ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

A Study on Prediction and Scheduler for Foot Traffic of University Canteens Based on Gray Prediction and BP Neural Network

Yan An[1,a], Yang Yuqi[1,b], Jiang Xinyang[1,c], Mo Hanxiang[2,d], Duan Boya[3,e,*]

[1]*Faculty of Economics and Management, North China Electric Power University, Beijing, 102200, China*
[2]*Faculty of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102200, China*
[3] *Physical Education Department, North China Electric Power University, Beijing 102200, China*
[a]*1831240802@qq.com*, [b]*204947211@qq.com*, [c]*1797145252@qq.com*, [d]*1294112341@qq.com*, [e]*1831240802@qq.com*
**Corresponding author*

Abstract: *In the current context of epidemic prevention and control, the resumption of university education places greater emphasis on the prediction and regulation of foot traffic in public areas. Using the university canteens as an example, predicting the foot traffic during the dining period benefits the canteens staff's reasonable scheduling, reducing the potential virus transmission risk caused by the dense crowd, as well as providing time- sharing service for the distribution of the canteens foot traffic, reducing dining waste and practicing diligence and frugality, and helping to alleviate the crowded queue during the dining period. Based on field research on canteen patronage data, this paper combines gray theory, neural network technology research, and patronage information prediction research to adapt to the nonlinear characteristics of patronage, optimize the performance of the prediction model, and improve the accuracy of the prediction model. The results are used to determine patronage density and the number of canteen windows. This paper used factor analysis to build a refined foot traffic guidance and schedule according to each index and put it into the smart canteen website.*

Keywords: *M/M/1 queuing model, foot traffic prediction, gray prediction, BP neural network, factor analysis*

1. Introduction

The socialization reform of university logistics is the important driver of university development, where new technologies and models are regarded as radical as the lifeline. How to promote high-quality development of college logistics comes to be a long-term concern for academics. The traditional college logistics is inefficient and cannot adapt to the characteristics of non-linear dining of student groups. Therefore, based on the existing technology and the actual situation of investigation data, this paper intends to combine the advantages of gray prediction and BP neural network for mathematical modeling and propose the construction scheme of smart canteen. [1]This research will enrich the theory of crowd prediction model in university logistics and provide new ideas for modernization of university logistics, which can be widely used in crowd prediction and regulation in major universities and commercial fields.

2. Data selection

The data collected during the epidemic shutdown in 2022 was chosen to analyze each level of the canteens at North China Electric Power University. By measuring the data for 30 days and choosing the data using a mix of infrared measurement and control and manual inspection, 30 sets of actual and trustworthy data were created in an Excel sheet from February 28 to April 8 working days.

ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

3. Forecasting model

3.1 Gray Forecast Model

The Gray Forecast Model (GFM), which is a forecasting technique that creates mathematical models and forecasts using little or no information.[2] A technique for anticipating systems with uncertainty is gray forecasting.

The characteristic quantity at a future moment or the duration to attain a specific characteristic quantity can be predicted using gray prediction, which builds a model from isochronous observations. [3] The true values of dining patronage on the first floor of a canteens during an epidemic at North China Electric Power University were tested by a rank-ratio test, and the initial non-negative data series were set as

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$$

For the grade ratio computation, substitute the following equation.

$$\sigma(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \sigma(k) \in \left(\mathrm{e}^{-\frac{2}{n+1}}, \mathrm{e}^{\frac{2}{n+1}} \right)$$

Table 1: Gray prediction accuracy table.

Development factor a	Gray role volume b	Posterior test difference ratio C value
0.001	3217.562	0.34

All of the level ratios of the translation-transformed series, as determined by the analysis using SPSS statistical software, fall within the range of (0.938, 1.067), indicating that the translation-transformed series are appropriate for the creation of the gray prediction model (Table 1).

Construct the matrix B of 30 sets of data and the quantity vector Y, respectively

$$B = \begin{bmatrix} -z(2) & 1 \\ -z(3) & 1 \\ \vdots & \vdots \\ -z(n) & 1 \end{bmatrix} Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}$$

Then the column of least squares estimated parameters of the grey differential equation satisfies

$$u = [ab]^T = (B^T B)^{-1} B^T Y$$

Build the model and solve for the generated and reduced values, and solve based on the formula to get the prediction model

$$\hat{x}^{(1)}(k) = [x^{(0)}(1) - \frac{b}{a}]\mathrm{e}^{-a(k-1)} + \frac{b}{a}$$

$$k = 1, 2, \ldots, n$$

After cumulative reduction, the reduced predicted values were obtained (Table 2).

Table 2: Grey forecast results for the following three days.

