Performance Evaluation of Concrete Slabs of Existing Bridges using Neural Networks

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Abstract

This paper presents a novel approach for developing a performance evaluation system for concrete slabs of existing bridges. The system evaluates the performance of concrete slabs under deterioration on the basis of expert knowledge. Characteristic features of this study are the definition of bridge performance, the performance evaluation system, and the use of neural networks. The proposed approach performs inference in the network, facilitates refinement of the knowledge base embedded in the system by the back propagation method, and prevents not only the inference mechanism of the system but also knowledge base after machine learning from becoming a black box. The numerical examples and conclusions reveal that the proposed approach demonstrates real potential for practical applications.

Keywords: performance evaluation; durability; load-carrying capability; expert system; fuzzy; machine learning; neural network

1. Introduction

During the past decade, the number of deteriorated bridges has increased dramatically in many countries. For this reason, the management of existing bridges has become a major social concern worldwide. Therefore, there is a significant demand for maintenance and renewal planning. In order to perform an appropriate management for existing bridges, a broad array of optional corrective strategies needs to be evaluated. The evaluation process has to consider the condition state of bridge elements, and lifetime performance measures related to safety and economy [1,2,3,4].

This paper presents an approach for developing a performance evaluation system for concrete slabs of existing bridges. The proposed system categorizes a deteriorated element of an existing bridge into one of the following five groups: "unsafe," "severe deterioration," "moderate deterioration," "mild deterioration," and “safe.” To develop a system to evaluate load carrying capability and durability with limited information such as the results of simple visual inspection and the specification data, it is necessary to embed into the evaluation system the knowledge of experts. The technique for developing an expert system is used in this study. A characteristic feature of the system is the use of neural networks to evaluate the performance and facilitate refinement of the knowledge base embedded in the system. Generally, although a neural network is a powerful machine-learning tool, the inference process of the network becomes a “black box,” which renders the representation of knowledge in the form of rules impossible. However, the neural network proposed in the present study has the capability to prevent an inference process and knowledge base from becoming a black box. It is very important that the system is capable of clearly explaining how the performance is calculated since, in general, the road networks represent important investment, that have to be carefully monitored. The effectiveness of the neural network and machine learning method is verified by comparison of the diagnostic results of bridge experts and those of the proposed system.

2. System outline

The outline of the proposed system is explained in this section. Specially, the role of the system in a bridge inspection schedule, and the inference process and input data to evaluate performance are explained.

2.1 System development concept

Fig. 1 shows the schematic of the bridge inspection schedule. Table 1 provides definitions for each type of inspection defined in Fig.1. Detailed inspections are performed if a serious defect is identified during either post construction, routine, ad hoc, or emergency inspections. The detailed inspection is carried out to identify an appropriate maintenance method using non-destructive testing data. The scheduled inspection is visual-based. The purpose of the inspection is data collection not only to find out a serious defect but also to evaluate the degree of the deterioration of bridge elements. The proposed system is used to evaluate the performance related to the deterioration of bridge elements using the results of a scheduled inspection, and evaluates the necessity of maintenance. The engineer or bridge administrator uses the system after a scheduled inspection in order to estimate the need for detailed inspection and the frequency of the inspection. The role of the other methods of inspection is only to confirm serious defects. It is natural that the confirmed defects are recorded at each inspection to predict the development of the deterioration.

The system proposed in this paper evaluates performance based on the load-carrying capability and durability using the results of a scheduled inspection. These two measures of performance are applied as indices to consider the necessity for maintenance. Specifically, the load-carrying capability is defined as the performance of bridge determined by the ability of bridge components to carry loads and used to indicate the need for strengthening. Then, the durability is defined as the resistance of bridge components to material deterioration determined by the rate of deterioration and used to indicate the need for repair. Both load carrying capability and durability are assigned a soundness score on a scale of 0 to 100. The output score is categorized into one of the following 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 "unsafe," "severe deterioration," "moderate deterioration," "mild deterioration," and “safe,” respectively. In the present study, "safe" indicates that the concrete slabs have no defects; "mild deterioration" indicates that there is no serious defect; "moderate deterioration" indicates that there are some defects which need continuous inspection; "severe deterioration" indicates that the slabs should be repaired and/or strengthened; and "unsafe" indicates that the slabs should be removed from service and replaced.

2.2 Performance evaluation process

In the proposed system, the bridge performance is evaluated according to a diagnostic process, which is modelled on the inference mechanism used by experts for rating bridges. In a previous study[5], the Fuzzy Structural Modelling (FSM) method[6] was used to create the diagnostic process of durability and load-carrying capability for main girders and slabs of existing concrete bridges. For instance, Figs.2 to 4 show the diagnostic process for concrete slabs. Figs. 2 and 3 explain the processes for evaluating the load carrying capability and the durability, respectively. Each process is expressed by a hierarchical structure and has some judgment items. The bold-faced characters such as “Load carrying capability” and “Level of slab execution” in these figures, are judgment factors. These judgment items are evaluated by about 40 input data items, such as technical specifications, traffic volume, and results of visual inspection. The terms between parentheses in Fig.2 such as [span of slab (T-5)] and [bridge grade (T-4)] are input data items. 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, as shown in Fig. 4. 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 “Condition state of cracking over haunches,” “Condition state of cracking over supports,” “Condition state of cracking around center of slab,” and “Degree of material deterioration,” are diagnosed from the results (i.e., soundness scores) of lower-rated judgment items and/or input data as shown in Fig.4. Then, the higher-rated judgment items for evaluating the load carrying capability, such as “Level of slab design,” “Live load from the viewpoint of traffic,” “Condition state of all defects,” and “Influence of bridge widening,” are also evaluated from the results of lower-rated judgment items and/or input data as shown in Fig.2. Similarly, the higher-rated judgment items for evaluating the durability, such as “Level of slab execution,” “Condition state of all defects” and “Level of service condition,” are also evaluated from the results of lower-rated judgment items and/or input data as shown in Fig.3. Finally, the judgment items are “Level of durability” and “Level of load carrying capability.” Each of these judgment items is assigned a soundness score, on the scale 0 to100, which is output from the system. The output score is categorized into one of the following five groups: 0-12.5, 12.6-37.5, 37.6-62.5, 62.6-87.5 and 87.6-100. Durability and load carrying capability are classified as "unsafe," "severe deterioration," "moderate deterioration," "mild deterioration," and “safe,” respectively, as previously stated.

2.3 Input data

The input data for evaluating concrete slabs of an existing bridge are technical specifications of the specified bridge, environmental conditions, traffic volume, and other information that can be obtained through simple visual inspection. Figs.5 to 7 give the list of the input data necessary to evaluate the durability and the load carrying capability for concrete slabs with the proposed system. The item number such as T-1 and S-1 in Figs.5 to 7, corresponds to the number in the parentheses attached to input data items in Figs.2 to 4. The number S-*.2 shown in Fig.4 indicates that the maximum value out of three values obtained from S-1.2, S2-2, and S-3.2 is entered into the system.

3. Rule-based Inference

This section deals with knowledge representation and rule-based computing of inference of the proposed system. The inference process that evaluates “Condition state of cracking” in the dotted box of Fig.4, is explained as an example of inference of the system.

3.1 If-then rules

Knowledge expression

As stated in Section 2.2, the system evaluates the performance of a bridge element according to the diagnostic process. The hierarchical structure expresses the relationships between judgment items and input data or between judgment items, as shown in Figs.2 to 4. In practice, these relationships are expressed by “if-then” rules. In the knowledge base of the system, the diagnostic process is stored in the form of “if-then” rules. Consequently, the inference of the system is drawn from these rules. The total number of rules to evaluate the level of load carrying capability is almost 700 (i.e., the exact number is 699). The knowledge representation of the system is given as:

$$R^i : if \;\; x_1 \;\; is \;\; A_{i_1 1} \;\; and \ldots and \;\; x_m \;\; is \;\; A_{i_m m} \;\; then \;\; y \;\; is \;\; B_i \tag{1}$$

where R^i = the ith if-then rule, $x_1, \cdots, x_m$ = the input variables (the input data items, such as technical specifications and visual inspection), y = the output item (the judgment item), $A_{i_1 1}, \cdots, A_{i_m m}$ = the linguistic variables (which are expressed by fuzzy sets, crisp sets, etc.) , $i_1,\cdots i_m$ = the identification number of membership function related to a linguistic variable, and B_i = the soundness score on the scale 0 to 100. For example, Table 2 shows the if-then rules for evaluating the judgment item "Condition state of cracking." The first if-then rule, R^1, indicates the following statement: If ([Crack conditions] are {severe}) and ([Maximum crack width] is {huge}) then ([Condition state of cracking] is 0.0). The preconditions are called the antecedents. The postcondition is called the consequent. The input variables x_1 and x_2 are [Crack conditions] and [Maximum crack width], respectively; the output item y is [Condition state of cracking]; i_1=1,2,3 due to the fact that the linguistic variable $A_{i_1 1}$ has three sets {not severe}, {moderate}, and {severe}; A_{11}, A_{21} and A_{31} indicate the sets {not severe}, {moderate}, and {severe} as shown in Figs. 8 (a); i_2=1,2,3,4 due to the fact that the linguistic variable $A_{i_2 2}$ has four sets {very small}, {small}, {large}, and {huge}; A_{12}, A_{22}, A_{32}, and A_{42} indicate the sets {very small}, {small}, {large}, and {huge} as shown in Figs. 8 (b); and B_1=0.0, B_2=16.5, B_3=33.5,···, B_{12}=100.0 as shown in column (4) of Table 2.

Initial rule formation

Each of the judgment items in Figs. 2 to 4 has an associated set of if-then rules. Table 2 shows the if-then rules for evaluating the judgment item "Condition state of cracking," in the dotted box in Fig. 4. For example, Rule No.1 expresses the following statement: If ([Crack conditions (S-1.1)] are {severe}) and ([Maximum crack width (S-1.2)] is {huge}) then ([Condition state of cracking] is 0.0). As shown in S-1.1 and S-1.2 of Fig.7, the input data form of [Crack conditions (S-1.1)] is formatted so that the inspector can answer a multiple-choice question. When the inspector answers the multiple-choice question for [Crack conditions (S-1.1)], the input to the system is 0.0 if the choice is [③not severe], 0.5 if the choice is [②moderate], and 1.0 if the choice is [①severe]. The input data form of [Maximum crack width (S-1.2)] is formatted so that the inspectors can enter a numerical value. In this study, the values of multiple-questions were set to the crisp sets, and then the quantity data such as bridge age, span of slab and maximum crack width were set to the fuzzy sets. Therefore, the values obtained from [Crack condition (S-1.1)] and [Maximum crack width (S-1.2)] were set to the crisp and fuzzy sets, respectively. Figs. 8 (a) and (b) show the membership functions related to the crisp sets and fuzzy rules for evaluating “Condition state of cracking,” respectively. These rules have three kinds of crisp sets for a value obtained from input item [Crack conditions (S-1.1)]: {severe}, {moderate}, and {not severe}. The fuzzy sets for a value obtained from input item [Maximum crack width (S-1.2)] are {huge}, {large}, {small}, and {very small}. It is noted that the number of fuzzy sets, the initial form of membership functions for fuzzy sets, and the initial values of soundness score in each rule, should be set through discussions with bridge experts. If the multiple-choice question for input item [Crack conditions] has many categories, fuzzy sets would be set to the item[7]. The use of sets such as fuzzy sets enables the reduction of the number of rules; it prevents the number of rules form exploding.

3.2 Rule-based Computing

This section describes in detail the inference process performed in the system. The inference process of each judgment item is performed in four steps and starts from the evaluation of the lowest-rated judgment items such as “Condition state of cracking” and “Condition state other than cracking.”

[Step 1] Input data

Input data are entered into the computer. When the lowest-rated judgment items are evaluated, input data are the results in Figs. 5 to 7. When the higher-rated judgment items are evaluated, input data are the results in Figs. 5 to 7 and/or soundness scores of lower-rated judgment items on a scale of 0 to 100.

[Step 2] Calculate the grade of membership functions used in antecedents of if-then rules

The rules of the system employ some linguistic sets in antecedents of “If-then” rules. These sets are expressed by membership functions. Consequently, from the values of input data, the grades of membership functions used in antecedents are first calculated. In the system, the values such as the results of multiple-choice questions and the continuous values such as maximum crack width are set to crisp sets and fuzzy sets, respectively. For example, the membership functions for [Crack conditions (S-1.1)] and [Maximum crack width (S-1.2)] are shown in Fig.8. As mentioned in Section 3.1, the results of multiple-choice questions are translated into numerical values and entered into the system. Specially, when the higher-rated judgment items are evaluated, the soundness scores of lower-rated judgment items as input data are set to the membership functions shown in Fig.9. The soundness scores as output are categorized into one of the following five groups: "unsafe," "severe deterioration," "moderate deterioration," "mild deterioration," and “safe.” However, the scores as input data are transformed into the grade of three membership functions with Fig.9, because it prevents the number of rules from increasing.

