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A STUDY ON THE OPTIMAL FUEL LOADING PATTERN DESIGN IN PRESSURIZED WATER REACTOR USING THE ARTIFICIAL NEURAL NETWORK AND THE FUZZY RULE BASED SYSTEM

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ABSTRACT

The Optimal Fuel Shuffling System(OFSS) is developed for optimal design of PWR fuel loading pattern. In this paper, an optimal loading pattern is defined that the local power peaking factor is lower than predetermined value during one cycle and the effective multiplication factor is maximized in order to extract maximum energy. OFSS is a hybrid system that a rule based system, a fuzzy logic, and an artificial neural network are connected each other. The rule based system classifies loading patterns into two classes using several heuristic rules and a fuzzy rule. A fuzzy rule is introduced to achieve more effective and fast searching. Its membership function is automatically updated in accordance with the prediction results. The artificial neural network predicts core parameters for the patterns generated from the rule based system. The back-propagation network is used for fast prediction of core parameters. The artificial neural network and the fuzzy logic can be used as the tool for improvement of existing algorithm's capabilities. OFSS was demonstrated and validated for cycle 1 of Kori unit 1 PWR.

I. INTRODUCTION

In Pressurized Water Reactors(PWRs), the fuel reloading problem has significant meaning in terms of both safety and economics. The fuel integrity is severely challenged if the local power peaking factor is too high. Thus the local power peaking factor(P_{max}) must be kept lower than predetermined value through one cycle. On the other hand, from the economic point of view, the cycle burnup may be maximized under the given number of fresh fuel assemblies. Therefore the general problem of in-core fuel management for a PWR consists of determining the fuel reloading policy for each cycle that minimize unit energy cost under the constraints imposed on various core parameters, e.g., a local power peaking factor or an assembly burnup.

In last two decades, many researchers have tried an automatic optimization of the fuel reloading patterns using various algorithms such as direct search algorithms[1, 2], backward diffusion method[3], variational techniques[4], monte carlo integer programming[5], simulated annealing method[6, 7], linear programming[8], and knowledge based system[9, 10]. All of the optimization approaches introduced above are not ensure the global optimum solution because of the limitation of their searching algorithms. They only find near optimal solutions.

To resolve these limitations, we suggest two possibilities: a) very effective searching, and b) very fast prediction of core parameters with reasonable accuracy. If these two are ensured, existing methods can improve their performances. To meet and demonstrate these two possibilities, we developed a prototype expert system, the Optimal Fuel Shuffling System(OFSS) using an artificial neural network(ANN) and a fuzzy rule based system(FRBS). ANN offers the very fast prediction of core parameters with reasonable accuracy and FRBS offers the very effective searching. Therefore, existing methods listed above can improve their performance and ability by use of the artificial neural network and/or the fuzzy rule based system. For example, if ANN is used with the simulated annealing method, the fast prediction of ANN will elevate the performance of the simulated annealing method.

This system finds the patterns that the value of P_{max} is lower than the reference value and the cycle length is maximized. The cycle length can be determined from the effective multiplication factor, k_{eff} without soluble boron at beginning-of-cycle(BOC). Therefore the effective multiplication factor at BOC is determined as the objective function which is represented the cycle length.

The rule based system classifies the loading patterns into two classes, good and bad ones using several heuristic rules and a fuzzy rule. A fuzzy rule is introduced in order to achieve more effective and fast searching. Bad patterns are discarded because it is obvious that these patterns violates the criteria such as local power peaking limit, maximum burnup limit, etc.. ANN predicts P_{max} and k_{eff} at BOC for the good patterns generated from a fuzzy rule based system(FRBS). According to prediction results, the membership function of a fuzzy rule in the rule based system is updated more optimally.

In Sec. II, we describe on the overall structure and the computational procedures of OFSS. In Sec. III, it is described on the rule based system with fuzzy rule and the artificial neural network. Also the development strategies for these two sub-systems are explained. The demonstration and the validation of OFSS were performed for cycle 1 of Kori unit 1 PWR. These demonstration results are described in Sec. IV.

