APPLICATION OF NEURAL NETWORK FOR SELECTION OF AIRPORT RIGID PAVEMENT MAINTENANCE STRATEGIES

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Key words: rigid pavement, neural network, machine learning.

ABSTRACT

Maintenance strategy selection has been an important link within the management system for airport rigid pavement. Suitable maintenance strategies will guarantee maintenance success. The maintenance personnel investigating pavement distress usually base their maintenance strategy suggestions on expert knowledge and experience. Nevertheless, in practical situations we often see examples of distress taking place following maintenance, which indicates that the maintenance strategies previously selected can not effectively repair the pavement. Other methods and materials have to be adopted for maintenance so as to ensure pavement performance. This paper uses the machine learning theory of the neural network, conducting a questionnaire survey on experts to accumulate knowledge by way of case learning and inferring. This is aimed at enhancing capability of selecting more appropriate strategies for repair of pavement distress, thus to ensure pavement service performance. Furthermore, this paper suggests that feed-back and learning capabilities of maintenance materials be established, allowing the system to learn continuously, ensuring applicability of maintenance materials as well as upgrading maintenance effects.

INTRODUCTION

Since the development of the Back-Propagation Neural Network (BPN) and the Hopfield Neural Network (HNN), there has been considerable breakthrough in theory establishment and module development for the neural network itself. The scope of application has also been widening gradually. In pavement engineering and related fields, there has been satisfactory achieve- ment in pavement evaluation, design, prediction and image identification, *etc.* [4, 6, 7, 8]. Moreover, the Transportation Research Board (TRB) issued a document for circulation in 1999, which exclusively targeted introducing research applying the neural network module to fields related to geological engineering and pavement engineering [9].

If we concentrate on the field of pavement maintenance, the more substantial relevant studies include that of Abdullah M. Alsugair [3], who announced in 1995 the application of the neural network to suggest the pavement maintenance strategies selection module. He first classified the pavement distresses into 19 types and 13 maintenance strategies. He further classified each distress type into 3 severity levels, in accordance with the definitions of the U.S.N. Battalion. Thus, the neural network framework established by him consists of a total of 57 input data and 13 maintenance strategies output data. What the user has to do is input data based on the pavement conditions. In return, the system will suggest the suitable maintenance method.

Alsugair announced again in 1998 the implementation of BPN to establish an expert system for rigid pavement repairs [2]. His data was mainly from the city network data for Riyadh in Saudi Kohn. He first simplified the original 19 distress types and 13 maintenance strategies to 12 distress types and 5 maintenance strategies based on the area characteristics. He further established neural modules for maintenance strategy selection through on-site data collection (9311 groups), including characteristics selection, example pretreatment for training, etc. He then found out the most suitable hidden layers and node numbers by way of sensitivity analysis. He also quoted the Pavement Condition Index (PCI) in his paper. The user must first find out the PCI value for the pavement, input the data according to the applicable module, then obtain the maintenance strategies proposed by the system.

In recent years, Ashraf M. Abdelrahim and K. P. George announced using the neural network for selecting pavement maintenance methods in the 79th TRB

(2000) [1]. With respect to input value, they proposed adopting the three parameters of distress condition, traffic volume, and road grade as the input items for the neural network. Through entering these input parameters into the neural network for induction, the system is able to suggest the most suitable maintenance strategies.

Although the neural network in relation to pavement maintenance has been widely studied, the current maintenance systems based on this module suggest only maintenance methods, not materials. The evaluation and selection of maintenance strategies should also include suitable material selection. If on-site pavement engineering personnel use improper materials, even if their method is correct, cases of failure still occur frequently. Maintenance work methods selected by the pavement maintenance personnel haven't changed much over the years. On the other hand, since maintenance materials have evolved so quickly, various areas and experts have various grading systems for various kinds of materials. One should consider the materials' effects, maintenance personnel's working skills, environment, etc. Therefore, the study at hand has also taken into account that maintenance materials tend to change, and expects to establish neural network methods that are capable of receiving feed-back in order to target better method/material selection and enhance continuous learning thereof.

