Performance Evaluation System for Concrete Slabs of Existing Bridges

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Summary

This article presents a new performance evaluation system for concrete slabs of existing bridges. The system evaluates the performance of the structure with reference to material deterioration and load carrying ability based on the results of a simple visual inspection and technical specifications. A neural network is employed because it enables for inference in the network, facilitates refinement of the knowledge base embedded by use of the Back-Propagation method, and prevents the technique from becoming a black box. The system was applied to existing concrete slabs, all of which were components of steel-concrete composite girder bridges, in order to examine the learning capability of the system and the acquisition of training data sets for the refinement of the knowledge base.

Keywords: Performance evaluation, Load-carrying capability, Durability, Expert system, Fuzzy set theory, Concrete slab; walls; Machine Learning, Neural network

1. Introduction

The management of existing bridges has become a major social concern in many developed countries due to the large number of bridges exhibiting signs of significant deterioration. This problem has increased the demand for effective maintenance and renewal planning. In order to implement an appropriate management procedure for a structure, a wide array of corrective strategies must be evaluated with respect to not only the condition state of each defect but also safety, economy and sustainability.

This article presents an approach for developing a performance evaluation system for the concrete slabs of existing bridges. The system evaluates performance based on load carrying capability and durability from the results of a visual inspection and specification data, and outputs the necessity of maintenance. It categorizes the slab as either unsafe, severe deterioration, moderate deterioration, mild deterioration, or safe. The technique employs an expert system with an appropriate knowledge base in the evaluation. A characteristic feature of the system is the use of neural networks to evaluate the performance and facilitate refinement of the knowledge base. Generally, although a neural network is a powerful machine-learning tool, the inference process 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 detailing how the performance is calculated since the road network represents a huge investment. The effectiveness of the neural network and machine learning method is verified by comparison of diagnostic results by bridge experts.

- **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 a viewpoint of traffic**
    - Traffic volume of large-size vehicle (T-8)
    - Road classification (T-7)
  - **Condition state of whole defects**
    - * See Fig. 3
  - **Influence of bridge widening**
    - Type of widening (T-10, T-11)

Fig. 1 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 whole defects**
    - * See Fig. 3
  - **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 of 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 a viewpoint of traffic**
      - Traffic volume of large-size vehicle (T-8)
      - Road classification (T-7)

Fig. 2 Durability diagnostic process

2. System Outline

The outline of the proposed system is explained in this chapter. The role of the system in an exiting bridge management system and the inference process and input data used to evaluate the performance are presented. The expert system was developed in Visual Basic and C and runs on a personal computer.

2.1 Performance Evaluation System

The proposed system is used to evaluate the load-carrying capability and durability with respect to the deterioration of members using the results of scheduled visual inspections, and outputs the necessity of maintenance. It is employed after a scheduled inspection and is intended to be used to

- **Condition state of whole defects**
  - **Condition state of cracking over haunch**
    - **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 supporting points**
    - **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 deposition (S-7)
    - **Degree of freezing and thawing action**
      - Condition of road surface (I-5)
      - Cold area (T-16)
    - Bridge age (T-2)

Fig. 3 Condition state of defect diagnostic process

estimate the need for a detailed inspection to identify an appropriate maintenance method and the frequency of the inspection. These two aspects of performance are applied as indices to consider the necessity for maintenance. Specifically, the load-carrying capability is determined from the load carrying ability of individual components and used to indicate the need for strengthening. The durability is then defined as the resistance of the bridge component to material deterioration determined from the rate of deterioration and used to indicate the need for repair. Both are assigned a soundness value on a scale of 0-100. 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 unsafe, severe deterioration, moderate deterioration, mild deterioration, and safe, respectively. A categorization of "safe" indicates that the member has no structural 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 member should be repaired and/or strengthened; and "unsafe" indicates that the member should be removed from service.

