SUBSECTION OF PAVEMENT DESIGN PARAMETERS USING NEURAL NETWORKS

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ABSTRACT

Destruction of pavement is considered as a damage-accumulative process. This process can be simulated or calculated with mechanical principles and the overlap method. When this process is carried out, the input parameters (supporting status of roadbed, material characteristics and traffic variation) will become the key to the simulation method. The magnitude and duration of these parameters are variable, which will significantly affect pavement performance within the pavement's lifespan or some other period. Therefore simulations usually divide pavement life into time increments. However, the environment and traffic do not vary strictly according to any prescribed year, season or month, and it is also impossible for existing data to be consistent within the time increments. Thus pavement life should be divided flexibly. The issue is therefore how to specify input sub-sections. In this paper, with the use of neural networks and MATLAB software, the sub-section parameters were done according to existing temperature, rainfall, and traffic data. It is important to correctly use existing environmental and traffic data. These input parameters are then used in pavement design and analysis. In this way, the pavement will be guaranteed good performance and long life.

Keywords: Pavement design parameter; Subsection and forecast; Neural networks

1. INTRODUCTION

In the last 15 years, an expressway network of more than 30 000 km has been built in China. This expressway network has had a significant effect on people's lifestyle and work, as well as promoting economic development. However, with the rapid development of the expressway, premature pavement distress has also become an issue. Premature pavement distress includes fatigue, rutting and moisture damage. In recent years, many research projects have focused on premature pavement distress, and inadequate design was considered to be one of the main reasons. Although today's design system used in China is known as the theoretical or mechanistic method, its parameters are empirical, which means that all the parameters are derived not from tests nor databases but from designers. The design is confused regarding practical pavement requirements. It has now come to be realised that it is important to obtain data from the site, and the use of these data is the main issue. In general, distress of a pavement is thought of as an accumulative damage process. This process can be simulated or calculated using mechanistic principles and the overlap method. When this method is used, the input parameters of design (supporting status of roadbed, material characteristics and traffic variation) are the key to the simulation procedure. The magnitude and duration of these parameters are variable, which significantly affect pavement performance during the pavement's life or over some other designated period. For example, when we design HMA for a high-temperature area, we need temperature data and duration of the temperature. Therefore the simulations and design usually divide pavement life or another designated period into time increments. However, the environment or traffic do not vary strictly in accordance with the relevant year, season or month, and neither will the existing data be consistent with the time increments. Thus the division of pavement life should be flexible. The concern is therefore to specify the sub-sections of the parameters. In this study, with the aid of neural networks and MATLAB software, the parameter sub-sections were specified according to existing temperature, rainfall and traffic data. It is important to correctly apply existing environmental and traffic data. These input parameters are then used in pavement design and analysis. In this way good performance and long life of the pavement will be guaranteed.

2. NEURAL NETWORKS

A neural network is a non-linear, self-adapting dynamic system. It is also a signal-processing system. It consists of many nerve cells and can simulate mental functions such as reminding, remembering and reasoning. The great advantage of the neural network is that it can self-adapt sample data. When there are any inaccurate data, it can differentiate them by network training, and then decrease their coefficient. Consequently, it can provide tools for automatically selecting characteristics and produce useful data trends for sub-sections and forecasting. Figure 1 is a model of a basic nerve cell. X_1, X_2,…… , X_n are the inputs of the nerve cell, W_{i1}, W_{i2}…… W_{in} are the coefficients of X_1, X_2, ……, X_n respectively, θ is the value of the cell, and Y_i is the output.

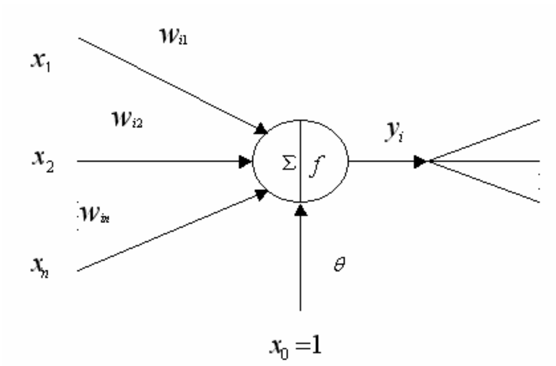


Figure 1. Model of a basic neural cell.

