Zeitschrift:	IABSE reports = Rapports AIPC = IVBH Berichte
Band:	72 (1995)
Artikel:	Concrete bridge rating expert system with machine learning
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DOI:	https://doi.org/10.5169/seals-54678

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Concrete Bridge Rating Expert System with Machine Learning

Système expert avec apprentissage-machine pour l'évaluation de ponts en béton

Ein Expertensystem mit Maschinenlernen zur Einstufung von Betonbrücken

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SUMMARY

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The aim of this study is to develop a concrete bridge rating expert system with machine learning, employing a combination of neural network and bi-directional associative memories. Introduction of machine learning into this system facilitates knowledge base refinement. By applying the system to an actual bridge in service, it has been verified that the employed machine learning method using results of questionnaire surveys of bridge experts is effective for the system.

RÉSUMÉ

Le but de l'étude était de réaliser un système expert avec apprentissage-machine pour l'évaluation de ponts en béton, combinant un réseau neuronal avec des mémoires associatives bidirectionnelles. L'introduction de l'apprentissage-machine augmente la qualité de la base de connaissance. L'application de ce système au cas réel d'un pont en exploitation démontre l'efficacité de l'introduction de l'apprentissage-machine, utilisant les informations fournies par les spécialistes.

ZUSAMMENFASSUNG

Ziel der vorliegenden Studie ist die Entwicklung eines Expertensystems zur Brückenbeurteilung, das ein neuronales Netzwerk mit zweiseitigen assoziativen Gedächtnissen kombiniert. Die Einführung des Maschinenlernens vereinfacht die Verfeinerung der Wissensbasis. Durch Anwendung des Systems auf eine in Betrieb stehende Brücke wurde festgestellt, dass die Lernmethode mittels strukturierten Erhebungen unter Brückenfachleuten wirkungsvoll ist.

1. INTRODUCTION

The authors have been working for some time on the development of a Concrete Bridge Rating Expert System[1,2] that can evaluate the serviceability of concrete bridges on the basis of knowledge and experience acquired from domain experts. The final goal of the present system is to evaluate the structural serviceability of bridges on the basis of the specifications of target bridges, environmental conditions, traffic volume, and other subjective information such as one obtained through visual

inspection. The inference mechanism in the system first selects a membership function (Π function parameters) defined in the knowledge base on the basis of the knowledge acquired from domain experts to achieve the lowest level subgoals of the diagnostic process. The inference mechanism then combines the subgoals with a higher level subgoals according to Dempster's rule of combination and repeats this process[1]. In evaluating the serviceability which is evaluated by a combination of "load carrying capability" and "durability" of a target bridge, which is the final goal of the expert system, the inference mechanism performs fuzzy mapping considering the degree of influence and the degree of confidence, and outputs the result of serviceability evaluation of the bridge accordingly. It has become known, however, that for certain types of inputs, the system sometimes outputs inconsistent results because the relevant knowledge base in the system while maintaining the integrity of the system. Consequently, the procedure of knowledge base management needs to be simplified by introducing machine learning into the expert system.

In this study an inference system combining the neural network[4] and the bidirectional associative memory (BAM)[5] was constructed as part of the Concrete Bridge Rating Expert System. The results of questionnaire surveys conducted on domain experts during field tests were used as teacher data (objective criteria) to give the system the ability to learn and verify the effectiveness of the learning method.

2. SYSTEM DESCRIPTION

Fig. 1 shows the configuration of the expert system. The knowledge base, the inference engine, the associative memory and the submodels (neural network models) of the system are constructed on a personal computer (NEC PCH98 U100), and the learning module runs on a UNIX workstation (SONY NEWS). The expert system is all written in C language.

Fig. 2 illustrates the inference process of this system. As a first step, the system asks a series of basic questions for the lowest level subgoals regarding the specifications of the bridge, environmental conditions, traffic volume, the conditions of cracks, etc. and asserts the answers from the user as fact clauses. Then the system searches all relevant fact clauses according to the inference rules. The system asks new questions if the message number for a found fact clause is "q" and

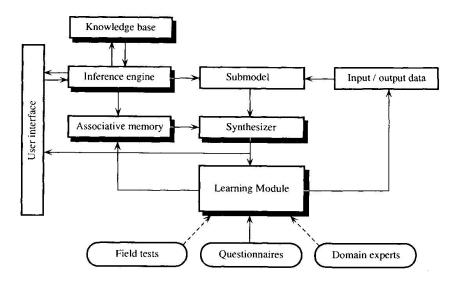


Fig. 1 System Configuration(New System)



asserts the responses to those questions as new fact clauses. If the found clause has a numeral, the system outputs a corresponding message. When having found all relevant facts by repeating this forward-chaining inference, the system moves on to the stage of associative memory and neural network inference. First, the associative memory determines the degree of match of the antecedent and calculate the weight for the consequent in the associative memory. The system then combines the outputs obtained here with the outputs from the consequent neural network model to give a diagnosis. The diagnosis given here is actually a set of soundness indicators calculated as the probabilities of the five possible conditions, namely, safe, slightly safe, moderate, slightly dangerous, dangerous. The system can also evaluate bridges with respect to the need for repair or strengthening and the remaining service life of both of the floor slab and the main girder. If a diagnosis is not a proper one, input/output data (teacher data) is modified on the basis of such information as the results of questionnaire surveys so as to refine the knowledge base according to the back propagation algorithm. After that, the neural networks are run again to output a diagnosis reflecting the modification. If the diagnosis is a proper one, the certainty for the corresponding rule is altered and the Concrete Bridge Rating Expert System returns to the startup menu.