2.2 Performance Evaluation Process

The bridge performance is evaluated according to a diagnostic process, which is modeled on the inference mechanism used by domain experts for rating bridges. Figs.1 to 3 show the diagnostic process for concrete slabs [1,2]. Each process is expressed as a hierarchical structure and includes

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 sub 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 on main girders □② Left or right wheels on a main girder □③ Both left and right wheels 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 (Affecting the breaking of vehicle) □② small
T-13	Traffic signal near approach	□① exist □② none
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. 4 Investigation sheet (Technical specification)

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 approximately 40 input data items, such as technical specifications, traffic volume, and the results of a visual inspection. The characters within parentheses such as [Span of slab (T-5)] and [Bridge grade (T-4)] are input data items.

In the inference system, 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. 3, 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 haunch," "Condition state of cracking over supporting points," etc., are diagnosed from the results of lower judgment items and/or input data. Then, after evaluating the higher-rated judgment items, the final judgment items including "Level of durability" and "Level of load carrying capability" are evaluated. Each of these judgment items is assigned a soundness score as detailed in the previous section. The other judgment items have identical classification.

2.3 Input Data

The input data for evaluating a concrete slab are shown in Figs.4 and 5. The item number such as T-1 and S-1 corresponds to the number in the parentheses attached to the input data items in Figs.1 to 3. For example, S-*.2 shown in Fig.3 indicates that the maximum value from S-1.2 to S-3.2 is entered into the system.

3. Rule-Based Inference and Computing Structure for Machine Learning

This chapter presents the knowledge representation, rule-based computing and neural network architecture for the diagnostic process. The section of Fig.3 enclosed within a dotted box, namely,

Slab		
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 supporting points**	□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 deposition	□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 overall direction □② two directions □③ one direction □④ no cracking
Road surface		
I-1	Drainpipe	□① present (go next) □② not present(go to I-3)
I-2	Drainpipe blockage	□① Large number of blocked drainpipes □② Several blocked drainpipes □③ none
I-3	Flatness of road surface	□① uneven □② slightly uneven □③ even
I-4	Vibration (vibration while driving over the bridge)	□① serious □② not serious
I-5	Condition of road surface (Potholes, Cracks)	□① serious □② not serious □③ none

Fig. 5 Visual inspection sheet (Slab & Road surface)

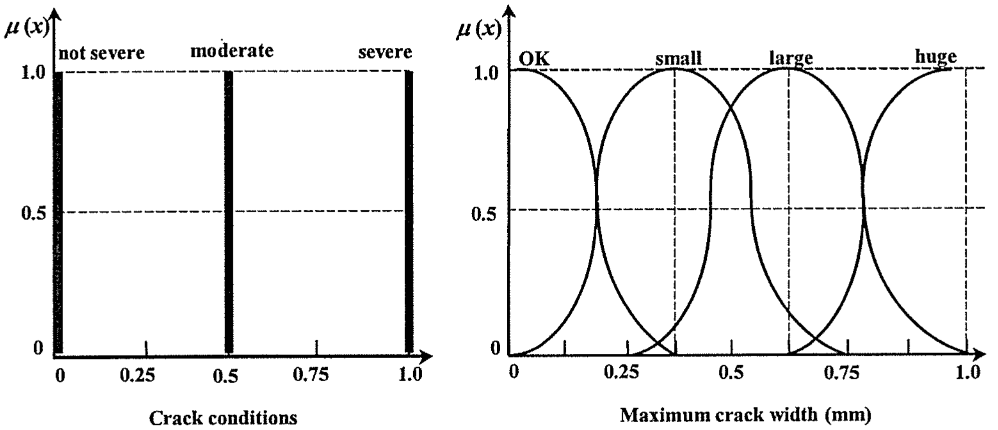
the inference process that evaluates "Condition state of cracking," is explained as an instance of the inference mechanism of the system.

