Neuro-Fuzzy Algorithm for Nuclear Reactor Power Control: Part I

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Abstract

A neuro-fuzzy algorithm is presented for nuclear reactor power control in a pressurized water reactor. Automatic reactor power control is complicated by the use of control rods because of highly nonlinear dynamics in the axial power shape. Thus, manual shape controls are usually employed even for the limited capability during the power maneuvers. In an attempt to achieve automatic shape control, a neuro-fuzzy approach is considered because fuzzy algorithms are good at various aspects of operator's knowledge representation while neural networks are efficient structures capable of learning from experience and adaptation to a changing nuclear core state. In the proposed neuro-fuzzy control scheme, the rule base is formulated based on a multi-input multi-output system and the dynamic back-propagation is used for learning. The neuro-fuzzy power control algorithm has been tested using simulation responses of a Korean standard pressurized water reactor. The results illustrate that the proposed control algorithm would be a practical strategy for automatic nuclear reactor power control.

I. Introduction

In a nuclear plant, reactor power changes can be accomplished by core reactivity compensation and power distribution control. Reactivity compensation accounts for the reactivity associated with the changes in both power level and transient xenon level and is provided by a combination of control rod position, boron concentration, and primary average coolant temperature adjustments. Power distribution control is performed to maintain the core thermal margin within operating and safety limits. Power distributions, usually axial shapes, are monitored and controlled during power maneuvers. Power shape control is complicated by the use of control rods because it is highly coupled with reactivity compensation. There have been some studies to develop a core control strategy that minimizes the effect on the reactivity due to shape control.[1-4] Power shape control, however, is not easy to be automated with a conventional proportional-integral-derivative (PID) controller. Thus, manual shape controls are still usually employed even for the limited load-following capability of nuclear plants. A reactor control strategе called "mode K" was proposed to overcome such a limitation.[5] The "mode K" implements a

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heavy-worth bank dedicated to axial shape control, independent of the existing regulating banks. The heavy bank provides a monotonic relationship between its motion and the axial shape change, which allows automatic control of the axial power distribution. In real issues, changes in core design are necessary to adapt "mode K" to the plants in operation or under construction. Recently, alternative approaches[6-9] by the implementation of advanced control algorithms have been presented, but to an experimental reactor rather than a commercial one.

In an attempt to achieve automatic shape control for a commercial reactor without any design modification of the associated systems, a neuro-fuzzy appoach is consider in this study. Fuzzy algorithms[10] are good at various aspects of operator's knowledge repesentation of manual control rule-base, while neural networks[11]11 are efficient structures capable of lerning from data-base of good experience and adaptation to a changing nuclear core state. The proposed neuro-fuzzy control algorithm has been developed and tested for a Korean standard pressurized water reactor plant.[12]

II. Neuro-Fuzzy Power Control Algorithm

The neuro-fuzzy control scheme, shown in Fig. 1, consists of three layers; input layer, hidden layer, and output layer. Input parameters are fuzzified into linguistic variables through the corresponding membership functions in the input layer. Linguistic control decisions are made in the hidden layer by the action rule developed based on the operator's control strategy. The Mamdani minimum operation rule is used as an inference method to implement the preceding action rule. Linguistic control variables are defuzzified into control output parameters in the output layers. The center of area method is used in this process. In the meanwhile, the membership functions for fuzzification and weighting factors for defuzzification are determined through the training with the operation data by the learning scheme of neural networks. Dynamic back-propagation is employed for this purpose.

In the Korean standard pressurized water reactor, a change in boron concentration and insertion/withdrawal of the regulating control element assembly (CEA) and the part-strength CEA (PSCEA) are used to control the reactor power. During load-maneuvering operations, an operator manually changes the boron concentration and the PSCEA position to maintain reactivity and power distribution within the desired range, while the regulating CEAs are moved automatically by the reactor regulating system (RRS) to reduce the coolant average temperature deviation from the programmed reference value. A neuro-fuzzy power control algorithm, which can take the place of a highly experienced operator, has been developed to perform this load maneuvering operation automatically. This algorithm is a multi-input multi-output (MIMO) system consisting of five inputs and two outputs. The five input parameters describing the core conditions used in the algorithm are as follows:

1. rate of reactivity change: $d\rho/dt$,
2. % error of axial power distribution: $(\triangle I - \triangle I_{ref}) * 100$,
3. error of core average coolant temperature: T_{avg}-T_{prog},
4. position of regulating CEAs: between 0% and 100%,
5. position of PSCEAs: between 0% and 100%.

