Probabilistic Forecasting Model of Pavement Performance Based on BP Neural Network

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ABSTRACT: Applying BP(Back Propagation) neural network to the forecasting of pavement performance promotes the idea that neural network can be combined with Markov random process, trains neural network with fix structure by making use of time series of performance state of pavement and thus establishes the neural network probabilistic forecasting model of pavement performance.

KEY WORDS: BP neural network, pavement performance, Markov random process, Time series.

1 INTRODUCTION

Forecasting of pavement performance provides basis for making decisions of pavement maintenance and plays a main part in pavement management system. Factors that influence the change of pavement performance, such as load, environment, material performance and maintenance level are variable in different degree, so changes are not fixed. Obviously, deterministic models can not assure reliable estimated outcome (Yao, 1993). Markov model would reflect the indeterminacy of these changes in the form of probability distribution, as a result, it has been widely used in the net management system. At present, transfer probability matrix is usually determined by deterministic regression equation or judging with experience, which greatly restricts its adaptability and accuracy, meanwhile, the assumed conditions of establishing Markov model lead to the limitation of the random process which is different from actual situation. With the development of pavement management system, gradual improvement of detecting system and constant accumulation of historical data, we begin trying to solve problem with new method. This paper attempts to combine the idea of Markov random process, make use of neural network technology, and aims at time series of pavement performance got by detecting objects to establish probabilistic forecasting model.

2 BP NEURAL NETWORK

Since 1980s', artificial neural network has been paid attention to again, which has gained rapid development and application in various fields with abundant pleasant achievements. BP network is a kind of forwarding one, which is more mature in technology and most widely used. It is named by learning and training process of the reverse spread of error .Its multilayer net structure provides physical basis for dealing with complex problems. It changes the I/O problem of samples into one about nonlinear optimization, by which changeable parameters in the net can help to get more precise solutions. In recent years various studies have adopted artificial neural networks and BP algorithms, in brief, these techniques aren't discussed in detail here.

3 PAVEMENT PERFORMANCE STATE TRANSFER FUNCTION

Random process views pavement as a system (process) with several states. Influenced by outer conditions, pavement system changes constantly. As a result, pavement state transfers subsequently. Random process abstracts the stimulation of this transfer into state-transferring probability matrix. Theoretically, the state of pavement in certain period is not only related to its past history but its various changes in different period, that is

$$x^T(t+1) = a_t x^T(t)P(t) + a_{t-1}x^T(t-1)P(t-1)P(t) + \ldots + a_0 x^T(0)P(0)P(1)\ldots P(t)$$

$$= \sum_{i=0}^{t} \mathbf{a_i x(i)} \prod_{k=i}^{t} \mathbf{P(k)} \tag{1}$$

Where: a_i : the state influencing coefficient in each period

If non-aftereffect or time-postulation is introduced, this random process would become Markov's. Then (1) can be simplified to:

$$x^T(t+1) = x^T(t)P \quad \text{or} \quad x^T(t_0+t) = x^T(t_0)P^{\,t} \tag{2}$$

Assuming conditions used in Markov models simplify and visualize the model, but in many cases they are not tatty with changing regularity of the real system. While models in the equation (1) are closer to the actual situation but hard to realize. Therefore, in the author's opinion, quantizing changes of system's state only by transfer matrix will badly restrict the complication of problems and accuracy of model establishment, then introducing new technology through new methods should be considered.

First, we regard these changes as a discrete time series equation and abstract the state-transferring process to a function F, and then get Eq. (4):

$$\{ x(0), x(1), \ldots, x(t), \ldots \} \tag{3}$$

$$x(t+1) = F(x(t)) \tag{4}$$

In Markov's model, this function is realized by linear transferred probability matrix, Eq. (2). Actual system does not always change in an invariable linear way, so nonlinear mobile BP network is used to work this state-transferring probability postulating that the node number of both output and input are the dimensions number of state space, then network become the reflection from R^n to R^n.

$$G: R^n \rightarrow R^n, Y=G(X) \quad X,Y \in R^n \tag{5}$$

We can generate a net mapping G by collecting and training according to sample set (x(t), x(t+1)) of time series to realize the F function which has finished its state transfer in the random process.

4 BP NEURAL NETWORK PROBABILISTIC MODEL ESTABLISHMENT

Pavement performance has many aspects. Data information duplicated yearly records changing regularity of research objects, based on which BP neural network probabilistic model is established by using the function mentioned above. Considering current standards classify estimation grades of performance into five classes, which correspond to five-dimension state vector space. The following will detail the establishing process of the five-dimension neural network probabilistic model.

4.1 Establishing Sample Set

Assuming that in a certain district there are Q sub-objects, one of whose historical performance state composes separately Q time series:

$$\{x_1(1),x_1(2),\ldots,x_1(TS)\};\{x_2(1),x_2(2),\ldots,x_2(TS)\};\ldots;\{x_Q(1),x_Q(2), \ldots, x_Q(TS)\} \quad (6)$$

Among these sets $x_i(t)=[\, x_{i1}(t), x_{i2}(t), x_{i3}(t), x_{i4}(t), x_{i5}(t)]^T$ is the state vector in the i^{th} sequence of t^{th} step length. If each pavement section is viewed as a sub-object, the states inside the sub-objects are related to each other. Then make it a sequential structure, in which each sub-object is independent and concurrent structure among each sequence will form a cell array (7). The more pavement section's situation sequence you mastered and the longer the time step is, the more all-round information of objects as a whole you will get. This structure will help renew the model.