[Step 3] Calculate the fitness of each rule to input values

Step 3 calculates the fitness of each rule to input values, whereas Step 2 calculates the fitness of each proposition in antecedents to input values, that is, the grade of membership functions used in antecedents. The fitness of each rule employs the following equations using the grades of membership functions estimated in Step 2:

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

$$\mu_i = \prod_{j=1}^{m} A_{i_j j}\left(x_j\right) \tag{3}$$

where $\hat{\mu}_i$ = the fitness of ith rule to input values, $A_{i_j j}(x_j)$ = the grade of a membership function, i = the identification number of if-then rule, j = the identification number of input variable and linguistic variable, x_j = the input variable, $A_{i_j j}$ = the membership function for the input variable x_j, i_j = the identification number of membership function related to a linguistic variable, m = the number of input variables to evaluate a judgement item, and n = the total number of if-then rules used to evaluate a judgment item. Eq. (3) indicates that all grades of membership functions in antecedents of the same rule are multiplied.

In the case of the evaluation of “Condition state of cracking,” i = 1,2,···,12 (see Table 2); the antecedents have two input variables (i.e., j = 1,2); the input variables x_1 and x_2 (i.e., m = 2) are [Crack conditions] and [Maximum crack width]; i_1=1,2,3 and i_2=1,2,3,4 due to the fact that the number of sets for input variables x_1 and x_2 is 3 and 4, respectively (see Figs. 8 (a) and (b)). The membership functions A_{11}, A_{21}, and A_{31} for input variable x_1 indicate the functions for the sets {not severe}, {moderate}, and {severe} (see Figs. 8 (a)); the membership functions A_{12}, A_{22}, A_{32}, and A_{42} for input variable x_2 indicate the functions for the sets {very small}, {small}, {large}, and {huge} (see Figs. 8 (b)).

[Step 4] Calculate a soundness score for a judgment item

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

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

where $\hat{\mu}_k$ = the fitness value of kth rule, which is acquired by Eq. (2), ω_k = the soundness score described in consequents of kth rule, and n = the total number of if-then rules used to evaluate a judment item. Consequently, a judgment item is assigned a soundness score on a scale of 0 to 100.

In the case of the evaluation of “Condition state of cracking,” n =12 as shown in Table 2, and ω_1=0.0, ω_2=16.5, ω_3=33.5,···, ω_{12}=100.0 as shown in the column (4) of Table 2.

As an example of the inference calculation algorithm stated above, the inference process of “Condition state of cracking” diagnosis in the dotted box in Fig. 4, is described in the following. The diagnosis requires the input data [Crack conditions (S-1.1)] and [Maximum crack width (mm)(S-1.2)]. To illustrate this calculation, suppose that [Crack conditions (S-1.1)] = [②moderate] and [Maximum crack width (mm) (S-1.2)] = [0.75mm], as the results of a visual inspection. After these results are entered into computer as Step 1, the system initiates an inference for calculating a soundness score of judgment item “Condition state of cracking”. The grades of membership functions are calculated as Step 2. In this example, since the value of [0.5] that expresses [②moderate] is entered into the computer as the inspection value of [Crack conditions (S-1.1)], this value matches the membership function A_{21}, which express the crisp set {moderate}. Therefore, the grade of membership function {moderate} is 1.0 (see Fig. 8 (a)). The grades of membership functions A_{11} and A_{31} are 0.0, because the value doesn’t match the crisp sets; namely, {not severe} and {severe}. Similarly, considering the inspection value of [Maximum crack width (mm)], which is [0.75], the value matches two membership functions A_{32} and A_{42}, which express the fuzzy sets {large} and {huge}. Therefore, these grades of membership functions are 0.8 and 0.2, respectively (see Fig. 8 (b)). The grades of membership functions A_{12} and A_{22} are 0.0, because the value doesn’t match the fuzzy sets; namely, {very small} and {small}. The left-hand section table in Fig. 10 indicates the fitness of each proposition in antecedents to the inspection results. For instance, the propositions ([Crack conditions (S-1.1)] are {severe}) and ([Maximum crack width (S-1.2)] is {huge}) in rule No.1 have the fitness values 0.0 and 0.2, respectively. Next, as Step 3, the fitness of each rule is calculated. The values of fitness of rule given in the middle section in Fig. 10 are estimated by Eq. (2) and Eq. (3). Therefore, the fitness of rule No.1 to the input values (i.e., [Crack conditions (S-1.1)] =0.5(②moderate) and [Maximum crack width (mm) (S-1.2)]=0.75 is 0.0; $\hat{\mu}_1 = \{A_{31}(x_1 = 0.5) \times A_{42}(x_2 = 0.75)\} / (\mu_1 + \mu_2 + \cdots + \mu_{12}) = (0.0 \times 0.2) / (0.0 + \cdots + 0.2 + 0.8 + \cdots + 0.0) = 0.0$. Rules No.5 and No.6 have the fitness of 20% and 80%, respectively. Finally, as Step 4, the soundness score is calculated by Eq. (4). For this example, the expert system outputs the soundness score of 38.2 as the diagnosis result to the input data. The soundness score of 38.2 is the total sum of multiplication of the fitness of rule and the soundness score in same rule number; y = (0.0×0.0) + (0.0×16.5) + (0.0×33.5) + (0.0×50.0) + (0.2×25.0) + (0.8×41.5) + (0.0×58.5) + (0.0×75.0) + (0.0×50.0) + (0.0×66.5) + (0.0×83.5) + (0.0×100.0) = 38.2 (see Fig. 10 and Eq.(4)).

4. Neural network and machine learning

This section concentrates on the architecture of inference system using a neural network and the machine learning methodology of knowledge base. In order to explain these methods, the inference system that evaluates "Condition state of cracking" (see Fig.4) is illustrated in detail as an example.

4.1 Neural network architecture for a diagnostic process

As mentioned in Sections 2 and 3, the relationships drawn in Figs.2 to 4 are expressed by "if-then" rules using linguistic sets. Consequently, the inference of the system is drawn from these rules. If-then rules can be written directly 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 are transformed to a multi-layer neural network. In other words, the neural network could be identified with a diagnostic process. The structural characteristic of multi-layer neural network enables the introduction of back propagation method [8,9,10] as a machine learning method to the system. Therefore, the network is capable of performing inference and machine learning. 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 neural network proposed in the present study contributes to prevent an inference process from becoming a black box.

A set of if-then rules used to evaluate a judgment item is expressed by a multi-layer neural network that has three or five layers. Each of the networks is connected with the other neural networks that evaluate higher- and/or lower-rated judgment items according to the diagnostic process in Figs. 2 to 4. Fig. 11 illustrates the combined neural network that evaluates the level of load carrying capability. Each circle in Fig.11 represents a five-layer neural network; the square also represents a five-layer neural network, and the triangle a three-layer neural network.

The manner for constructing the neural network, which evaluates a judgment item, is as follows. The number of layers of a neural network depends on the type of input data. When the input data used to evaluate a judgment item include continuous quantity data, such as maximum crack width and soundness score, the inference mechanism for evaluating this item has a five-layer neural network. For example, the rules and membership functions in Table 2 and Fig. 8 are implemented in the computer as the neural network illustrated in Fig. 12. In the present study, the layers of the network are referred to as layers (A), (B), (C), (D), and (E) (see Fig. 12). The layers (A), (B), and (C) are only necessary to the membership functions as shown in Figs. 8 (b) and 9. However, these layers are not necessary to the functions for crisp sets since the form of the functions does not need to be modified with machine learning. Consequently, when a judgment factor is evaluated only by input values of multiple-questions, the inference mechanism is constructed by a multi-layer neural network consisting of the layers (C), (D), and (E). For example, the inference mechanism for the judgment item “Condition state other than cracking” is constructed with a three-layer (C), (D), and (E) neural network.

The neural network that evaluates the judgment item “Condition state of cracking” in the dotted box of Fig.4 is illustrated in Fig.12. These 5 layers have neurons of three different types [7]. The neurons in layers (A), (C) and (E) are linear neurons. The neurons in layer (B) are sigmoid neurons, and the neurons in layer (D) are normalization neurons. The connections from layer (C) to layer (E) express a rule. For instance, the neuron 1 in layer (D) connects the neurons I and IV in layer (C) because Rule No.1 in Table 2 is “If ([Crack conditions] are {severe}) and ([Maximum crack width] is {huge}) then ([Condition state of cracking] is 0.0”. The boxes on connection lines and the other boxes on neurons are the weight and the bias, respectively. A boxed value represents the initial connection weight between neurons or the initial bias for a neuron. The manner in which the initial values of weight and bias are set is next described. The layers (A), (B), and (C) in the network are identified with the sets other than crisp sets in antecedents of rules. If the membership function of a fuzzy set is an increasing or decreasing function, the form is identified by a sigmoid function; a sigmoid neuron is employed in layer (B) for an increasing or 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. For instance, the membership function of fuzzy set {huge} for input item [Maximum crack width], A_{42} in Fig.8 (b), is expressed by the weight between the neuron I_2 in layer (A) and the neuron *a* in layer (B), the neuron *a* and the weight between the neuron *a* in layer (B) and the neuron IV in layer (C). Therefore, when an input value for [Maximum crack width] is input in the neuron I_2, the neuron IV in layer (C) outputs the grade of membership function for fuzzy set {huge}. The initial setting-up method of the weights (ω) and the biases (θ) in layers (A), (B), and (C) is stated in reference [7]. It is noted that the input value of [Crack conditions] is transformed as shown in the dotted box of Fig.12. The transformed values are entered directly into the layer (C) neurons. The weights between neurons in layers (C) and (D) are all 0.5. The initial weights between neurons in layers (D) and (E) are set according to Table 2. These weights between layers (D) and (E) express soundness scores described in consequent of each rule. Consequently, when input data are entered into the system, layers (A), (B), and (C) perform the processing of [Step 1] and [Step 2] in inference algorithm stated in Section 3.2. Next, layers (C) and (D) perform the processing of [Step 3]. Finally, layers (D) and (E) perform the processing of [Step 4]. In other words, when input data are entered into layer (A) neurons, the neurons in layer (C) output the grades of membership functions for linguistic sets. After that, the neurons in layer (D) calculate the fitness of each rule. The layer (E) neuron output a soundness score. If the neural network expresses a diagnostic process for evaluating a lower-rated judgment item, the output of layer (E) neuron (i.e., soundness score) would be used as an input value for evaluating a higher-rated judgment item.

4.2 Machine learning

As stated in Section 4.1, each judgment item is evaluated with a three- or five-layer neural network, and each network is combined with the neural network that evaluates a higher- and/or lower-rated judgment item as shown in Fig.11. Therefore, applying the back propagation algorithm to the network as a machine learning method is easy because the structure of neural network is multi-layer. The algorithm uses gradient descent to tune network parameters (i.e., weights and biases) to best fit a training set of input-output pairs (i.e., training examples). As a result, the machine learning process can be explained based on Fig.11. The combined network illustrated in Fig.11 is able to carry out the machine learning using the back propagation algorithm. Each three- or five-layer neural network used to evaluate a judgment item as shown in Fig.12 is also capable of performing machine learning; the circle, square, and triangle in Fig.11 modify the weights and biases by themselves. In addition, each weight and bias is set for a specific purpose. Therefore, the network is capable of modifying rules by altering these parameters. More specifically, each circle in Fig. 11 is a five-layer neural network that only modifies the weights of the layers (D) and (E) by machine learning. The square is a five-layer neural network that modifies (1) the weights between neurons in layers (A) and (B), (2) the biases of layer (B) neurons, and (3) the weights between neurons in layers (D) and (E) by learning. The triangle is a three-layer neural network that only modifies the weights of the layers (D) and (E) by machine learning. It is noted that it is not necessary to improve the membership functions for soundness scores shown in Fig. 9. Therefore, the modification of parameters in the layers (A), (B), and (C) is carried out only to the fuzzy set network. For example, these modifications in the neural network shown in Fig.12 indicate that the form of membership functions for fuzzy sets used in antecedents of if-then rules, and the soundness score stated in consequents of rules are improved by back propagation algorithm. The weights of layers (A) and (B) and the biases of layer (B) neurons are used in order to express membership functions in antecedents of if-then rules. Consequently, weight alteration after learning indicates the slope alteration of the corresponding membership function, and bias alteration after learning indicates the axis movement of the membership function in the horizontal direction. In the learning of weights between layers (D) and (E), the proposition in consequent of each rule is changed. For instance, if the weight between the neuron 9 in layer (D) and the neuron O_1 in layer (E) neuron is changed from 50.0 to 75.0 by machine learning, the proposition described in consequent of Role No.9 is changed from ([Condition state of cracking] is 50.0) to ([Condition state of cracking] is 75.0).