The difference between the power of the top half and bottom half of the core is defined as $\triangle I$; I_{ref} is the target value at full power, all rods out and xenon equilibrium conditions.

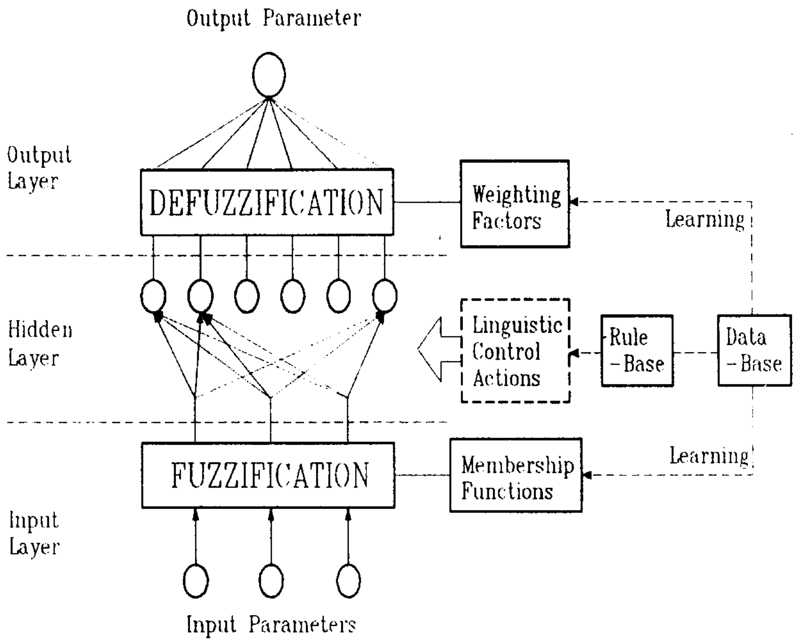


Fig 1. Structure neuro-fuzzy control algorithm

The two output parameters for the algorithms are defined as follows:

1. rate of change of the boron concentration: dppm/dt,
2. speed of the PSCEA movement: % of active core length /dt.

Ⅲ. Fuzzification, Decision-Making Logic, and Defuzzification for MIMO System

The value of the reactivity change rate, $d\rho/dt$, measured in units of % $\triangle\rho$/hr, comes from the power defect and xenon effects. This input is defined as the linguistic variable of reactivity rate (RTR). The primary fuzzy set is categorized as negative large (NL), negative medium (NM), negative small (NS), negative near zero (NZ), positive near zero (PZ), positive small (PS), positive medium (PM), and positive large (PL) which has triangular membership functions as shown in (a) of Fig. 2. The linguistic variable of delta I error (DIE) and coolant temperature error (CTE) are introduced to the error of axial power distribution and the error of average primary coolant temperature, respectively. The primary fuzzy set of DIE has three terms, negative (NE), around target (AT), and positive (PO). These fuzzy sets have triangular membership functions as shown in (b) of Fig. 2, which have a crossover point at ± 5%. The primary fuzzy set of CTE has three terms; negative (NE), zero (ZE), and positive (PO). The membership functions of these fuzzy sets are also triangular forms as shown in (c) of Fig. 2, and have a crossover point at ± 2°F.

The input parameters of the regulating CEAs' and the PSCEAs' positions are defined as the linguistic variables of CEAs' position (CEAPO) and PSCEAs' position (PSCPO), respectively. The primary fuzzy sets of CEAPO and PSCPO are composed of same five linguistic values, such as insertion limit (IL), near insertion limit (NIL), around center (AC), near withdrawal limit (NWL), and withdrawal limit (WL), which are discretized and have membership functions as shown in (d) of Fig. 2. The insertion and withdrawal limits are defined depending on the core conditions such as power level and power distribution.