II. OVERALL STRUCTURE OF OFSS

In this section, we propose a new method to design the optimal fuel loading pattern. This method uses a hybrid technology combined an artificial neural network and a fuzzy rule based system. The hybrid concept of this method is shown in Fig. 1.

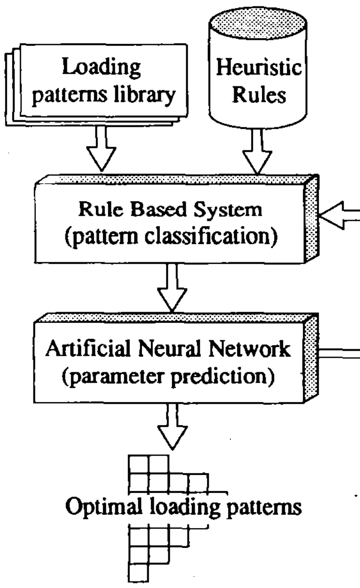


Fig. 1 Hybrid concept for optimal fuel loading pattern design

Two systems, the ANN and the FRBS are connected each input and output. At first, the FRBS searches fuel loading patterns with ordinary and fuzzy heuristic rules. Ordinary heuristic rules can be called in terms of *"static rules"*, which are unchanged until loading patterns searching ends. On the other hand, a fuzzy heuristic rule is improved optimally according to prediction results by modification its membership function. A back-propagation network(BPN), a kind of a feed-forward network, is used to predict core parameters, P_{max} and k_{eff}. BPN receives the survived loading patterns from the FRBS and predicts P_{max} and k_{eff} very quickly. OFSS determines if a current pattern is better than the reference one by these prediction results. Detailed descriptions for above two systems are given in next section.

The logical procedure of OFSS is as follows: *Step 1*. Initialization. OFSS loads the knowledge base such as heuristic rules and facts for the rule based system, the trained connection weights of BPN, and initialize the membership function of a fuzzy rule. *Step 2*. Searching for fresh fuel loading. At first, the fuzzy rule based system starts to load the fresh fuel assemblies with depth first searching algorithm. If a pattern satisfying the heuristic rules is found, that pattern is send to Step 3, otherwise the searching is ended. *Step 3*. Searching for once and twice burned fuel loading. After all fresh fuel assemblies are loaded, the fuzzy rule based system starts to load the once and the twice burned fuel assemblies. *Step 4*. Prediction of P_{max} and k_{eff} using BPN. For the pattern generated from Step 3, BPN predicts two core parameters, P_{max} and k_{eff}. If the value of P_{max} is less than the predetermined reference value and the value of k_{eff} is greater than the reference one, that pattern is stored. This step is repeated until the patterns generated in Step 3 are exhausted. *Step 5*. Improvement of a fuzzy rule. The membership function of a fuzzy rule is updated according to the results of Step 4, and Step 2 is performed, again.

Logic flow diagram such as above ones is shown in Fig. 2. Being performed OFSS, a few patterns which are better than the reference one are generated and one can select one of them ac-