In this study, the learning rates were adjusted by trial and error in order to minimize the difference between the target output and the system output. The adopted range of the learning rate is 0.01 to 1.00. The role of the learning rate is to moderate the degree to witch weights and biases are changed as each step. The optimization of the learning rates and the comparison between the back propagation algorithm and the other machine learning algorithms are areas for future research.

5. Practical Application

This section deals with the application of the proposed system to existing bridges. It is applied to existing concrete slabs (four spans), all of which are components of steel-concrete composite girder bridges, in order to examine the learning capability of the system and the acquisition of training examples for the refinement of the knowledge base embedded within the system. The four slabs considered are components of four different bridges (A, B, C, D) and are referred to as A(Span 3), B(Span 3), C(Span 3) and D(Span 3) as indicated in Figs.13, 14, 15, and 16, respectively. For example, A(Span 3) represents the third span concrete slab of bridge A (see Fig.13). In the present study, the survey covered four spans of four bridges. The expert system is developed in Visual Basic and C programming languages and runs on a personal computer. It is noted that this study does not contain enough input data and target values to predict the reliability and robustness of the proposed system. Therefore, the capability of decreasing errors between the target values and the system outputs was tested as the first step for reliability and robustness predictions.

5.1 Visual Inspection and Questionnaire Survey

The purpose of visual inspection of existing bridges is to collect inspection data to be entered into the system, and the purpose of the questionnaire survey of domain experts is to acquire data necessary for learning. The combination of the results of visual inspection and of questionnaire survey was used as training examples (i.e., training data) for carrying out machine learning. The inspection record sheets are formatted so that the respondents can answer multiple-choice questions, and enter numerical values as shown in Figs. 6 and 7. The experts also use the inspection results to fill out the questionnaires. The questionnaire sheets are formatted so that the respondents can answer the soundness scores of judgment items in the form of a score on a 0-100 scale in increments of 5 points. The sheets have questions for evaluating all the judgment items shown in Figs. 2 to 4. The partial questionnaire sheets are shown in Fig. 17. In this survey, there was no enough time for experts to fill out the questionnaires to all judgment items. Consequently, the questionnaires to the lowest-rated judgment items such as condition state of cracking and condition state other than cracking, were cut off in the present study; the experts were given eleven questions including the evaluations of level of load carrying capability, level of durability, level of slab design, level of slab execution, condition state of all defects, level of service condition,

condition state of road surface, condition state of cracking over haunch, condition state of cracking over supports, condition state of cracking around center of slab, and degree of material deterioration.

Visual inspection of concrete slabs A (Span 3) to D (Span 3) (see Figs.18, 24, 29, and 33, and the associated photographs (Figs. 19-23, 25-28, 30-32, and 34-42)) and the questionnaire survey were conducted by three experts who are referred to as ***a***, ***b*** and ***c*** in the study. The field of expertise of each expert, the types of bridges that each expert deals with, each expert's experience measured in years, and the concrete slabs surveyed by each expert are summarized in Table 3. The input data for evaluating the bridge-A concrete slab (Span 3) are summarized in Table 4, which includes each expert's visual inspection result of road surface and slab. These results show that there is some dispersion in the slab inspection results of each expert. The dispersion indicates that it is necessary to improve the inspection method. The evaluation results (i.e., soundness scores of each higher-rated judgment item) for bridge-A slab (Span 3) of each expert are drawn in Fig. 43. The solid-line, dotted line, and bold-solid-line are the questionnaire results of experts ***a***, ***b*** and ***c***, respectively. Domain expert ***a*** filled out the questionnaires to all higher-rated judgment items. However, domain experts ***b*** and ***c*** did not fill out the questionnaire related to the "Level of slab design," and then expert ***c*** did not answer the "Level of load carrying capability." Fig. 43 reveals the difference between the evaluation results of each expert. It is noted that the knowledge of three experts *a*, *b*, and *c* is not included into the initial knowledge base of the proposed system; the initial knowledge base, such as the diagnostic process in Figs. 2 to 4, was acquired from another expert (i.e., expert *d*). However, in the questionnaire survey, the experts *a*, *b*, and *c* answered each soundness score after agreeing to follow the diagnostic processes shown in Figs. 2 to 4.

5.2 Effectiveness of Machine Learning

In the test of the capability of the proposed system to decrease errors between the target values and the system outputs, the networks used to evaluate the lowest-rated judgment items (e.g., condition state of cracking) were combined with the networks used to evaluate these items at the immediate upper level (e.g., condition state of cracking over haunches). The resulting combined networks carried out machine learning. For example, as shown in Fig.11, the networks to evaluate the condition state of cracking and the condition state other than cracking were connected to the network to evaluate the condition state of cracking over haunches. This is due to the fact that the questionnaires at the lowest-rated judgment items, such as condition state of cracking, were cut off in this study. The number of training examples for machine learning of the system is illustrated in Fig.44. The capital and small letters indicate the concrete slabs and experts, respectively. For example, the symbol “Aa” represents a training example made of the combination of visual inspection results of concrete slabs A (Span 3) and those of questionnaire survey, which are the results of expert ***a***. Therefore, there are eight training examples (i.e., training data) for machine learning: Aa, Ba, Ab, Bb, Cb, Db, Ac, and Bc. The ratio of the numbers in the figure is referred to as an answer ratio to each questionnaire. The total number of questions in the questionnaire survey is 11 due to cutting off the questionnaires at the lowest-rated judgment. In addition, expert ***a*** answered all questions. However, experts ***b*** and ***c*** did not answer all question as mentioned previously. The bold-solid lines in Fig.45 represent the questionnaire results that are the target values. The numbers [1] to [11] in the charts correspond to the same numbers in Fig. 43. In order to examine the validity of the learning capability of the system and the acquisition method of training examples for machine learning of the system, the training patterns were analyzed by using each training example as shown in Fig.44. The training patterns are summarized in Table 5 and illustrated in Fig.44. The symbol “ - ” in the table means that a machine learning was carried out with the training examples connected by the symbol. Therefore, the case 02 indicates that the learning was carried out by using training examples Aa and Bb at the same time. The symbol “→” means that the machine learning was performed with the right-hand training data set or training example after finishing the machine learning using the left-hand training data set or training example. For example, the machine learning of the case 05 was done by using the data set of case 04 including the training examples Ac and Bc, at first. After that, the next machine learning was carried out with the data set of case 03 including the training examples Ab, Bb, Cb, and Db; the knowledge base refined with case 04 was rerefined with case 03. Finally, the refinement of knowledge base with case 01 including training examples Aa and Ba was done.

The machine learning results using these training patterns are summarized in Table 6. The numerical values represent an overall error, calculated by summing the difference between the target values (i.e., the questionnaire results of each judgment item given by expert) and the system output after learning or before learning. The case 00 shows the comparison results between the questionnaire results and the system output before learning (i.e. using the initial knowledge). The percentages in parentheses mean the total agreement ratios related to the five categories such as "unsafe," "severe deterioration," "moderate deterioration," "mild deterioration," and “safe,” as stated in Section 2.2. The table shows a tendency for the total sum of error to decrease when the number of training examples increases. The total sum of error in Case 05 and Case 09, which used all training examples, is smaller than that associated with the others. The trend indicates the necessity to increase the number of training examples used for learning and acquire training examples for various deterioration conditions. The details in the shaded areas shown in Table 6, are illustrated in Fig.45. The solid, bold-solid, and dotted lines are referred to the output of the system before learning, the questionnaire results of an expert (i.e., the target values), and the system output after learning, respectively. The comparison of the diagnostic results of experts with those of the proposed system reveals the validity of applying the neural network and machine learning methods proposed to the knowledge modification embedded in the performance evaluation system. In fact, the charts in Fig.45 indicate that the shapes of the system output after learning are similar to the shapes of the questionnaire results of experts; the dotted lines are similar to the bold-solid lines. The differences in the results are due to the following reasons:

1. Initial tuning of knowledge base embedded in the system was insufficient. The number of fuzzy sets for each input item, the initial form of membership functions, and the initial values of soundness score in each rule should be set by extensive discussions with bridge experts.
2. Each expert might have his own diagnostic process, which might be different from the diagnostic process applied to the proposed system. However, in the questionnaire survey, the experts evaluated each judgment item after agreeing with the diagnostic process in Figs. 2 to 4.

6. Conclusions

1. When limited data provided by simple visual inspections is the only information available, the performance of deteriorated structures can be better evaluated by using expert knowledge.
2. Neural networks represent a technology suitable for application to performance evaluation of existing structures.
3. Close agreement between the diagnostic results of experts and the output of the system after learning confirms the effectiveness of the learning method for the case of performance evaluation of concrete slabs of existing bridges.
4. In order to enhance the reliability of the expert system, the knowledge base must be refined through application to a greater number of bridges under various deterioration conditions. The reliability of

the acquisition method of training data has to be evaluated and improved.

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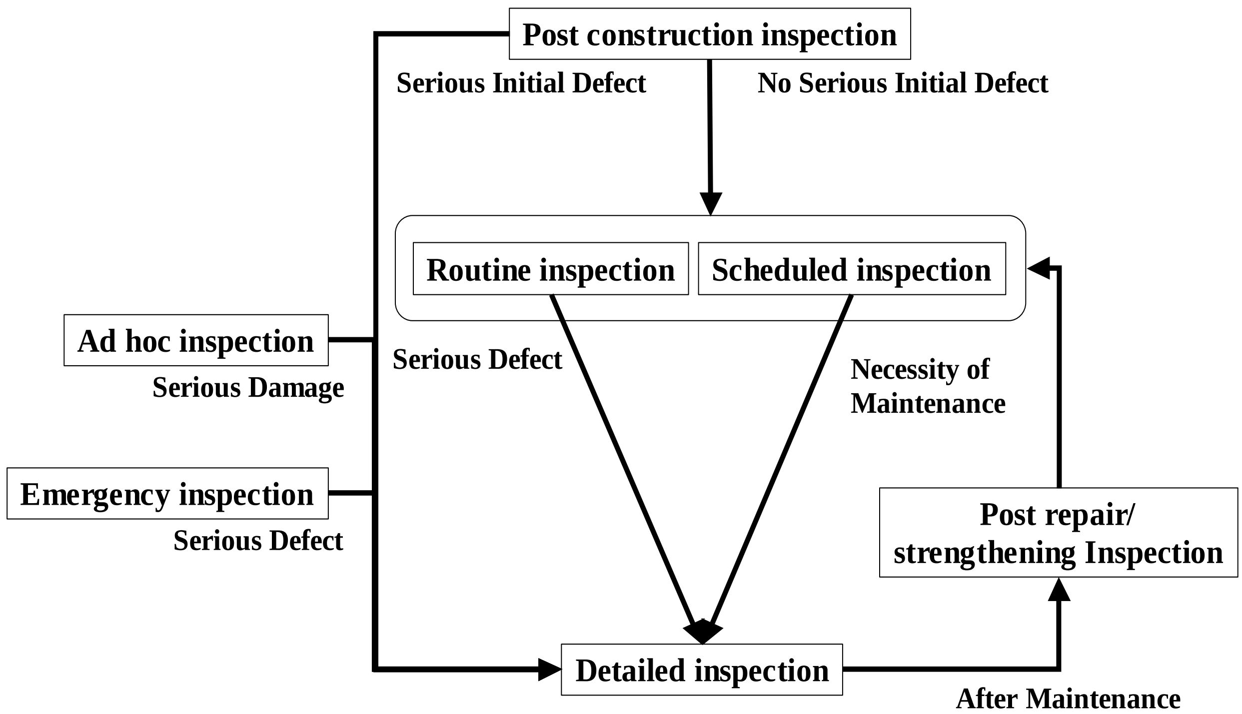


Fig.1. Bridge Inspection Schedule

Level of load carrying capability

- **Level of slab design**
  - **Validity of design criterion**
    - Span of slab (T-5)
    - Bridge grade (T-4)
  - **Validity of reinforcement bars' arrangement**
    - Code (T-3)
    - Crack conditions (S-3.1)
    - Direction of cracking around the center of slab (S-11)
  - **Validity of slab thickness**
    - Thickness of slab (T-6)
- **Live load from the viewpoint of traffic**
  - Traffic volume of large-size vehicle (T-8)
  - Road classification (T-7)
- **Condition state of all defects**
  - See Fig. 4
- **Influence of bridge widening**
  - Type of widening (T-10,T-11)