3.1 Initial rule formation

The hierarchical structures shown in Figs.1 to 3 express the relationships between judgment items and input data or between judgment items. In practice, these relationships are expressed by "If-Then" rules. In the knowledge base, the diagnostic process is stored in the form of "If-Then" rules. Consequently, the inference of the system is drawn from these rules. Table 1 shows the "If-Then" rules for evaluating the judgment item "Condition state of cracking." For example, rule No.1 expresses the rule; 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

Table 1 If-then rules for evaluating "Condition state of cracking"

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



(a)Membership function for crack conditions (b)Membership function for maximum crack width

Fig. 6 Membership functions for input data

data form of [crack conditions] is formatted such that the inspector can answer the relevant multiple-choice question. The value of 0.0 is inputted into the system for an evaluation of [not severe], 0.5 for [moderate] and 1.0 for [severe]. In this way, the results of the multiple-choice questions are translated into numerical values and entered into the system. The input data form of [maximum crack width] is formatted such that the inspector can enter a numerical value. Therefore, the crisp sets and fuzzy sets are set to the [crack conditions] and [maximum crack width], respectively. These rules have three types of crisp sets for input item [Crack conditions] such as {severe}, {moderate} and {not severe}. The fuzzy sets for input item [Maximum crack width] are {huge}, {large}, {small} and {OK}. Values such as the results of the multiple-choice questions and the continuous values such as the maximum crack widths are set to crisp sets and fuzzy sets, respectively. However, if the multiple-choice question for input item [Crack conditions] includes many categories, fuzzy sets would be set to item [3]. The use of fuzzy sets enables for the reduction of the number of rules and limits the number of rules. Fig. 6 shows the membership functions related to the fuzzy rules and crisp sets for evaluating "Condition state of cracking."

The number of fuzzy sets for each input item, the initial form of membership functions for fuzzy sets and the initial values of soundness score in each rule should be set by discussion with bridge experts. However, the initial settings in this study were established by the authors because of the time required to acquire initial rules from domain experts and to perform the diagnostic process. The acquisition of initial knowledge is an important issue in the development of an expert system.

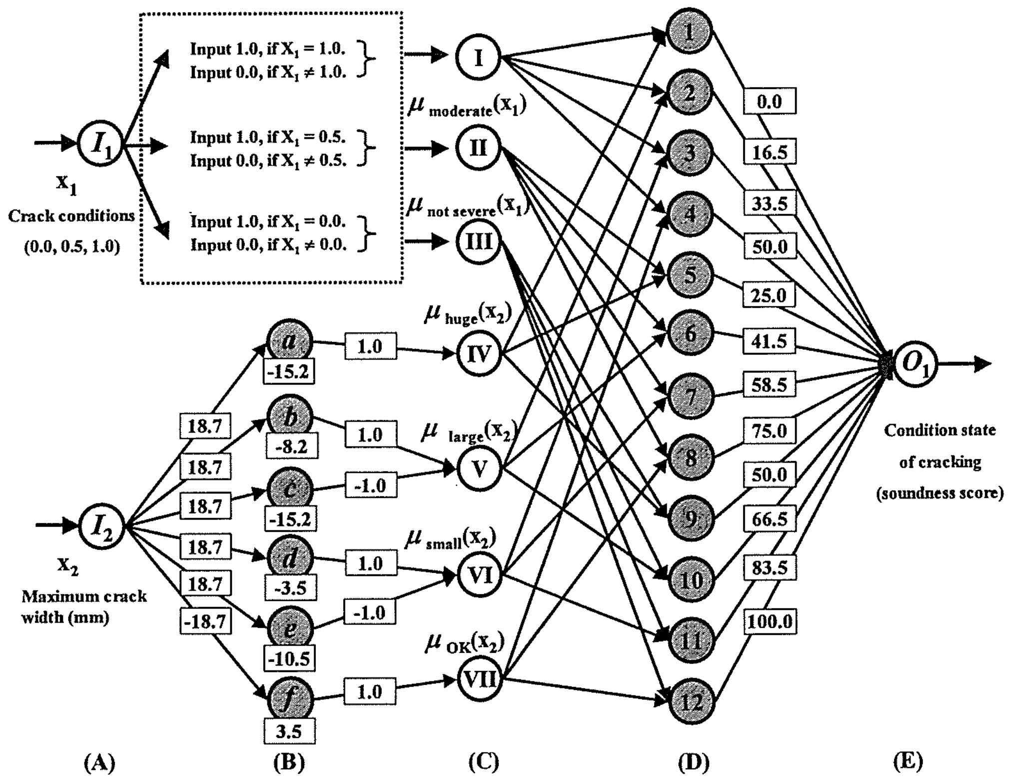


Fig. 7 Neural network for evaluating "Condition state of cracking"

For details of rule-based computing methods for evaluating a soundness score of a judgment item with "If-Then" rules, refer to references 3 to 5.