Although traditional expert systems knowledge seems transparent, adding new information and revising existing information have been relatively difficult. This paper thus adopts the machine learning module of the neural network to create a primitive expert system that is suitable for the selection of airport rigid pavement maintenance, employing a BPN that is most widely used by the public and is most representative for performance learning. This paper makes suggestions for maintenance strategies, pertaining to maintenance work method and maintenance materials. Consequently the expert system established by the neural network is divided into two modules. The first module suggests that the user selects a suitable maintenance work method. After the user has selected a certain work method, the system will follow the reasoning of the first module and the suitable maintenance materials under that work method to the user. The flow chart for using the neural network to suggest the maintenance measure strategy is illustrated in Figure 1.

FRAMEWORK OF NEURAL NETWORK MODULES FOR SELECTING MAINTENANCE STRATEGIES

This paper suggests that the maintenance strategy be divided into two modules for suggesting work method

and for suggesting maintenance materials. Regarding the former, since the changes of work methods over time have been rather minor, there will be probably few changes in the principles of selecting work methods within forthcoming years. On the other hand, new materials are developed continuously. The same materials even have their application scope, area, etc. change from time to time due to their maintenance effects. For instance, some materials have outstanding effects when used in some countries, but have their maintenance effects compromised when introduced into other countries, due to impacts of environmental conditions such as varying weather, immature skills, etc. Nevertheless, after continuous trials and tests over the years, due to upgraded skills or revised application scope, maintenance effects have been improved. This paper aims to establish a proper neural network of work method and maintenance materials, in order to continuously enhance selection capabilities.

1. Neural network module for suggesting maintenance method

When encountering rigid pavement distress, the airport pavement engineer usually suggests work methods by considering many factors. This paper has deduced six factors through reviewing documents and interviewing experts: distress types, severity levels, distress causes, maintenance methods (ordinary or urgent), weather, and budget. The more considerable factors will bring high volume questions. Thus, under the premise of being capable of replicating expert-deduced factors and maintaining the questionnaire response quality, this paper first obtains the weighted proportions of various considerable factors in pavement maintenance. This is accomplished with the input of
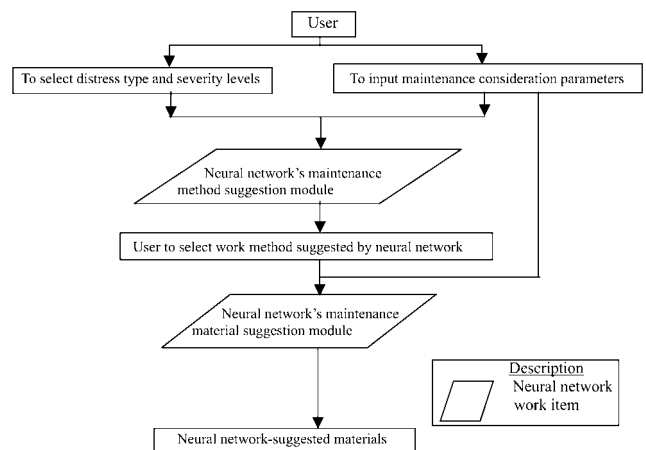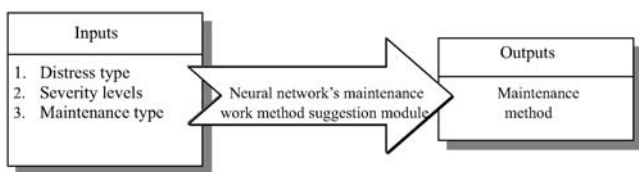

Fig. 1. Flow chart of neural network's maintenance strategy suggestion module.

