of consequence part of the fuzzy model. The parameters of linear combination will be learned.

The Fig 6 show the overall flow chart for the iterative calculation. At first, the learning data is used for determining the number of the rules using the above FCM algorithm. The constant C means the initial rule number. The next process determines the parameters of the premise and consequence part of the rules.

### III. Implementation of fuzzy controller

The fuzzy controller for process control can be implemented as the function block diagram in the DCS system. The output and performance of the fuzzy controller is verified by the MATLAB tool. The following figure shows the definition diagram of parameter for the fuzzy controller. After determining the structure and the various parameters of the fuzzy control system, the operator or the engineer types the engineering data into input forms. The data to input are the number of input/output data, the number of fuzzy rules, the number of the membership functions, the minimum/maximum values of the process input data, the characteristic values of each membership functions and the parameters of the output.

번호	이름	코드번호	수치	설명
S6		1 to 5		Number of Input Variable
S7		1 to 2		Number of Output Variable
S8		2 to 8		Number of Fuzzy Rule
S9		2 to 5		Number of Function
S10				Min Value of No.1 Input Data
S11				Max Value of No.1 Input Data
S12				1st arg (1st Func.) of No.1 Input Data(MIN)
S13				2nd arg (1st Func.) of No.1 Input Data(MIN)
S14				1st arg (1st Func.) of No.1 Input Data(MAX)
S15				2nd arg (1st Func.) of No.1 Input Data(MAX)
S16				1st arg (2nd Func.) of No.1 Input Data(MIN)
S17				2nd arg (2nd Func.) of No.1 Input Data(MIN)
S18				1st arg (2nd Func.) of No.1 Input Data(MAX)
S19				2nd arg (2nd Func.) of No.1 Input Data(MAX)
S20				1st arg (3rd Func.) of No.1 Input Data(MIN)
S21				2nd arg (3rd Func.) of No.1 Input Data(MIN)
S22				1st arg (3rd Func.) of No.1 Input Data(MAX)
S23				2nd arg (3rd Func.) of No.1 Input Data(MAX)
S24				1st arg (4th Func.) of No.1 Input Data(MIN)
S25				2nd arg (4th Func.) of No.1 Input Data(MIN)
S26				1st arg (4th Func.) of No.1 Input Data(MAX)
S27				2nd arg (4th Func.) of No.1 Input Data(MAX)
S28				Min Value of No.2 Input Data
S29				Max Value of No.2 Input Data

Fig. 7. The definition function block diagram.

The following figure shows the download function of the defined parameters. The data are downloaded to the designated

real time control station.

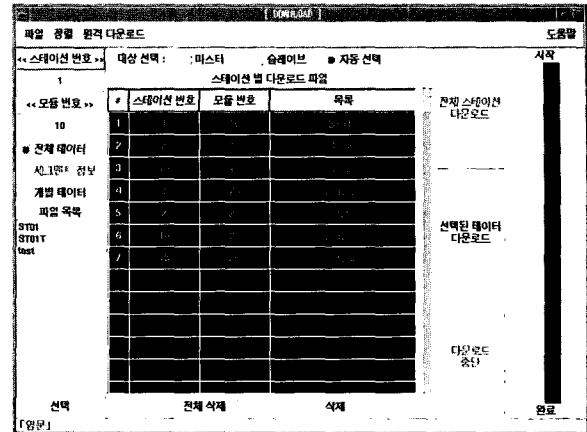


Fig. 8. The download function of the parameters

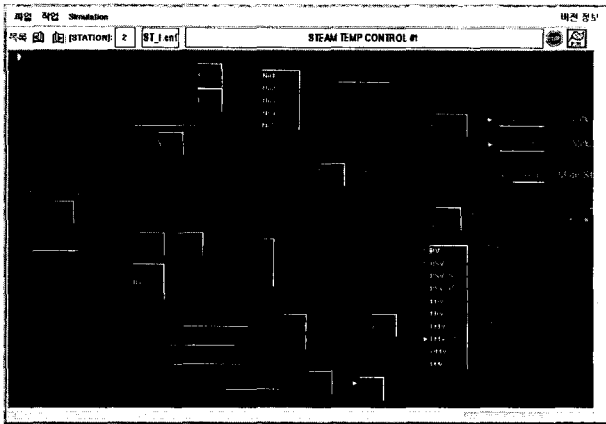
The Fig.9. shows the overall view for the DCS system that our fuzzy controller is implemented.