Fig.2. Load carrying capability diagnostic process for concrete slabs

Level of durability

- **Level of slab execution**
  - **Quality of execution**
    - Depth of concrete cover (S-9)
    - Forming of concrete honeycomb (S-8)
  - **Space between reinforcement bars**
    - Forming of concrete honeycomb (S-8)
    - Reinforcement bars' arrangement in spalling parts (S-10)
- **Condition state of all defects**
  - See Fig. 4
- **Level of service condition**
  - **Condition state of road surface**
    - **Rainwater permeation**
      - Condition of road surface (I-5)
      - Drainpipe (I-1)
      - Choking of drainpipe (I-2)
    - **Impact due to driving on the bridge**
      - Impact (I-4)
      - Flatness of road surface (I-3)
  - **Position of load action**
    - Position of large-size vehicle wheels during passing (T-9)
  - **Brake of vehicle**
    - Slope of bridge (T-12)
    - Traffic signal near approach (T-13)
  - **Live load from the viewpoint of traffic**
    - Traffic volume of large-size vehicle (T-8)
    - Road classification (T-7)

Fig.3. Durability diagnostic process for concrete slabs

- **Condition state of all defects**
  - **Condition state of cracking over haunches**
    - **Condition state other than cracking**
      - Spalling of concrete cover (S-1.4)
      - Condition of free lime (S-1.3)
      - Condition of road surface (I-5)
    - **Condition state of cracking**
      - Crack conditions (S-1.1)
      - Maximum crack width (S-1.2)
  - **Condition state of cracking over supports**
    - **Condition state other than cracking**
      - Spalling of concrete cover (S-2.4)
      - Condition of free lime (S-2.3)
      - Condition of road surface (I-5)
    - **Condition state of cracking**
      - Crack conditions (S-2.1)
      - Maximum crack width (S-2.2)
  - **Condition state of cracking around center of slab**
    - **Condition state other than cracking**
      - Spalling of concrete cover (S-3.4)
      - Condition of free lime (S-3.3)
      - Condition of road surface (I-5)
    - **Condition state of cracking**
      - Direction of cracking around center of slab (S-11)
      - Crack conditions (S-3.1)
      - Maximum crack width (S-3.2)
  - **Degree of material deterioration**
    - **Condition state other than cracking**
      - Condition of road surface (I-5)
      - Area of potential spalling (S-4)
      - Condition of free lime (S-5)
    - **Degree of corrosion progress of reinforcement**
      - Corrosion environment (T-14,T-15)
      - Maximum crack width (max S-*.2)
    - **Condition state of reinforcement corrosion**
      - Condition of exposed reinforcement in spalling parts (S-6)
      - Rust deposit (S-7)
    - **Degree of freezing and thawing action**
      - Condition of road surface (I-5)
      - Cold area (T-16)
    - Bridge age (T-2)

Fig.4. Condition state diagnostic process for concrete slabs

Technical specifications

T-1	Bridge name	
T-2	Year of construction (Bridge age)	(years)
T-3	Code (Applied specification)	□① 1926 □② 1964 □③ 1983, 1990 or 1994
T-4	Bridge grade	□① Third □② Second □③ First
T-5	Span of slab	m
T-6	Thickness of slab	cm
T-7	Road classification	□① main route □② secondary route
T-8	Traffic volume of large-size vehicle	(Total number/12hrs)
T-9	Position of large-size vehicle wheels during passing (wheel load)	□① Both left and right wheels pass on main girders □② Left or right wheel passes on a main girder □③ Both left and right wheels pass between main girders
T-10	Widening of bridge	□① done □② not done
T-11	Type of widening	□① separated □② fixed
T-12	Slope of bridge	□① large (breaking of vehicle) □② small
T-13	Traffic signal near approach	□① exists □② does not exist
T-14	Industrial area	□① yes □② no
T-15	Harbor area or near coast	□① yes □② no
T-16	Cold area	□① yes □② no

Fig.5. Investigation Sheet (Technical specification)

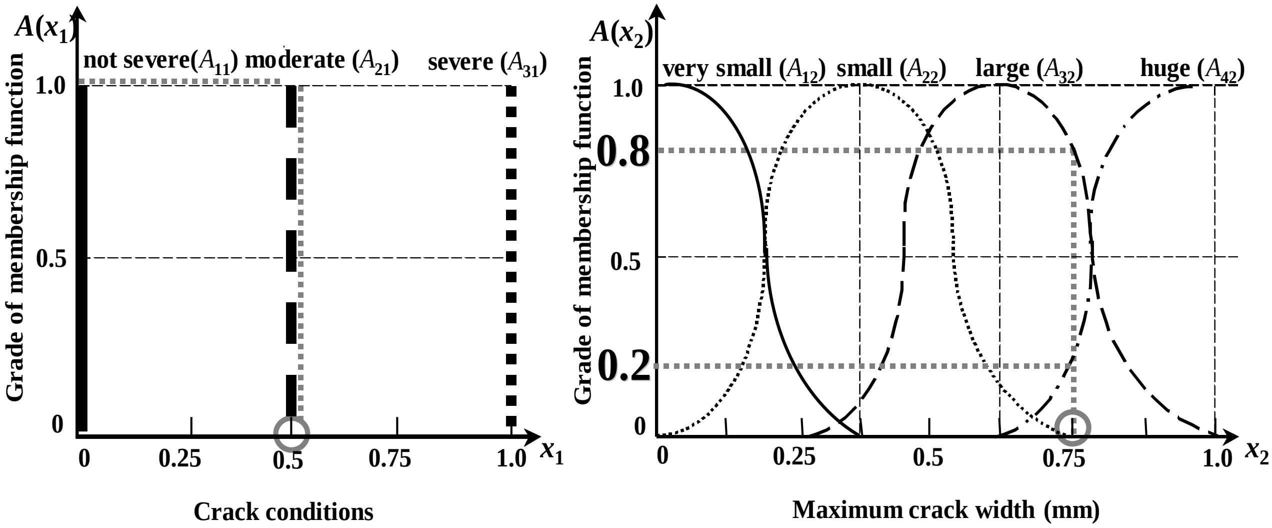
Road surface

I-1	Drainpipe	□① exists (go next) □② does not exist (go to I-3)
I-2	Choking of drainpipe	□① great number of choking drainpipes □② few choking drainpipes □③ none
I-3	Flatness of road surface	□① uneven □② slightly uneven □③ even
I-4	Impact (feeling impact while driving on the bridge)	□① serious □② none
I-5	Condition of road surface (Potholes, Cracks)	□① serious □② not serious □③ excellent

Fig.6. Visual inspection sheet (Road surface)

S-1	**Cracking over haunches**	□① yes (go next) □② no (go to S-1.3)
S-1.1	Crack conditions	□① severe □② moderate □③ not severe
S-1.2	Maximum crack width	mm
S-1.3	Free lime	□① serious □② not serious □③ none
S-1.4	Spalling of concrete cover	□① serious □② not serious □③ none
S-2	**Cracking over supports**	□① yes (go next) □② no (go to S-2.3)
S-2.1	Crack conditions	□① severe □② moderate □③ not severe
S-2.2	Maximum crack width	mm
S-2.3	Free lime	□① serious □② not serious □③ none
S-2.4	Spalling of concrete cover	□① serious □② not serious □③ none
S-3	**Cracking around center of slab**	□① yes (go next) □② no (go to S-3.3)
S-3.1	Crack conditions	□① severe □② moderate □③ not severe
S-3.2	Maximum crack width	mm
S-3.3	Free lime	□① serious □② not serious □③ none
S-3.4	Spalling of concrete cover	□① serious □② not serious □③ none
S-4	Area of potential spalling	□① large □② small □③ nothing
S-5	Free lime on slab	□① serious □② not serious □③ none
S-6	Exposed reinforcement in spalling part	□① yes □② no
S-7	Rust deposit	□① serious □② not serious □③ none
S-8	Forming of concrete honeycomb	□① serious □② not serious □③ none
S-9	Depth of concrete cover	□① insufficient □② sufficient □③ unknown
S-10	Reinforcement bars' arrangement in spalling parts	□① dense □② normal □③ unknown
S-11	Direction of cracking around center of slab	□① many directions □② two directions □③ one direction □④ no cracking

Fig.7. Visual inspection sheet (Slab)



(a)Membership function for crack conditions

(b)Membership function for maximum crack width

Fig.8. Membership functions for input data

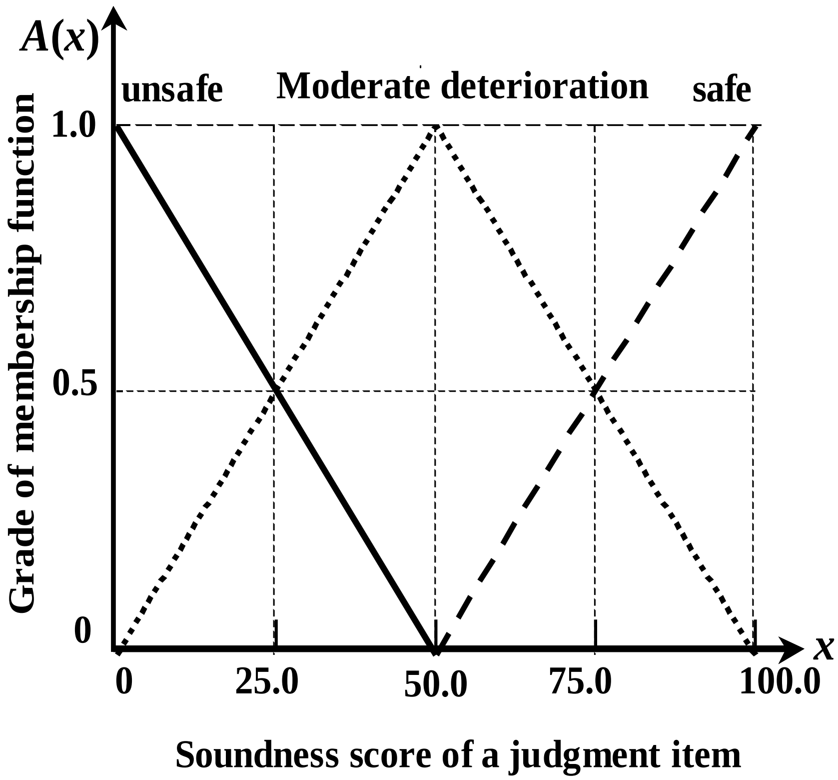


Fig.9. Membership functions for soundness score of a judgment item

No.	antecedents: Crack conditions	antecedents: Maximum crack width		Fitness of rule		consequent: soundness score	
1	severe (0.0)	huge (0.2)	(0.0) × (0.2) = 0.0	0.0	×	0.0	= 0.0
2	severe (0.0)	large (0.8)	(0.0) × (0.8) = 0.0	0.0	×	16.5	= 0.0
3	severe (0.0)	small (0.0)	(0.0) × (0.0) = 0.0	0.0	×	33.5	= 0.0
4	severe (0.0)	very small (0.0)	(0.0) × (0.0) = 0.0	0.0	×	50.0	= 0.0
5	moderate (1.0)	huge (0.2)	(1.0) × (0.2) = 0.2	0.2	×	25.0	= 5.0
6	moderate (1.0)	large (0.8)	(1.0) × (0.8) = 0.8	0.8	×	41.5	= 33.2
7	moderate (1.0)	small (0.0)	(1.0) × (0.0) = 0.0	0.0	×	58.5	= 0.0
8	moderate (1.0)	very small (0.0)	(1.0) × (0.0) = 0.0	0.0	×	75.0	= 0.0
9	not severe (0.0)	huge (0.2)	(0.0) × (0.2) = 0.0	0.0	×	50.0	= 0.0
10	not severe (0.0)	large (0.8)	(0.0) × (0.8) = 0.0	0.0	×	66.5	= 0.0
11	not severe (0.0)	small (0.0)	(0.0) × (0.0) = 0.0	0.0	×	83.5	= 0.0
12	not severe (0.0)	very small (0.0)	(0.0) × (0.0) = 0.0	0.0	×	100.0	= 0.0
			Total sum 1.0				Total sum 38.2