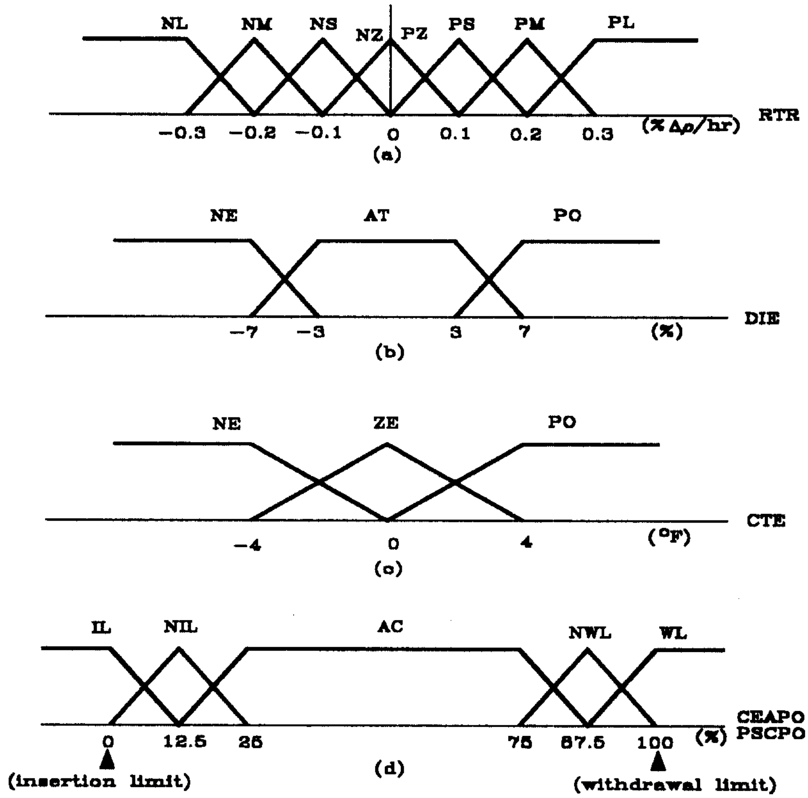


Fig 2. Membership functions for input parameters, TR(a), DTE(b), CTE(c), CEAPO and PSCPO (d).

Some simplification of the input parameters is required to set up the rule base, which is based on the operator's control actions that can not be made at once with many input parameters. The operational knowledge was examined by introducing a new linguistic variable, supplementary boron requirement (SBR). Three input parameters, CTE, CEAPO, and DIE, are used to obtain the fuzzy value of SBR. Figure 3 shows the overall fuzzy power control algorithm developed for load follow operations.

In the first step, all input values are fuzzified as described earlier. Then, the CTE and the CEAPO are combined by 'Rule-1', which is tabulated in Table I, to generate a new linguistic variable defined as the combined CEAPO and CTE (CCT). The terms of CCT are temperature positive (TP), CEA bottom (CB), CEA center (CC), CEA top (CT), and temperature negative (TN). To obtain the fuzzy set and its value for the CCT, defuzzification and fuzzification processes are accomplished with the triangular type membership functions shown in (a) of Fig. 4.

In the next step, the linguistic variable of SBR is generated by combining the CCT and the DIE by ~Rule-2' as shown in Table II. The SBR has three terms such as negative boron requirement (NBR), zero boron requirement (ZBR), and positive boron requirement (PBR), which have triangular membership functions as shown in (b) of Fig. 4.

Control action rules have been developed as shown in Table III based on the theoretical background of a MIMO system.

