Prediction of the Quantity of Boxed Meals Preparation by High-Speed Train Based on ELM

Feifei Zhou*, Hao Yang, Jiahe Wang, Xi’an Sun and Xu Wu
College of Transportation, Beijing Jiaotong University, Shangyuan Village, Haidian District, Beijing, China
Email: 17251186@bjtu.edu.cn

Abstract. Meal service is an important part of the railway transportation service, and when preparing the number of boxed meals before departure, the train must meet the needs of the train passengers for self-catering and food service. The demand of meals avoids causing too much waste. Extreme learning machine has the characteristics of fast learning speed and generalization ability, and has a wide range of applications in neural network prediction, this paper from the train perspective, by applying and improving the ELM model and using some of the high-speed train data from the Beijing-Qingdao section for model training. A prediction error analysis was performed to verify the reasonableness and feasibility of the model for the prediction of boxed meals.

Keywords. High-speed train, The quantity of boxed meals preparation, ELM prediction.

1. Introduction
Meal service is an important part of the railway transportation service, and when preparing the number of boxed meals before departure, the train must meet the needs of the train passengers for self-catering and food service. The demand of meals avoids causing too much waste. Extreme learning machine has the characteristics of fast learning speed and generalization ability, and has a wide range of applications in neural network prediction, this paper from the train perspective, by applying and improving the ELM model and using some of the high-speed train data from the Beijing-Qingdao section for model training. A prediction error analysis was performed to verify the reasonableness and feasibility of the model for the prediction of boxed meals.

2. The Research Background
China's high-speed railway network is "driving according to the map", and the train operation map shows the running time and the stopping and passing time of trains at each station. The line chart is the basis for safe and punctual rail transportation. In the past, with lagging rail development and severe capacity shortages, railroads had little market awareness and seldom considered adjusting their train operating charts, which were generally based on one basic map is mainly prepared every two years, with only one or two minor adjustments in between. In recent years, the Shanghai Railway Bureau, for example, the Shanghai-Kunming and Beijing-Shanghai railways within the Shanghai Railway Bureau, the existing lines have been successfully transformed, and has built and opened a number of high-speed railways, every time a new line is opened, a new map needs to be implemented. According to the principle of "driving with flow and stopping with no flow", the Shanghai Railway Bureau has made weekend and daily map, and on weekends and holidays in the future, the train schedule will be weekly.
Due to the use of multiple trains and the future development of railways towards "one map per day", the crew will not be able to control the operation of trains as much as in the past, and the nature of passengers on the corridor is well known, so it is even more difficult to determine the amount of meals prepared for trains. There are a large number of scholars who have done research on the sanitation of railway boxed meals, and some scholars who have made a study on the passengers' Preference did the survey. For high-speed rail meals sale prediction, there is Yanquan Li using passenger ticket data and meal sale data, using LSTM neural network and MLP neural network for training [1].

In this paper, the research idea is to analyse the factors that affect the sale of boxed meals in trains from the perspective of trains first, build a model capable of predicting the amount of boxed meal preparation in trains based on historical data and relevant factors through ELM principles, and learn and train the sale of boxed meals using some trains from Beijing to Qingdao in September 2019.

3. Affecting Factors
Although food and beverage prices are the most sensitive factor influencing train passengers' food orders, the type, packaging, and taste of boxed meals have a significant impact on the sale are also affected to some extent [2-3]. However, the price, type, and quality of cold-chain boxed meals rationed by the rationing base do not change in the short term over a certain period of time. So for specific trains, there are four main factors that affect boxed meals sale.

3.1. Train Running Date
The main purposes of passenger travel are business travel, work in two places, schooling, visiting friends and relatives, leisure and vacation, work and other. Since study and working life are now rotated every Monday, the proportion of travel purposes of passengers on the train is not quite the same. Generally speaking, the main groups of travellers are those who travel for business on weekdays, those who travel for leisure on weekends, and those who travel for work and holidays on holidays. Visits to family and friends are predominant.

Due to the different purposes of travel, during the week, people's travel demand and travel choices on working days and rest days are somewhat different. Therefore, the weekly passenger flow distribution refers to the distribution of passenger flow in a week, and "one day" is the basic unit of weekly passenger flow distribution. The week is the basic unit of the cycle of people's production and life, and this pattern of activities can also be reflected in the daily fluctuations of passenger flow in a week. There is a difference in the size of the daily passenger flow between weekdays and rest days due to the different purposes for which people travel, and seven days a week. There are also differences in the distribution of passenger traffic at various times of the day, which together form the characteristics of the weekly distribution of passenger traffic. The week also serves as a cycle of people's production and life, and such work and life patterns will be reflected in the fluctuations of passenger flow during the week [4].