[Step 2] **[Step 3]** **[Step 4]**

Fig.10. Inference process

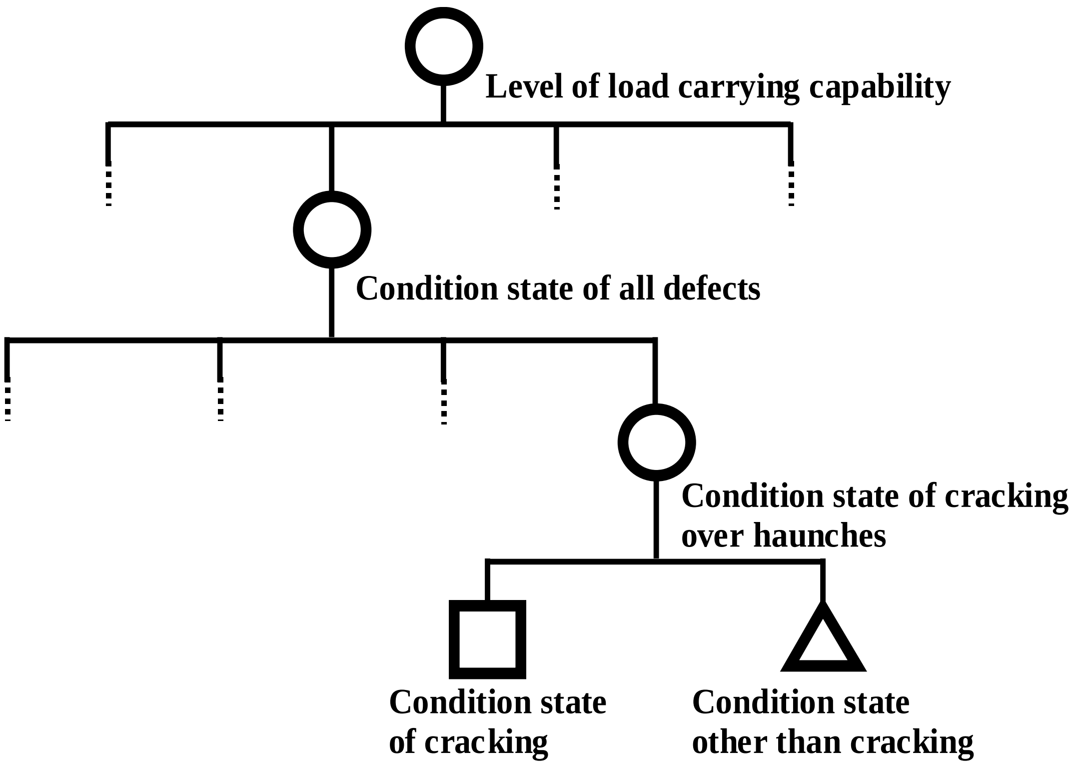


Fig.11. Neural Network for evaluating "Level of load carrying capability"

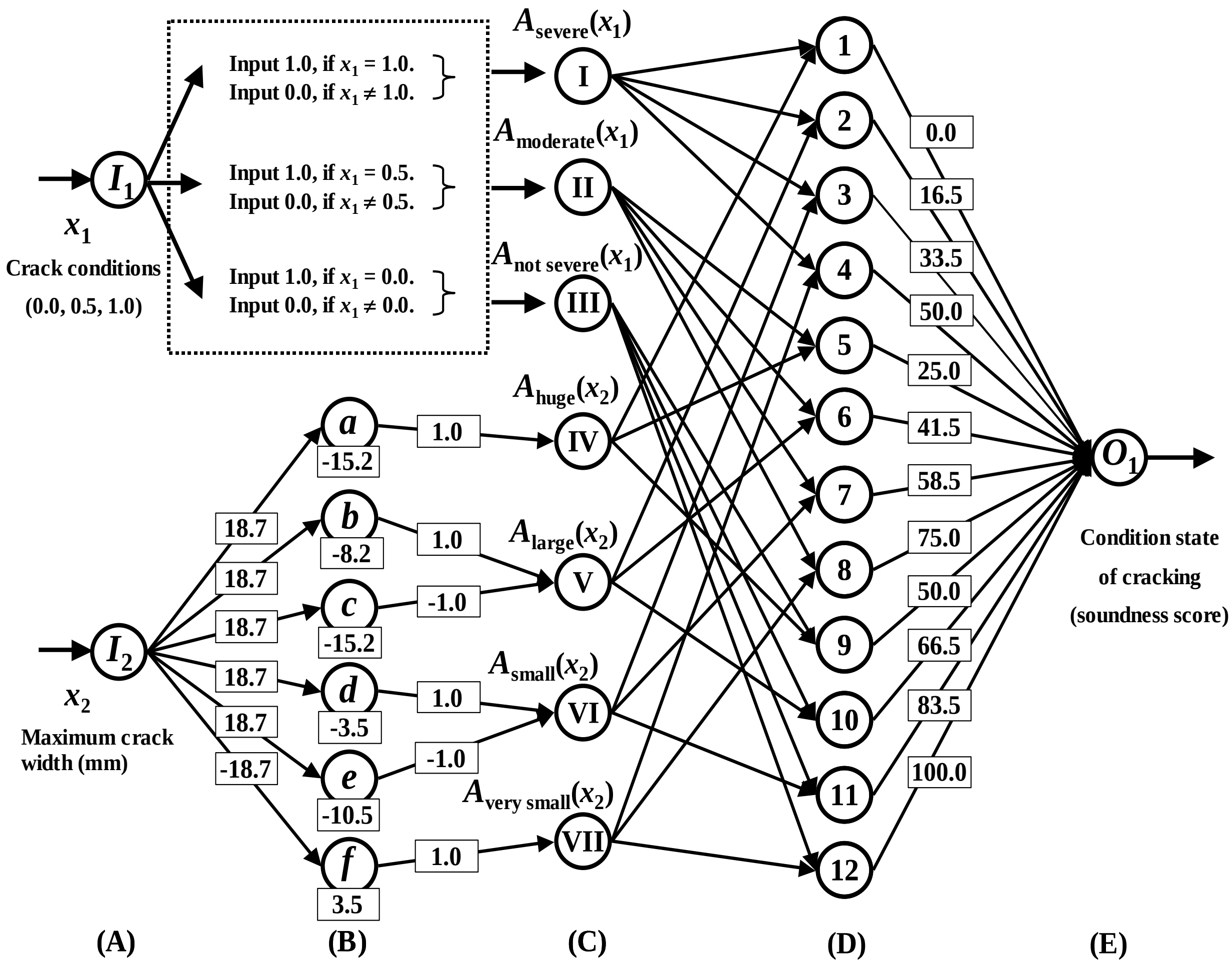


Fig.12. Neural Network for evaluating “Condition state of cracking”