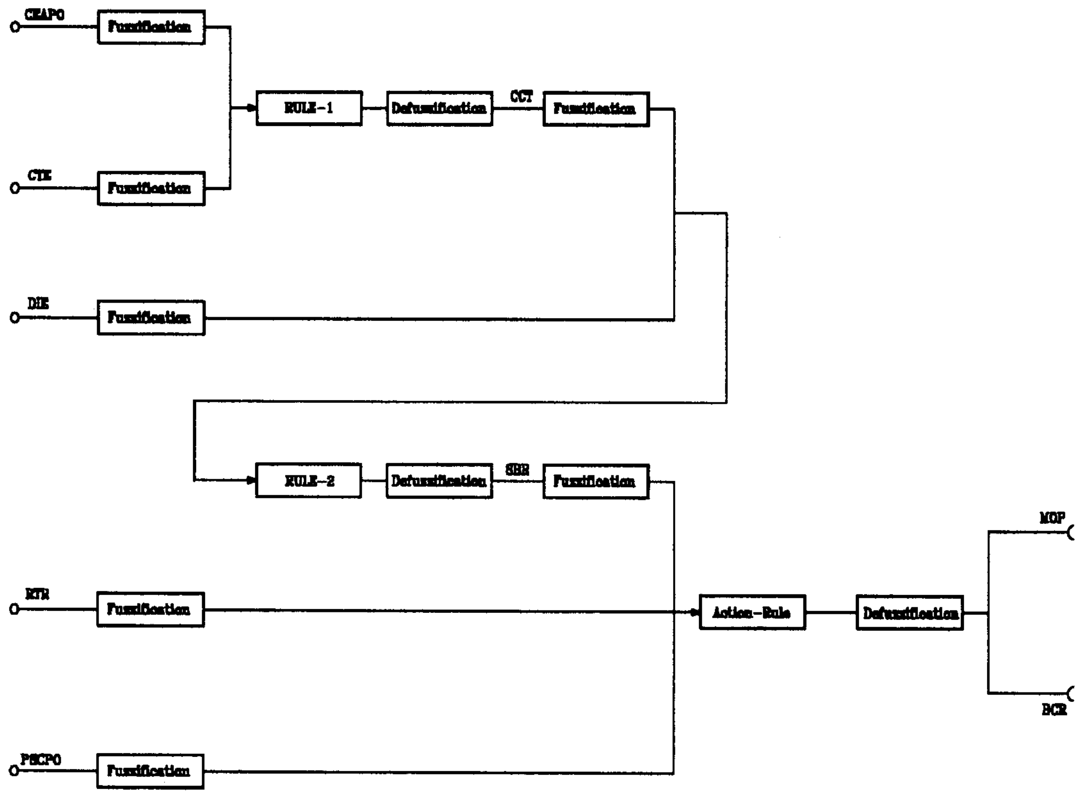


Fig 3. Schematic diagram of the overall neuro-fuzzy power control algorithm.

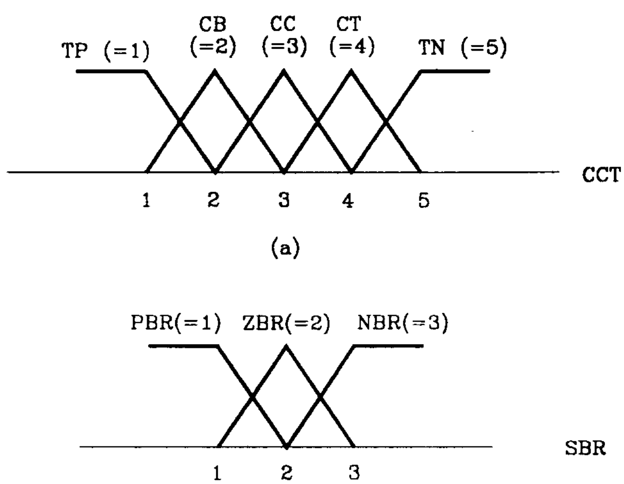


Fig 4. Membership functions for (a) CCT and (b) SBR

Table I. Rule-1 which determines the CCT

	CEAPO				
CTE ↓	IL	NIL	AC	NWL	WL
NE	*	*	*	*	TN
ZE	TP**	CB	CC	CT	TN
PO	TP	*	*	*	*

* : Not Happen

** : If CTE is ZE and CEAPO is IL, then CCT is TP

Table II. Rule-2 which determines the SBR

	DIE		
CCT ↓	NE	AT	PO
TP(1)	PBR	PBR	PBR
CB(2)	PBR*	ZBR	NBR
CC(3)	PBR	ZBR	NBR
CT(4)	PBR	ZBR	NBR
TN(5)	NBR	NBR	NBR

*IF CCT is CB and DIE is NE, then SBR is PBR

$$R = \{R^1_{MIMO}, R^2_{MIMO}, \cdots, R^n_{MIMO}\},$$

where R^i_{MIMO} represents the rule : if (x is A_i and, ⋯, y is B_i) then (z_1 is C_i, z_q is D_i) :

