rehabilitation may increase abruptly almost simultaneously.

2. Damage in steel structures are predominantly found in high-tension bolts, bearings and expansion joints. Corrosion and fatigue cracking also constitute importance damage mechanisms. On the other hand, damage in concrete structures mainly involves cracks, corroded bars, water leakage or spalling of cover concrete. The relevant design codes have been revised to reflect new technological advances from recent research, which has significantly contributed to the decrease in damage in newly constructed bridges.
3. In this paper, a set of real expenditure data on maintenance and rehabilitation for a certain route of the Hanshin Expressway was used in a macro study of lifecycle costs. Reasonable estimate of the expenditure curve can be obtained using a least-squares or logarithmic fitting method. The study demonstrates that lifecycle cost depends significantly on the lifecycle selected, and the long lifecycle does not necessarily render the minimum lifecycle cost. It should be noted that defining the target time in service is very important.

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DEVELOPMENT OF CONCRETE BRIDGE RATING EXPERT SYSTEM (*BREX*) IN JAPAN

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ABSTRACT

The aim of the present study is to develop a concrete bridge rating expert system for deteriorated concrete bridges, constructed from a hierarchical neural network in order to carry out fuzzy inference and machine learning. The proposed system evaluates the performance of concrete bridges on the basis of a simple visual inspection and technical specifications. The neural network applied in this study facilitates refinement of the knowledge base by use of the Back-Propagation method, and prevents the inference mechanism of the system from becoming a black box. In this study, the training set for machine learning is obtained from inspection of actual in-service bridges and questionnaire surveys of bridge experts. Furthermore, comparisons between the diagnostic results of bridge experts and those of the proposed system are presented so as to demonstrate the validity of the system's learning capability.

INTRODUCTION

The authors have for some time been developing an expert system which can be used to evaluate the performance of existing concrete bridges on the basis of knowledge and experience acquired from domain experts [1-4,6,7]. The proposed expert system is called the concrete Bridge Rating EXpert system (*BREX*). The objective of the present system is to evaluate the present performance of target bridge members in terms of factors such as serviceability, load-carrying capability,

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and durability. The input data for rating a concrete bridge are the technical specifications of the target bridge, environmental conditions, traffic volume, and other subjective information that can be obtained through simple visual inspection. In the present study, load-carrying capability and durability are used to estimate serviceability. Load-carrying capability is defined as the aspect of bridge performance that is based on the load-carrying capacity of a bridge member, and durability is defined as the ability of a bridge member to resist material deterioration and is based on the rate of material deterioration of the member. These two aspects of bridge performance are applied as indices for considering the necessity of performing maintenance on deteriorated bridges. Specifically, load-carrying capability is applied as an index for estimating the necessity of strengthening, and durability is applied as an index for estimating the necessity of repair.

In the expert system, the performance of a target bridge is evaluated according to a diagnostic process, which is modeled on the inference process domain experts employ for rating an existing concrete bridge. This process is expressed by a hierarchical structure and has twelve main judgment items. The ultimate goal of this process is "serviceability." The hierarchical structure expresses the relationship between judgment items and input data, such as inspection data and technical specification data, or between judgment items. In practice, these relationships are expressed by "If-then" rules with fuzzy variables. Consequently, the fuzzy inference of the expert system is drawn from these rules. Naturally, these rules could be written directly into a computer in a computer language. In this study, however, these rules are implemented in a computer after a set of the rules relating judgment items and input data or relating judgment items is transformed to a hierarchical neural network. In other words, hierarchical neural networks identify a diagnostic process. The system can easily refine the knowledge base; that is, "If-then" rules with fuzzy variables, by use of a machine learning method. More specifically, the system refines the knowledge base by applying the Back-Propagation method [9]. Therefore, since the network is capable of performing fuzzy inference and machine learning, the system can be called a Neuro-Fuzzy expert system. Generally, although a neural network is a powerful machine learning tool, the inference process of a neural network becomes a "black box," which renders the representation of knowledge in the form of rules impossible. However, the hierarchical neural network proposed in the present study contributes to prevent an inference process from becoming a black box. As described later, the effectiveness of the hierarchical neural network and machine learning method was verified by comparison of the diagnostic results of bridge experts and those of the proposed system.