3.2 Neural Network Architecture for a Diagnostic Process

As mentioned above, the relationships shown in Figs.1 to 3 are expressed by "If-Then" rules with linguistic sets. Naturally, these rules could be input in a computer language. In this study however, the rules are implemented after a set of the rules for evaluating a judgment item is transformed into a multi-layer neural network. In other words, the neural network expresses a diagnostic process. For instance, the rules and membership functions shown in Table 1 and Fig. 6, are implemented as illustrated in Fig. 7. The boxes on connection lines and neurons are the weight and threshold, respectively.

The following is the method for constructing the neural network. If input data for evaluating a judgment item are expressed by the fuzzy sets in the antecedents of "If-Then" rules, the inference mechanism for evaluating a judgment item would be constructed with a multi-layer neural network consisting of 5 layers, as shown in Fig. 7 [3,4]. In the present study, the layers of the network are referred to as layers (A), (B), (C), (D) and (E). Layers (A)-(B)-(C) are identified with the fuzzy sets in the antecedents of the rules. The neural network enables for the modification of the form of the membership functions for the fuzzy sets. It is not necessary to express the membership functions except the functions for fuzzy sets by the neural network because these membership functions do not need to modify the form. Consequently, if there are no fuzzy sets in the "If-Then" rules, the inference mechanism can be constructed by a multi-layer neural network consisting of 3 layers (C), (D) and (E). The weights between layer (C) neurons and layer (D) neurons are all 0.5. The initial weights in layers (D) and (E) express soundness scores described in consequents of the fuzzy rules. For more details of the manner in which the initial values of weight and threshold are set, refer to the reference 3.

Table 2 Domain expert data

Domain Expert	Position	Field of expertise	Experience (Approximate years)	Surveyed Bridges
A	Designer	Steel bridges	20	A(Span 3), B(Span 3)
B	Contractor	Steel bridges	30	A(Span 3), B(Span 3), C(Span 3), D(Span3)
C	Maintenance	Concrete bridges, Steel bridges	30	A(Span3), B(Span3)

The structural characteristics of the multi-layer neural network shown in Fig. 7 enables for the introduction of the Back-Propagation method [6,7] as a machine learning method to the system. In addition, each weight and threshold is set for a specific purpose as stated above. Therefore, the network is capable of modifying rules by altering these parameters. The modification indicates that the form of membership functions for fuzzy sets used in antecedents of the "If-Then" rules, and the soundness score stated in consequents of the rules are improved by the Back Propagation algorithm. The machine learning method and the modification of the rules are presented in references 3 and 4.

4. Practical Application

The proposed system was applied to existing concrete slabs (four spans), all of which were components of steel-concrete composite girder bridges, in order to examine the learning capability of the system and the acquisition of training data sets for the refinement of the knowledge base embedded within the system. The slabs were all components of different bridges and are referred to as A(Span 3), B(Span 3), C(Span 3) and D(Span 3). For example, A(Span 3) represents the third span concrete slab of bridge A. In the present study, the survey covered four spans of four bridges.

4.1 Visual Inspection and Questionnaire Survey

The purpose of the visual inspection is to collect inspection data to be entered into the system. The questionnaire survey of the domain experts is used to acquire teacher data necessary for learning. The combination of the visual inspection results and the questionnaire survey results was used as training data for 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. 4 and 5. The domain 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 higher-rated judgment items as shown in Figs. 1 to 3, in the form of a score from 0-100 in increments of 5 points [3]. The sheet includes 11 questions for evaluating the higher-rated judgment items such as "Level of load carrying capability," "Level of durability", "Level of slab design," and "Level of slab execution." In this survey, there was insufficient time to answer all of the questions. Consequently, the questions for the lowest-rated judgments such as "Condition state of cracking" and "Condition state other than cracking," were not used in the present study.