There are various kinds of neural models that can be used to classify data. The following models are used frequently: ART1 (Adaptive Resonance Theory), Apperceiving model, BP model, LVQ model and self-organising model. ATR1 requires that the input should be in binary format, so complex transformation is needed. The Apperceiving model can only classify some linear and simple modes. The BP model and LVQ model are of the "tutor-training" type. The input layers and competitive layers of the self-organising feature map (SOM) are fully mutually connected. Sometimes the cells of the competitive layers are linked and side-restrained. It can map discretional input modes into a single-dimensioned or double-dimensioned graph, and keep the same topological structure. In other words, through self-organising learning of the input modes, it can give results for the subsection. Therefore the self-organising feature map (SOM) was ultimately selected consideration.

The SOM was proposed in 1981, and can simulate the self-organising characteristic-mapping function of the mental neural system. It is a kind of competitive learning network which can do a self-organising study without supervision, and it can classify the input data according to their distribution in the input interspaces. In the SOM network, the neighbouring neural cells can identify the adjacent parts of the input interspaces. Therefore the SOM network can study not only the distribution of the input, but also the on-training topology structure.

3. SUB-SECTION PROCESS

Table 1 shows typical temperature data from the weather station in Guangdong province of China. The information in Table 1 includes monthly Extreme Highest, Average Highest, Average, Average Lowest and Extreme Lowest.

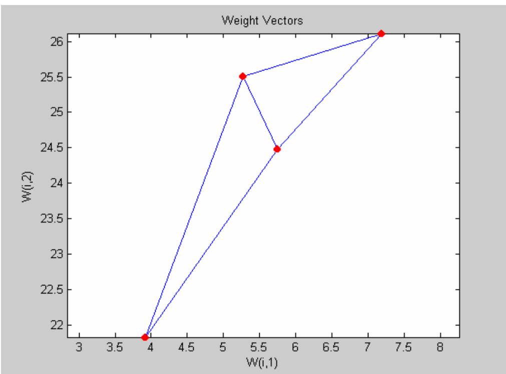
Table 1. Statistical data of monthly temperature in canton (ºC).

Tem	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
Extreme Highest	28.4	29	30.7	33.2	35.8	35.3	38.7	36.6	36.6	33.6	32.7	29.8
Average Highest	19.5	19.5	22.5	26.1	29.4	30.9	32.1	31.9	31	28.7	25.1	21.4
Average	14.6	15.3	18.5	22.3	25.7	27.6	28.4	28.1	27	24.3	20.3	16.2
Average Lowest	11.1	12.3	15.7	19.6	23	24.9	25.5	25.2	24.8	22.3	16.8	12.6
Extreme lowest	0.9	0.2	4.8	8.7	14.8	19	20	21.1	16.9	11.7	4.9	1.7

For the average temperature, with the NNTOOL (Neural network tool) of MATLAB®, twelve two-dimensioned vectors are input in the form of a 12 × 2 matrix and the results can be obtained as shown in Table 2. In Table 2, the data are classified into three, five and six groups, respectively.

Table 2. The data classified into three, five and six groups respectively (ºC).