The Qth sequence

$$\{[x_1(1), x_2(1), \ldots,x_Q(1)], [x_1(2), x_2(2), \ldots,x_Q(2)],\ldots, [x_1(TS), x_2(TS), \ldots,x_Q(TS)]\} \quad (7)$$

The first sequence

This array becomes a sample set data bank of pavement performance, among which ($x_i(t)$, $x_i(t+1)$) is a sample group of input and output on net. After training and learning, this net system will become an entire probabilistic model by searching for the regularity adapting to the whole of the objects.

4.2 Network Design

To a special problem, there is no strict standard to define the neural network so far. Although some literatures (Liao, 1998, Li , 1998, Jiao, 1992) provide experienced instruction, usually certain trial calculating is necessary, by which BP structure showed in Figure 2 is assured. The input terminal are divided into five input nodes by five-dimension state vectors: the first hidden layer has 15 nodes ($H^{(1)}=15$), each of which uses sigmold transfer function f_1 (Figure 1-a); the second has 5 nodes ($H^{(2)}=5$),using sigmold transfer function f_2 as the first layer working and it outputs $o^{(2)}$---output state vector wanted; and the third, a controlling layer, has only one node using liner transfer function f_3(Figure 1-b). This node is assumed to be connected with nodes in the second layer with the weight of $w_{1i}^{3,2}=1$(i=1, 2… 5), which is used to guarantee the elements' summer of state vector that the second layer outputs is 1.

4.3 Network Training

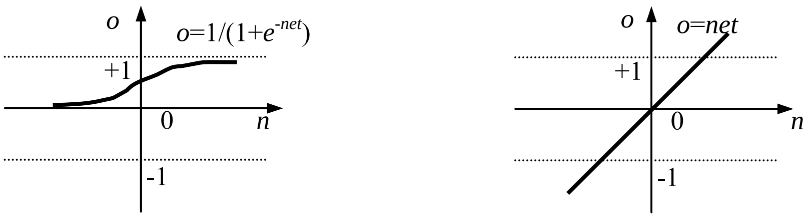
Training the determinate network with sample set of model-establishing objects and adjusting continually the indeterminate parameters (weight W and bias b),we can get an unshaped probabilistic network model when these parameters gets optimized. The specific algorithms are various and cover lots of technique problems. In addition, because of the limitation of the paper, we will not refer to them but focus on batch BP algorithm. After the training reaching precision expected and the net parameters being defined, neural network becomes probabilistic model of pavement performance. The effect of forecasting can be known through simulated experiment which feeds back information used to further instruction for network in order to train optimized mode.

$$net_i = \sum_{j=0}^{n} w_{ji} x_j \tag{8}$$

$$u_i = f(net_i) \tag{9}$$

$$o_i = g(u_i) = h(net_i) \tag{10}$$

When neural networks have not intrinsic state, that $o_i = u_i$, $h = f$. The f was called transfer functions



(1-a) (1-b)

Figure1: Transfer function

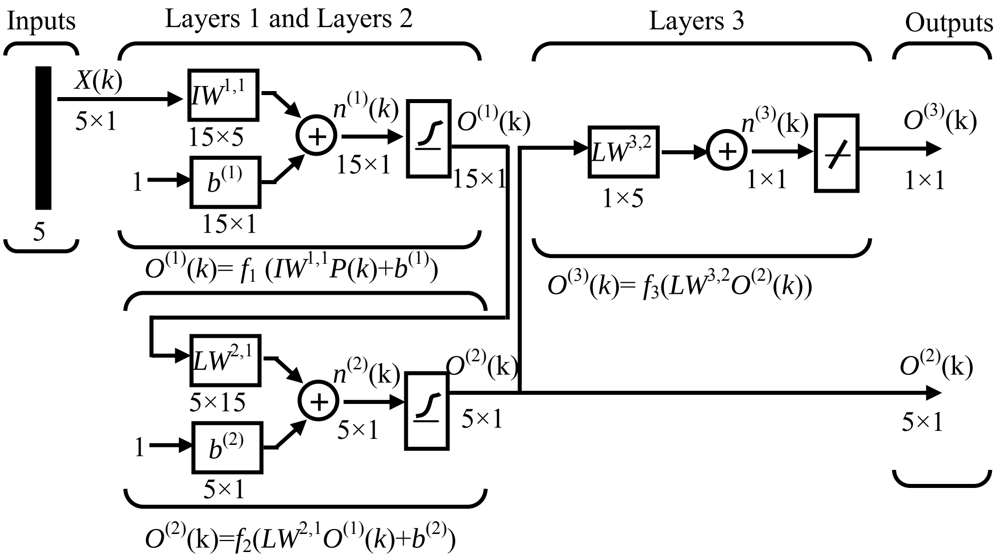


Figure2: Structure information of BP neural networks random chain model

5 ANALYSIS OF EXAMPLES

Literature (Chenjie, 1999) established decay equation by means of regression analysis according to pavement condition index (PCI), data of Dalian section of Shen-Da expressway in 1996-1997. This equation is used to forecasting and analyzing PCI of per kilometer's pavement from 1998-2002.