PERFORMANCE EVALUATION OF EXISTING CONCRETE BRIDGES

In the expert system, the target bridge is diagnosed according to a diagnostic process, which is modeled on the inference mechanism used by domain experts for rating bridges (See Fig. 1). In a previous study, the authors used the Fuzzy Structural Modeling (FSM) method [10] to create the diagnostic process for main girders and slabs. Each process employs twelve main judgment items. These judgment items are evaluated by about 90 input data items, such as technical specifications, traffic volume, and results of visual inspection. The process is a hierarchical structure in which the ultimate goal is "serviceability."

For instance, Fig. 1 shows the diagnostic process for main girders. The lowest-rated judgment items, such as "Condition state of cracking" and "Condition state other than cracking," are first evaluated by use of input data such as visual inspection data and technical specifications. The "Condition state of cracking" is evaluated from inspection data such as [Crack conditions] and [Maximum crack width (mm)]. Next, the higher-rated judgment items, such as "flexural cracks," "shear cracks," and "material deterioration," are diagnosed from the results of lower judgment items and/or input data. The damage degree of "flexural cracks" is determined from the results of "Condition state of cracking" and "Condition state other than cracking." Then, the higher-rated judgment items, such as "whole damage," "execution of work," and "service conditions," are also evaluated from the results of lower judgment items and/or input data. The final judgment item is "serviceability," which is evaluated according to the results of "load-carrying capability" and "durability." Each of these judgment items is assigned a soundness score, on a scale of 0-100, which is output from the expert system. The output score is categorized into one of five groups: 0-12.5, 12.6-37.5, 37.6-62.5, 62.6-87.5 and 87.6-100. These groups are classified as "dangerous," "slightly dangerous," "moderate," "fairly safe," and "safe," respectively. In the present study, "safe" indicates that the bridge has no problems; "fairly safe" indicates no serious damage; "moderate" indicates the presence of some damage that requires continuous inspection; "slightly dangerous" indicates that the bridge should be repaired and/or strengthened; and "dangerous" indicates that the bridge should be removed from service and requires rebuilding. In the expert system, the relationships between judgment items and input data and those between judgment items are expressed by "If-then" rules with fuzzy variables. In addition, by introduction of machine learning into the expert system, these rules are implemented by hierarchical neural networks. A hierarchical network expresses a set of rules for evaluating a judgment item.

FUZZY INFERENCE OF BREX

Knowledge Representation

The expert system evaluates the performance of a target bridge according to the diagnostic process, which expresses the relationships between judgment items and input data or between judgment items, as shown in Fig. 1. In the knowledge base of the system, the diagnostic process is stored in the form of "If-then" rules with fuzzy variables. Consequently, these rules enable the system to perform fuzzy inference.

The knowledge representation of the system is as follows.

$$R^i : if\ x_1\ is\ A_1\ and \cdots and\ x_m\ is\ A_m\ then\ y\ is\ B_i \tag{1}$$

where, R^i : ith fuzzy rule

$x_1, \cdots, x_m$: input items (input data such as technical specifications and results of visual inspection)

y : output item (diagnosis item; that is, judgment item)

$A_1, \cdots, A_m$: fuzzy variables

B_i : constant (soundness score on the scale of 0-100)

For example, If ([Crack condition] is serious) and ([Maximum crack width] is huge) then ([Condition state of cracking] is 0.0). This rule is used in order to evaluate the judgment item "Condition state of cracking."

Fuzzy inference process

This section describes in detail the fuzzy inference process performed in the expert system. The portion of Fig. 1 enclosed in a dotted box; namely, the inference process that evaluates "Condition state of cracking," is explained as an instance. Table 1 shows the fuzzy rules for evaluating the judgment item "Condition state of cracking." For example, Rule No. 12 expresses the following fuzzy rule; If ([Crack conditions] is OK) and ([Maximum crack width] is OK) then ([Condition state of cracking] is 100.0). Since these rules employ some fuzzy expressions; namely, antecedents of the rules employ some fuzzy propositions, the initial form of membership functions for fuzzy rules must be prepared. Fig. 2 shows the membership functions related to the fuzzy rules for evaluating "Condition state of cracking." Table 2 shows an excerpt of the inspection sheet used for the system. The solid circles indicate inspection results. The inference process of "Condition state of cracking" diagnosis is described below, and is performed in 4 steps.

[Step 1] Input of data

Input data are entered into the computer. As shown in Fig. 1, the diagnosis of "Condition state of cracking" requires the input data [Crack conditions] and [Maximum crack width (mm)]. In the present study, these input data are acquired by simple visual inspection (See Table 2). Therefore, the values of G1-1 and G1-2 in Table 2; that is, 0.7 and 0.5 (mm), are used as the input data for the diagnosis.