Table III. Action Rule which determines the BCR and the MOP

when SBR is ZBR

PSCPO →	IL		NIL		AC		NWL		WL	
RTR ↓	BCR	MOP	BCR	MOP	BCR	MOP	BCR	MOP	BCR	MOP
NL	DS	WB	DS	WB	DS	WB	DM	WS	DL	NA
NM	NA	WB	NA	WB	NA	WB	DS*	WS*	DM	NA
NS	NA	WS	NA	WS	NA	WS	NA	WS	DS	NA
NZ	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PZ	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PS	BS	NA	NA	IS	NA	IS	NA	IS	NA	IS
PM	BM	NA	BS	IS	NA	IB	NA	IB	NA	IB
PL	BL	NA	BM	IS	BS	IB	BS	IB	BS	IB

when SBR is PBR :

PSCPO →	IL		NIL		AC		NWL		WL	
RTR ↓	BCR	MOP	BCR	MOP	BCR	MOP	BCR	MOP	BCR	MOP
NL	NA	WB	NA	WB	NA	WB	DS	WS	DM	NA
NM	NA	WS	NA	WS	NA	WS	NA	WS	DS	NA
NS	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
NZ	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PZ	BS	NA	BS	NA	BS	NA	BS	NA	BS	NA
PS	BM	NA	BS	IS	BS	IS	BS	IS	BS	IS
PM	BL	NA	BM	IS	BS	IB	BS	IB	BS	IB
PL	BX	NA	BL	IS	BM	IB	BM	IB	BM	IB

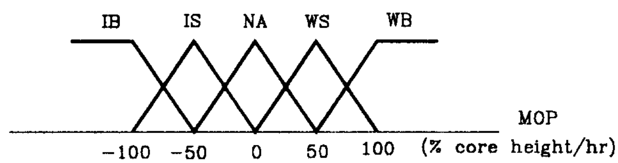
when SBR is NBR :

PSCPO →	IL		NIL		AC		NWL		WL	
RTR ↓	BCR	MOP	BCR	MOP	BCR	MOP	BCR	MOP	BCR	MOP
NL	DM	WB	DM	WB	DM	WB	DL	WS	DX	NA
NM	DS	WB	DS	WB	DS	WB	DM	WS	DL	NA
NS	DS	WS	DS	WS	DS	WS	DS	WS	DM	NA
NZ	DS	NA	DS	NA	DS	NA	DS	NA	DS	NA
PZ	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PS	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PM	BS	NA	NA	IS	NA	IS	NA	IS	NA	IS
PL	BM	NA	BS	IS	NA	IB	NA	IB	NA	IB

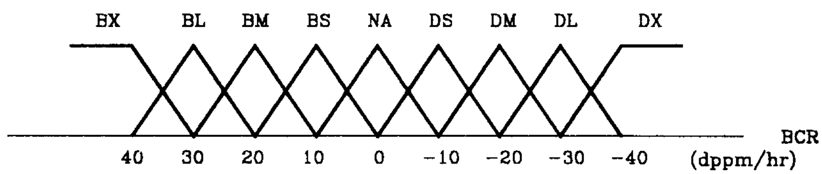
*If SBR is ZBR, RTR is NM, and PSCPO is NWL, then BCR is DS and MOP is WS. when SBR is NBR :

The PSCEA motion is defined as the linguistic variable of motion of PSCEA (MOP) which is categorized as: insertion big (IB), insertion small (IS), no access (NA), withdrawal small (WS), and withdrawal big (WB). The membership function of this fuzzy set is shown in (a) of Fig. 5. The maximum speed of PSCEA motion is limited to 100% of core height/hr because a higher speed can result in spurious distortion of power distribution.

The remaining reactivity is compensated for by changing the boron concentration. The boron concentration change is defined by the linguistic variable of boron change requirement (BCR), which has a primary fuzzy set of boration extra large (BX), boration large (BL), boration medium (BM), boration small (BS), no access (NA), dilution small (DS), dilution medium (DM), dilution large (DL), and dilution extra large (DX). The membership functions of these sets are shown in (b) of Fig. 5.



(a)



(b)

Fig 5. Membership functions for output CCT (a) and SBR (b).

The Mamdani's minimum operation rule was used as inference method to implement the above action rule:

$$Z^l = A \times B = \int_{U \times V} \mu_A(u) \wedge \mu_B(v)/(u, v),$$

where Z^l is the fuzzy implication function of l-th control action for the minimum operation rule, A and B are fuzzy sets in universe U and V with membership functions μ_A and μ_B, and u and v are the elements of universe U and V. The COA method was used for the defuzzification of MOP and BCR having the membership functions of (a) and (b) of Fig. 5, respectively. The COA method generates the center of gravity of the possibility distribution of a control action:

$$f = \frac{\sum_{l=1}^{M} w^l \mu_z^l}{\sum_{j=1}^{M} \mu_z^l},$$

where f is a control action in the output layer, w^l is the weighting factor, and μ_z is the membership function with the number of the quantization level of the output, M.

