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NEURAL NETWORK FOR AUTOMATED STRUCTURAL DESIGN: ITS APPLICATION TO ITER FIRST WALL DESIGN

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ABSTRACT

This paper describes a novel method of automatically searching a multi-dimensional design window using a multilayer neural network. Quasi-optimum solutions are also obtained through searching the design window. The present method is implemented in the automated structural design system developed by the present authors. This system is successfully applied to a structural design of the ITER(International Thermonuclear Experimental Reactor) first wall.

1 INTRODUCTION

The first wall of fusion reactors will be required to operate in the severe environment where mechanical, electromagnetic and thermal loadings occur in a complicated manner and various failure phenomena such as melting, yielding and fracturing are competing among others. In designing such a structure, it seems very important to determine the design window that schematically indicates an area of satisfactory solutions in a permissible design space. The design window may give us more meaningful information than one satisfactory or optimum solution. However very few researches have been performed on the determination of the design window so far.

The present authors have been engaged in the development of an AI-based design automation system for nuclear structural components for several years (Yoshimura et al., 1990a, 1990b). In this system, the boundary tracing method which is commonly utilized in computer image processing was applied to automatically search the design window (Yoshimura et al., 1991). In this algorithm, the system starts searching the edge of the design window after finding one satisfactory solution using an empirical design modification approach. The boundary tracing method is applicable to only the problems with two design variables.

This paper first summarizes two methods of searching a multi-dimensional design window. Quasi-optimum solutions are also obtained through searching the design window. Secondly, a novel search method using a multilayer neural network is presented to improve the efficiency of searching the design window. To demonstrate performances of the present method, they are utilized to obtain the design windows of the ITER (IAEA, 1991) first wall.

2 SEARCH METHODS OF MULTI-DIMENSIONAL DESIGN WINDOW

The search methods considered here are the Whole-area Search Method (WSM) and the Boundary Swelling Method (BSM), both of which can search even a doughnut-shaped design window. Besides, quasi-optimum solutions are obtained in the searching process as described later.

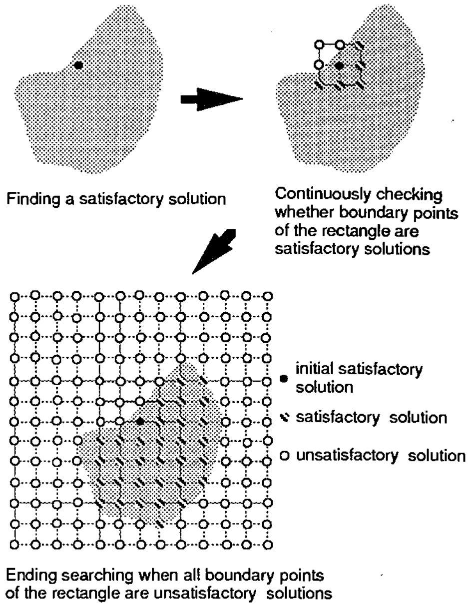


Fig.1 Algorithm of BSM in Two-Dimensional Design Space

2.1 Whole-area Search Method (WSM)

The algorithm of the WSM is as follows. At first, a lattice is generated in the design space that is determined by engineers empirically. Then all intersection points of the lattice are examined one by one whether they are inside a design window or not. The WSM can search even plural design windows. However, the number of points to be examined tends to become extremely huge.

2.2 Boundary Swelling Method (BSM)

The basic concept of the BSM in the case of searching a two-dimensional design window is schematically illustrated in Fig.1. Here, one satisfactory point needs to be found at first, and a rectangle is generated so that the initial satisfactory point is located at the center of it. Secondly, eight boundary points of the rectangle are checked whether they are satisfactory points. After that, the rectangle is enlarged in an outward direction by twice of a unit step of searching. Then the boundary points of the swelling rectangle are checked again. This searching process is iterated until all the boundary points of the swelling rectangle becomes unsatisfactory. This algorithm is easily applicable for searching a design window of more than three dimension.