A visual inspection of slabs A (Span 3) to D (Span 3) and the questionnaire survey were conducted by three domain experts ***a***, ***b*** and ***c***. The position of each domain expert, the types of bridges that each expert deals with, each experts experience measured in years and the concrete slabs surveyed by each expert are summarized in Table 2. The input data for evaluating the bridge A concrete slab (Span 3) are summarized in Table 3, which includes each experts visual inspection results of the road surface and slab. These results show that there is some inconsistency in the slab inspection results of each expert. This suggests that it is necessary to improve the inspection method in order to develop a more consistent system. The bridge A slab (Span 3) evaluation results are presented in Fig. 8. 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 to the "Level of slab design,"

Table 3 Bridge A (span 3) input data including visual inspection results

No.	Input items	Inspectors(Domain experts)		
		a	b	c
T-1	Bridge name	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 sub 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 on middle part between main Girders		
T-10	Widening of bridge	② not performed		
T-11	Type of widening	-		
T-12	Slope of bridge	② small		
T-13	Traffic signal near approach	② no		
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 none	② none	② none
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 none	③ none	③ none
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 supporting points**	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 spalled region	② no	② no	① yes
S-7	Rust deposition	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	①overall direction

and expert *c* did not answer the "Level of load carrying capability" due to insufficient experience in these areas. The data reveals that there is a significant difference between the evaluations. The following would be the reason of the difference: Each domain expert evaluated the same concrete slab. However, the concrete slab of the different deterioration condition was diagnosed by each expert because the slab inspection results were different as shown in Table 3. As one more reason, thought Figs.1 to 3 were attached to the questionnaire sheets as appendixes, each expert might fill out the questionnaires with his own diagnostic process.

Table 4 Training patterns

No.	Training data sets & Training patterns
Case01	[Aa (11/11) – Ba (11/11)]
Case02	[Ab (10/11) – Bb (10/11)]
Case03	[Ab (10/11) – Bb (10/11) – Cb (10/11) – Db (10/11)]
Case04	[Ac(9/11) – Bc(9/11)]
Case05	[Case04] → [Case03] → [Case01]
Case06	[Case04] → [Case02] → [Case01]
Case07	[Ac (9/11) → Ab (10/11) → Aa (11/11)]
Case08	[Bc (9/11) → Bb (10/11) → Ba (11/11)]
Case09	[Case07] → [Case08] → [Cb (10/11)] → [Db (10/11)]

Table 5 Total error

No.	Aa	Ab	Ac	Ba	Bb	Bc	Cb	Db	Sum(Ave%)
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%)

4.2 Effectiveness of Machine Learning

The 8 training data {Aa, Ba, Ab, Bb, Cb, Db, Ac, Bc} were acquired from the results of the visual inspections and questionnaire surveys. The capital and lowercase letters indicate the concrete slabs and domain experts, respectively. The variety of training patterns summarized in Table 4 were performed using these training data in order to test the learning capability of the system and to examine the acquisition of training data sets for machine learning. The numerical number in the parentheses is the answer rate of each questionnaire. The symbol " – " represents machine learning carried out with the training data sets connected by the symbol. For example, case 02 indicates that the learning was performed using sets Aa and Bb. The symbol "→" means that the machine learning was performed with the right-hand training data set or training data after completing machine learning using the left-hand training data set or training data.