[Step 2] Calculate the grade of membership functions used in antecedents
(See Fig. 2 and Fig. 3)

The rules of the expert system employ some fuzzy propositions in antecedents of "If-then" rules. In the present study, a fuzzy set is expressed by membership functions. Consequently, from the values of input data for evaluating a judgment item, the grades of membership functions used in antecedents are first calculated. In this example, since the inspection value of [Crack conditions] is 0.7, this value matches two membership functions, which express the fuzzy set for {not serious} and that for {serious}. Therefore, these grades of membership functions are 0.8 and 0.4, respectively (See Fig. 2 (a)). However, the grade of membership function that expresses the fuzzy set for {OK} is 0.0, because the inspection value doesn't match the membership function. Similarly, considering the inspection value of [Maximum crack width (mm)], which is 0.5, the value also matches two membership functions, which express the fuzzy set for {small} and that for {large}. Therefore, these grades of membership functions are both 0.8 (See Fig. 2 (b)). The other grades of membership functions are 0.0, because the value doesn't match the other fuzzy sets; namely, {OK} and {huge}. The left-hand section table in Fig. 3 indicates the fitness of each fuzzy proposition in antecedents to the inspection results; namely, [Crack conditions]=0.7 and [Maximum crack width (mm)]=0.5.

[Step 3] Calculate the fitness of each rule to input values (See Fig. 3)

Whereas Step 2 calculates the fitness of each fuzzy proposition in antecedents to input values, Step 3 calculates the fitness of each rule to input values. As shown in Fig. 3, the fitness of each rule employs the following equations from the grades of membership functions estimated in Step 2.

$$\hat{\mu}_i = \frac{\mu_i}{\sum_{k=1}^{n} \mu_k} \tag{2}$$

$$\mu_i = \prod_j \mu_{i_j j}(x_j) \tag{3}$$

where, $\hat{\mu}_i$: fitness of ith rule to input values, such as inspection results

$\mu_{i_j j}(x_j)$:grade of a membership function

i : identification number of fuzzy rule

j : identification number of input variable and fuzzy variable

x_j : input variable

$\mu_{i_j j}$: fuzzy variable for input variable x_j

i_j : identification number of fuzzy set on fuzzy variable $\mu_{i_j j}$

n : the number of fuzzy rules

Eq. (3) indicates that all fitness values of fuzzy propositions in the same fuzzy rule are multiplied; that is to say, all grades of membership functions in the same rule are multiplied. Therefore, when the inspection results [Crack conditions] =0.7 and [Maximum crack width (mm)]=0.5 are entered into the system, the values given in the right-hand section in Fig. 3 are estimated by Eq. (2) and Eq. (3). Rule No. 2 and Rule No. 3 both have a fitness of 17%, and Rule No.6 and Rule No.7 both have a fitness of 33%.

[Step 4] Calculate a soundness score for a judgment item (See Fig. 4)

In the final step, a soundness score for a judgment item is calculated from the fitness of rule acquired in Step 3 and soundness scores described in consequents of fuzzy rules. A soundness score for input values is estimated by the following equation.

$$y = \sum_{k=1}^{n} \hat{\mu}_k \omega_k \tag{4}$$

where, $\hat{\mu}_k$: fitness value of kth rule, which is acquired by Eq. (2)

ω_k :soundness score described in consequents of *k*th fuzzy rule

Consequently, a judgment item is assigned a soundness score on a scale of 0-100. For example, when the input [Crack conditions] =0.7 and [Maximum crack width (mm)]=0.5 is entered, the expert system outputs the soundness score of 42.2 as the result of diagnosis of input data (See Fig. 4).

FUZZY INFERENCE BASED ON NEURAL NETWORK

Structure of fuzzy inference system using a hierarchical neural network

In the expert system, the inference mechanism for evaluating a judgment item is constructed with a hierarchical neural network consisting of 5 layers, as shown in Fig. 5 [5,8]. The knowledge for diagnosing "Condition state of cracking"; that is to say, Table 1 and Fig. 2 (fuzzy rules and membership functions for fuzzy sets), are implemented in the computer by the neural network shown in Fig. 5. Therefore, the neural network can carry out the fuzzy inference mentioned in the previous section. In the present study, the layers of the network are referred to as layers (A), (B), (C), (D) and (E), respectively. These layers have neurons of three different types. The neurons in layers (A), (C) and (E) are linear neurons. The neurons in layer (B) are sigmoid neurons. The neurons in layer (D) are referred to as normalization neurons which employ Eq. (2). The Arabic numerals in the layer (D) neurons correspond to the number (No.) in Table 1. Therefore, clearly the connections from layer (C) to layer (E) express a fuzzy rule. A boxed value represents the initial connection weight between neurons or the initial threshold for a neuron.

