RAILWAY TRACK PERFORMANCE ANALYSIS USING NEURAL NETWORKS

Feng CHEN
Associate Professor
Faculty of Civil & Architecture Engineering
Northern Jiaotong University
Beijing, 100044, P. R. China
Fax: 86-010-63240217
E-mail: fengchen@center.njtu.edu.cn

Luis FERREIRA
Associate Professor
Aust Housing & Urban Research Institute &
School of Civil Engineering
Queensland University of Technology
GPO BOX 2434 Brisbane 4001, Australia
Fax: 61-07-38641827
E-mail: l.ferreira@qut.edu.au

Jiang ZHANG
Research Associate
Faculty of Civil & Architecture Engineering,
Northern Jiaotong University,
Beijing, 100044, P. R. China
Fax: 86-010-63240217
E-mail: jackzj@netease.com

Abstract: This paper describes the use of an artificial intelligence approach to analise track data obtained from field measurements. A neural network approach developed and applied to data from a track recording vehicle. The paper describes relevant software that can be used to intelligently classify patterns in the measured data so as to give a reasonable evaluation of track performance. The paper discusses the artificial neural network approach, the data structure for a track recording vehicle and introduces the algorithmic of the selected neural reverse propagation network. The paper also describes the required analysis, the general plan and the modular division of the intelligent processing software applicable for track measuring data. Finally, the paper analyzes a data set from the Jingjiu rail line in China.

Key words: artificial neural networks, track recording vehicle, BP algorithmic, railway track.

1. INTRODUCTION

Railway track is one of the most critical railway infrastructure assets, given its potential to impact on railway operating costs and on the level of customer service which rail is able to provide. Measurement of track performance using manual or automatic inspection means, is a key component of any track asset management system.

A review of computer aided rail track maintenance and renewal systems identified nearly 20 tools of varying scope currently used in different countries. The most comprehensive maintenance decision support model is the MARPAS system of British Rail (see Hope, 1992, for example), MARPAS accounts for engineering factors in track maintenance through degradation models based on relationships using axle loads, speeds, and train consist. Some other models which require a readily usable database of a system's characteristics are as follows:

Burlington Northern (BN) has its Advanced Railroad Electronics System (ARES) developed primarily for train scheduling (Ferguson, 1991) but it also stores details of bridges, track geometry, and rail characteristics; BN also has its Track Management System (TMS) used for forecasting track condition (Hide et al, 1991). The Track Management Advisory System (TMAS) of Canadian Pacific (CP Rail) requires a database of track segments (Roney and McIlveen, 1991). Trask and Fraticelli, 1991, reported on Canadian National Rail's (CNR) Track Degradation Model (TDM) which uses the engineering department's databases that contain physical plant and track component condition information (visual and automated). TRACS, the Total Right-of-way Analysis and Costing System described by Martland and Hargrove, 1993, is a generic system which requires the user to have information about specific equipment and track characteristics if it is to be applied to a particular route. ECOTRACK has been developed in Europe by the International Union of Railways together with the European Rail Research Institute (ERRI, 1995). It is a decision support system for track renewal and maintenance based on expert systems technology.

US based comprehensive axle load studies led to the development of models which consider engineering and business factors in trading off increased maintenance costs against equipment savings (Hargrove, 1990; Kalay, 1995). Most of these models are based upon historical data obtained from local measurements of track condition and of maintenance activity and costs, expected lifetimes of track components, and locally developed algorithms which extrapolate the data for future maintenance planning.

An integrated track degradation model has been developed in Australia (Zhang, et al., 1997). This integrated model is used to predict track degradation by mechanistic analysis and to aid track maintenance planning based on degradation analysis and maintenance condition limits within a set of given resources and overall maintenance budget.

Currently, most of the track measurement and data collection and analysis is undertaken manually. This usually requires large amounts of labour, material and time for raw data acquisition, sorting and analysis. This is a low efficiency and high labour intensive work. In addition, the results are usually subjected to a high level of operator subjectivity and human error leading to high levels of subjectivity and uncertainty in the results. In order to improve the working efficiency of data processing, reduce the uncertainty factor caused by human error and enhance the objectivity and standardization, an improved system is proposed here.