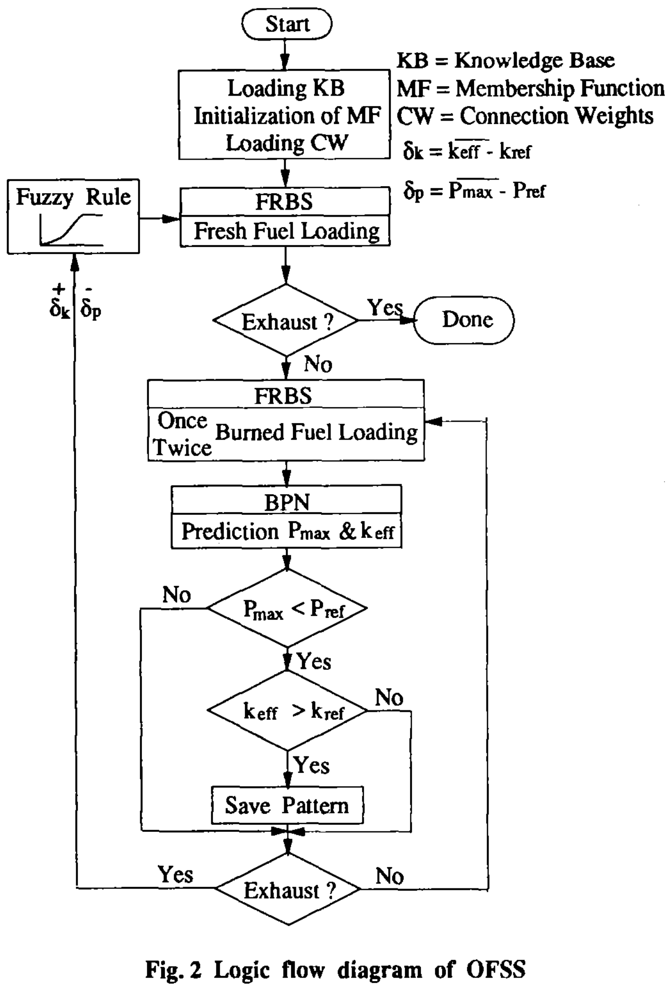


Fig. 2 Logic flow diagram of OFSS

cording to his experience and knowledge. This system is installed on the workstation, SUN 4/75 and is developed using Quintus prolog and C languages and X window system for graphical user interface.

III. DEVELOPMENT STRATEGIES OF OFSS

III.1. Development of the fuzzy rule based system

Human experts cannot predict core parameters of a given loading pattern, quantitatively, but they can classify which patterns are good or bad in broadly using their own heuristic knowledge. In this paper, the rule based system is developed to imitate these human's ability. Fig. 3 shows the structure of a rule based system for a fuel loading pattern classification. This system is developed using the Quintus prolog language.

The inference engine has two searching algorithms, depth-first and breadth-first. In this paper, both of two searching algorithms are used to take merits of two algorithms. Depth-first searching algorithm is used for the fresh fuel assembly loading and breadth-first searching algorithm is used for the once and the twice burned fuel assembly loadings.

The knowledge base of this rule based system consists of heuristic rules and facts. Heuristic rules are divided into two classes: a fuzzy rule and ordinary heuristic rules. Facts express factual knowledge related to the problem domain, i.e., a reactor

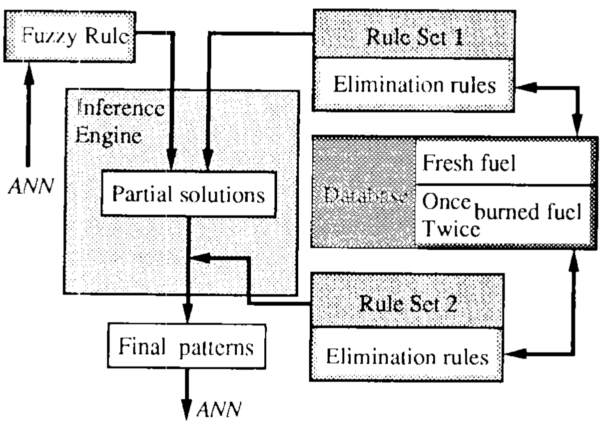


Fig. 3 Structure of the fuzzy rule based system for the fuel loading pattern classification

core geometry and fuel assemblies.

The heuristic rules used in this rule based system can be written in natural language form as follows: ***rule-1***: Fresh fuel loading into the core position which a distance from the center is smaller than that of position $x sub m$ is forbidden. ***rule-2***: Fresh fuel loading should maintain the checkerboard pattern, unless the considered core position is one with a reflector on two sides. ***rule-3***: If the fresh fuel is loaded into the inside position which has control rod bank, this loading is forbidden. ***rule-4***: Twice-burned fuel loading into core periphery positions is forbidden. ***rule-5***: Twice-burned fuel loading should maintain the