3. VERIFICATION OF EFFECTIVENESS OF THE EXPERT SYSTEM

3.1 Comparison with Previous System[1,2]

The newly developed Concrete Bridge Rating Expert System was used to evaluate the serviceability of an actual bridge. The results of evaluation by this system were compared with results obtained from the previous system to verify the reliability of the acquired initial knowledge.

The bridge evaluated here was a reinforced concrete T-girder bridge[6] that had been constructed with relatively poor execution of work. The main girder then had flexural cracks, shear cracks and cracks due to the corrosion of reinforcing bars. Particularly cracks due to corrosion were rather wide, and water leakage, free lime and spalling of cover concrete around those cracks were

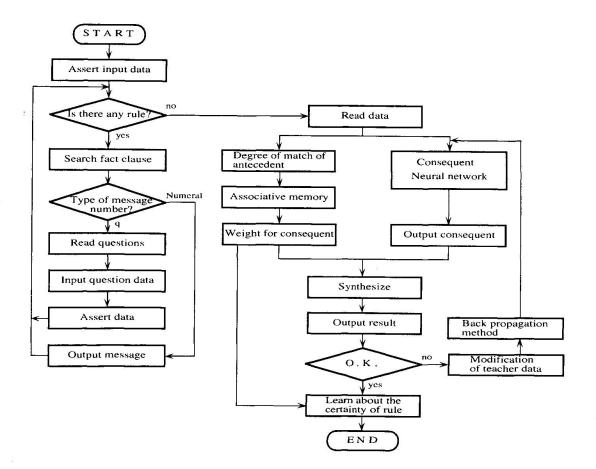


Fig. 2 Inference Process in Inference Engine of the Concrete Bridge Rating Expert System(New System)

noticeable. Tables 1 and 2 show the results of evaluation of the main girder of this bridge by the previous (original) system and the new system. Except for the subgoals for the design of the main girder, the original system and the new system gave similar results(see Tables 1 and 2). With respect to the design of the main girder, since the original system combines membership functions to higher level subgoals following Dempster's rule of combination in the inference process, the degree of uncertainty tends to increase as the inference process progresses. This resulted in the inconsistency of showing two peaks, namely at "slightly dangerous" and "slightly safe" (see Table 1). By contrast, the new system gave results somewhat centering around a single peak (see Table 2). Errors contained in these results need to be corrected through neural network-based learning. In the other respects the results obtained from the original system and the new system showed fair agreement (see Tables 1 and 2).

From above, it can be concluded that the new system has acquired the knowledge of the original system very accurately. Various problems found in diagnoses given by the system[3], however, indicate that the knowledge needs to be refined.

3.2 Refinement of Knowledge Based on Results of Questionnaire Survey

In this section, the refinement of knowledge in the consequent neural network is performed based on teacher data (objective criteria) obtained from questionnaire surveys on domain experts.

The results of the questionnaire surveys were divided into five categories, each corresponding to 20 points on a scale of 100. These categories were related to the probability of states ranging from dangerous to safe output from the system, and the data thus obtained was used as teacher data (objective criteria). By use of this data, the knowledge was refined according to the back propagation algorithm. Of the evaluation items for the reinforced concrete T-girder bridge mentioned earlier, shown below is the process of knowledge refinement for the subgoals related to cracks in the main

Judgment factor	Mean soundness score	Danger	Slightly danger	Moderate	Slightly safe	Safe
Design	47.0	0.151	0.273	0.161	<u>0.371</u>	0.044
Execution of work	17.4	0.338	0.605	0.056	0.000	0.000
Service condition	76.0	0.000	0.000	0.167	0.644	0.189
Flexural crack	60.9	0.000	0.173	0.447	0.191	0.189
Shear crack	60.9	0.000	0.186	0.435	0.186	0.194
Corrosion crack	39.6	0.260	0.457	0.016	0.051	0.217
Whole damage of girder	50.9	0.127	0.285	0.293	0.106	0.189
Load-carrying capa. of girder	56.2	0.099	0.185	0.293	0.210	0.213
Durability of girder	49.8	0.146	0.308	0.136	0.244	0.166
Serviceability of girder	51.7	0.161	0.245	0.201	0.221	0.173

