A Neural Network Model for Calculating Metro Traction Energy Consumption

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Abstract. Due to the difficult of parameters calibration in existing three metro traction energy consumption models, this research first develops a gray related hierarchy analysis model to determine the main factors mainly considering the operational data. Furthermore, a traction energy consumption model based on neural network model is accordingly proposed to calculate the traction energy consumption of metro of one line due to statistics data which are gained by gray related hierarchy analysis model. It is found that the relative error of predicted values and actual values is a maximum of 8.61%, a minimum of 0.01% and the average relative error is 3.12% by using the operation data from one of Beijing subway lines. Results indicate that the model can predict traction energy consumption of a single metro line with high accuracy.

Introduction

There are several factors can impact on power consume of train operation, such as driving tactics of the train, alignments of the track, attributes of the train, operation management of the rail transport system, natural environment and others[1]. The need for reasonably find out primary ones among them, and then correctly calculate the traction energy consumption becomes urging. As far, there are three existing energy calculation models of urban transit system which are: the regression analysis model based on data (MBD) [2-4], the calculation model based on electric power (MBE) [5-7] and the calculation model based on kinematic methods (MBK) [8-11]. Most of them aim at traction consume of traditional or high speed train but urban railway. The characteristics of urban railway traffic system are short distance between neighboring stations; frequently start/stop and relative low speed, and all these should be taken account of for its measure model of traction consumption.

According to the characteristics of existing three kinds of metro traction energy consumption models, it is necessary to search a new model for calculating metro traction energy consumption. In this paper, based on factors analysis traction power consumes, mainly factors are ranked according to the gray relation. Moreover, measure model of urban railway system power consume based nerve net are set up, combining data from railway company. For later research, the precision of these models are well evaluated.

This paper is organized as follows. Section 2 describes energy consumption factor and the mathematical expression of the traction energy consumption model based on neural network. In section 3, a numerical example is presented for the model. Section 4 summarizes the paper.

Modelling

Grey Relational Degree Analysis of Energy Consumption Factors

There are several factors that differently influence energy consumption level. If they are all imported to a model, it will lead to too long time of network practicing and low efficiency. Only choosing these prominent factors can improve net practicing. Considering these prominent factors normally has
partly unknown information, grey relational degree analysis is used to rank them by calculating their relational degree. Main factors that influence urban rail transit traction energy consumption system are chosen and partly unknown, so this system is a typical gray system. Gray relational degree analysis model of urban rail transit traction energy consumption system is formulated in which the traction energy consumption of one urban mass transit line has been studied.

According to the results, it is concluded that the importance order of urban transit train traction energy consumption factors is, average passenger flow per day (its relational value is 0.86) > techno-velocity (0.72) > average temperature per month (0.68). The first one is important factors; the latter two ones are distinct factor. There are 29 groups of groups of samples that its rational vales are greater than 0.80, of all average passenger flow 41 sample. Then it is clearly more than the numbers of 12 sample of techno- velocity or 7 sample of average temperature per month.

Qualitative and quantitative analyses prove train traction energy consumption has relationship with several factors. The factors can be used to determine network structure parameters and input variables at the neural network modeling, the next stage.

**Traction Energy Consumption Model Based on Neural Network**

Manpower neural network is one of systems can study and sum up via known data and experiments. In this paper, system energy consumption model is built using neural network method and operational data of urban transit traffic, and is evaluated.

MLP model, short for Multi-Layer Perceptron model, is made up of input layer, output layer and hidden layer. In theory, neural units of each layer and its neighbor layer link each other and a model may have not only one hidden layer. But in fact, the MLP model with only one hidden layer can supply enough hidden neural units. In this paper, the MLP model with three layers, mean one input, one hidden and one out layers, is suggested.

**Input Layer.** The number of input neural units is equal to the number of input variables in the model. The value of passenger flow per day is obvious relative with average fully loaded ratio for same transit line, so one of these two factors can be chosen as the input variable according to its relationship degree to transit line unit energy consumption.