To that end, the paper deals with the application of neural networks in the analysis of the track geometric status. This artificial intelligent approach can simulate the thinking mode of the track maintenance operator/planner and can be used to solve the problem encountered by pattern identification and clustering.

2. NEURAL NETWORK MODEL FOR AUTOMATIC CLASSIFICATION OF TRACK DATA

2.1 Model Description

Classification of the data collected by the track recording vehicle is essentially a complex non-linear mapping process, the mapping can be described as follows:

$$D \rightarrow T \tag{1}$$

Where D represents the data set collected by the track recording vehicle, i.e. the statistic result of the track section which can be described as:

$$D=\{(d_1,d_2,d_3.....d_7)\,|\,d_i=(ds_{i1},ds_{i2},ds_{i3},ds_{i4}),ds_{ij}\in(0,+\infty),i=1\sim 7,j=1\sim 4\} \tag{2}$$

Each element of the set D is a 7-dimension vector, representing the profile, gauge, cross-level, warp, vertical acceleration and horizontal acceleration respectively. Each vector is a 4-dimention vector representing 4 classes. Our aim is to classify the 7 set data.

T represents the classification set with 4 classes, namely:

$$T=\{t_1,t_2,......,t_4\} \tag{3}$$

The four classes indicate the following four status: qualified; relatively qualified (repair should be done accordingly); not qualified (repair must be done); and severe damaged (repair must be done immediately).

Where, f is the mapping of D to T, we need to find the relationship of this mapping and simulate it by the mechanism of artificial neural networks.

2.2 Encoding of Data Information

The above descriptions shows clearly that to find out the mapping of set $D\in R^{28}$ to set $T\in\{0,1\}^4$, you should only make the raw data of set D as the input of the network, let alone the meaning of the data. However, the data of the T set is to be coded, as for the mapping function f of the BP network is a S-shape and its domain is known as [0,1], so one string of four digital binary is used to encode the element of set T. The class I is indicated by 1000, class II by 0100, class III by 0010 and so on. Thus, the translation of the relevant value of the binary string will become the value of the set T.

2.3 Neural Network Model

A neural network can be easily established when the issue is well characterized and encoded. Here we introduce a network with 28 input and 4 output nodes, after testing once and again, one layer of implication node is selected, which has 8 neurons.. Figure 1 shows the topological structure of this network.

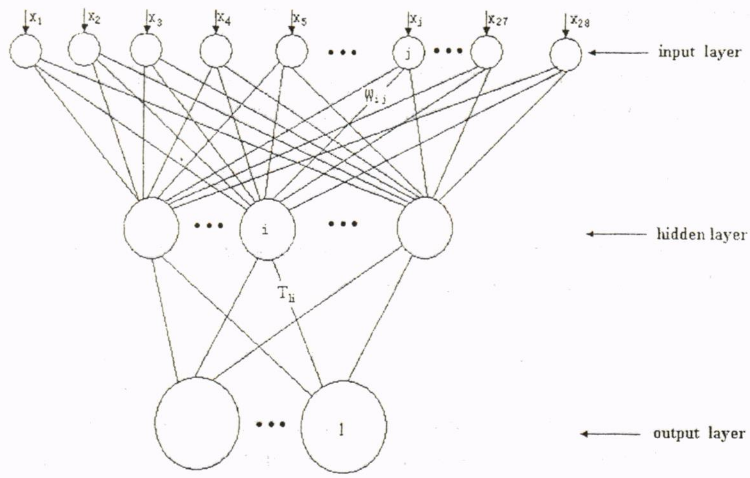

Figure 1. Topological Structure of This Network

This is a BP network, with the input layer on the top and the output layer on the bottom. Each layer is fully inter-connected with the upper and the lower layers. Each neuron adopts an S-shape function as the mapping function of input and output. The learning algorithmic is the reverse propagation.