Table 1. Weight values for experts' pavement maintenance consideration factor hierarchy analysis

No	Consideration factors	Weight value	Order
1	Distress type	0.217	2
2	Severity levels	0.352	1
3	Distress cause	0.157	4
4	Maintenance type (ordinary, urgent or temporary)	0.199	3
5	Weather	0.048	5
6	Budget	0.027	6

Fig. 2. Schematic of neural network's maintenance method suggestion module.

several experts through the Analytic Hierarchy Process (AHP), which, after verification of consistency and deriving the vector, is capable of deducing the weights of priority various factors (as summarized in Table 1). The Analytic Hierarchy Process (AHP) is a powerful and flexible decision making process to help people set priorities and make the best decision when both qualitative and quantitative aspects of a decision need to be considered. Thus, this paper adopts the considerable factors of higher weighted proportions as the neural network variables to simulate the thoughts of experts when considering maintenance methods. Then these factors are used as the input data for the neural network, while the output data is mainly the suggested maintenance method. The schematic diagram of the neural network suggested maintenance method is shown in Figure 2.

With respect to the above-mentioned input and output data for the neural network, the principle for selecting these items is based on the characteristics of independence, need, sufficiency, usefulness, etc. as possessed by these factors. Since the neural network is to obtain weighted values for the network by way of numeric values in order to represent the information in such cases, the data of the cases has to be converted into numeric value data. This paper uses the input and output nodes (processing units) to represent the status of all symbolic data, and divides the data into several categories. For example, regarding the severity of the distress type "spalling of joints", it can be classified into 3 nodes: low, medium and high:

Node #1 = spalling of joints, "low" severity level

Node #2 = spalling of joints, "medium" severity level

Node #3 = spalling of joints, "high" severity level

The same treatment method is also applied to other input and output data, such as maintenance type, which is divided into two nodes of ordinary or urgent repair. The framework for the neural network input nodes is then completed by adhering to this method. The output nodes for this method are the maintenance methods. The commonly used maintenance methods for domestic airports are summarized into seven methods: no repair necessary, sealing method, partial depth repair, full depth maintenance for part of slabs, complete plate overhaul, grouting for stabilizing foundation, or temporary covering treatment. The same framework is used for the input nodes to convert the domestic airport rigid pavement maintenance methods into seven nodes. Furthermore, there are frequently two or more suggestions concerning maintenance methods. Several maintenance work methods can be provided at the same time for the user's choice, so the output nodes are of non-mutual expelling status, which will be described in detail in the example forms:

Output processing units

Node #1 = do nothing

Node #2 = sealing

Node #3 = partial depth repair

Node #4 = full depth maintenance for part of slabs

Node #5 = complete slab overhaul

Node #6 = grouting for stabilizing foundation

Node #7 = temporary covering treatment

The neural network then uses the inputs and outputs of the nodes for neural network training and testing. In the future, simply inputting the parameters of the input nodes will be capable of executing recall procedures through the trained neural network to obtain input variables and deduce output variables. This means that after inputting distress categories, grades, and maintenance requirements, the suggested maintenance work methods can be deduced and evaluated (There may be

more than one value).

3. Neural network module for suggesting maintenance materials

Presently, studies abroad on applications of the neural network for suggestion of pavement maintenance strategies primarily focus on maintenance work methods. In practice, airport pavement repair are primarily emergency or temporary repairs, which usually involve relatively limited maintenance work methods. Since recurrence of distress following repairs often takes place, our conclusion is that only through coordination of proper maintenance work methods with proper maintenance materials can we achieve satisfactory maintenance effects. Therefore this study has attempted to similarly use the neural network to suggest maintenance materials by taking into account the factors considered by airport pavement engineers in selection of maintenance materials.

Thus, we set up suitable neural network modules for selection of maintenance materials. The factors of maintenance work methods, maintenance types (ordinary or urgent) and maintenance effects, etc. can be inferred from expert maintenance engineers by way of interview and document review. This enhance maintenance material selection. Since maintenance work methods vary, the materials available for selection vary as well. Therefore, this study has established proper modules for every different maintenance work method. At the same time, the mechanism of continuous learning and feed back of maintenance effects is also taken into consideration. Hence the concept of "satisfaction" is brought forth with definition we designed as follows:

"For specific maintenance work methods, specific maintenance materials are used respectively, while applicability of various materials is evaluated in tandem. Availability of materials, costs, workability, repair speed, effects, durability, as well as other relevant information are considered."