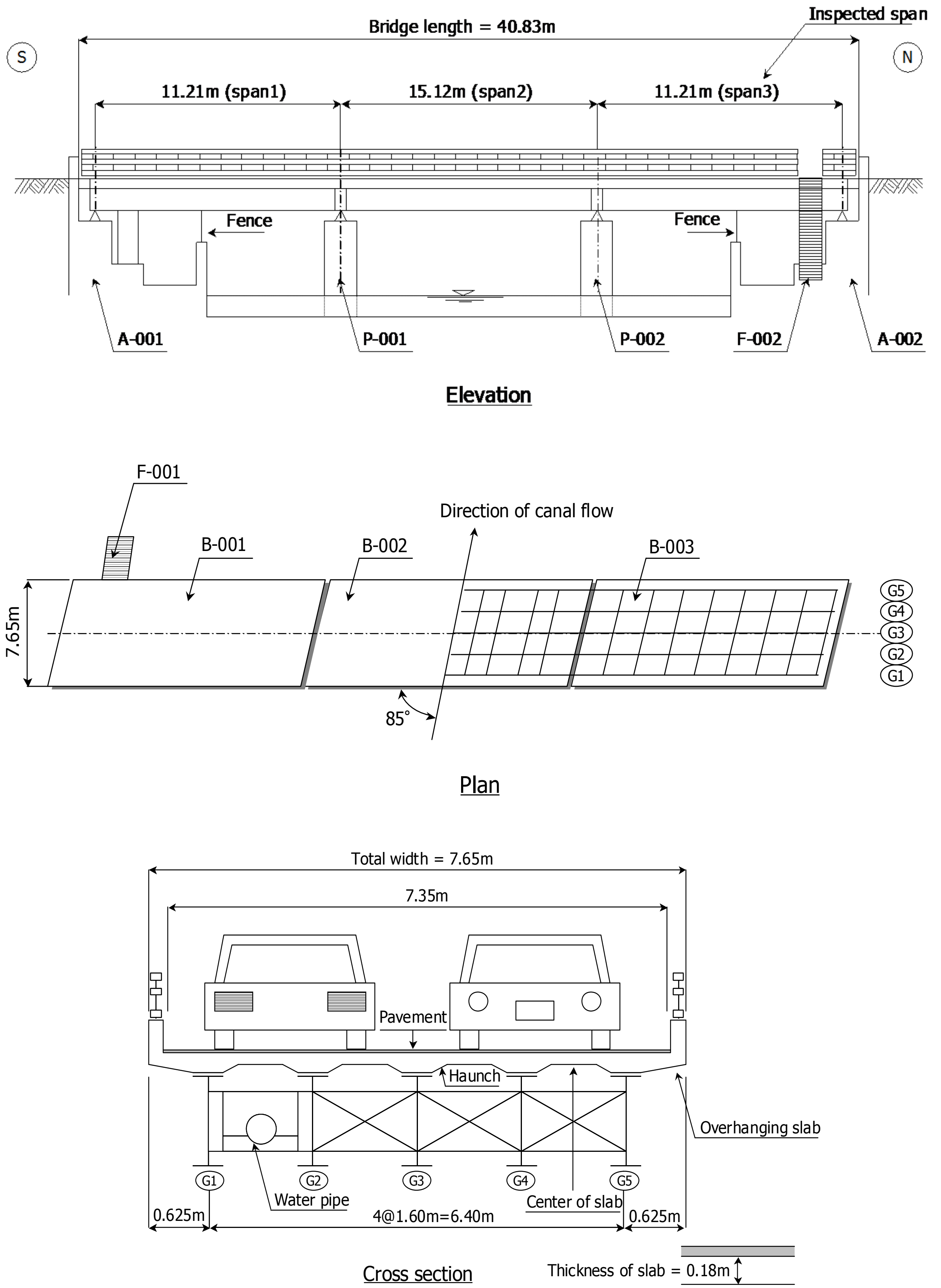


Fig.13. Bridge A

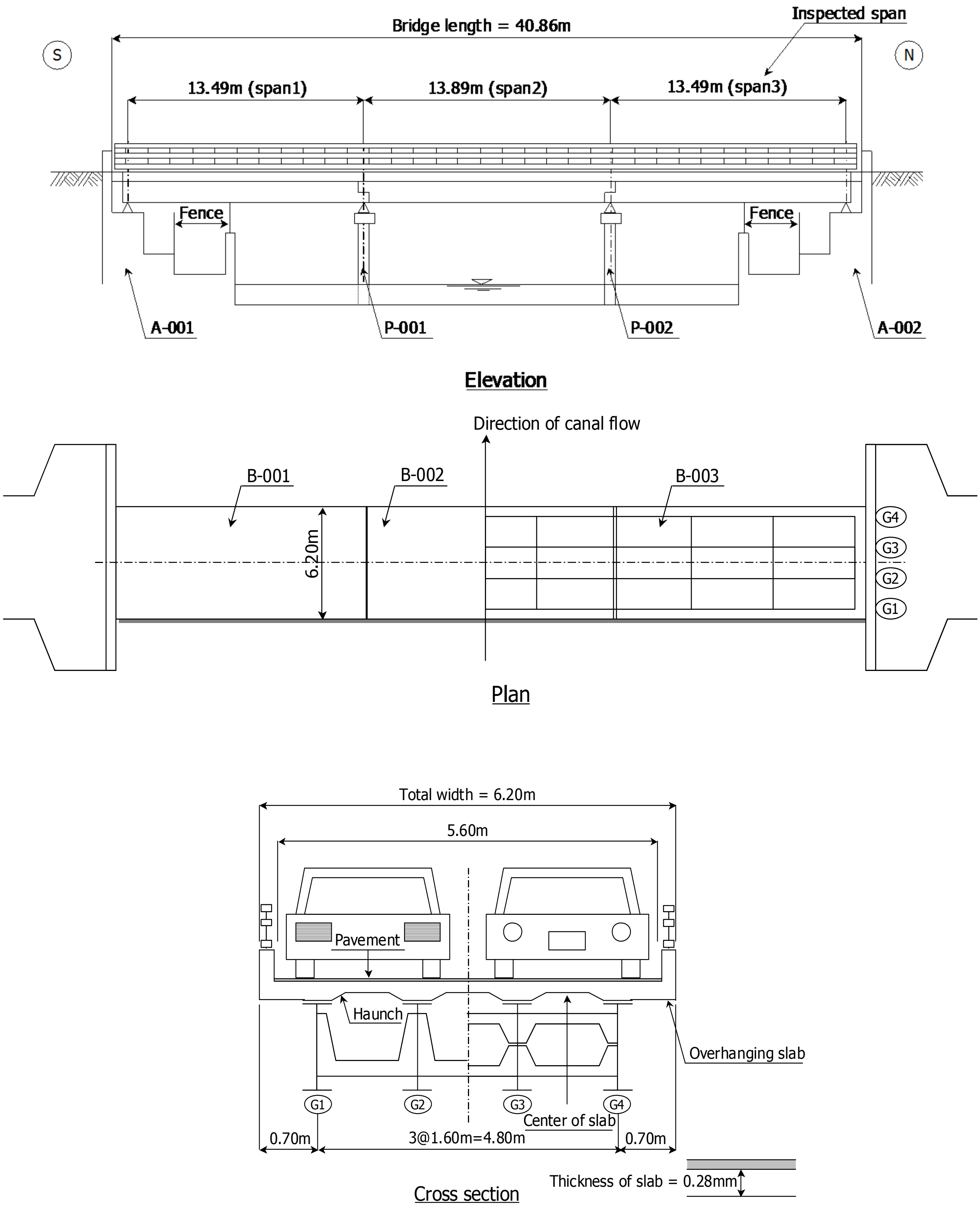


Fig.14. Bridge B

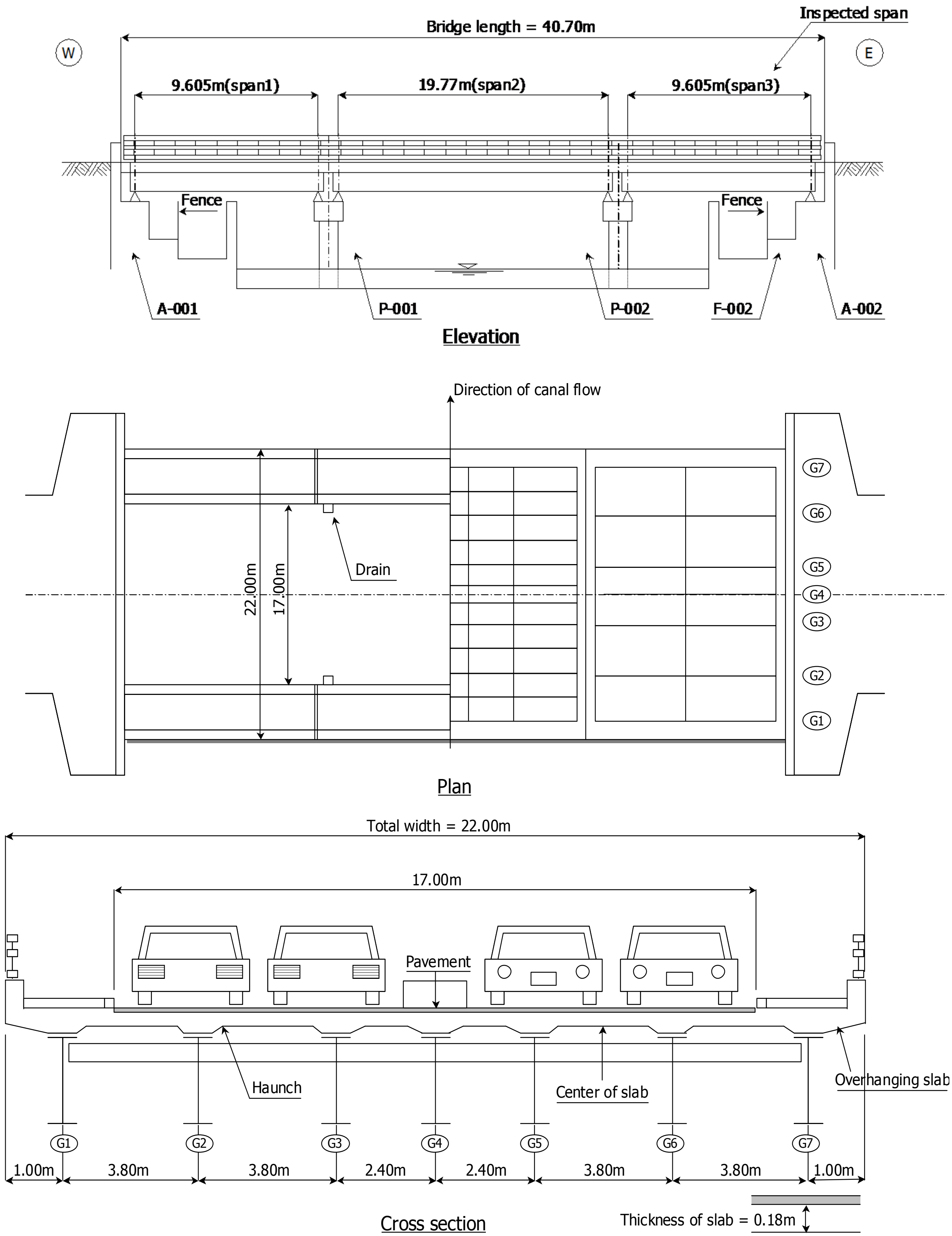


Fig.15. Bridge C

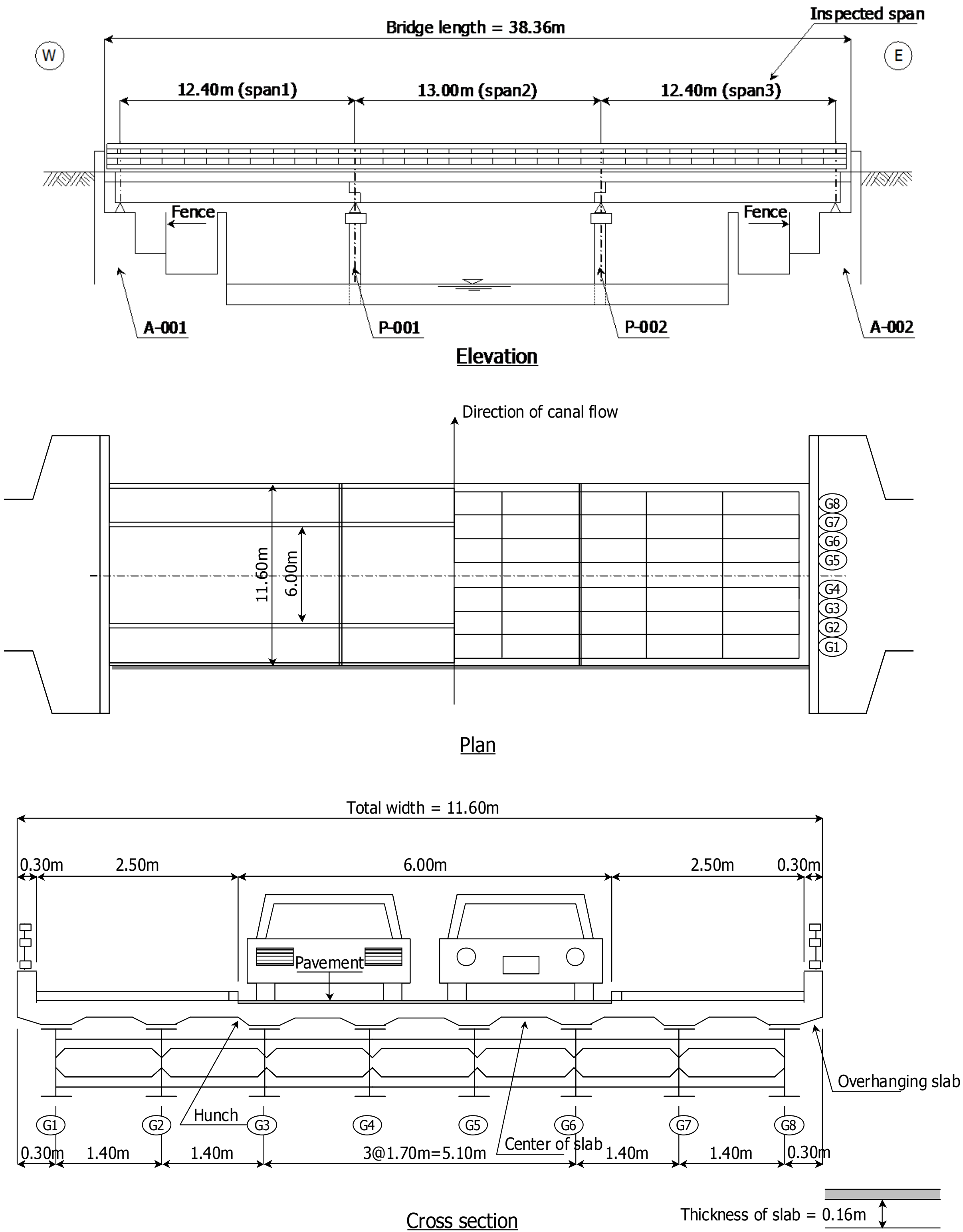


Fig.16. Bridge D

① **What is the level of load carrying capability?**

Level of load carrying capability

Unsafe			**Severe deterioration**					**Moderate deterioration**					**Mild deterioration**					**Safe**		
0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100