Ⅳ. Learning Scheme of Neural Networks

The learning scheme of neural networks has been incorporated into the fuzzy algorithm described in the previous section. This blending of neural and fuzzy is capable of learning from the data-base of good experience and adaptation to a changing nuclear core state. The dynamic back-propagation method for learning scheme is implemented to the MIMO system for reactor power control as follows:

For the data set of input and output parameters ($\underline{x}^p$, $\underline{y}^p$) from manual operation data-base, an error function, which is to be minimized as a performance index for learning, is defined as:

$$e^p = \frac{1}{2} \left(f(\underline{x}^p) - y^p\right)^2 \tag{1}$$

where $\underline{x}^p$ is a set of input parameters for p-th output parameter y^p.

The implication function, f, come through the hidden layer of neuro-fuzzy scheme in Fig. 1, can be described as follows. For a general treatment, all membership functions are assumed to be of Gaussian-type, while they were simplified into triangular forms in real application:

$$f(\underline{x}) = \frac{\sum_{l=1}^{M} \overline{w^l} \left[\prod_{i=1}^{n} a_i^l \exp\left(-\left(\frac{x_i - \overline{x}_i^l}{\sigma_i^l}\right)^2\right) \right]}{\sum_{l=1}^{M} \left[\prod_{i=1}^{n} a_i^l \exp\left(-\left(\frac{x_i - \overline{x}_i^l}{\sigma_i^l}\right)^2\right) \right]} \tag{2}$$

where $\overline{x}_i^l$, σ_i^l are the mean value and standard deviation of the Gaussian- type membership function for i-th input parameter contributing to l-th control action, and $\overline{w^l}$ is the weighting factor of output contributed from l-th control action.

The basic learning scheme is that the parameters of $\overline{w^l}$, $\overline{x}_i^l$, σ_i^l are trained in order to minimize the error function ep through the dynamic back-propagation method as follows:

Train $\bar{w}^l$

$$\bar{w}^l(k+1) = \bar{w}^l(k) - \alpha \frac{\partial e}{\partial \bar{w}^l}|_k \tag{3}$$

where, α = constant stepsize

$l = 1, 2, \ldots, M,\ k = 0, 1, 2, \ldots$

Introducing z^l, the outcome of the hidden layer, the partial derivative of error function with respect to the weigting factor can be derived as follows:

$$a = \sum_{l=1}^{M} (\bar{w}^l z^l) \tag{4}$$

$$b = \sum_{l=1}^{M} (z^l) \tag{5}$$

$$z^l = \prod_{i=1}^{n} \exp\left(-\left(\frac{x_i - \bar{x}_i^l}{\sigma_i^l}\right)^2\right) \tag{6}$$

Then, by the chain rule,

$$\frac{\partial e}{\partial \bar{w}^l} = (f-y)\frac{\partial f}{\partial a}\ \frac{\partial a}{\partial \bar{w}^l} = (f-y)\frac{1}{b}\ z^l \tag{7}$$

Substituting Eq.(7) to Eq.(3), the following learning algorithm for weighting facor $\bar{w}^l$ can be obtain:

$$\bar{w}^l(k+1) = \bar{w}^l(k) - \alpha \frac{f-y}{b}\ z^l \tag{8}$$

Train $\bar{x}_i^l$

$$\bar{x}_i^l(k+1) = \bar{x}_i^l(k) - \alpha \frac{\partial e}{\partial \bar{x}_i^l}|_k \tag{9}$$

where, $i = 1, 2, \ldots, n;\ l = 1, 2, \ldots, M;\ k = 0, 1, 2, \ldots$

Similarly to the previous case,

$$\frac{\partial e}{\partial \bar{x}_i^l} = (f-y)\frac{\partial f}{\partial z^l}\ \frac{\partial z^l}{\partial \bar{x}_i^l} = (f-y)\frac{\bar{w}^l - f}{b}\ z^l\ \frac{2(x_i^p - \bar{x}_i^l)}{\sigma_i^{l\,2}} \tag{10}$$