Next, is described the manner in which the initial values of weight and threshold are set. The layers (A)-(B)-(C) in the network identify the fuzzy sets in antecedents of fuzzy rules. If the membership function of a fuzzy set is an increasing function or a decreasing function, the form is identified by a sigmoid function; a sigmoid neuron is employed in layer (B) for an increasing function or a decreasing function. If the membership function is a convex function, the form is identified by the combination of two sigmoid functions; two sigmoid neurons are employed in layer (B) for a convex function. Then, the weights (ω) between layer (A) neurons and layer (B) neurons, and the thresholds(θ) of the (B) neurons are calculated according to the following equations.

① Approximation of decreasing function

$$\begin{cases} \omega = -h / A \\ \theta = hB / A \\ x_1 = B - A, \mu(x_1) = 1.0, x_1 \in X \\ x_2 = B + A, \mu(x_2) = 0.0, x_2 \in X \\ x_1, x_2 \in X \end{cases} \tag{5}$$

② Approximation of increasing function

$$\begin{cases} \omega = h / A \\ \theta = -hB / A \\ x_1 = B + A, \mu(x_1) = 1.0, x_1 \in X \\ x_2 = B - A, \mu(x_2) = 0.0, x_2 \in X \\ x_1, x_2 \in X \end{cases} \quad (6)$$

③ Approximation of convex function

$$\begin{cases} \omega_1 = h / A \\ \omega_2 = h / C \\ \theta_1 = -h(B - A) / A \\ \theta_2 = -h(B + C) / C \\ x_1 = B, \mu(x_1) = 1.0 \\ x_2 = B - 2A, \mu(x_2) = 0.0 \\ x_3 = B + 2C, \mu(x_3) = 0.0 \\ x_1, x_2, x_3 \in X, x_2 < x_3 \end{cases} \quad (7)$$

Note that h is a real number, which satisfies $f(h) \approx 1.0$. where, $f(h)$: sigmoid function. In the present study, $h = 3.5$. In the case of approximation of an increasing function or a decreasing function, the weights between layer (B) neurons and layer (C) neurons are set to 1.0. In the case of approximation of a convex function, the weights between layer (B) neurons and layer (C) neurons are set to –1.0 for smaller threshold and 1.0 for larger threshold. In addition, initial weights between layer (C) neurons and layer (D) neurons are all 0.5. The initial weights between layer (D) neurons and layer (E) neurons are set according to Table 1. These weights express soundness scores described in consequents of fuzzy rules. Consequently, when input data are entered into the system, layers (A)-(B)-(C) perform the processing of [Step 1] and [Step 2] described earlier. Next, layers (C)-(D) perform the processing of [Step 3]. Finally, layers (D)-(E) perform the processing of [Step 4].

Modification of Fuzzy Rule by Machine Learning

In the hierarchical network shown in Fig. 5, each weight and threshold is set for a specific purpose as mentioned above. Therefore, the network is capable of modifying fuzzy rules by altering these parameters, such as weight and threshold. Thus, applying the Back Propagation algorithm to the network as a machine learning method is easy, because the structure of neural network is hierarchical. More specifically, the elements modified by machine learning are the weights between layer (A) neurons and layer (B) neurons, the thresholds of layer (B) neurons, and the weights between layer (D) neurons and a layer (E) neuron. The weights of layers (A)-(B) and the thresholds of layer (B) neurons are used in order to express membership functions in antecedents of fuzzy rules. Consequently, weight alteration after learning indicates the slope alteration of the corresponding membership function, and threshold alteration after learning indicates the axis movement of the membership function in the horizontal direction. In the learning of layers (D)-(E) weight, the proposition in consequents of fuzzy rules is changed. For instance, if the weight between a layer (D) neuron and a layer (E) neuron is changed from 0.0 to 1.0, the proposition described in consequents of fuzzy rule is changed from ([Condition state of cracking] is 0.0) to ([Condition state of cracking] is 1.0).

VERIFICATION OF EFFECTIVENESS OF MACHINE LEARNING

The proposed expert system is developed in Visual Basic and C programming languages and runs on a personal computer. In this section, the expert system is applied to seven existing bridges (nine spans), all of which are RC T-girder-type bridges, in order to test validity of the learning capability. These target bridges stand in Yamaguchi Prefecture.