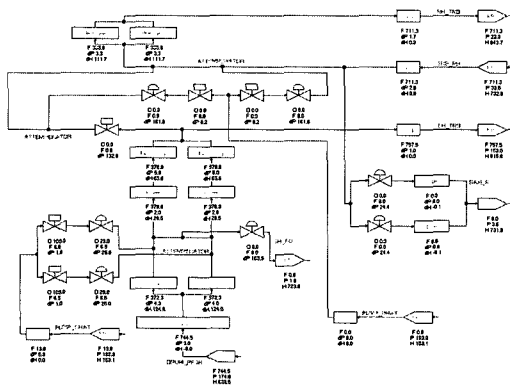
Fig. 9. The overall view of the DCS

### IV. Experimental Results

For the experimental verification, the experimental system is composed of the DCS system and the simulator system. The DCS system is responsible for the control and the simulator corresponds to the process. The following figure shows the experimental configuration for the SH steam temperature control systems. Fig.10.(a) shows the fuzzy controlled function block diagram in the DCS and Fig.10. (b) represent the process block diagram in the simulator.



(a) The control function block diagram of DCS

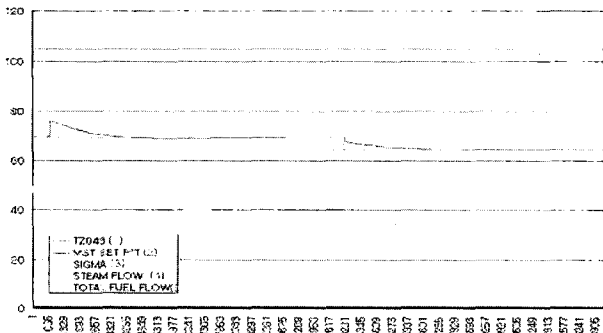


(b) The process of the simulator

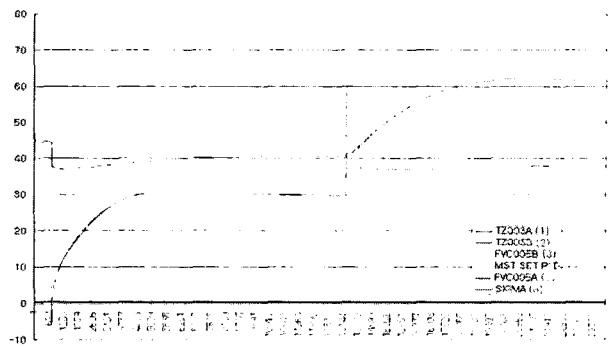
Fig. 10. The Experimental configuration Systems

The following figure shows the process characteristics in the simulator. The responses of the closed loop system are shown by the changes of the operating points between 540°C and 529°C.

The system represents the first order system including large time constant. The settling time is about 450 seconds. The data are gathered in the file system in the simulator.



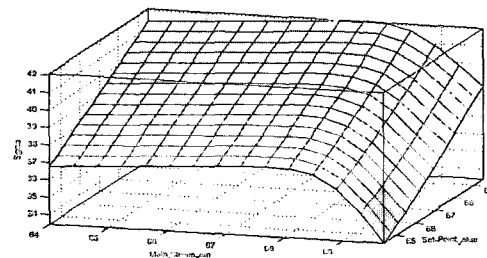
(a) The main Control part



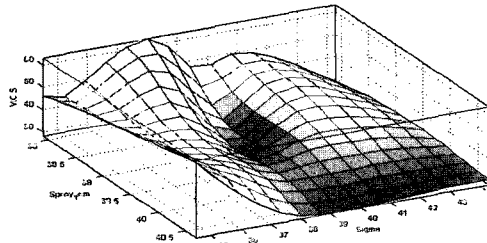
(b) The sub. control part

Fig. 11. The responses of the simulator system

We can get the parameters of the rules for the two fuzzy controllers using a fuzzy clustering algorithm and the previous data. The following figures shows the input-output spaces for the fuzzy controllers. They represents the nonlinear and smoothing characteristics of the relations between the input and the output.