The machine learning results using these training patterns are summarized in Table 5. The numerical values with parentheses represent the overall error calculated by summing the difference between the questionnaire results with the evaluation scores of each judgment item given by the domain expert and the output of the system after learning or before learning. Case 00 shows the comparison results between the questionnaire results and the output of the system using the initial knowledge before learning. The percentages in parentheses represent the agreement ratios related to the five assessment categories (unsafe etc). The table shows a tendency for the total sum of error to decrease when the number of training data increases. The total error in Cases 05 and 09, which used all training data, are the lowest values. This indicates that it is necessary to increase the number of

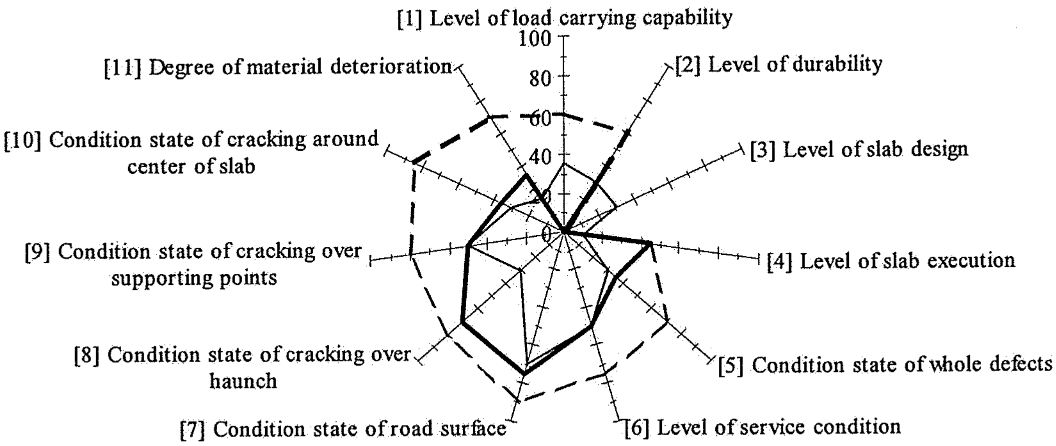


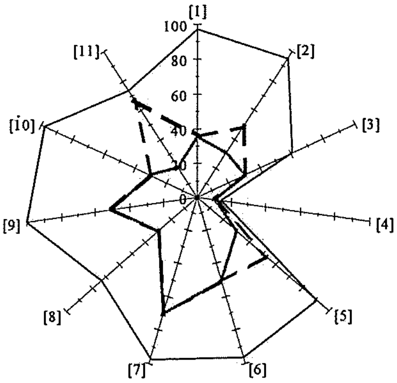
Fig. 8 Results of bridge A (span 3) evaluation by domain experts

training data used for learning and acquire training data for various deterioration conditions. The details in the shaded areas shown in Table 5, are shown in Fig.9 as radar charts. The solid-line, bold-solid-lines and dotted lines represent the output of the system before learning, the questionnaire results and the output of the system after learning, respectively. The numerical numbers in parentheses correspond to the numbers in Fig. 8. It can be seen that the form of the output of the system after learning is similar to the domain expert assessments. However, there are some deviations in the figure and the percentages in Table 5 are low. The reasons for this are as follows:

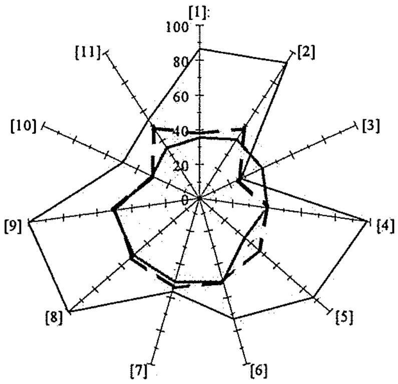
1. The initial tuning of the knowledge base embedded in the system was insufficient. The number of fuzzy sets for each input item, the initial form of membership functions and the initial values of soundness scores in each rule should be set by discussion with bridge experts.
2. Expert diagnostic processes will differ and are different to the diagnostic process applied to the proposed system. Consequently, there is a possibility that the training data sets acquired from some domain experts contain inconsistency data. However, the total errors of case 05 and case 09 shown in Table 5, which used the training data sets proposed by all three different domain experts, are the lowest of all the results, suggesting a need for more training data.
3. The questionnaire survey may not be sufficiently detailed and the definitions of each category in the questionnaire were unclear. There is a possibility that the experts interpreted these classifications indifferent ways.