Questionnaire survey of domain experts and Visual inspection of bridges

The purpose of the questionnaire survey of domain experts is to acquire teacher data necessary for learning, whereas, the purpose of visual inspection of bridges is to collect inspection data to be entered into the system. The domain experts also use the inspection results to fill out the questionnaires. The results of questionnaire survey and visual inspection were used as training data for carrying out machine learning. In the present study, for collecting training data, visual inspection of bridges and the questionnaire survey were conducted over 2 days. Seven domain experts from four construction consulting companies in and around Yamaguchi Prefecture participated in the survey. The survey covered nine spans of seven bridges. One set of survey forms, prepared for each span, consists of three different handouts; inspection record sheets (8 pages) to be used to record visual inspection results, a model drawing of each bridge on which the respondents write down whatever comes to mind during inspection, and questionnaire sheets (10 pages) to obtain teacher data required for machine learning. The inspection record sheets are formatted so that the respondents can choose a score from an 11-point rating scale ranging from 0.0 to 1.0 in increments of 0.1, answer multiple-choice questions, and enter numerical values (See Table 2). The questionnaire sheets are formatted so that the respondents can answer in the form of a score on a 0-100 scale in increments of 5 points (See Fig. 6).

Practical application and Verification of the expert system

Table 3 summarizes the questionnaire results of main girder diagnosis by domain experts. The numerical values in parentheses represent averages of scores assigned by the four domain experts, out of the total of seven, who have more than 10 years' experience. The letters S, f-s, M, s-d, and D in the table represent safe, fairly safe, moderate, slightly dangerous, and dangerous. These labels classify the average values in parentheses into five categories, the criteria used by the respondents for this categorization having been mentioned earlier. A number appearing after a bridge name indicates span number. Tables 4 and 5 present the diagnosis results of main girders before learning and after learning, respectively. As mentioned earlier, in the present study, the Back Propagation method was applied as a learning method. The resubstitution method was applied to the system as a training method. The training method uses all combinations of questionnaire survey and visual inspection; nine sets for nine spans, as training data for machine learning. Therefore, the data of a diagnosed bridge also include the training data. Evaluating the judgment items of a target bridge span on the basis of knowledge modified by the above training method is equivalent to evaluating the judgment items of an already-encountered span after completing learning sessions for a number of spans. The shaded areas in the tables indicate the following: gray shading indicates a system output value that deviates one order from the teacher value (See Table 3), and black shading indicates an output value that deviates two or more orders from the teacher value. The total error at the bottom of the table is a span-by-span sum of errors for each judgment item. Comparison of these outputs (Table 4 and Table 5) with the questionnaire survey results (Table 3) reveals that of the 108 judgment items (9 spans × 12 judgement items) for the main girders, 42 items before learning and 88 items after learning show agreement with the questionnaire results, 58 items before learning and 20 items after learning show deviation of one order from the teacher value, and 8 items before learning show deviation of two or more orders from the teacher value. Thus, the total agreement ratios before learning and after learning are 38.9 and 81.5 percent, respectively. Improvement of agreement ratio shows the validity of applying the machine learning method to the system. However, since the reliability of the system depends on information on the distribution of bridge damage used for neural network learning, we must increase the number of sample bridge data sets used for learning and acquire data sets for various damage conditions.

Next, modification of fuzzy rules is shown in order to verify the effectiveness of the applied neural network structure. Refinement of fuzzy rules for evaluating "Condition state of cracking" is presented as an example. Fig. 7 and Fig. 8 show the membership functions used in antecedents of fuzzy rules before learning and after learning, respectively. The symbols in the figures indicate the following: ①,②, and ③ indicate the membership functions of fuzzy sets {OK}, {not serious}, and {serious} for input data [Crack conditions] respectively, and Ⅰ, Ⅱ, Ⅲ, and Ⅳ indicate the membership functions of {OK}, {small}, {large}, and {huge} for input data [Maximum crack width (mm)]. respectively. Table 6 shows the weight modification between layer (D)-(E) neurons. No. in the table indicates rule number, which corresponds to Table 1. Comparing Fig. 7 and Fig. 8, we notice that after learning, the horizontal width of membership function Ⅰ is reduced by 2/3. The reduction indicates that the system after learning treats the input value of [Maximum crack width (mm)], which is smaller than that before learning, as the fuzzy set of {OK}. The other membership functions after learning are similar to those before learning. As a result of comparison of the weights before learning and