Substituting Eq.(10) to Eq.(9), the following learning algorithm for $\bar{x}_i^l$ can be obtained:

$$\bar{x}_i^l(k+1) = \bar{x}_i^l(k) - \alpha \frac{f-y}{b}\ (\bar{w}^l - f)\ z^l\ \frac{2(x_i^p - \bar{x}_i^l(k))}{\sigma_i^{l\,2}(k)} \tag{11}$$

Train $\bar{\sigma}_i^l$

Similarly, the learning algorithm for σ_i^l is:

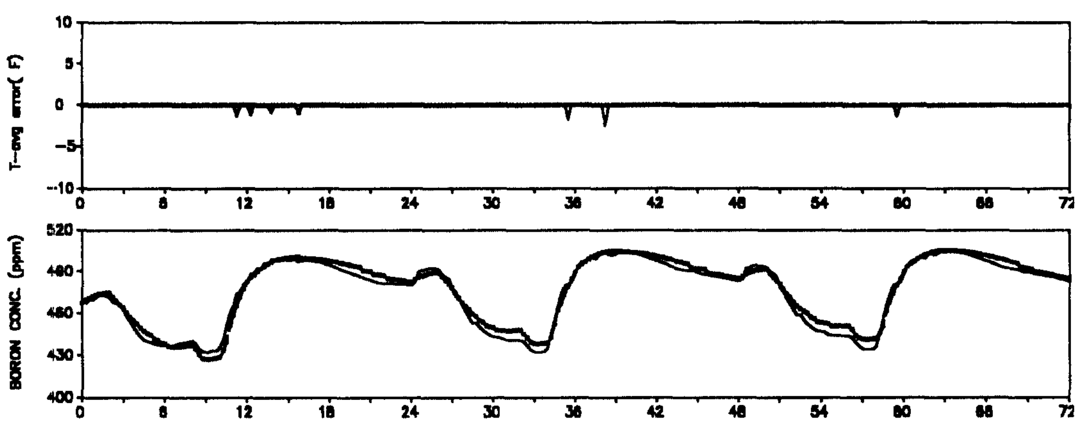
$$\bar{\sigma}_i^l(k+1)=\bar{\sigma}_i^l(k)-\alpha\frac{\partial e}{\partial\bar{\sigma}_i^l}\Big|_k$$
$$=\bar{\sigma}_i^l(k)-\alpha\frac{f-y}{b}(\bar{w}^l-f)z^l\frac{2(x_i^p-\bar{x}_i^l(k))}{\sigma_i^{l3}(k)} \qquad (12)$$

Equations (8), (11) and (12) performs the learning algorithm by training the parameters, $\bar{w}^l$, $\bar{x}_i^l$, σ_i^l, as the normalized error, (f-y)/b, is being back-propagated into the layer of $\bar{w}^l$ updating the value of $\bar{w}^l$ and as the normalized error multiplied by $(\bar{w}^l-f)\ z^l$ is being back-propagated into the layer of z^l updating the values of $\bar{x}_i^l$ and σ_i^l.

For reactor power control, the data set of two input parameters RTR and PSCPO, and two output parameters MOP and BCR has been utilized to implement the neural learning scheme based on the manual operation data at the beginning of core cycle.

V. Testing and Evaluation

A typical 100-50-100 (%), 14-2-6-2 (hr) load change pattern has been evaluated for the performance capability between manual control and neuro-fuzzy control. The evaluated daily load cycle maintained the power initially at 100% power for 14 hours, followed by a power decrease from 100% to 50% in 2 hours, followed by 6 hours at the reduced power level of 50% power. The load cycle was completed by increasing power to full rated power in 2 hours. This load cycle has been tested at the beginning of cycle (BOC: 2000 MWd/tonne U). A three-dimensional nodal code, ROBUST[13], was used for simulation. As part of the evaluation performed, Fig. 6 illustrates the behavior of a number of key core parameters: error of Tavg, boron concentration, △I, CEA position, PSCEA position, and the power operating limit (POL) with the power level. As shown, the above parameters are varied in a typical load maneuvering pattern within the operational limit. One of findings is that an output parameter of BCR has been well trained by the neural learning scheme. Those results promise automation of nuclear reactor power control by the proposed-neuro-fuzzy algorithm.