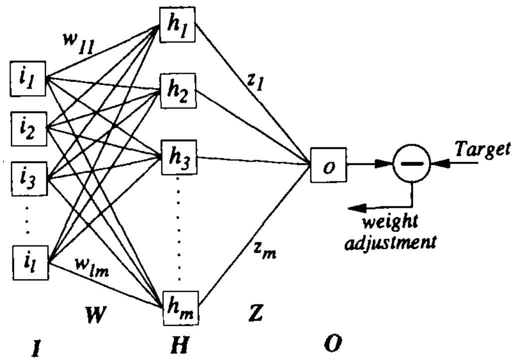


Fig. 4 The general structure of the three layered BPN

checkerboard pattern, unless the considered core position is (2, 1) and (2, 2). ***rule-6***: Once-burned fuel loading should maintain the checkerboard pattern in lines 2, 3, and 4.

rule-1 is a fuzzy rule. In rule-1, the position x_m is determined by fuzzy logic and is updated optimally. Results and demonstrations of the rule based system are described in Sec. IV.

III.2. Fuzzy logic within the rule based system

The fuzzy rule[11] is referred in Sec. III.1, "*rule-1*" of the rule based system. "*rule-1*" means that if a fresh fuel assembly is loaded into near center position, the local power peaking factor at that position can be exceeded the limit value. This meaning may be generally accepted in qualitative terms but the nearest position which is permitted loading of a fresh fuel assembly can not be determined.

In traditional rule based system[9, 10], this nearest position is determined as fixed one by heuristic knowledge of a system designer, for example, "$x_m = 33$" or "$x_m = 31$" etc.. However we used the fuzzy membership function(MF) to determine this nearest position and this MF is updated with the prediction results by the artificial neural networks.

MF is initialized as following equation:

$$p(x^2) = \begin{cases} \frac{1}{26}x^2 & x^2 \le 26 \\ 1 & 26 \le x^2 \le 37 \end{cases} \tag{1}$$

In Eq. (1), x^2 is the square of distance from the center of reactor core when it is assumed that one side of a fuel assembly equals to 1. $p(x^2)$ represents the possibility that a fresh fuel assembly can be loaded at that position. This MF is updated with the results by following two logics:

1. The produced pattern is better than reference one. That is, P_{max} of the produced pattern is smaller than P_{max} of the reference one and k_{eff} of the produced pattern is larger than k_{eff} of the reference one.

$$p_{n+1}(t^2) = (1-\alpha)p_n(t^2) + \alpha,\ t^2 > x_m^2 \tag{2}$$

2. The produced pattern is worse than reference one. That is, P_{max} of the produced pattern is larger than P_{max} of the reference one.

$$p_{n+1}(t^2) = (1-\beta)p_n(t^2),\ t^2 < x_m^2 \quad (3)$$

where α and β are the proportional coefficients for P_{max} and k_{eff}, respectively. Based on the above two logics, MF adjustment sequence is as follows:

1. MF initialization by Eq. (1).
2. Generation of random number, r ranged 0 to 1.
3. Take the minimum value among xs which $p(x^2) > r$. This is the nearest position permitted fresh fuel loading.
4. Rule based system is performed with the nearest position determined step 3, and the BPNs predict core parameters. And then MF is updated by Eqs. (2) or (3) with the prediction results.
5. Go to step 2 until searching is ended.

III.3. Core parameter prediction using BPN

In this paper, we developed the very fast core parameter prediction system using BPN. This system predicts P_{max} and k_{eff} at BOC condition for the given fuel loading patterns. BPN used in this paper consists of one input layer, one output layer, and one hidden layer as shown in Fig. 4. Each layer is composed of neuron(s) used as the fundamental building block of the back-propagation network. A neuron calculates a weighted sum of inputs applied either from the outside or from the previous layer. After this summation is calculated the activation function, F is applied to modify it, thereby producing the output signal. Two networks are constructed, one for prediction of P_{max} and another for prediction of k_{eff}. Both are three layered networks. P_{max} network has 21 input layer neurons, 150 hidden layer neurons, and 18 output layer neurons. k_{eff} network has 400 hidden layer neurons and others are same as P_{max} network. Detailed descriptions on the determination of the number of each layer neurons are given in reference 13.