Predicted order	Predicted value
1	678.8155172746629
2	677.0365891670808
3	675.2586616212502

The findings revealed that on the next three days, there were roughly (keeping whole number portions) 679, 677, and 675 people on the first level of the first canteens.

ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

3.2 Neural network

With no link between neurons in the same layer and forward connections between neurons in other levels, a neural network consists of an input layer, an output layer, and one or more implicit layers. By selecting the right network topology in accordance with the object's complexity, it is possible to map any nonlinear function from the input space to the output space.

BP neural networks are mainly used for:

(1) Function equivalence: teaching a network to equivalence a function with an input vector and an associated output vector.

(2) System identification and prediction: tying it to the input vector by means of a particular output vector;

(3) Classification: putting the input vector into the proper designated category.

(4) Data compression: lessen the output vector's dimension for transmission or storage[4].

In this instance, the relationship between the overall population of the canteens and the population during each period is trained using the input vector and corresponding output vector. The three-time periods (11:40 to 12:00, 12:30 to 12:20, and 12:20 to 12:40) are utilized as the desired output value Y and the gray prediction result is used as the neural network's input value X. The trilateration method is used to prevent the "overfitting" phenomena. Seventy percent of the data is utilized as training samples, fifteen percent as validation samples, and fifteen percent as test samples. [5] Using the Levenberg technique, the hidden layer's mean square error is calculated to be 6 nodes, or 108.49(Table 3).

Table 3: BP neural network prediction results.

Number of times	Total number of people	11:40 - 12:00	12:00 - 12:20	12:20 - 12:40
1	679	458.7946	192.4905	25.5365
2	677	458.7946	192.4905	25.5365
3	675	458.7946	192.4905	25.5365

4. The density of crowds

The foot traffic per unit area of the canteen is defined as "crowd density," and its calculation unit is "number of people/square meter." Using the predicted foot traffic data, it is possible to compare the difference in the density of people in different canteens over time.

The density is obtained by substituting the cafeteria area. (Table 4)

Table 4: Predicted density of the first floor of a canteen.

Number of people in the canteen	Time Periods	Canteen area	Crowd density
458.79	11:40——12:00	933.24	0.49161
192.49	12:00——12:20		0.20626
25.53	12:20——12:40		0.027356

5. The number of canteen windows

Use the M/M/n queuing model for multi-service waiting systems. We obtained some statistics from the measurements. Among them, λ is the number of people per hour in the canteen,μ is the rate of reception for students at the canteen windows, which is equal to 120 people per hour, c is the number of windows opened in canteens. Under the premise $100\% > \frac{\lambda}{c \cdot 120} \geq 70\%$ of ensuring the utilization

ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

of the canteen, by the formula:

$$P_0 = \frac{1}{\sum_{i=0}^{c-1} \frac{1}{i!} (\frac{\lambda}{120})^i + \frac{1}{c!(1-\frac{\lambda}{120c})} \cdot (\frac{\lambda}{120})^c}$$

$$W = \frac{1}{c!} (\frac{\lambda}{120})^c \cdot \frac{\frac{\lambda}{120c}}{(1-\frac{\lambda}{120c})^2} \cdot \frac{P_0}{\lambda}$$

The following results were obtained (Table 5).

Table 5: Number of windows to be opened on the first floor of a canteen.

Number of people per hour in the canteen	Time periods	Number of windows that should be opened (pcs)
1376.37	11:40——12:00	12—16
577.47	12:00——12:20	5—7
76.59	12:20——12:40	2

6. Pedestrian flow instruction and scheduling

6.1 Factor analysis

The factor analysis is used to find out several main components that have the greatest influence on the overall factors, thus achieving the purpose of dimensionality reduction of indicators.[6] The weights of each indicator are calculated as $Ti = \frac{\lambda i\%}{\sum_{i=1}^{k} \lambda i\%}$. (Ti denotes the weight of component I in reflecting the overall information, $\lambda i\%$ denotes the contribution rate of component I, and $\sum_{i=1}^{k} \lambda i\%$ denotes the cumulative contribution rate of K components).[7] Also the weight of each indicator in the factor is calculated by the factor loading of each indicator: $Ti = \frac{|\vartheta ij|}{\sum_{i=1}^{k} |\vartheta ij|}$. (Ti denotes the weight of the indicator in a component, $|\vartheta ij|$ denotes the absolute value of the factor loadings of I indicator on component j, $\sum_{i=1}^{k} |\vartheta ij|$ denotes the algebraic sum of the absolute values of the factor loadings of all indicators in that component).