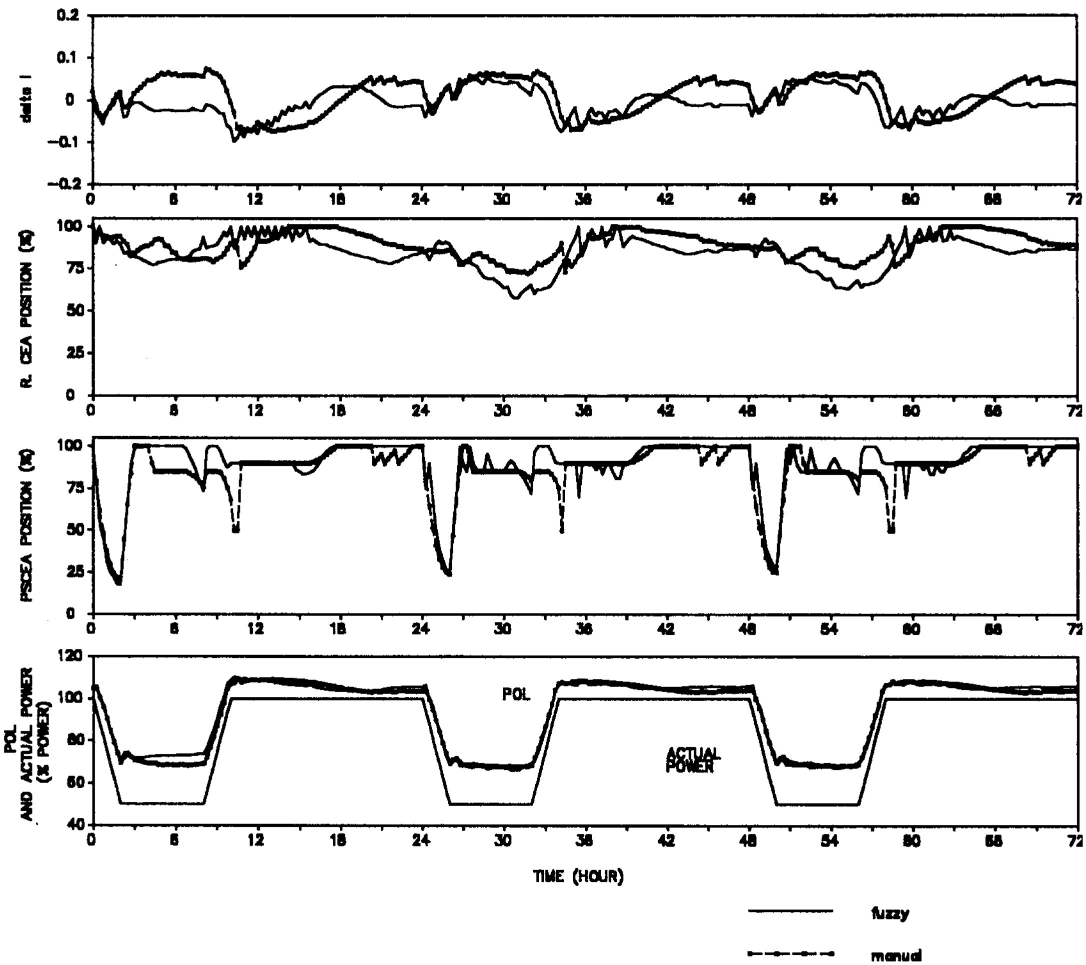


Fig 6. Reactor core parameters during daily load-follow operation at BOC

Ⅵ. Conclusions and Recommendations

A neuro-fuzzy power control algorithm has been proposed for load-follow operations for automatic reactor power control in a Korean standard pressurized water reactor. Neuro-fuzzy control has been found to enable precise, well performing load maneuvering, based on the knowledge of experts and operating data, and it is found to be an approach to automatic reactor power control without necessitating any changes in core design. Fuzzy control for load maneuvering could contribute to a reduction of human errors during certain operations normally utilizing manual control. The results of the simulation for the plant using the neuro-fuzzy power control algorithm imply that this method can be a practical control strategy for automatic reactor power control. In the next phase of the research to be published as part II, more refinements will be made in the neural learning scheme for adaptation to a changing core conditions through the core life.

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