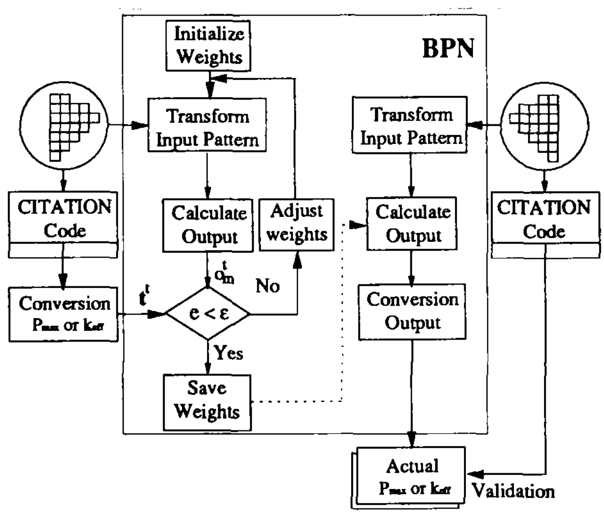
Learning of a back-propagation network is performed by adjusting the weights to minimize the squared error, that is

$$\frac{\partial E}{\partial z_{jk}} = 0 \quad (4)$$

where z_{jk} is the k-th connection weight of the j-th neuron.

In order to minimize the squared error, z_{jk} must be adjusted to the reverse direction of the slope of E verse z_{jk}. Detailed descriptions on the learning algorithms are given in our last study[13].

A given *1/8* core loading pattern must be transformed in a vector form so that it can be used as the input pattern of the BPN. We convert an one-eighth core loading pattern to numeric vector having 21 elements[13].



Learning Stage Prediction Stage

Fig. 5 Overall learning and prediction procedure of the core parameter prediction system

The output of the network is P_{max} and k_{eff} at BOC condition. These two parameters for a given loading pattern are obtained using the QCC code developed in KAIST. Then P_{max} and k_{eff} are normalized between 0 and 1 and are converted $1 times 18$ binary vector by the group-and-weight scheme[12] which has 2 groups and 9 bits in each group, respectively. Thus the input layer has 21 neurons and the output layer has 18 neurons. Training patterns are composed of the transformed input vectors and output values. 1000 different training patterns are generated randomly.

Fig. 5 shows the learning and prediction procedure of the BPN which is used in this study. In learning stage, all connection weights are initialized between -0.1 and 0.1, randomly. These weights are adjusted to minimize the squared error for 1000 training patterns. If the averaged error is less than the convergence criteria, ε which is set to 0.005, the weights are saved and the learning is completed.

In prediction stage, un-trained loading patterns are converted to the network input vectors and the network calculates the output vectors without further adjustment of the connection weights. Then, these output vectors are converted actual P_{max} or k_{eff} and compared to the reference code outputs. In this study, 100 un-trained loading patterns are generated, randomly. The prediction results for these 100 un-trained patterns are shown in Fig. 6. The x-axis of Fig. 6 represents the target values obtained by the reference QCC code and the y-axis represents the output values predicted by the BPN.

In case of P_{max} prediction, 95% of the un-trained patterns are predicted within ±*6.0%* error, maximum and average prediction error for the 100 test patterns are *6.976 %* and *2.491 %*, respectively. In case of k_{eff} prediction, all of the un-trained patterns are predicted within ±*0.3%* error, maximum and average prediction

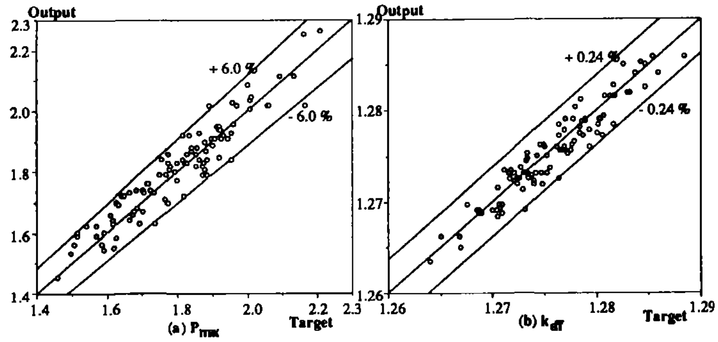


Fig. 6 The prediction results for 100 un-trained loading patterns

error for 100 test patterns are *0.272%* and *0.096%*, respectively. In SUN4/75 workstation, QCC code takes 10~20 seconds cpu to calculate output for one loading pattern. The other hand, BPN predicts after *0.084* sec cpu. Thus BPN predicts about 100 times as fast as the QCC code.