2.4 Mathematical Analysis for The Network Structure

Actual output of output node:

$$o_l = f(\sum_i T_{li} y_i - \theta_l) = f(net_l)$$
$$net_l = \sum_i T_{li} y_i - \theta_l \quad (4)$$

Output of hidden node:

$$y_i = f(\sum_j w_{ij} x_j - \theta_i) = f(net_i)$$
$$net_i = \sum_j w_{ij} x_j - \theta_i \quad (5)$$

Where x_j = output of the jth node of input layer; x_{ij} = weight of the interconnection between node i of the input layer and node j of the hidden layer; and y_i = output of the node i of the input layer, T_{li} = weight of the interconnection between node j of the hidden layer and the node of output layer.

The error, E, is defined as the sum of squared differences between the actual network output (o_l) and the target output (t_l) at the output layer:

$$E = \frac{1}{2}(t_l - o_l)^2 = \frac{1}{2}(t_l - f(\sum_i T_{li} f(\sum_j w_{ij} x_j - \theta_i) - \theta_l))^2 \quad (6)$$

This error is used to adjust the weights of the connections feeding into the output layer by using the relationship:
Where

$$T_{li}(k+1) = T_{li}(k) + \Delta T_{li}$$

$$\Delta T_{li} = -\eta \frac{\partial E}{\partial T_{li}} = \eta \delta_l y_i \quad (7)$$

and

$$\delta_l = (t_l - o_l) * f'(net_l)$$

Similarly, adaptation of weights for the hidden layer of processing elements is given by:
Where

$$W_{ij}(k+1) = W_{ij}(k) + \Delta W_{ij}$$

$$\Delta W_{ij} = -\eta' \frac{\partial E}{\partial W_{ij}}$$

$$\frac{\partial E}{\partial W_{ij}} = -\delta'_{li} x_j \quad (8)$$

$$\delta'_i = f'(net_i) \delta_l T_{li}$$

The procedure for adjusting the threshold term θ
For the output node:

$$\theta_l(k+1) = \theta_l(k) + \Delta\theta_l$$

$$\Delta\theta_l = \eta \frac{\partial E}{\partial \theta_l} = \eta \delta_l \quad (9)$$

For the hidden node:

$$\theta i_i(k+1) = \theta_i(k) + \Delta\theta_i \quad (10)$$

$$\Delta\theta_i = \eta' \frac{\partial E}{\partial \theta_i} = \eta' \delta'_i$$

Where, k is a repeat number, θ_l, θ_i = thresholds for the node l in the output and node i in the hidden layer.

We use the sigmoid function:

$$f(x) = \frac{1}{1-e^{-x}} \tag{11}$$

Its derivative is:

$$f'(x) = f(x) * (1 - f(x)) \tag{12}$$

Thus

$$f'(net_k) = f(net_k) * (1 - f(net_k)) \tag{13}$$

For the output node:

$$\begin{aligned} o_l &= f(net_l) \\ f'(net_l) &= o_l(1 - o_l) \end{aligned} \tag{14}$$

For the hidden node:

$$f'(net_i) = y_i(1 - y_i) \tag{15}$$

Total error E, for the network and all patterns p

$$\begin{aligned} E_K &= \sum_{k=1}^{p} e_K \le \varepsilon \\ e_K &= \left| t_l^K - o_l^K \right| \end{aligned} \tag{16}$$

Where, p is the number of training patterns (x (k)), t is target output, a training pair is (x (k), t (k)).

2.5 Network Implementation

Implementation of the network is divided into two stages, namely: training and running. During the training stage, some of the collected and classified data are encoded using the method described above and input into the network for repeated iterative computation until the criteria is satisfied. All the information of the trained network are stored in the weight section of the network. During the running stage, all the data obtained are input into the input layer of the neural network to calculate the relevant output values, using the weight value of the trained network. It should be noted that the current output value of the network is the data in section [0,1]. Since the S-shape function is used to compress any of the real numbers into the [0,1] section, we need to round off these decimal fractions to 0 or 1 to determine the corresponding class for each input data group.

3. TRAINING FOR THE PRACTICABILITY OF THE ARTIFICIAL NEURAL NETWORK

By means of the BP network model mentioned above, track data collected on the Jingguang and

Jingjiu railway lines by the track recording vehicle, have been used to train the network. The training is terminated until the result is satisfied. In application, the data is to be used as an input to the neural network. After estimation, the output is a classification mode. It should be noted that the network output has applied the so-called S-shape function. Therefore, the result is the decimal fraction between the [0,1] groups. At this moment, according to the principle of "picking up the big one", we select the maximum value from the four values and make it as 1, and other values as 0. Thus the final result is a 4-dimension binary string mapped to a final comment based on our encoding mode.