The number of points to be searched in the BSM is much less than that in the WSM. However, the BSM can not search plural design windows, and an initial satisfactory point needs to be known a priori.

3 PRINCIPLE OF AUTOMATIC DESIGN WINDOW SEARCH USING NEURAL NETWORK

3.1 Network Architecture and Learning Algorithm

Fig.2 shows a unit of a neural network which has multiple input and a single output data. The relation between the input and the output data is formulated as follows:

$$H_j = f(U_j) = 1/\{1 + \exp(-2U_j/U_o)\} \quad (1)$$

$$U_j = \sum_{i=1}^{I} W_{ji} \cdot I_i - \theta_j \quad (2)$$

where H_j is the real-valued output of the j-th unit, U_j is the total input to the j-th unit, f is the activation function, i.e. the sigmoid function here, U_0 is the temperature constant, W_{ji} is the connecting weight between the i-th and the j-th units, I_i is the input from the i-th to the j-th units, θ_j is the bias value of the j-th unit, and l is the number of input data, respectively.

The multilayer neural network consists of multiple layers, each of which posesses a number of units. The basic algorithm of training the network is as follows. At first the following error E is defined :

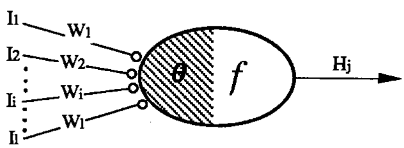


Fig.2 SchematicView of Unit of Neural Network

$$E \equiv E_p = \sum_{k=1}^{n} \frac{1}{2}(T_{pk} - O_{pk})^2 \qquad (3)$$

where E_p is the error for the p-th learning pattern, T_{pk} is the teaching data corresponding to the k-th output unit for the p-th learning pattern, O_{pk} is the output from the k-th output unit for the p-th learning pattern, and n is the number of output units, respectively. In the training process, the connecting weights W_{ji} and the bias θ_j are modified iteratively based on the steepest gradient method to minimize the error above. Through the training, the network obtains the ability of outputting the similar data to the teaching data. This training algorithm is called the error back propagation (Rumelhart et al., 1986). In the present study, the error back propagation algorithm with the moment method is employed to attain stable convergence in training processes.

3.2 Main Features of Multilayer Neural Network

The attractive features of the multilayer neural network can be summarized as follows (Mochizuki et al., 1991) :

(a)One can automatically construct a nonlinear mapping function from multiple input data to multiple output data in the network through a learning process of some or many learning patterns.

(b)The network has a feature of so-called "generalization", i.e. a kind of interpolation, so that the trained neural network estimates appropriate output data even for unlearned patterns.

(c)The trained network operates quickly in an application process. The computational power required for the operation of the trained network may be equivalent to only that of a personal computer.

(d)It is theoretically proven that any kinds of continuous mappings can be approximately realized by the multilayer neural network with one hidden layer at least.

3.3 Automatic Design Window Search

In searching design windows based on the present search methods, whether a searched point is a satisfactory solution is checked through computational mechanics simulations, e.g. FEM, from the standpoint of accuracy. However, the finite element calculations at every searched points are very time-consuming especially in the design of high temperature structural components because both thermal and stress analyses are to be executed. Thus, the search method using a neural network that can perform nonlinear mapping very fast is proposed here to improve the efficiency of searching design windows.

As shown in Fig.3, this method consists of three phases. At first, finite element analyses are performed to prepare learning data sets and unlearning data sets for the neural network. The unlearning data sets are to prevent the neural network from "overlearning", which is a phenomenon such that the estimation error of unlearning data sets increases largely even though the learning process advances. Secondly, an error-back-propagation neural network is trained using a number of the learning data sets. Here, the design parameters are given to the network as input data, while the physical values, i.e. temperature and equivalent stress, are given to it as teaching data. After this training process, the trained network can imitate a response of the FEM analyzer. Finally, a multi-dimensional design window is searched using the trained network.