In the neural network suggested maintenance material module set up in this paper, neural network modules are established for each of the four maintenance methods of: seam filling, partial depth repair, full depth maintenance for part of plates, and complete plate overhaul. Moreover, experienced engineering experts of domestic pavement maintenance personnel, as well as maintenance contractors, etc. are interviewed for comments about each work method. Furthermore, commonly used maintenance materials for every local work method in the country (including information of brands, commercial names, etc.) are extensively collected. The neural network is then established based on the above

obtained data. The schematic is shown in Figure 3.

Like the neural network suggested maintenance method module, node inputs and outputs are used for training and testing the neural network. In the future, one can obtain input variables and estimated output variables by simply inputting the parameters of the input nodes capable of executing recall procedures through the trained neural network. This means that after inputting distress work methods, maintenance requirements and selected maintenance materials, the satisfaction values for that selected maintenance material can be predicted (There will be only one value). It should be noted that this module predicts the satisfaction of each maintenance material under its specific maintenance work method and requirements. Therefore, when an expert system is established in the future, it will sort the maintenance materials in order of satisfaction values. The system will then automatically evaluate and select the maintenance materials of higher satisfaction. This way desired maintenance effects can be better ensured.

It is true that there should be a certain degree of satisfaction for the system-suggested maintenance materials. However, frequently because of defects due to human errors, materials or weather (e.g. improper execution, inferior QC for maintenance materials, etc.), the repaired distress gets distressed again. This results in low post-repair satisfaction. Hence such a maintenance material case can be deemed as a failure. In the future, under the same maintenance conditions, the system might suggest this maintenance material again, thus causing recurrence of maintenance failure. On the other hand, if after the system-suggested maintenance materials are used and subjected to lengthy observation, and they do indeed provided excellent maintenance effects and higher satisfaction, then this maintenance material case can be considered successful. These failed or successful cases can be incorporated into the system for automatic learning. Thus, in the future, under the same maintenance conditions, the maintenance materials with high satisfaction rating can be more easily assessed and selected by the system, while those with low rating can be replaced by those materials with higher rating. This pattern of feed-back and auto-
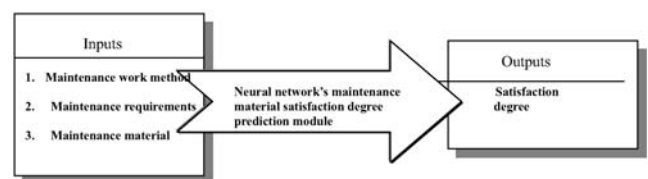

Fig. 3. Schematic of neural network's maintenance material suggestion module.

matic learning is this paper's research focus in the maintenance material module.

This paper attempts to carry out feed-back training for maintenance materials, since the neural network has gradually increasing learning ability. That is, it has the ability of inputting training examples from time to time, and gradually revising the information [10]. So if the system suggests maintenance materials, the user can deduce the post-maintenance satisfaction rating for that material in the future. This allows the system to learn automatically, and to revise its information data base automatically, which will then prepare the system to face other challenges.

HOW THE EXAMPLES ARE GENERATED

Data is the key factor which determines whether the neural network will succeed or not. Regretfully, maintenance records in Taiwan domestic airports are incomplete, so it is not easy to obtain data. According to documents, the sources of neural network cases include the following: (1) program simulation-generated examples, (2) recorded data, (3) questionnaire to experts [11].

As to the field of rigid pavement maintenance, currently there are no programs of finite element analysis in relation to simulated on-site distresses reparation. Furthermore lab testing has been unable to comprehensively simulate on-site distresses and maintenance conditions. As a result, obtaining information from these two methods is very difficult. So this paper adopts a questionnaire to obtain examples, further combining the neural network module for learning so as to facilitate the selection of proper maintenance strategies.