Fig.17. Partial questionnaire sheets

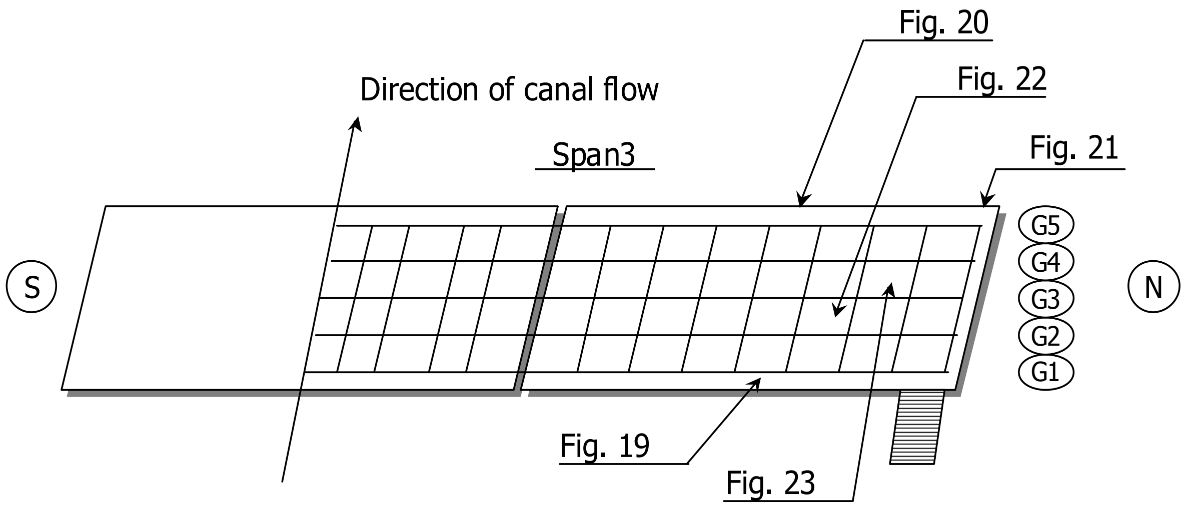


Fig.18. Bridge A : location of photos

Fig.19. A1: Defects on overhanging slab

Fig.20.   A2: Defects on overhanging slab

Fig.21. A3: Defects around supports

Fig.22. A4: Defects over haunches

Fig.23. A5: Defects around center of slab

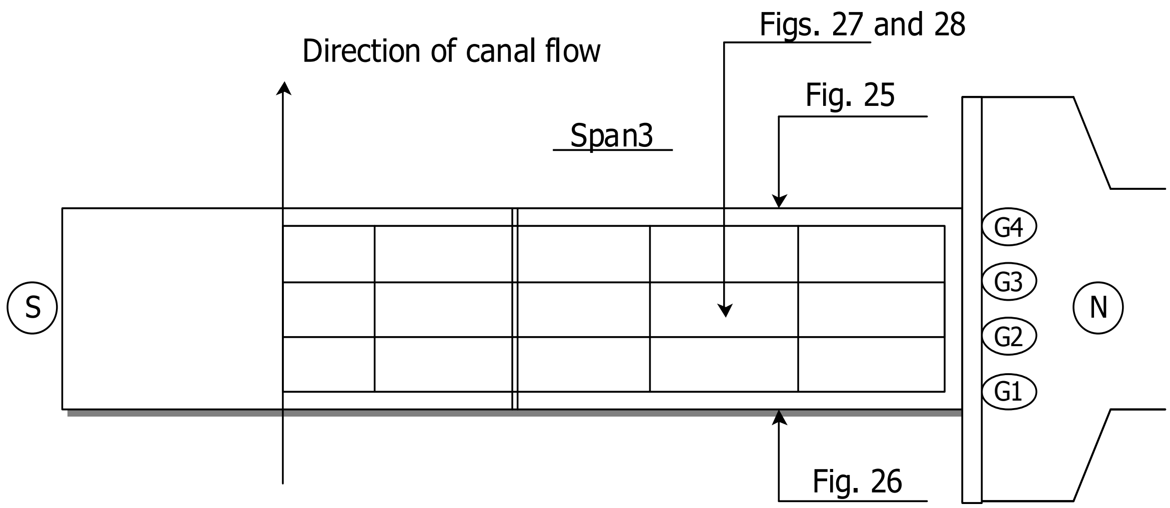


Fig.24. Bridge B : location of photos

Fig.25. B1: Defects on overhanging slab

Fig.26. B2: Defects on overhanging slab

Fig.27.   B3: Defects around center of slab

Fig.28. B4: Defects around center of slab

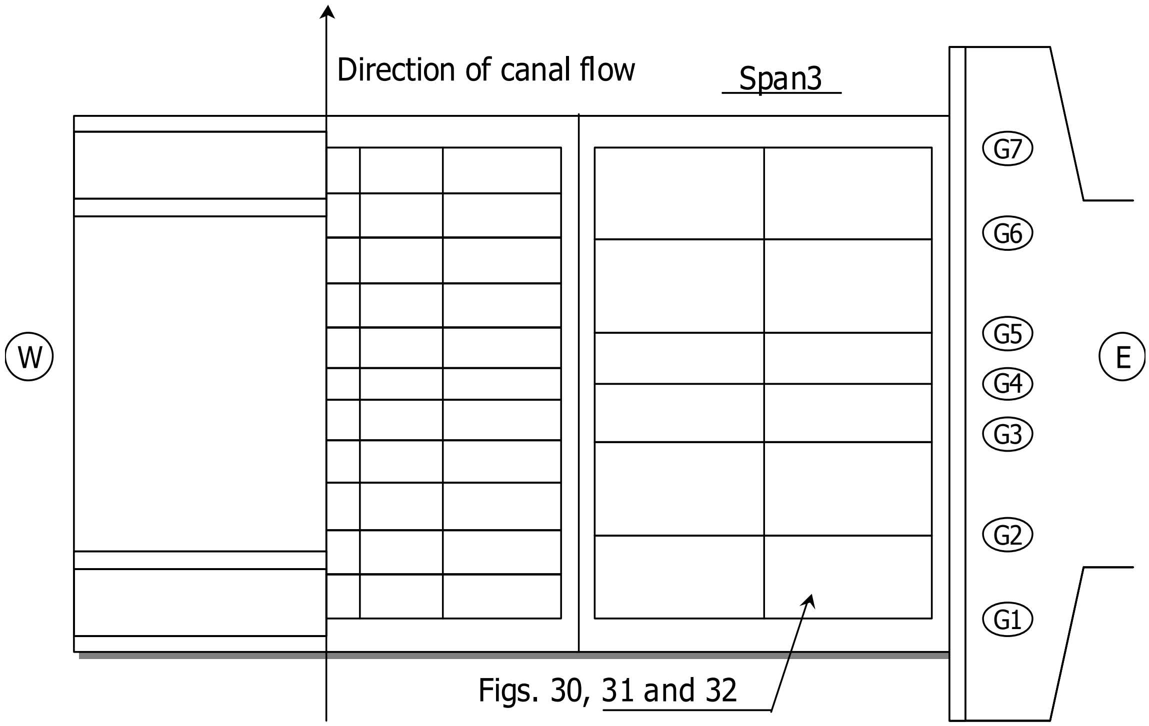


Fig.29. Bridge C : location of photos

Fig.30.   C1: Defects over supports(around drain pipe)

Fig.31. C2: Defects around center of slab

Fig.32. C3: Defects over haunches

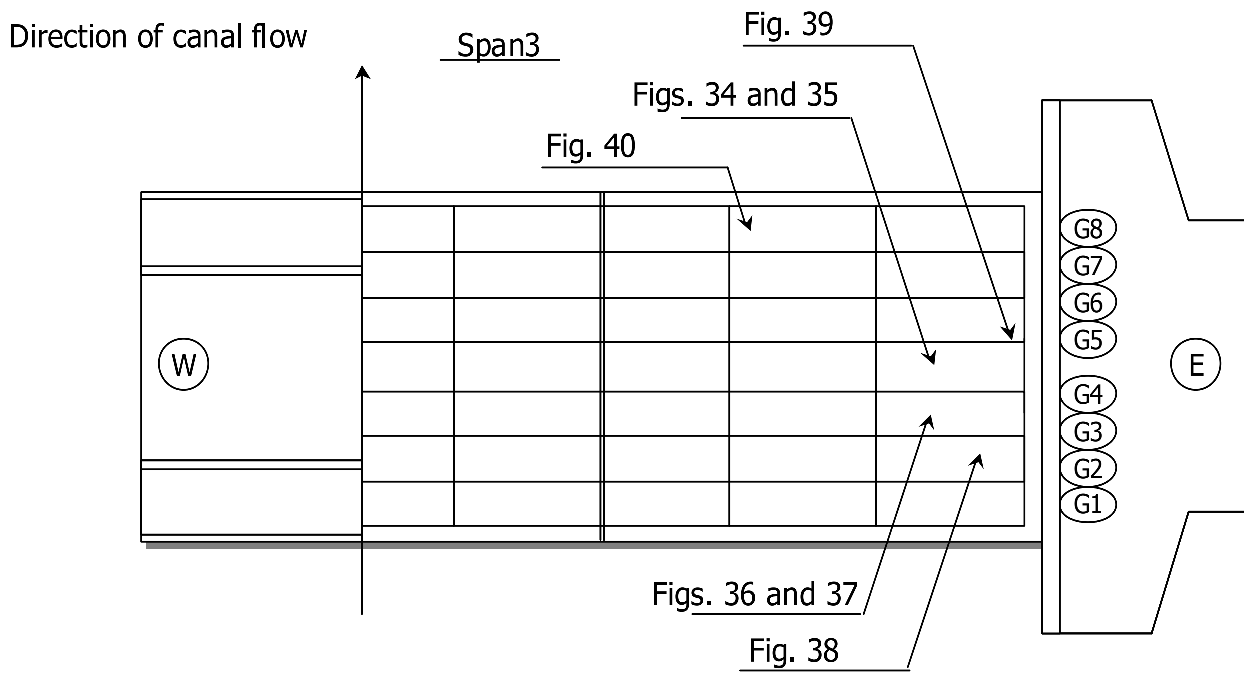


Fig.33. Bridge D : location of photos

Fig.34. D1: Defects around center of slab (This part was repaired in the past)

Fig.35. D2: Defects around center of slab

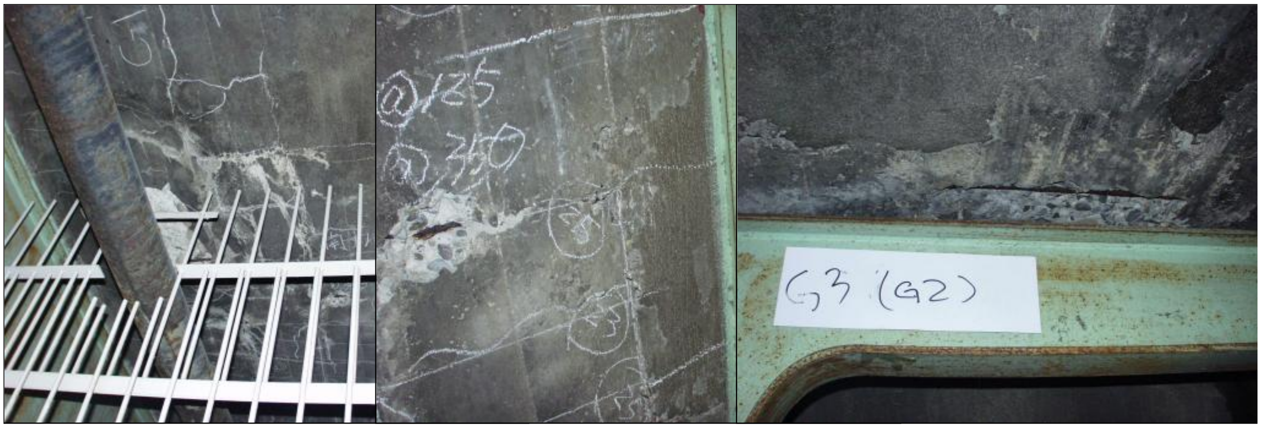


Fig.36. D3: Defects around center of slab

Fig.37. D4: Defects around center of slab

Fig.38. D5: Defects over hunches (around drain pipe)

Fig.39. D6: Defects over supports

⌋

Fig.40.   D7: Defects around center of slab (under sidewalk)

Fig.41. D8: Defects of pavement (Left-hand:span3, right-hand:span2)

Fig.42. D9: Defects of pavement (Span1)

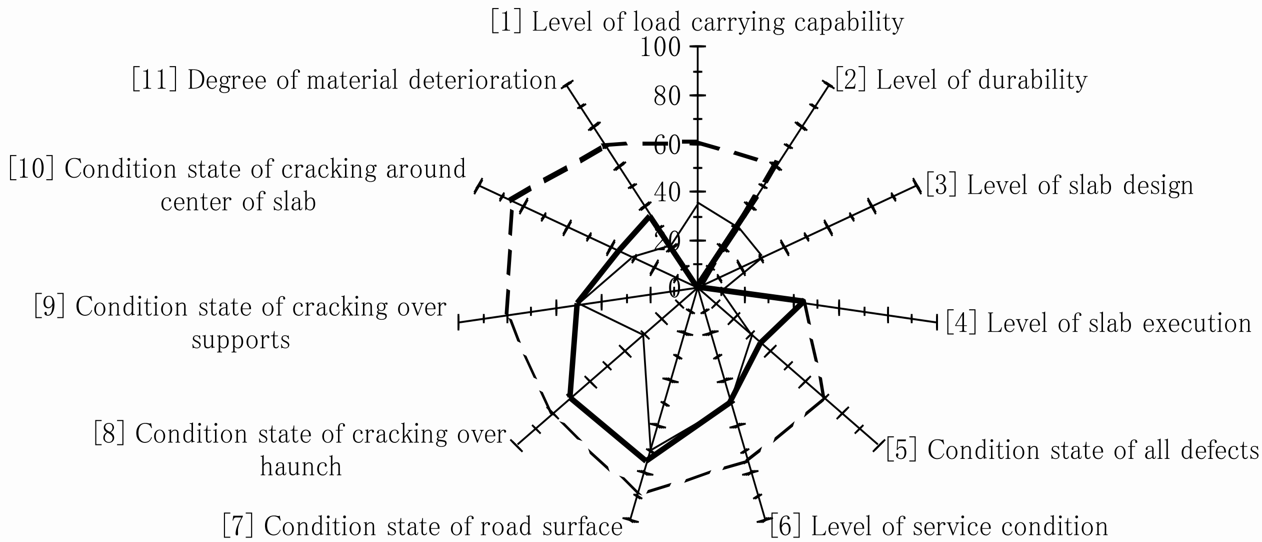


Fig.43. Results of bridge A concrete slab (Span 3) evaluation by three domain experts a, b and c

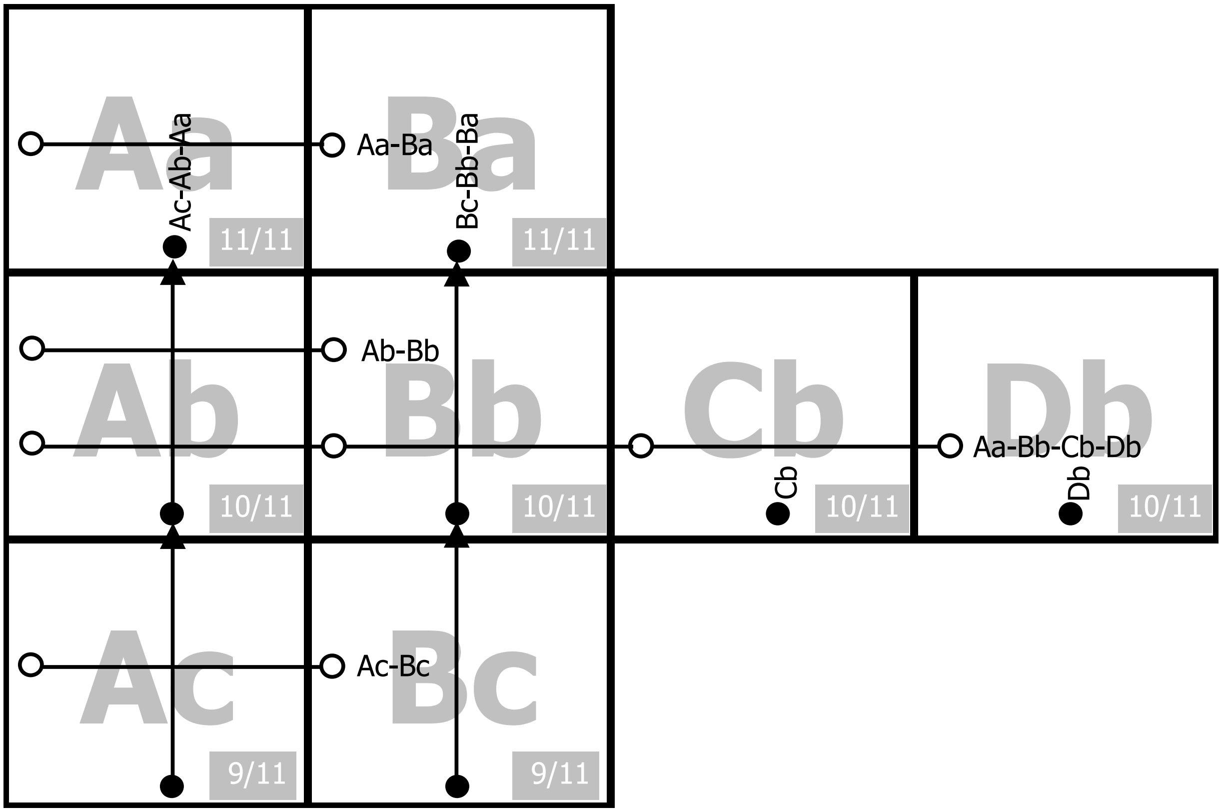
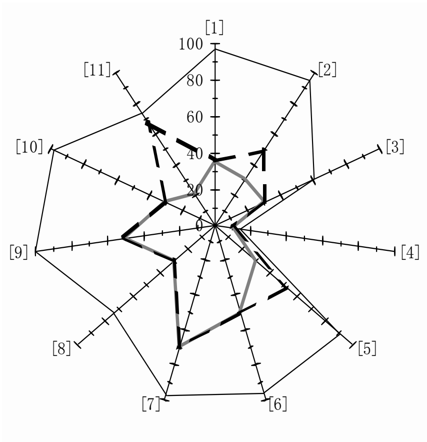
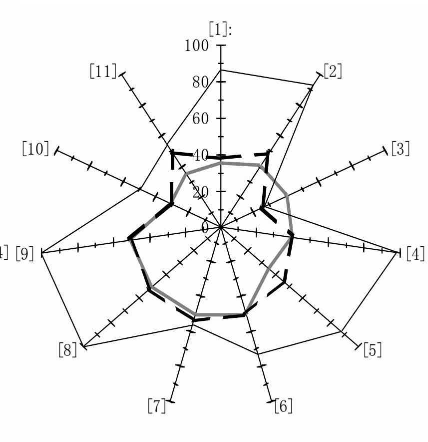