Table 6: Explain total variance.

composition	covariance matrix			factor load squared value			sum of squared rotational factor loadings		
	eigenvalue	percentage of variance	cumulative variance percentage	eigenvalue	percentage of variance	cumulative variance percentage	eigenvalue	percentage of variance	cumulative variance percentage
1	1.944	64.798	64.798	1.944	64.798	64.798	1.918	63.926	63.926
2	1.056	35.202	100.000	1.056	35.202	100.000	1.082	36.074	100.000
3	5.551E-17	1.850E-15	100.000						

In this paper, the structural model of pedestrian flow on the first floor of the canteens of North China Electric Power University is based on the determination of the weights of each indicator in reflecting a

ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

certain time interval, which is obtained through factor analysis. Table 5 shows the total explained variance of the number of people, area and number of windows in the first floor of the canteens of North China Electric Power University, which were obtained by factor analysis.

From the table, two main components were identified based on the eigenvalues and variance percentages, and these two components summarized most of the information of the three time periods. Therefore, the variables other than these two variables were considered to have little influence on the variance, and the first two components were accepted as the main components (Table 6).

Table 7: Factor loading matrix after orthogonal rotation.

Indicators	Ingredients	
	1	2
first floor of canteens I 11:40——12:00	0.041	0.999
second floor of canteens I 12:00——12:20	0.990	0.138
third floor of canteens I 12:20——12:40	0.967	0.255

Table 8: Weight of each indicator in each factor.

	1	2
first floor of canteens I 11:40——12:00	0.02	0.717
second floor of canteens I 12:00——12:20	0.495	0.099
third floor of canteens I 12:20——12:40	0.483	0.182

The weights of each factor are different, and the weights of each indicator in each factor are different, because each factor is a collection of indicators(Table 7).

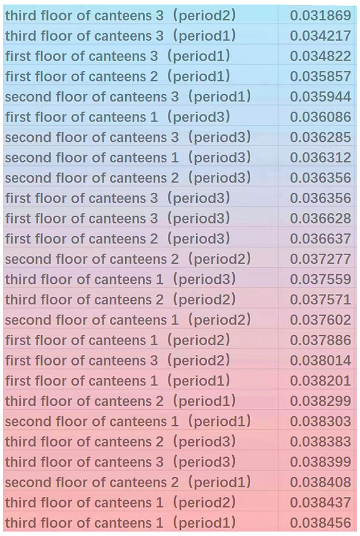
Since each factor is a collection of indicators, and indicators are the smallest functional unit of research weights(Table 8), the final weight of each indicator can be calculated based on each factor and the indicator weights in each factor (the formula is:

Final weight of each indicator = 0.64 × weight of factor 1 + 0.36 × weight of factor 2) (as shown in Table 9)

Table 9: Structural model of the flow of people on the first floor of a canteen in North China Electric Power University.

Indicator Model	Weighting model
The first period of the first floor of canteens I	0.272038
The second period of the first floor of canteens I	0.352647
The third period of the first floor of canteens I	0.375315

6.2 Web page expression



third floor of canteens 3（period2)	0.031869
third floor of canteens 3（period1)	0.034217
first floor of canteens 3（period1)	0.034822
first floor of canteens 2（period1)	0.035857
second floor of canteens 3（period1)	0.035944
first floor of canteens 1（period3)	0.036086
second floor of canteens 3（period3)	0.036285
second floor of canteens 1（period3)	0.036312
second floor of canteens 2（period3)	0.036356
first floor of canteens 3（period3)	0.036356
first floor of canteens 3（period3)	0.036628
first floor of canteens 2（period3)	0.036637
second floor of canteens 2（period2)	0.037277
third floor of canteens 1（period3)	0.037559
third floor of canteens 2（period2)	0.037571
second floor of canteens 1（period2)	0.037602
first floor of canteens 1（period2)	0.037886
first floor of canteens 3（period2)	0.038014
first floor of canteens 1（period1)	0.038201
third floor of canteens 2（period1)	0.038299
second floor of canteens 1（period1)	0.038303
third floor of canteens 2（period3)	0.038383
third floor of canteens 3（period3)	0.038399
second floor of canteens 2（period1)	0.038408
third floor of canteens 1（period2)	0.038437
third floor of canteens 1（period1)	0.038456