There are varying suitable maintenance materials for varying maintenance methods. For the purpose of continuous learning and achieving feed-back, this paper establishes only one neural network module for each maintenance method, further promoting satisfaction. The pavement experts need only to input the satisfaction rating for maintenance effects in connection with the selected work method, the maintenance type and the selected maintenance materials. As maintenance effects are very related to time lapsed, the satisfaction rating for maintenance effects tends to become lower along with lapse of time. Thus a fixed time limit should be specified. In view of the fact that the warranty period for pavement maintenance work contracts is usually one year, the experts are required to indicate their satisfaction after the one-year warranty.

While operation of the neural network is executed in way of numeric data computation, generally experts do not have the concept of numeric value scales. Hence, when the questionnaire was designed, considering con-

venience and friendliness, the experts were asked to adopt the method of converting expression variables into numeric values. The satisfaction rating is classified into 7 degrees of varying strength, scaled by experts' choice from: very dissatisfied, dissatisfied, slightly dissatisfied, not clear, fairly satisfied, satisfied, and very satisfied. With respect to the method of converting satisfaction expression degrees into specific numeric values, various satisfaction degrees and their corresponding values can then be obtained by using the expression conversion and right/left point method as provided by Chen and Hwang [5].

SYSTEM OPERATION

This system operates by way of numeric value calculation, so the Excel spread sheet is adopted for this operation. There are more than 300 functions in Excel 2000, which can assist the information engineers by processing various types of computations. In addition, connection between Excel and Visual Basic is very easy, and combining Excel with Visual Basic for Application (VBA) makes it even more powerful.

The second stage is numeric value deducing. Thus this study employs PCNeuron as the package software of set-up tool for performing neural network training and testing [10]. Since this program is executed under DOS conditions, it has to first proceed with data processing and format transforming via Excel before linking with Visual Basic. The framework for the maintenance method and material suggestion module is as illustrated in Figure 4.

With respect to making maintenance method suggestions by the neural network, it mainly executes recall procedures. This means that once a network with satisfactory accuracy has been set up, then those example cases which are to be deduced can be input into the trained network for obtaining the deduced output values
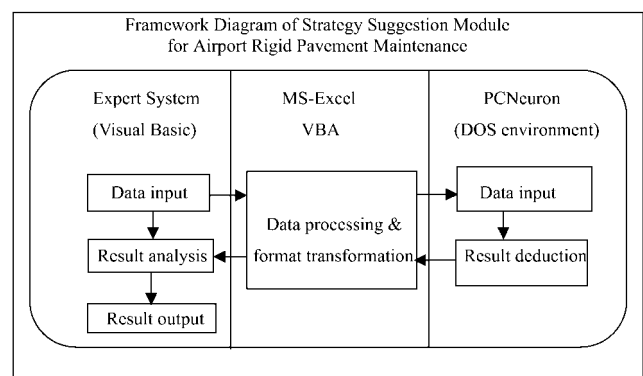

Fig. 4. Framework figure of strategy suggestion module for airport rigid pavement maintenance.

for respective process units. So after the user has input the relevant maintenance conditions through the user interface which is established by this system, VB will convert these data into the parameter files required for PCNeuton execution through data processing and format conversion by Excel.

When the neural network has completed its recall procedures, its output data will similarly be transmitted back to the VB program via Excel data conversion. These are sorted by order and the top three suggestion values are selected. Then the user can obtain the neural network suggested maintenance method as well as its suggestion values. When the neural network makes suggestions about maintenance materials, it also executes recall procedures for finding suitable materials. Its difference from the suggestion of the maintenance work method is that the output vector of this module is a process unit – satisfaction. So the material suggested by this system should be the maintenance material that meets the highest satisfaction value. Therefore, after the user has input the maintenance conditions, the system will enter all maintenance materials one after another into the neural network for executing recall. Thus, the satisfaction values will be computed for individual maintenance materials under the maintenance conditions as input by the user. Then, after sorting the satisfaction values in order, the top three materials can be selected. These are the suitable maintenance materials suggested to the user.