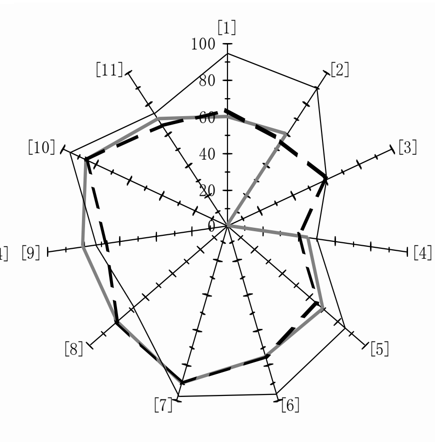
Fig.44. Training data sets



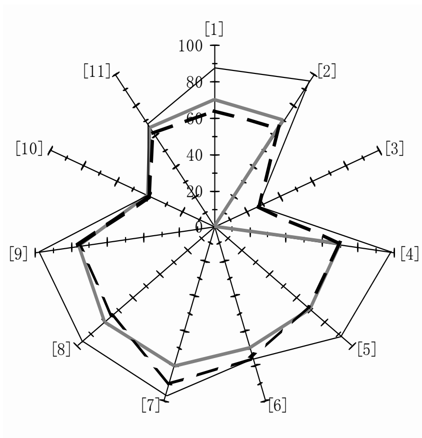
Case 01 Aa



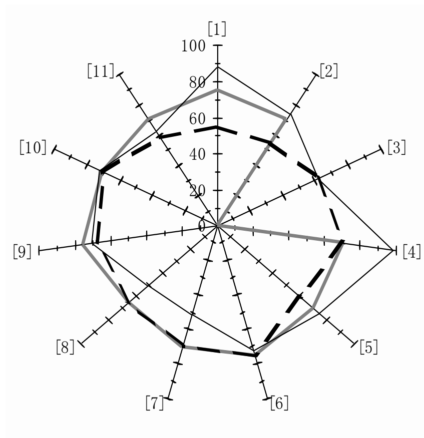
Case 01 Ba



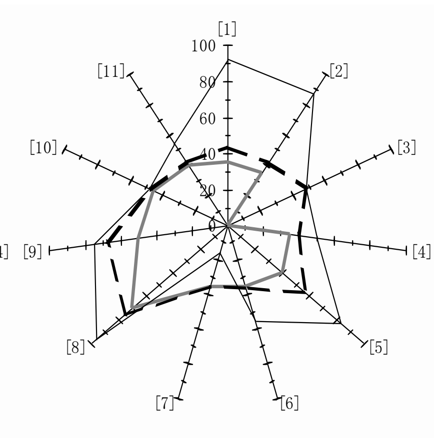
Case 03 Ab



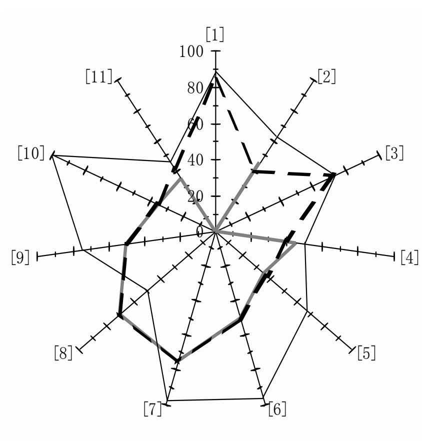
Case 03 Bb



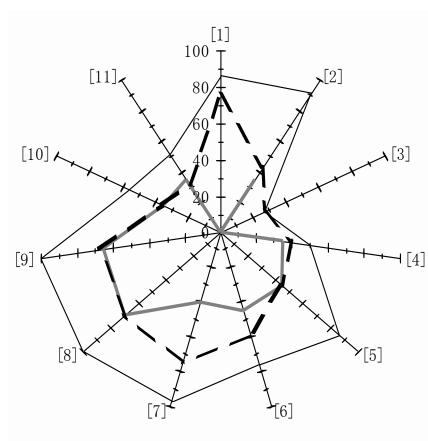
Case 03 Cb



Case 03 Db



Case 04 Ac



Case 04 Bc

Fig.45. Evaluation results

Table 1: Definition of Inspections

Type of inspections (1)	Definition (2)
Post construction inspection	Inspections carried out immediately after completion of construction to find initial defects.
Routine inspection	Inspections carried out to find defects that may cause accidents.
Scheduled inspection	Inspections carried out to estimate the need for detailed inspection and the frequency of the inspection.
Detailed inspection	Inspections carried out to identify the repair and strengthening methods.
Ad hoc inspection	Inspections carried out after natural calamities such as earthquakes and traffic accidents.
Emergency inspection	Inspections carried out after an accident on the bridge due to a specific defect, emergency inspections are also carried out on similar bridges.
Post repair/strengthening inspection	Inspections carried out immediately after repair/strengthening actions to find defects.

Table 2: If-then rules for evaluating "Condition state of cracking"

No. (1)	antecedents		consequent
	Crack conditions (2)	Maximum crack width (3)	Condition state of cracking (soundness score) (4)
1	severe	huge	0.0
2	severe	large	16.5
3	severe	small	33.5
4	severe	very small	50.0
5	moderate	huge	25.0
6	moderate	large	41.5
7	moderate	small	58.5
8	moderate	very small	75.0
9	not severe	huge	50.0
10	not severe	large	66.5
11	not severe	small	83.5
12	not severe	very small	100.0

Table 3: Expert Data

Expert (1)	Field of expertise (2)	Type of bridge involved (3)	Experience (App. years) (4)	Surveyed Bridges (5)
a	Bridge Design Engineer	Steel bridges	20	A(Span 3), B(Span 3)
b	Bridge Construction Engineer	Steel bridges	30	A(Span 3), B(Span 3), C(Span 3), D(Span3)
c	Bridge Maintenance Engineer	Concrete bridges, Steel bridges	30	A(Span3), B(Span3)

Table 4: Span 3 of bridge A input data including visual inspection results

No. (1)	Input items (2)	Inspectors(Domain experts) a (3)	b (4)	c (5)
T-1	Bridge name	Bridge A		
T-2	Year of construction (Bridge age)	1937 (63 years)		
T-3	Code (Applied specification)	① 1926		
T-4	Bridge grade	③ First		
T-5	Span of slab	1.6 m		
T-6	Thickness of slab	28 cm		
T-7	Road classification	② secondary route		
T-8	Traffic volume of large-size vehicle	1000 (Total number/12hrs)		
T-9	Position of large-size vehicle wheels during passing (wheel load)	③ Both left and right wheels pass between main girders		
T-10	Widening of bridge	② not done		
T-11	Type of widening	-		
T-12	Slope of bridge	② small		
T-13	Traffic signal near approach	② does not exist		
T-14	Industrial area	② no		
T-15	Harbor area or near coast	② no		
T-16	Cold area	② no		
I-1	Drainpipe	② does not exist	② does not exist	② does not exist
I-2	Choking of drainpipe	-	-	-
I-3	Flatness of road surface	③ even	③ even	③ even
I-4	Impact	② none	② none	② none
I-5	Condition of road surface	③ excellent	③ excellent	③ excellent
S-1	**Cracking over haunches**	① yes	① yes	① yes
S-1.1	Crack conditions	③ not severe	③ not severe	③ not severe
S-1.2	Maximum crack width	0.1	0.15	0.5
S-1.3	Free lime	② not serious	② not serious	② not serious
S-1.4	Spalling of concrete cover	② not serious	③ none	③ none
S-2	**Cracking over supports**	② no	① yes	① yes
S-2.1	Crack conditions	-	③ not severe	③ not severe
S-2.2	Maximum crack width	-	0.15	0.1
S-2.3	Free lime	③ none	② not serious	② not serious
S-2.4	Spalling of concrete cover	② not serious	③ none	③ none
S-3	**Cracking around center of slab**	① yes	① yes	① yes
S-3.1	Crack conditions	③ not severe	③ not severe	③ not severe
S-3.2	Maximum crack width	0.1	0.15	0.15
S-3.3	Free lime	③ none	③ none	③ none
S-3.4	Spalling of concrete cover	② not serious	③ none	② not serious
S-4	Area of potential spalling	② small	③ nothing	③ nothing
S-5	Free lime on slab	② not serious	② not serious	① serious
S-6	Exposed reinforcement in spalling part	② no	② no	① yes
S-7	Rust deposit	③ none	③ none	③ none
S-8	Forming of concrete honeycomb	① serious	② not serious	② not serious
S-9	Depth of concrete cover	③ unknown	③ unknown	② sufficient
S-10	Reinforcement bars' arrangement in spalling parts	③ unknown	③ unknown	③ unknown
S-11	Direction of cracking around center of slab	③ one direction	③ one direction	①many directions

Table 5: Training patterns

No. **(1)**	**Training patterns** **(2)**
Case01	[Aa – Ba]
Case02	[Ab – Bb]
Case03	[Ab – Bb – Cb – Db]
Case04	[Ac – Bc]
Case05	[Case04]→[Case03]→[Case01]
Case06	[Case04]→[Case02]→[Case01]
Case07	[Ac→Ab→Aa]
Case08	[Bc→Bb→Ba]
Case09	[Case07]→[Case08]→[Cb]→[Db]

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Table 6: Total error

No. (1)	Aa (2)	Ab (3)	Ac (4)	Ba (5)	Bb (6)	Bc (7)	Cb (8)	Db (9)	Sum(Ave%) (10)
Case00	508 (0%)	146 (60%)	242 (22%)	395 (9%)	157 (40%)	302 (0%)	99 (50%)	275 (30%)	2124 (26%)
Case01	90 (73%)	179 (50%)	161 (44%)	57 (64%)	145 (30%)	138 (22%)	171 (30%)	229 (20%)	1170 (42%)
Case02	397 (0%)	19 (90%)	192 (22%)	316 (0%)	28 (80%)	245 (0%)	67 (50%)	194 (40%)	1458 (35%)
Case03	409 (0%)	35 (90%)	153 (44%)	323 (9%)	37 (80%)	245 (0%)	65 (60%)	62 (60%)	1329 (43%)
Case04	314 (18%)	127 (50%)	21 (78%)	198 (45%)	123 (40%)	66 (56%)	194 (20%)	136 (40%)	1179 (43%)
Case05	43 (82%)	219 (30%)	63 (67%)	37 (82%)	142 (40%)	108 (22%)	194 (20%)	78 (40%)	884 (49%)
Case06	50 (82%)	197 (30%)	79 (67%)	38 (82%)	142 (30%)	112 (33%)	184 (30%)	152 (30%)	954 (48%)
Case07	70 (73%)	189 (40%)	80 (67%)	168 (55%)	111 (50%)	150 (11%)	153 (30%)	162 (30%)	1083 (45%)
Case08	301 (18%)	114 (50%)	221 (11%)	52 (64%)	136 (30%)	148 (33%)	190 (20%)	128 (60%)	1290 (36%)
Case09	121 (36%)	180 (50%)	77 (44%)	123 (45%)	67 (60%)	138 (33%)	125 (50%)	34 (80%)	865 (50%)