Number of group		First	Second	Third	Fourth	Fifth
3	Month	5 - 10	4, 11	1 - 3, 12		
	Average value	26.9	21.3	16.5		
4	Month	5 - 10	4	11	1 - 3, 12	
	Average value	26.9	22.3	20.3	16.5	
5	Month	5 - 9	10	4	11, 12	1, 2, 3
	Average value	21.7	24.3	22.3	18.3	16.13
6	Month	5 - 9	10	4	11, 12	1, 2, 3
	Average value	21.7	24.3	22.3	18.3	16.13



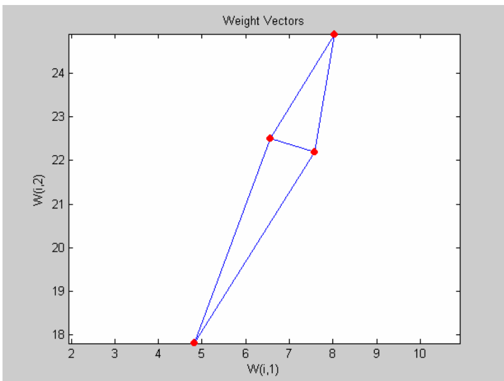


Figure 2. Training figures (three groups) with step 85 and step 100 respectively.

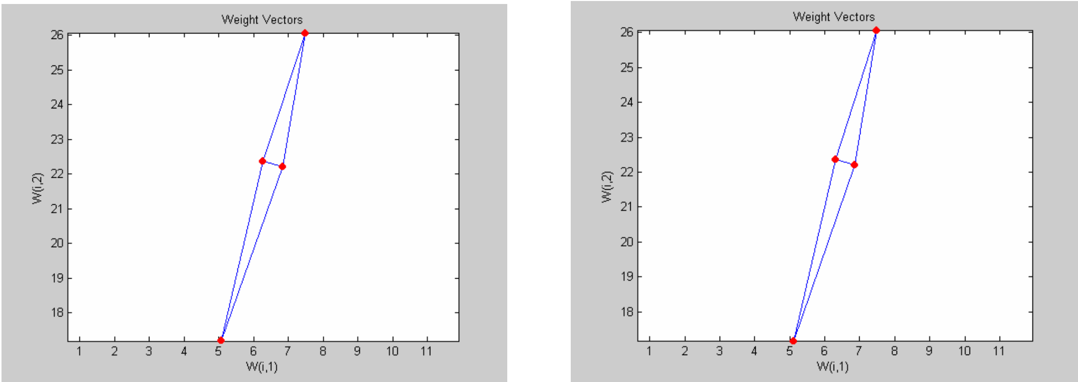


Figure 3. Training figures (four groups) with step 85 and step 100 respectively.

From the sub-section results above, we find that the effect is not good when it is divided into five or six groups. Although the value of the 12th temperature is among the fifth group, it is classified in the fourth group. Here we have to disregard the results. As for the situation of three and four groups, we find from the training figures (Figure 2 and 3) that the latter are much steadier and the effect is much better than any other. On the other hand, four groups are also consistent with the concept of “four seasons of the year”, which is according to nature. Thus we can determine the temperature magnitude and its duration. The designer could use these results for pavement or HMA design, which is more reasonable than if the designer decides on the design conditions. All other results of four groups are listed in Table 3. From Table 3 it can be seen that high temperatures occur from May to July every year and the temperature in other months is normal.

Table 3. Sub-section results of each item (ºC).

Item \ Group		First	Second	Third	Fourth
Extreme highest	Month	5 - 10	4	11	1, 2, 3, 12
	Average value	36.1	33.2	32.7	29.5
Average highest	Month	5 - 10	4	11	1, 2, 3, 12
	Average value	30.7	26.1	25.1	20.7
Average	Month	5 - 10	4	11	1, 2, 3, 12
	Average value	26.9	22.3	20.3	16.2
Average lowest	Month	5 - 10	4	11	1, 2, 3, 12
	Average value	24.3	19.6	16.8	12.9
Extreme lowest	Month	5 - 9	10	4	1, 2, 3, 11, 12
	Average value	17.3	11.7	8.7	2.5

The rainfall figures of the weather station in Guangdong province is shown in Table 4.

Table 4. Rainfall figures (mm).

Month	1	2	3	4	5	6	7	8	9	10	11	12
Average rainfall	27.2	43	58.1	133.3	247.3	326.6	327.4	346	269	96.2	35.9	23.5

In the same way, the grouping results are obtained (Table 5). It should be noted that when the grouping calculation was carried out, even if the group number was set to four, the computer still classified the rainfall data into three groups. This means that for existing data three groups may be the best choice.