IV. RESULTS AND VALIDATIONS

In Secs. II and III, we have discussed on the computation logics and development strategies of OFSS sub-systems. Under the basis of these logics and strategies, OFSS was developed and installed on SUN 4/75 workstation and was demonstrated for the first cycle of Kori unit 1 PWR.

Fig. 7 shows the final screen displays of OFSS. This window is composed of five parts such as the reference pattern display(RPD) part, the current pattern display(CPD) part, the message display(MD) part, the fuzzy membership function display(FMFD) part, and the rank table display(RTD) part. The loading pattern shown in RPD of Fig. 7 was loaded at first cycle of Kori unit 1 nuclear power plant, actually. So, we selected this pattern as the reference fuel loading pattern. As shown in RPD of Fig. 7, P_{max} and k_{eff} of the reference pattern are *1.5005* and *1.2642*, respectively. Of course, this values may be different from the real values of the first cycle because the burnable poisons and soluble boron are not considered. Therefore, OFSS finds the patterns satisfying following two conditions:

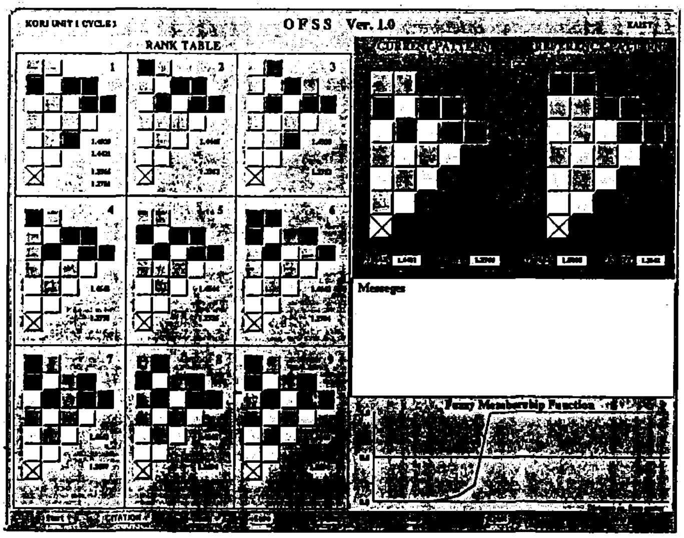


Fig. 7 Final Screen of OFSS

$$P_{max} < 1.06 \times P_{max}^{ref}, \quad k_{eff} < 0.9976 \times k_{eff}^{ref} \tag{5}$$

where $P_{max}^{ref} = 1.5005$ and $k_{eff}^{ref} = 1.2642$. In Eq. (5), the coefficients, 1.06 and 0.9976 are the weighting factors considered the prediction error ranges of BPNs.

As shown in Fig. 7, RTD is filled with the fuel loading patterns better than the reference pattern and the fuzzy membership function is fully adjusted. In RTD of Fig. 7, two numbers, which are located at right-bottom of each box except the first, represent the core parameters of each pattern. Four numbers in the number one box of RTD represent the followings in order:

-. *Power peaking factor by prediction of BPN is 1.4939.*
-. *Power peaking factor by the QCC code is 1.4421.*
-. *Effective multiplication factor by prediction of BPN is 1.2766.*
-. *Effective multiplication factor by the QCC code is 1.2751.*

From this result, we can conclude that OFSS can find the optimal fuel loading patterns better than the reference one. The reference loading pattern was loaded according to out-in loading scheme, that is, all fresh fuel assemblies were loaded at periphery positions. But, as shown in RTD of Fig. 7, the maximum power peak can be reduced although the fresh fuel assemblies are loaded at some inner positions.

The use of a fuzzy MF greatly reduces searching space and time of the rule based system. Table I shows the comparison between the results of RBS using and not using the fuzzy MF.