3.2. Train Running Time
The running time of trains consists mainly of the moment of departure and the duration of the journey. The longer the train runs, the longer the average travel time of passengers increases. According to the survey, if the travel time of passengers is less than two hours, the probability of buying a boxed meal is almost zero. If the travel time is more than 3 hours, if they do not bring their own food, they are more than 50% likely to buy a boxed meal, and the probability increases with the length of the journey. Those within 2 to 3 hours are affected by whether the travel time is during the meal period.

Since trains do not provide boxed lunches to passengers mainly during meal times, according to the research, the time slots for providing boxed lunches on trains are: Breakfast is served at 6:30 a.m. ~8:30 a.m.; Lunch is served at 11:00 a.m. ~13:00 p.m.; Dinner is served at 17:00p.m. ~19:00 p.m. . If the prime time of the meal accounts for the longer the running time of the train, the more likely it is that passengers will buy a boxed meal, and the number of sales will increase.
3.3. Passenger Traffic
Since trains are a moving and relatively enclosed environment, the number of train occupants determines the size of the boxed meals market and how many passengers are carried determining the size of the market demand for boxed meals is the most important factor that affects the sale volume of boxed meals. Generally speaking, there is a certain positive correlation between the number of boxed meals sold and the volume of passenger traffic. In order to avoid air freight and redundant seats, except for special areas and special corridors, the railway bureaus will "drive according to the flow". In other words, it is adjusted according to the passenger flow, so the occupancy rate of the trains only fluctuates within a certain range. At present, there are two types of HSR trains: 8 trains and 16 trains, with a passenger capacity of 576 and 1,193 people, with an average attendance of about 70%.

3.4. Number of Train Stops
The sale of train boxed meals are not only related to the date and time of operation of the train, but also to the passengers. High-speed railway passenger trains also include the following types of stops: one-stop direct train, large-stop direct train, station-stop train, and alternating-stop train [5]. From the train’s point of view, the number of stops is related to the frequency of renewal of passengers on this train. For every stop at a station, a portion of the passengers on the train are replaced. When the train has the same mileage, the more stops the train makes, the shorter the average distance travelled by the passengers transported by the train, the reduction in the average travel time This results in a corresponding reduction in the likelihood of their eating on the train, with the number of stops being inversely related to the amount of boxed meals preparation.

4. Model Building

4.1. Model Principle
Extreme Learning Machine (ELM) is a Learning algorithm for solving single-hidden neural network based on feedforward neural network proposed by Huang Guangbin Etc [6]. It can be considered as a special feedforward neural network, which is suitable for supervised learning and unsupervised learning. ELM is characterized by the fact that the weight of the hidden layer node is given randomly or artificially, and no update is required, and only the output weight is calculated during the learning process. The overview of ELM is shown in the figure 1.

![Figure 1. Overview of ELM.](image)

The biggest feature of ELM is that for traditional neural networks, especially the feedforward neural network of single hidden layer, it is faster than the traditional learning algorithm on the premise of ensuring the learning accuracy: the connection weights of the input layer and the hidden layer and the threshold of the hidden layer can be set randomly, and do not need to be adjusted after setting. This is different from BP neural network, which needs to adjust weights and thresholds in reverse. So you can reduce the computation by half. The weight of the connection between the hidden layer and the output layer is determined by solving the equations at one time without iterative adjustment. ELM consists of the input layer, the hidden layer, and the output layer. For a single hidden layer
neural network, ELM can randomly initialize the input weight and bias and get the corresponding output weight. The output function of the hidden layer is as follow (1):

$$f_L = \sum_{i=1}^{l} \beta_i \hat{h}(x) = \hat{h}(x)\beta$$  \hspace{1cm} (1)

In the above formula, $x$ is the input of neural network and the output weight, and $\hat{h}(x)$ is the characteristic mapping or excitation function.

ELM only requires solving the output weights and is therefore a linear parametric model whose learning process is easy to converge at very small global values. N sets of learning data are known, and the learning of the ELM containing L implicit layer nodes and M output layer nodes has the following steps [7].

1. Random setting of node parameters: at the beginning of the calculation, ELM node parameters will be set randomly, that is, node parameters and input data independent. The random generation here can obey an arbitrary continuous probability distribution.

2. Calculate the output matrix of the implicit layer: the size of the implicit layer output matrix is N rows and L columns. It means that the number of rows is the number of input training data, and the number of columns is the number of implicit layer nodes. The output matrix is essentially the result of mapping N input data to L nodes.

3. Solve the output weight: the size of the output weight matrix of the implied layer is L rows and M columns, i.e. the number of rows is the number of nodes in the implied layer, and the number of columns is the number of nodes in the output layer. Unlike other algorithms, the ELM algorithm can have no error nodes at the output layer. The core of the ELM algorithm is to solve for the output weights so that the error function is minimal.