In the present search method, the finite element analyses have to be performed at phase 1. However, the number of the finite element analyses required here is much smaller than the search method without a neuro. Besides, as the trained network calculates physical values very quickly, it can be checked effectively whether a searched point is a satisfactory solution. Thus, by utilizing the trained neural network, even the WSM can be executed within a reasonable processing time.

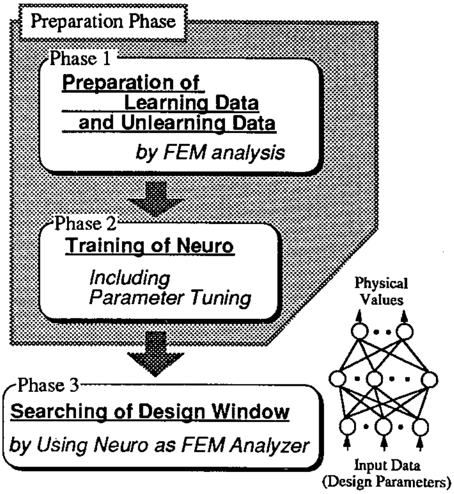


Fig.3 Schematic View of the Procedure of the Design Window Search Using Multilayer Neural Network

4 RESULTS AND DISCUSSIONS

4.1 Problem description

The ITER first wall currently has two candidate designs regarding to cooling channel, i.e. rectangular and circular channels. Here, the present system is applied to search the design windows of the two design models.

The design models are shown in Figs.4(a) and 4(b). The mother material of the wall is subjected to membrane tensile loading, F(=9.8[N]), which might be caused by electromagnetic loading and pressure from the breeder blanket, and to the surface heat loading, Q_blanket(=0.15[MW/m^2]) on the blanket-side surface and to the volumetric heat loading Qv_SUS316(= 20.0[MW/m^3]). The armor is also subjected to the surface heat loading, Q_plasma(=0.15[MW/m^2]) on the plasma-side surface and to the volumetric heat loading Qv_armor(=6.0[MW/m^3]). The temperature and the pressure of the cooling water are 100.0[°C] and 1.5[MPa], respectively. The heat transfer coefficient between the armor and the mother materials is 1000.0[W/m^2°C] and that between the cooling water and the mother material is 20000.0[W/m^2°C]. The 316 stainless steel and CX-2002U are utilized as the mother material of the wall and the armor material, respectively. The wall with the armor is modeled with eight-noded isoparametric elements. A static thermal conduction analysis is performed. In an elastic thermal stress analysis, only the mother material is analyzed under the generalized plain strain condition. These finite element analyses are performed using the object-oriented analyzer developed by the present authors (Yoshimura et al., 1990a, 1990b). In this system, the FINAS code is implemented as a finite element code. The design criteria employed here are a geometrical constraint and two failure constraints. The failure constraints are as follows:

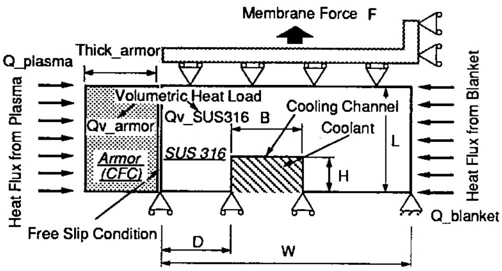
(a)$T_{max} < T_0$ (4)

(b)$\sigma_{max} < \sigma_0$ (5)

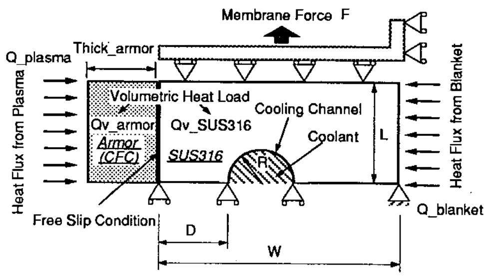
where T_{max} is the maximum temperature occurred in the mother material, T_0 a permissible value of temperature, σ_{max} the maximum equivalent stress and σ_0 a permissible value of equivalent stress, respectively. For the purpose of simplicity, T_0 and σ_0 are taken to be 400.0[°C] and a yielding stress, respectively. In this study, three-dimensional design windows of geometrical design parameters, i.e. D, L and W, are drawn.