Another goal of this module is automatic learning. Feed-back training is added in order to carry out continuous machine learning of the maintenance materials. That is, after the system suggests maintenance method and materials, the user can feed back and advise the system of the satisfaction degree for these maintenance materials throughout this module. If a certain maintenance material repeatedly fails to reach the anticipated effect, then gradually, after several cases of feed-back training, that maintenance material will no longer be recommended to users.. On the other hand, after much successful feed-back training, good maintenance materials will tend to be assessed and selected by the system more readily. This can better ensure maintenance effects. Therefore the addition of the feed-back training module to this research will permit users to first find and ascertain maintenance materials. Resultant personal judgment of distress repair satisfaction will provide further satisfaction expression variables. Then this new case can be used in order to train the neural network again, based on which a new weighted matrix file will be generated. In the future, when the system executes recall procedures, it will select the right maintenance materials through these newly weighted link and valve values.

SYSTEM VERIFICATION

During the preparation stage of the experimental system in this paper, we continually invited the experts to check the system structure and verify the results. The system was then modified, based on the comments made by the experts. In order to analyze the resulting difference between system deduction and the experts practical situations. We sampled four real cases were examined and compared. Final modified values were applied to system deduction, with its results listed in table 2.

In addition to real verification by experts, we also verified by comparing the difference between the system analysis results and the airport rigid pavement experts' logical modules for pavement maintenance problem solving. Take the maintenance work method selection as an example. We subjected the questionnaire results to analysis by 10 experts. Under identical conditions, if all the experts selected the same work method, this work method had a value of 1. If 9 experts chose the same work method, this work method was 0.9, and so forth. We further took 0.5 as a threshold value, with any work method value equal to or higher than 0.5 considered as 1, and a value lower than 0.5 considered as 0. This result was thus viewed as the correct, final integrated target value.

The results of every expert's questionnaire and those of the system's inference and evaluation were further compared with the final integrated target value. This was done by comparing the work methods selected through the experts' or the system's deduction. Under the same conditions, when the work method as deduced by expert and system evaluation, and selected through the final integrated target value was identical, it was given a score of 1. The contrary was given a score of 0. Lastly, we compared the scores of the experts' and the system's inference, for the purpose of evaluating the difference between the primitive system established by this project and other existing expert modules for solving pavement maintenance problems.

For all pavement distress conditions and various maintenance requirements, the comparison findings between each expert's questionnaire, as well as the system's inference and the final integrated target values, are as given in Table 3. From the findings in Table 2 and Table 3, three conclusions can be obtained, as detailed in following:

1. Table 2 indicates that there is little difference between scores obtained from system deduction and expert questionnaire. The reason is probably that common work methods are rarely available and haven't changed much in recent decades. Nonetheless new repair materials with upgraded functions, worker skills and environmental factors may result in

Table 2. The results of four real cases in other airfields were examined and compared by two professional experts