(a) The main part



(b) The sub. part

Fig. 12. The input-output space for the fuzzy controller

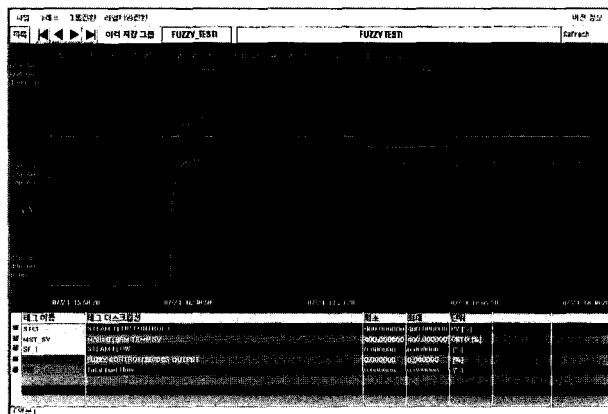


Fig. 13. The responses of the fuzzy controller

The Fig. 13. shows the result of the case of applying the fuzzy controller in the DCS. We can obtain the rapid response compared with the simulator control system. Our experiments can get the settling time of the about 150 seconds.

### V. Conclusion

In this paper, a fuzzy controller for the superheated steam temperature process is developed. And the controller is implemented in the function block of the DCS. The experiment has been achieved the through composition of the DCS and the simulator. The result has shown the good efficiency of the fuzzy controller.

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**Yigon Kim**

received the MS degree in avionic electric engineering from Hankuk aviation university, Seoul Korea, in 1986 and 1988 respectively. He received Ph.D. degree in electrical engineering from Chonnam National university in 1993. He performed research at Tokyo Institute of Technology

by research member in 1991 and at Iowa State University by visiting professor in 2000-2001. He is an associate professor in the School of ECC at Yosu National University. His interests fuzzy-Neuro Modeling and its application to diagnosis and control industrial systems.



**Young-Chul Bae**

received his B.S. degree, M.S and Ph. D. degrees in Electrical Engineering from Kwangwoon University in 1984, 1986 and 1997, respectively. From 1986 to 1991, he joined at KEPCO, where he worked ad Technical Staff. From 1991 to 1997, he joined Korea Institute of Science and Technology Information(KISTI), where he worked as Senior Research. In 1997, he joined the Division of Electron Communication and Electrical Engineering, Yosu National University, Korea, where he is presently a professor. His research interest is in the area of Chaos Nonlinear Dynamics that includes Chaos Synchronization, Chaos Secure Communication, Chaos Crypto Communication, Chaos Control and Chaos Robot etc.



**Sangdoon Shin**

received the B.S degree in Computer Science Department from Korea National Open University, Seoul Korea, in 2002. He received the M.S degree in electric engineering from Yosu National University, Yosu Korea, in 2004. From 1982 to 2001, he joined at KEPCO, where he worked I&C

Team, Thermal Power Plant.

In 2001, he joined the I&C Team, Honam Thermal Power Plant, Korea East-West Power Co.,Ltd, where he is Assistant Manager. From 1998 to 2003, Development of Integrated Distributed Control System for Analog APC Type Coal Fired Power Plant.



**Bong-Kuk Lee**

received the B.S. degree, M.S and Ph. D. degrees in Electrical Engineering from Inha University in 1983, 1986 and 1993, respectively. From 1986, he worked for the LG Industrial Systems. He is a senior research engineer in Control System Team at LGIS R&D Center. He interests

intelligent control and its applications in the area of industrial systems.