The network should be trained before application. In order to reach the accuracy of classification and considering that the output should be the value in the [0,1] section, the output error of each neuron selected should be controlled around 0.2 and must be less than 0.3. According to the calculation formula of the error, the total error of each sample should be 0.08. We select groups of track data collected by the recording vehicle in the upper direction of the Jingguang line and the lower direction of Jingjiu line for training. Each training uses 2011 samples, totalling 14450 trainings. Finally, the average error of the network has been reduced to the above value. The relationship between the training times and the sample error is shown in figure 2.

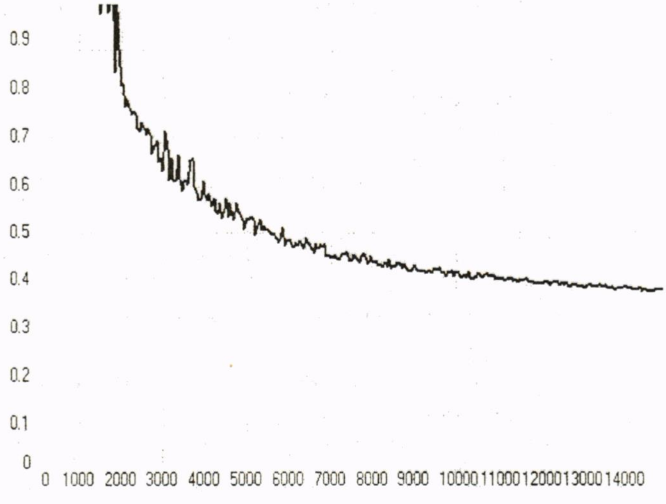

Figure 2. Training Times and Sample Error

In Figure 2, the X-axis is the training time, Y-axis is the square root of the average value of each sample error multiplied by 2.

4. AN EXAMPLE

Track data collected by a recording vehicle in the upper direction of the Jingjiu line, is taken as the example for the analysis which follows. The pattern of the raw data is shown as:

Km summary		Profile			Alignment			Gauge			Cross-level			Warp			Vertical accel.			Horizontal accel.			
km		C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	
0017	N	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
		2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	(V=063)
0016	N	2	0	0	0	0	0	0	0	0	10	0	0	2	0	0	0	0	0	0	0	0	
		2	0	0	0	0	0	0	0	0	22	0	0	2	0	0	0	0	0	0	0	0	(V=061)
0015	N	14	3	0	0	0	0	0	0	0	7	1	0	1	1	0	2	0	0	0	0	0	
		16	10	0	0	0	0	0	0	0	12	3	0	1	2	0	4	0	0	0	0	0	(V=056)
0014	N	4	0	0	0	0	0	0	0	0	7	1	0	5	3	0	1	0	0	0	0	0	
		6	0	0	0	0	0	0	0	0	11	9	0	5	4	0	1	0	0	0	0	0	(V=047)

By running the intelligent analysis software for track data, evaluation information for each section by is obtained as shown in Table 1.

Table 1. Evaluation Information – An Example

Location	Evaluation
0002	A lot of exception index in this section, in time repair is suggested! Main exception index: profile, length: 39
0003	Light exception index in this section, repair is not a must! Main exception index: profile, length: 18
0004	Light exception index in this section, repair is not a must! Main exception index: cross-level, length: 44
0005	Light exception index in this section, repair is not a must! Main exception index: cross-level, length: 30
0006	Light exception index in this section, repair is not a must! Main exception index: Horizontal acceleration, length: 0
0007	Light exception index in this section, repair is not a must! Main exception index: profile, length: 11
0008	Light exception index in this section, repair is not a must! Main exception index: profile, length: 13
0009	Light exception index in this section, repair is not a must! Main exception index: profile, length: 16

The general evaluation of the complete section gave the following results:

- General evaluation: Exception degree of this section is not very severe;
- Main exception index is the profile;
- Total length of each class: Class I: 67, Class II: 27, Class III: 0, Class IV: 0
- Average value of each exception class in this section is shown is Table 2.