Sample	Case 1		Case 2		Case 3		Case 4	
Repair area	West-South port		North port		East taxiway		Runway	
Distress type	Spalling of joints		Corner breaks		Transverse cracking		Popouts	
Severity levels	Medium		High		Medium		Medium	
Maintenance type	Ordinary		Ordinary		Urgent		Urgent	
Practical work method	Partly depth repair		Full depth maintenance for part of slabs		Sealing		Partly depth repair	
Practical material	Super high early strength concrete VISET-45		Normal portland cement concrete		Silicone (non-sag)		Super high early strength concrete VISET-45	
System deduction and experts' suggestion	Experts' suggestion	System deduction	Experts' suggestion	System deduction	Experts' suggestion	System deduction	Experts' suggestion	System deduction
Expert1	1.Work Method : Partly Depth Repair 2.Material : Super High Early Strength Concrete VISET-45	1. Work Method : (1)Partly Depth Repair (0.716) (2)Full Depth Maintenance for Part of Slabs (0.501) (3)Sealing(0.301) 2. Material (Partly Depth Repair) : (1)High Early Strength Concrete (0.812) (2)High Early Strength Cement/Normal Portland Cement+Wet Admixtures (0.759) (3)High Early Strength Cement/Normal Portland Cement+Desiccated dmixtures (0.751)	1. Work Method : Full Depth Maintenance for Part of Slabs 2. Material : Normal ortland Cement Concrete	1. Work Method : (1)Full Depth Maintenance for Part of Slabs (0.902) (2)Partly Depth Repair (0.632) (3)Overlay (0.454) 2. Material (Full Depth Maintenance for Part of Slabs) : (1)Normal Portland Cement Concrete (0.814) (2)High Early Strength Concrete (0.768) (3)Polymer ortland Cement Concrete (0.707)	1. Work Method : Sealing 2. Material : Silicone Sealant	1. Work Method : (1)Sealing (0.932) (2)Do Nothing (0.664) (3)Partly Depth Repair (0.342) 2. Material (Sealing) : (1)Silicone Sealant (0.997) (2)Rubberized Asphalt (0.602) (3)Rubberized Cement (0.432)	1. Work Method : Overlay 2. Material : Special Asphalt Concrete	1. Work Method : (1)Partly Depth Repair (0.806) (2)Overlay (0.656) (3)Full Depth Maintenance for Part of Slabs (0.574) 2. Material (Partly Depth Repair) : (1)High Early Strength Concrete (0.905) (2)High Early Strength Cement/Normal Portland Cement+Wet Admixtures (0.768) (3)High Early Strength Cement/Normal Portland Cement+Desiccated Admixtures (0.721)
Expert2	1. Work Method : Partly Depth Repair 2. Material : High Early Strength Cement/Normal Portland Cement+Wet Admixtures		1. Work Method : Full Depth Maintenance for Part of Slabs 2. Material : Normal Portland Cement Concrete		Do Nothing		1. Work Method : Partly Depth Repair 2. Material : Super High Early Strength Concrete VISET-45	

Table 3. Statistics of comparison scores between expert questionnaire and system-deduced results and final integrated target values

Subject	System deduction	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10
Score	1795	1633	1392	1635	1389	1690	1499	1648	1678	1656	1684

large variations of maintenance selection strategies by experts of varying areas. If repair material selection is deduced through the network learning and training system, the final outcome will be more practical. In the end, by way of real case study and comparison, system deduction has been verified as more reasonable than other work methods.

2. Table 3 indicates that all system-deduced scores are higher than the experts' scores. The scores were made comparison with the maintenance situation. If the system or experts have the same objective and reasonable, it will get a score. Therefore, the cumulate scores are 2016. This signifies that the system-deduced results are closer to the final integrated target values. The closer the scores to the final integrated target values, the more objective and reasonable the system-deduced results will be. This is evidence that this system's choice of airport rigid pavement maintenance strategies should be more objective, reasonable and effective than the existing one.

3. Although the system-deduced scores are higher than the experts' scores, the differences remain insignificant. Thus the system analysis conclusions are quite similar to the airport pavement experts' logical module for solving pavement maintenance problems. It is therefore demonstrated that this system possesses capability of providing suitable maintenance strategies.

CONCLUSIONS AND SUGGESTIONS

1. The maintenance strategy evaluation and selection system established in this paper has been demonstrated to possess the capability of providing suitable maintenance strategies. This has added maintenance materials for the training of the neural network. The system not only suggests selection of suitable maintenance materials, but also provides a feed-back training module, allowing the system to continue learning and updating automatically along with progression of time. This could enhance the selection of suitable and newly developed maintenance materials in the future, in order to ensure applicability.

2. It is not easy to collect information about airport pavement maintenance effects. Thus, the neural maintenance strategy evaluation and selection module currently established in this paper incorporates expert questionnaire to train the neural network. This is slightly different from the existing airport maintenance conditions. In the future, it is suggested that the airport pavement maintenance units keep track

and preserve all maintenance data in detail in order to facilitate continuous training for the neural network. This will enable the network to modify itself continuously based on the on-site examples. This can provide more appropriate maintenance strategies, and can also indirectly train experts.

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