**Hidden Layer.** The number of neural unit is very important to model performance. As so far, there is no analysis method can effectively ascertain the number of neural unit. But different experience methods can supply useful ways. In this paper, the rule describing emotional quotient researched by Ward is commended.

\[
N_h = \frac{N_{in} + N_{out}}{2} + \sqrt{N_s}
\]  

where as,

- \(N_{in}\) is the number of neural units at input layer;
- \(N_h\) is the number of neural units at hidden layer;
- \(N_{out}\) is the number of neural units at output layer;
- \(N_s\) is the number of practice groups of samples;

**Output Layer.** The number of output neural units is equal to the number of output parameters in the model. The output of model is the value of transit line unit traction energy consumption (kWh/100 c-km). The data is supplied by metro company.

**Numerical Examples**

During the single transit line energy consumption calculation, the characteristics of transit line and train are not the input variables because of their steadiness. In this paper, there are three the input variables in the energy calculation model, as average passenger flow per day, techno- velocity and average temperature per month.
Data Collection
The model data is of a subway line at a big city in China during January, 2010 and May, 2013.

MLP Modelling
Based on 41 month-data of this transit line, there are 41 group groups of samples to neural network modelling. 35 group groups of samples are used to set up neural network model and the rest 6 group groups of samples are used to evaluate model.

In the MLP model, $N_{in}$, the number of neural units at input layer is 3. $N_{out}$, the number of neural units at output layer is 1. $N_s$, the number of practice groups of samples is 35. It is concluded that $N_h$, the number of neural units at hidden layer is 8, according to Eq. 1.

Training Model
Taken of advantages of software MATLAB, the model has been trained with 3 input variables and 8 hidden variables. Assumed relational parameters for neural network, a variable and its convergent values 0.0001 are appointed at output layer. There are 500,000 train epochs. Considering the results are random by neural network, the ideal forecast performance must be the best one comparing to the other train results. The best performance is seen in Figure 1, the researching process is seen in Figure 2.

From Figure 1, it is concluded that there are rarely error between the forecast and operation values. In 6 groups of samples, the forecast value is slight higher than operation one in the 1st and 2nd groups,
is lower in the 3rd and 6th groups, and is almost at 4th and 5th groups. It is showed that the model has a well application. From Figure 2, the best performance is 0.00064934 at epoch 14282.

To validating the capability of trained model, it is necessary to evaluating it with the statistical method. During testing the trained MLP model, target values and forecast value are compared, with the relative error $\delta$ as index, seen in Eq. 2.

$$\delta = \frac{|p_i - t_i|}{p_i} \times 100\%$$

(2)

where as, $p_i, t_i$ are operation value and forecast value.

Relative errors are used to evaluating the model precision, and the values of consumption model evaluation results of single-line are seen in Table 1.

<table>
<thead>
<tr>
<th>Serial number</th>
<th>Operation value</th>
<th>Forecast value</th>
<th>Deviation</th>
<th>Relative error(%)</th>
<th>Average relative error(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>173.70</td>
<td>181.3885</td>
<td>7.69</td>
<td>4.43</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>165.90</td>
<td>170.9051</td>
<td>5.00</td>
<td>3.02</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>201.32</td>
<td>196.472</td>
<td>4.85</td>
<td>2.41</td>
<td></td>
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<tr>
<td>24</td>
<td>177.38</td>
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<tr>
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<td>221.08</td>
<td>220.5719</td>
<td>0.51</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>36</td>
<td>164.33</td>
<td>150.1884</td>
<td>14.14</td>
<td>8.61</td>
<td>3.12</td>
</tr>
</tbody>
</table>

From Table 1, all the values of $\delta$ are less than 10%. The maximum of $\delta$ is 8.61%, the minimum is 0.01%, and the average is 3.12%. It is concluded that the model precision is satisfied to describing urban transit traction energy consumption. So, neural network is effective method to forecast traction energy consumption of single-line.

There are still some shortages at BP neural network, such as:

(1) It is long time to finish train, because the frequency of learning is stable and network convergence speed is slow.

(2) The network has redundancy and enhance learn burden. There are no integrated theory to guide the hidden layer chosen, but experience and iterative text.

**Conclusions**

The primary objective of the study is to build a simulation model for estimating the energy consumption of metro trains. In this paper, we presented two methods, i.e. grey relational degree analysis and neural network model, which may help metro companies to predict traction energy consumption of a single metro line. With the operational data from a metro line, some numerical experiments were proposed. According to the simulation results, we can see that with the given operational data, the proposed model can predict traction energy consumption of a single metro line with high accuracy.

Further work will be devoted to consider the variable metro lines in different cities for generality.

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