The statistic curve of the exception section derived from the systematic computation is shown in Figure 3.

Table 2. Exception Class Values

Exception index	Exception class	Average exception times	Total exception length
Profile	1	7	167
Profile	2	0	27
Alignment	1	0	0
Gauge	1	0	0
Cross-level	1	4	144
Cross-level	2	0	25
Warp	1	1	21
Warp	2	0	5
Vertical acceleration	1	0	5
Horizontal acceleration	1	1	21
Horizontal acceleration	4	0	0

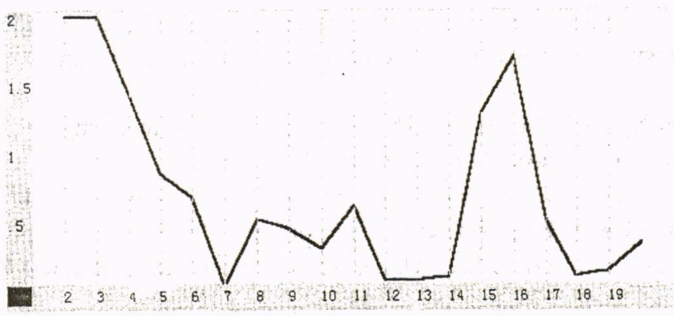

Figure 3. Statistic Curve for Exception Section

In Figure 3, the X-axis is the mileage of the measuring point, the Y-axis is the exception degree of the measured point. Figure 6 illustrates clearly the severe exception location of the track.

Comparison between our analysis result and the previous statistic result of the data, shows that the classification result of the artificial neural network and that of the statistic analysis is basically the same.

5. CONCLUSION

The automatic processing approach for the track measuring data discussed in this paper, it has following advantages:

- The system has high fault tolerance. This is the common characteristic of the artificial neural network system. The system can ignore unreasonable input information to ensure its proper operation;
- The system has high flexibility. In order to change the existing classification regulation, we

need only to re-train the present network;

- The result is given in the form of comment. It is better than the pure value used currently, more visible and more user-friendly; and
- The output formats adopted for the system provide easy management and evaluation of the data.

REFERENCES

Zhang, Y. J., Murray, M. H. and Ferreira, L. (1997a) Railway track performance models: degradation of track structure. **Road and Transport Research,** Melbourne, Vic., 6(2), 4-19.

Faghri., A., Martinelli., D. and Demetsky, M. J. (1997). Neural Network Applications in Transportation Engineering. **Artificial Neural Networks for Civil Engineers**: Fundamentals and Applications, pp, 137-159.

Hope, R. (1992). MARPAS relates track costs to traffic. **Railway Gazette International**,. Reed Business Publishing, Sutton, UK, Vol.148 No.3 pp.147-150.

Ferguson, D.C. (1991). The impact of ARES traffic planning on MOW operations. **Preprints of the International Heavy Haul Workshop**, International Heavy Haul Association, Vancouver, Canada, pp.118-120.

Hide, H., Jang, K. And Nykoluk, M. (1991). TM$ - a practical track maintenance planning and control system. **International Heavy Haul Workshop**, Vancouver.

Roney, M.D. And Mcilveen, E.R. (1991). Predicting the future for programmed track maintenance on CP rail. **International Heavy Haul Workshop**, Vancouver.

Trask, E. R. and Fraticelli, C. (1991). The track degradation model. **International Heavy Haul Workshop**, Vancouver.

ERRI, (1995), ECOTRACK, Decision support system for permanent way maintenance and renewal, Report 2, European Rail Research Instititute D 187, Utrecht.

Hargrove, M.B. (1990). Economics of Heavy Axle Loads. **Proceedings of Workshop on Heavy Axle Loads**, Paper 23, International Heavy Haul Assocication, Pueblo, USA, pp.23.0-23.7.

Kalay, S.F. (1995). Heavy axle load (HAL) overview. **1st Annual Research Review,** American Association of Railroads, Pueblo, USA, Vol.2, pp.367-394.

Hua, J. and Faghri, A. (1994). Application of Anns to IVHS. **73rd Annual Meeting, Transportation Research Board,** National Research Council, Washington, D.C.