In Table I, RBS not using the fuzzy MF used $x_m = [3, 3]$ in "rule-1". These two systems are executed on the same machine. Table I shows the execution results of the two systems, the num-

Table I Comparison between the searching space/time of RBS using and not using the fuzzy MF

Ordinary RBS			Fuzzy RBS	
Accumulated CPU(sec)	Number of patterns	Loading sequences	Number of patterns	Accumulated CPU(sec)
61	392	All fresh	126	22
175	4683	Twice 1	1276	145
457	22047	Twice 2	6139	221
1795	54079	Twice 3	15235	454
4148	76686	Twice 4	21592	893
6463	65836	Twice 5	18129	1306
7572	34841	Twice 6	9125	1531
7957	11370	Twice 7	2707	1627
8077	2212	Twice 8	471	1686
8145	2212	Once 1	471	1740
8242	2212	Once 2	471	1785
8318	2212	Once 3	471	1835
8400	2212	Once 4	471	1891
8499	2212	Once 5	436	1931
8594	**1582**	**Once 6**	**322**	**1949**

ber of generated patterns and the accumulated CPU times in each intermediate searching stage. In Table I, Intermediate stages of the fresh fuel loading are not shown because the fresh fuel loading is performed by the depth-first searching algorithm. As shown in Table I, the searching space when the fuzzy rule is used is much smaller than the searching space of the ordinary rule based system. The number of final patterns of the fuzzy rule based system is only *20.4%* of that of the ordinary rule based system. This result tell us that use of the fuzzy rule can reduce the problem space, greatly.

As mentioned early, the fuzzy MF is initialized as Eq. (1) and is updated optimally according to results. The update process

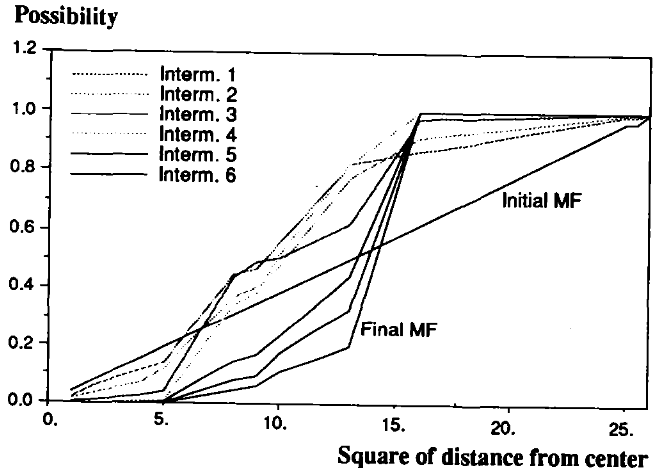


Fig. 8 Update Process of the fuzzy membership function

of the fuzzy MF is shown in Fig. 8. As shown in Fig. 8, MF is varied from quasi linear function to sigmoid shape function. The final MF has the shape similar to the threshold function. This presents that the nearest position permitted loading of fresh fuel assemblies can be determined.

V. CONCLUSIONS

In this paper, we developed the prototype expert system, the optimal fuel shuffling system(OFSS) for optimal design of PWR fuel loading pattern. This system is an integrated one that a rule based system, a fuzzy logic, and an artificial neural network are connected each other.

As the results of validation for the first cycle of Kori unit 1 PWR, OFSS generated optimal loading patterns better than the reference pattern. But we can not assert that the generated patterns is the global optimal pattern because of prediction error, thus we offered multiple solutions so that one can select one of the final patterns. Use of a fuzzy logic greatly reduced the searching space and time of the rule based system without any negative effects of its results. And the artificial neural networks predicted the core parameters much faster than numerical codes. Therefore, the technologies used in this paper, the artificial neural network and the fuzzy rule based system, can be used individually as the supporting tool for improvement of existing algorithm's capabilities.

This system may not be used as real reloading tool because of its assumptions such as consideration of BOC condition only and neglection of burnable poisons, but it can be used as the tool supporting fuel loading pattern designer that wants to obtain more optimal solutions.

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