The results in Table 3 indicate that in Guangdong province rainfall mainly occurs from May to September and is called the rainy season with a duration of about 5 months.

Table 5. Sub-section results of rainfall (mm).

Group		First	Second	Third	Fourth
Rainfall	Three groups	5 - 9	4	1 - 3 10 - 12	
	Average	303.2	133.3	47.3	
	Four groups	5 - 9	4	1 - 3 10 - 12	
	Average	303.2	133.3	47.3	

The monthly traffic distribution data from a highway toll station in Guangdong province is shown in Table 6.

Table 6. Traffic data (times).

Month	1	2	3	4	5	6	7	8	9	10	11	12
Traffic	74 680	88 900	75 464	72 710	70 368	63 844	68 722	74 458	73 756	74 488	67 658	72 210

The traffic data are divided into three, four, five and six groups with similar processing as above. In contrast to the training effects, it is much better when divided the data into four groups (Table 7). It can be seen that on this highway the data of the traffic distribution volume appears average. The heaviest traffic is in the first group and it appears from February to March, which is the period of the Chinese New Year. Fortunately, this period is not the hottest and rainiest season. However, the traffic in other periods of the year does not noticeably decrease.

Table 7. The subsection results of the traffic (times).

Group	First	Second	Third	Fourth
Results	2, 3	8, 9, 10	11, 12, 1	4, 5, 6, 7
Average value	82 182	74 234	71 516	68 911

4. CONCLUSIONS

The use of neural networks and MATLAB solves the question of sub-section or grouping of the pavement design parameters (temperature, rainfall and traffic). It is important to correctly use existing environmental and traffic data. In future research the effects of variations of the environment and traffic on pavement life will also be predicted by using extensive date bases. It may be possible to predict pavement performance over the entire life-span. In this way, the pavement will be guaranteed good performance and a long life.

5. REFERENCES

[1] Buch, N, 1997. Calibration of pavement design models using field data. Journal of Transportation Engineering, 123(2), pp 132–135.

[2] Ceylan, H, Tutumluer, E, and Barenberg, EJ, 2001. Modeling of concrete airfield pavements using artificial neural networks. http://citeseer.ist.psu.edu/256994.html.

[3] Ceylan, H, 2002. Analysis and design of concrete pavement systems using artificial neural networks. PhD thesis University of Illinois at Urbana-Champaign.

[4] Faghri, A and Hua, J, 1995. Roadway seasonal classification using neural networks. Journal of Computing in Civil Engineering, 9(3), pp 209–215.

[5] Huang, XM, 2000. Research into rut development based on annual road experiments. Journal of Southeast University (Natural Science Edition), 30(5).

[6] Lou, Z, Gunaratne, M, Lu, JJ and Dietrich, B, 2001. Application of neural network model to forecast short-term pavement crack condition. Journal of Infrastructure Systems, 7(4), pp 166–171.

[7] Neural Network Toolbox for MATLAB. http://www.mathworks.com/products/neuralnet/.

[8] Tarefder, RA, Luther White, L and Zaman, M, 2005. Neural network model for asphalt concrete permeability. Journal of Materials in Civil Engineering, 17(1), pp 19–27.

[9] Tarefder, RM and Zaman, M, 2004. Design and evaluation of neural networks for pavement rutting. http://www.pubs.asce.org/WWWdisplay.cgi?0412062.

[10] Wongputorn, P, Hullender, D, Woods, R and King, J, 2005. Application of MATLAB functions for time domain simulation of systems with lines with fluid transient. Journal of Fluids Engineering, 127(1), pp 177–182.

[11] Zayas, IY, Chung, OK and Caley, M, 1995. Neural network classification technique and machine vision for breadcrumb grain evaluation. The International Society for Optical Engineering, 2597, pp 292–308.