5. Conclusions

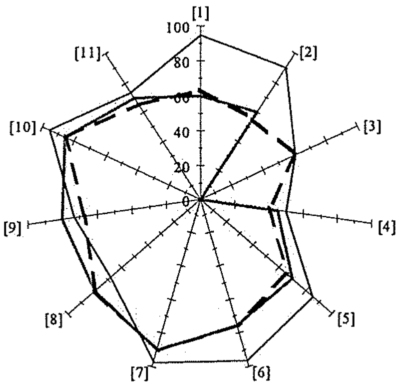
A performance evaluation system for concrete slabs with machine learning was proposed in the present study. The system was applied to concrete slabs on existing bridges in order to verify the effectiveness of the machine learning method. The knowledge base was refined from the results of questionnaire surveys of domain experts. Close agreement between the diagnostic results of the domain expert and the output of the system after learning confirms the effectiveness of the proposed learning method. In order to enhance the reliability of the expert system, the knowledge base must be refined through application to a greater number of bridges with various deterioration conditions. However, there is a possibility that the training data sets acquired from some domain experts contain inconsistency data. Therefore, it is necessary to improve the data acquisition and inspection methods.



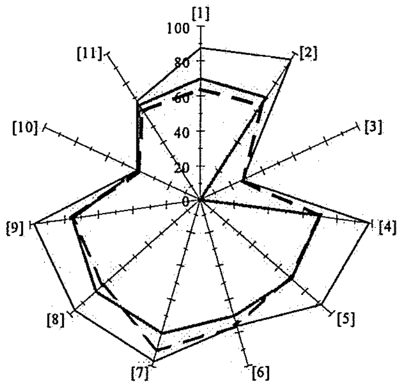
Case 01 Aa



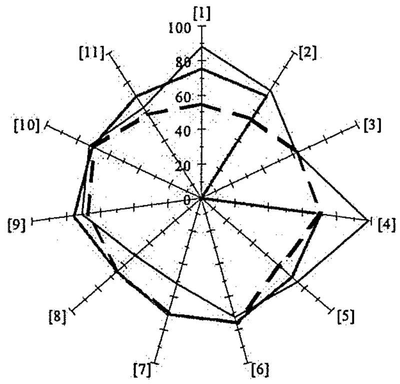
Case 01 Ba



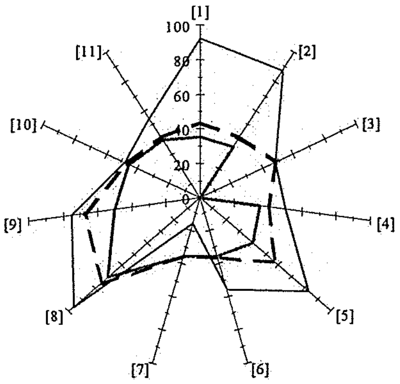
Case 03 Ab



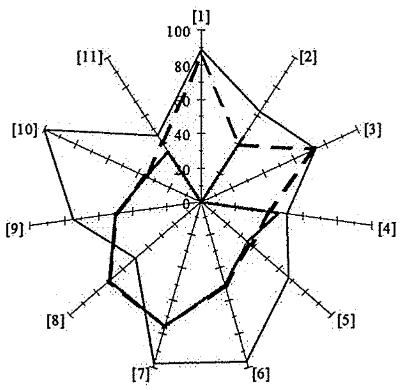
Case 03 Bb



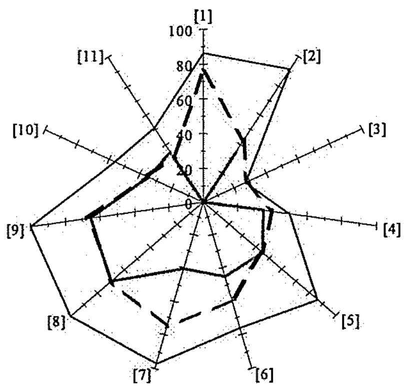
Case 03 Cb



Case 03 Db



Case 04 Ac



Case 04 Bc

Fig. 9 Evaluation results

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