4.2 Results

Fig.5 shows the three-dimensional design windows of the design models shown in Fig.4. Here the areas of both cooling channels are chosen to be the same as each other ,and the searching unit steps of D, L and W are 0.15[mm], 0.15[mm] and 0.5[mm], respectively. Both design windows are searched based on the WSM combined with the neural network approach. The employed multilayer neural networks are of three-layered type. The network used in the case of the rectangular channel model has five input units, twenty hidden units and two output units, while that of the circular channel model has four input units, twenty hidden units and two output units. The input units correspond to the geometrical design parameters, i.e. D, L, W, H and B in the case of the

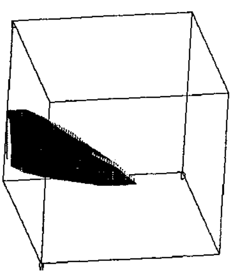


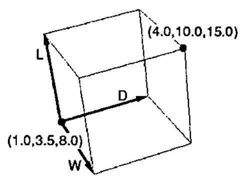
(a) Rectangular Cooling Channel Model



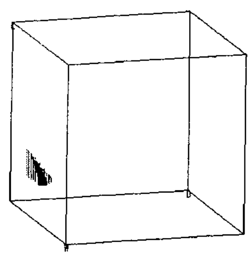
(b) Circular Cooling Channel Model

Fig.4 Design Models of ITER First Wall





(Bracketed coordinate denotes (D,L,W), the unit is [mm])



The number of searched points in Design Window = 356
The minimumvalue of σ_{max} takes the minimum value of 174.05[MPa] at D=1.45[mm], L=4.55[mm] and W=8.5[mm]

(a) Design Window of Rectangular Channel Model

The number of searched points in Design Window = 44
The minimumvalue of σ_{max} takes the minimum value of 166.35[MPa] at D=1.0[mm], L=4.85[mm] and W=10.0[mm]

(b) Design Window of Circular Channel Model

Fig.5 Comparison of Three-Dimensional Design Windows between Rectangular Cooling Channel Model and Circular Cooling Channel Model rectangular channel model ,and D, L, W and R in the case of the circular channel model, respectively. Two output units are for the maximum equivalent stress and temperature.

If these design windows are searched based on the WSM without the neural network, 10,651 and 6,233 finite element analyses have to be performed in the rectangular and the circular channel model cases, respectively. On the other hand, when using the WSM with the neural network approach, only 580 and 224 finite element analyses are executed in both cases. Here, the number of the finite element analyses denotes the sum of the number of the analyses for the learned and unlearned patterns as described in sec. 3.3. Although the neural network approach requires a training time, the searching process can be much more efficient.

It can be seen in Fig.5 that the design window of the rectangular channel model is larger than that of the circular one. This may be because the cooling capability of the rectangular channel is higher than that of the cirucular one and because the extent of the stress concentration around the corners of the rectangular channel is not so strong. When using the WSM, the distribution of the objective function over the searched design window and quasi-optimum solutions are simultaneously obtained. Therefore, one can choose a final design solution by considering these design windows and other issues such as the distribution of the objective function, manufacturability, integrity and cost.

5 CONCLUDING REMARKS

A novel method of searching a multi-dimensional design window using a multilayer neural network is proposed in this study. Its effectiveness is clearly demonstrated through obtaining the design windows of the ITER first wall.

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