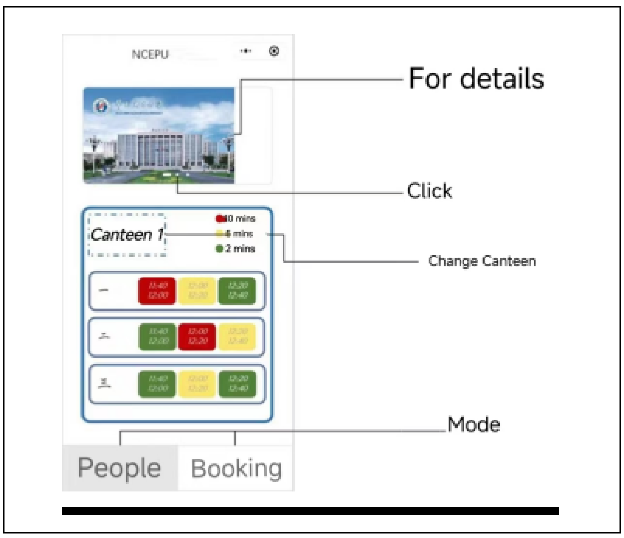


Figure 1: time period factor weightings. *Figure 2: website display.*

ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

Promoted to all 9 canteens (Figure 2) for 27 time periods (Figure 1), after comprehensive factor analysis and sorting, the 27 data were placed in the built website using the function and characteristics of gradient color, for which accurate prediction and guidance can be made for the flow of people.[8]

7. Model evaluation and improvement

7.1 Advantages

This paper mainly focuses on the prediction of canteen foot traffic in the context of smart campuses, and for the cyclical operation environment of a smart campus, the original data is generated and processed by gray theory, and the irregular original data is turned into a more regular generation series. Finally, we used factor analysis to build a refined foot traffic guidance and schedule according to each index and put it into the smart canteen website. Through repeated debugging, the prediction results are more accurate and can fit various situations well, providing a theoretical basis for the canteen side to prepare food quantity, avoiding waste and realizing CD-ROM, and relieving the pressure of crowded queues for teachers and students, reducing gathering and reducing risk. Through detailed study and analysis of its advantages and disadvantages and the limitations of the application environment, this model can be expanded and applied to similar fields such as college canteens and food service in the future.

7.2 Model improvement

The BP neural network has powerful learning ability but also has its own limitations and shortcomings [9]. There may be slow training or stagnation, local minima, and other unfavorable network training phenomena for which the algorithm should be improved for research. In addition, this paper lacks further logistic constraints and clustering analysis for improving accuracy and personalization.

8. Conclusion

Despite the limitations these are valuable in light of the findings combines gray theory, neural network technology research, and patronage information prediction research based on field research on canteen patronage data which are utilized to calculate the density of patrons and the quantity of canteen windows. In order to provide an accurate foot traffic guidance and schedule for each index and add it to the smart canteen website, this paper performed factor analysis.

This study will advance the theory behind the crowd prediction model used in university logistics and offer fresh suggestions for updating university logistics, both of which have broad applications in crowd management and prediction in top academic institutions and the business world. Therefore, future research should be conducted in more realistic settings to foot traffic.

References

[1] Shuwei Wang, Ronggui Zhou, Yanyan Chen. Study on pedestrian flow forecasting method in Beijing transportation hub areas [C]. Annual meeting of the transportation research board; Transportation Research Board. 2014

[2] Liu, Yang. (2011) Intermodal Transit Hub: Improving the Transfer Environment at the Li Shui Bridge Transportation Node in Beijing [D]. Master's Thesis, University of Washington,

[3] Tang Min An, Wang Xiao Ming, Yuan Shuang. Location Selection of Public Transit Transfer Hubs Based on Gray NN Model Improved by GA [C]. International Conference onuture Optical Materials and Circuit Design. 2013

[4] Zhenzhong Tian. Application of combined forecasting model based on improved grey neural networks in regional logistics demand [C]. International conference of logistics engineering and management; ICLEM 2010. 2011

[5] F ZHANG, J WU. Based on improved grey BP neural network of the regional logistics cost forecast [C]. Manufacturing Automation: Advanced Design and Manufacturing in Global Competition. 2004

[6] Fincannon, Tyler. (2017) Improving Regional Hydrology Forecasting for the North Central Texas Region Utilizing Conditional Ensemble Streamflow and Hydrometeorological Condition Predictions with Artificial Neural Network Modeling [D]. Master's Thesis, the University of Texas at Arlington.

[7] Zhe Gao, Xiaojiao Chen, Guannan Zhang. Fractional-order discrete grey models for China's electricity consumption forecasting [C]. Chinese Control and Decision Conference. 2020

ISSN 2616-5775 Vol. 5, Issue 11: 50-56, DOI: 10.25236/AJCIS.2022.051108

[8] Wenyan Guo, Xiaoliu Shen, Xinke Ma. Comparative Study of Grey Forecasting Model and ARMA Model on Beijing Electricity Consumption Forecasting [C]. International conference on mechatronics and automatic control systems . 2014

[9] Mammadova, Gulnara. (2010) Forecasting exchange rates using ARMA and neural network models [D]. Master's Thesis, Western Illinois University.