Table 1 Evaluation of RC T-Girder Bridge by Original System

Table 2 Evaluation of RC T-Girder Bridge by New System

Judgment factor	Mean soundness score	Danger	Slightly danger	Moderate	Slightly safe	Safe
Design	64.7	0.001	0.019	0.319	0.564	0.097
Execution of work	24.8	0.330	0.608	0.055	0.005	0.002
Service condition	70.0	0.014	0.026	0.144	0.575	0.241
Flexural crack	58.4	0.035	0.240	0.260	0.202	0.264
Shear crack	58.7	0.033	0.313	0.145	0.202	0.307
Corrosion crack	25.1	0.283	<u>0.698</u>	0.006	0.006	0.007
Whole damage of girder	52.0	0.148	0.222	0.208	0.227	0.195
Load-carrying capa. of girder	65.8	0.001	0.038	0.300	0.493	0.168
Durability of girder	52.6	0.058	0.165	0.394	0.352	0.031
Serviceability of girder	.58.9	0.019	0.109	0.343	0.464	0.065



girder (see Table 2). Table 3 shows the results of the questionnaire surveys (teacher data) regarding cracks in the main girder. Table 4 shows the results of evaluation by the system after the knowledge refinement of the consequent neural network based on the teacher data shown in Table 3. Figs. 3 and 4 show, in the form of membership functions, the results of evaluation regarding corrosion cracks and flexural cracks in the main girder before the knowledge refinement, the teacher data used in knowledge refinement, and the results of evaluation after the knowledge refinement.

As shown in Tables 2 and 4, and Fig. 3, the corrosion cracks in the main girder were judged "slightly dangerous" before knowledge refinement, while after the knowledge refinement they were judged "slightly safe". As for the flexural cracks in the main girder, the results of evaluation before the knowledge refinement showed more or less even distribution over the soundness scale, while those after knowledge base refinement shows a peak in the "moderate" range. This indicates that the degree of uncertainty decreased as a result of knowledge refinement (see Tables 2 and 4, and Fig. 4).

From above, it can be concluded that the accuracy of knowledge refinement in this system was considerably high, evidencing the effectiveness of the learning method of the system. In cases, however, where results of questionnaire surveys are used as teacher data (objective criteria), the reliability of the questionnaire results themselves becomes an important consideration. Teacher data might even be inconsistent to the extent of prohibiting knowledge refinement. It is desirable, therefore, that indicators related with more objective data obtained from reliable sources, such as field tests, be used as teacher data.

Table 3 Example of Teacher Data on Level of Cracks in Girder used for Knowledge Base Refinement

Judgment factor	Danger	Slightly danger	Moderate	Slightly safe	Safe
Flexural crack in girder	0.000	0.154	0.538	0.308	0.000
Shear crack in girder	0.000	0.308	0.231	0.231	0.231
Corrosion crack in girder	0.077	0.154	0.308	0.385	0.077

Table 4 Example of Output after Refinement of Knowledge on Level of Cracks(Girder)

Judgment factor	Mean soundness score	Danger	Slightly danger	Moderate	Slightly safe	Safe
Flexural crack	54.5	0.029	0.179	0.427	0.268	0.098
Shear crack	57.6	0.017	0.305	0.208	0.223	0.247
Corrosion crack	51.7	0.090	0.217	0.279	0.345	0.070

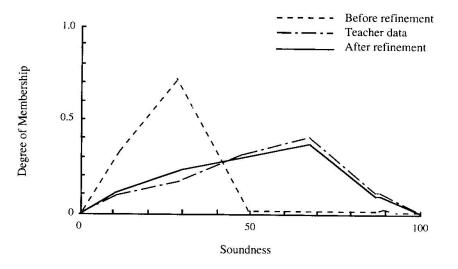


Fig. 3 Comparison of Outputs on Corrosion Cracks in Girder

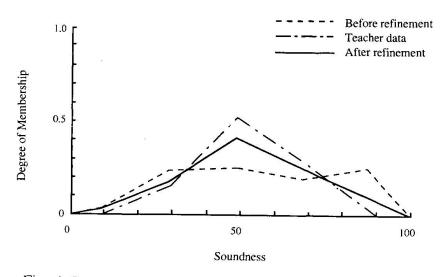


Fig. 4 Comparison of Outputs on Flexural Cracks in Girder

CONCLUSIONS 4

In this study a Concrete Bridge Rating Expert System with Machine Learning has been developed. Using neural networks, the developed system facilitates the modification of the knowledge base based on data such as results of questionnaire surveys conducted on domain experts. Independent neural networks constructed for individual rules help prevent the inference mechanism from becoming a black box. The time required for learning can also be reduced because the learning process involves only the networks concerned. The results of this study can be summarized as follows:

(1) As a method of modifying the knowledge base of the Concrete Bridge Rating Expert System, a learning method based on the neural network has been presented. And a new inference process similar to the conventional fuzzy inference has been developed by combining the neutral network and associative memory.

(2) The Concrete Bridge Rating Expert System was applied to the girder of an actual bridge to verify the results of evaluation. Good agreement between the results obtained from the original system and the new system confirmed that the knowledge for the new system was successfully acquired from the original system.

(3) The knowledge base was refined using neural networks on the basis of the results of questionnaire surveys on domain experts. Good results achieved as a result of knowledge base refinement evidences the effectiveness of the learning method in the system.

In order to enhance the reliability of the expert system, it is necessary to refine the knowledge base through application to more bridges. It is also necessary to clearly define the relationships between the outputs of the system and field data (e.g., linking numerical analysis programs) instead of relying solely on information obtained from visual inspection.

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