4.2. Data Processing

From the analysis of the influencing factors, the ELM model constructed in this paper has four input layers, input layer 1 is the number of stopovers, input layer 2 is the number of passengers on the day of operation, input layer 3 is the ratio of the dining phase of the train to the total running time, input layer 4 is the number of weeks on the day of operation of the train. According to the available data, there are 106 neurons in the input layer, which corresponds to 106 input variables. Two neurons were set up in the output layer to predict the sale of self-owned caterings based on the constructed ELM prediction model, and the predicted values were compared with the actual values to analyze the performance of the prediction model.

The ELM model built in this paper adopts single implicit layer neural network learning, the functional relationship between the input and output of the nodes in the implicit layer and the output layer is chosen as sigmoid function, the sigmoid function is formulated as follow (2), The image of the sigmoid function is shown in figure 2.

$$G(a, b, x) = \frac{1}{1 + \exp(a \cdot x + b)}$$  \hspace{1cm} (2)
4.3. ELM Algorithm MATLAB Code Introduction

According to the research on the application of ELM in regression fitting, the code of ELM is mainly divided into three parts: (1) main function, the running body of the code; (2) Elmtrain function, ELM training function body part; (3) Elmpredict function, ELM simulation test body part.

The main function code is mainly run by the following steps.

1. Data acquisition.
2. Data normalization processing. The initial data are cluttered and there are different scales, so all data need to be normalized.
   
   ```matlab
   [Pn_train,inputps] = mapminmax(P_train,0,1);
   Pn_test = mapminmax('apply', P_test,inputps);
   Pn_test1 = mapminmax('apply', num3,inputps);
   [Tn_train,outputps] = mapminmax(T_train,0,1);
   ```
3. Build/train ELM model. Comparison of evaluation results can be done by setting different numbers of data nodes.
   ```matlab
   [IW, B, LW, TF, TYPE] = elmtrain (Pn_train, Tn_train,120,'sig',0);
   ```
4. ELM model simulation test. Enter the data in (2) into the model for training.
   ```matlab
   Tn_sim = elmpredict (Pn_test,IW,B,LW,TF,TYPE);
   Tn_sim1 = elmpredict (Pn_test1, IW, B, LW, TF, TYPE);  
   T_sim = mapminmax ('reverse', Tn_sim, outputps); 
   T_sim1 = mapminmax ('reverse', Tn_sim1, outputps); 
   ```
5. Test the ELM model. Evaluate with a trained model and compare with the results of the simulation.
   ```matlab
   result = [T_test;T_sim];
   ```
6. Plotting.

5. ELM Run Results and Analysis

(1) The accuracy of the fit can be continuously improved by modifying a unique parameter, the number of nodes in the implied layer (LW), which reflects the superiority of the ELM algorithm. But as the number of nodes keeps increasing, the ELM will have "overfitting" problems. After repeated debugging, the combined effect of fitting and prediction is best when the node digits of the implied layer are 120.

When LW = 120, the fitting effect of boxed meals sale (T_test) and boxed meals sale (T_sim) predicted using the ELM model is shown in figure 3.

![Sigmoid function image](image-url)

Figure 2. Sigmoid function image.
Figure 3. Expectations VS forecasted results for boxed meals sale.

(2) ELM test set prediction error \(= T_{\text{test}} - T_{\text{sim}}\), prediction error between -0.13~0.15, as shown in figure 4.
ELM test set prediction error percentage=(\(T_{\text{test}}-T_{\text{sim}}\)) / \(T_{\text{sim}}\), prediction error percentages between -0.011 and 0.01, as shown in figure 5.

Figure 4. Prediction error of ELM test set.  
Figure 5. Percentage prediction error of ELM test set.

(3) In order to verify the accuracy of the ELM model prediction, we set two other data as the prediction group, where the expected output (\(T_{\text{sim1}}\)) represents the actual sale volume and the prediction output is the sale volume predicted by the ELM algorithm. As can be seen from the graph, when the expected output is 8, the predicted output is 7.4 with an error of -7.5%; when the expected output is 10, the predicted output is 11 with an error of 10%.
6. Conclusion
Train boxed meals sale are a dynamic, non-linear, complex system that is the result of multiple factors working together. The traditional linear model can only provide useful information about different segments [8], which is difficult to describe the changes of train lunch sale, and cannot provide more accurate prediction data. As we can see from the results and analysis of the ELM algorithm, ELM is characterized by strong generalization ability, high fit, and good prediction accuracy, which proves the feasibility of using ELM to predict the sale of boxed meals on trains.

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