$$PCI=100\ \{1-\exp[-(10.8/Y)^{1.2}]\} \tag{11}$$

This paper takes this part of data as real system data information of section K307-K363 to form data bank. Divide it into five sub-objects and determine each object's state vector time series according to state space I, then take it as a training set of neural network model. The optimized network will forecast the whole PCI condition of section K307-K363. The forecasting can be classified two kinds: one step forecasting (forecasting next year's state vector based on actual condition of each year) and recursive forecasting (forecasting next year's based on last year's outcome). Meanwhile, for comparison, function (11) is used to work out Markov's transfer probability array, with which the same forecasting work has done. Forecasting errors of these two models in each year are showed in table 1 and 2; errors of state vector are worked out by equation (12).

$$\Delta = \frac{\sqrt{(x_1 - x_1^0)^2 + (x_2 - x_2^0)^2 + (x_3 - x_3^0)^2 + (x_4 - x_4^0)^2 + (x_5 - x_5^0)^2}}{\sqrt{(x_1^0)^2 + (x_2^0)^2 + (x_3^0)^2 + (x_4^0)^2 + (x_5^0)^2}} \tag{12}$$

Table1: Error of Section K307-K363 Forecast by Neural Network's Probability Mode

year	1997	1998	1999	2000	2001	2002	Σ
One step	0.3912	0.1201	0.1475	0.1910	0.1204	0.2377	1.2081
Recursive	0.3912	0.2287	0.1879	0.3084	0.3344	0.4138	1.8644

Table2: Error of Section K307-K363 Forecast by Markov's Probability Mode

year	1997	1998	1999	2000	2001	2002	Σ
One step	0.0988	0.3167	0.2802	0.2441	0.1398	0.1423	1.2219
Recursive	0.0988	0.3638	0.4855	0.6044	0.6592	0.6842	2.8959

Table3: Traditional Markov Probability Transfer Matrix (regression precision s^2=2)

No.	1	2	3	4	5
1	0.9553	0.0447	0.0000	0.0000	0.0000
2	0.0000	0.9585	0.0415	0.0000	0.0000
3	0.0000	0.0000	0.9952	0.0048	0.0000
4	0.0000	0.0000	0.0000	0.9998	0.0002
5	0.0000	0.0000	0.0000	0.0000	1.0000

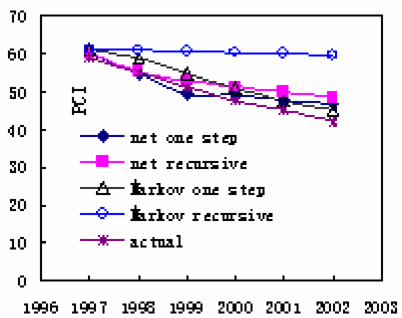


Figure3: Expected curves of pavement states in each year

Curves in Figure 3 are drawn according to the expectation worked out with middle value of state vectors which are forecast by each model in each year. Comparing Figure 3, Table 1 and Table 2, neural network probabilistic model forecasts more precisely than Markov's and coincides better with actual changing tendency, which indicates that as long as having plenty of storage cells, the neural network can in its entirety master the variation of regularity of pavement performance at different stages, and then solve problems in a dynamic way. Markov model, precise for just one year but goes far away from the expected curve if forecasts for many years. Experiments show that the higher the precision with which to work out Markov's transfer probabilistic array, the lower precision of forecasting will get. Contrarily, when s^2=17, high precise forecasting would be got. This indicates that decay function directly determines suitable objects of Markov's model and its forecasting precision. At the same time, in the process of establishing probabilistic array, static and normal method may not be tatty with the actual situation and is usually difficult to get an accurate determinate equation, which is the main cause that results in error.

6 CONCLUSION

Markov probability model is based on determinate function to statistic regression, which greatly restricts it. In the past, necessary regression data was got by transferring space to time, but to put space into proper time depends on experiences. So errors are unavoidable. Neural network can have a better solution to this problem. It researches regularities of states changing by training decay time series of pavement performance which are taken as samples without determinate functions and specific time.

Markov model introduced non-aftereffect and time-follow assuming conditions, which are not equal to the solution of actual dynamic problems. While neural network can study and memorize dynamic information of data in order to get reliable simulate effect. This feature is helpful to further accurate research for the road system and meanwhile related departments are demanded to pay more attention to collecting data of pavement performance.

Neural network has the characteristic of dynamic in real time and powerful ability of collection to information and will make up for each other's weakness if combined with random process of pavement performance, which is a valuable research on the change of pavement performance. Because of this, this paper makes Markov random process progress based on neural network both in theory and in practice

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