Traffic Demand Forecasting for EGCS with Grey Theory Based Multi- Model Method

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Abstract

Elevator traffic demand forecasting is the essential prerequisite for effectively implementing elevator group control system (EGCS). Considering that there exists lots of abnomal information in elevator traffic caused by subjectivity and occasionality in human behaviour and that observing traffic information continuously is costly and difficult, an improved grey forecasting based method using multi-model to forecast future elevator traffic demand of EGCS is proposed, the abnomal information which refers to outliers is processed, based on which a smoothing technique on original traffic data is conducted to transform the raw data into an increasing sequence, to further reduce the randomness of the observed traffic data and to make full use of regularity information. The proposed method not only avoid the theorrtical error of grey model per se, but also improved the forecasting accuracy, which is suitable for short period forecasting for elevator traffic demand. Simulation experiments show the validity of the proposed method.

Keywords: *Elevator Traffic Demand Forecasting, Elevator Group Control System (EGCS), Grey Model (GM), Abnormal Information, Multi-Model Forecasting, Smoothing Processing.*

1. Introduction

The increasing perfection of the function of modern high-rise buildings makes the elevator vertical transportation become more and more complicated. Elevator traffic demand forecasting deals mainly with the traffic conditions, evaluating the future traffic demand on real-time observed traffic data. Elevator traffic demand forecasting is the essential prerequisite for elevator traffic pattern recognition, selecting control strategy to effectively implementat EGCS [1]-[5].

Many studies have been done regarding the elevator traffic demand forecasting related problems based on, such as, neural network, exponential smoothing, fuzzy logic theory and so on, and significant progress has been made [6]-[9], but the problem to deal with both the abnormal traffic data according to the specified forecasting model and the the limited number of samples and the incomplete or insufficient information, has not been taken seriously. Therefore, the characteristics of elevator traffic demand make the applications of those methods not be effectively applied in some practical cases, and the satisfactory forecasting accuracy is hard to obtain. So, to develop effective forecasting method is of the utmost importance.

In this thesis, an improved grey prediction based method using multi-model to forecast the future elevator traffic demand of EGCS is proposed based on the following reasons.

1.1 Elevator Traffic Demand Possesses Obvious Grey Characteristics

For the elevator traffic system with EGCS, the passenger arrival process is a stochastic process [10], and the theory of grey system holds that any stochastic process is the grey variables changing in a certain amplitude range for a certain period of time [11]. The traffic flow of EGCS in the same time period of different working day may fluctuate differently to some extent, but stable in a long term.

Since obtaining the observed traffic data is costly and difficult as stated above, it is usually require that the traffic demand be forecasted based on less sample data, which provide opportunities for employing grey forecasting method.

1.2 The Essence of Grey Forecasting

Grey theory focuses on uncertain system with limited number of samples and amount of information, the valuable information is extracted by generating and developping operation on part of the known information to realize the correct understanding and effectively forecasting of the system operating regularity [12]. It can be simply stated that the development regularity of objects which contain incomplete information is forecasted based on the principle of grey system analysis. The core of which is Accumulating Generation Generators (AGO) whose aim is to increase the significance of system operating regularity by reducing the randomicity of the observed traffic samples, its forecasting technique is to set up grey forcasting mode extending from the past to the future on the basis of the past known or present unknown information employing small samples.

The remainder of this thesis is organized as follows. In Section 2, Problems description and modelling is discussed. In Section 3, the application of the proposed method to elevator traffic demand forecasting for EGCS is discussed in detail. In Section 4, simulation experiments and analysis are presented. And conclusions are drawn in Section 5.

2. Problems Description and Modelling

2.1 Description of Elevator Traffic Flow

The operation of EGCS is essentially to transport a certain amount of passengers in the building from their original floors to the ultimate destination floors in a timely manner. Traffic flow which indicates the traffic status of EGCS is expressed by the number of passengers, the period of passengers appearing, as well as the positions of passengers. It can be described by several kinds of data [13], but only part of the data which reflect the traffic characteristics inside the building are used in traffic analysis, which are the number of passengers entering and leaving the main terminal in specified time intervals, the total number of passengers within the building and the interfloor traffic conditions, etc. According to the characteristics of elevator traffic, the traffic flow is classified into four different traffic patterns: uppeak traffic; downpeak traffic; random interfloor traffic and lunch time traffic [1, 13]. The uppeak traffic pattern arises when all passengers are moving up from the main terminal floor, it occurs in considerable strength in the morning when prospective elevator passengers enter a building intent on travelling to destinations on the upper floors of the building. The downpeak traffic situation is observed when the dominant or only traffic flow is in a downward direction with all, or the majority of, passengers leaving the elevator system at the main terminal of the building. The random interfloor traffic is a characterization in which passengers are moving equally likely between floors, it exists for the majority of the working day in office buildings. Lunch time traffic occurs in the middle of the day and exhibits a dominant traffic flow to and from one or more specific floors, one of which may be the main terminal. Based on years of research, the 5 min. interval for traffic flow data collection has achieved general acceptance [13]-[15], on which the traffic data in a day are obtained at the main terminal every 5 min. interval along time axis under the two main traffic patrterns: uppeak traffic condition and downpeak traffic condition, and the traffic flow time series will be constituted, then the traffic demand forecasting models are constructed to forecast the traffic demand at the specified period of time in the future on the observed historical traffic data.

2.2 The Traditional Grey Model GM (1, 1)

The key technology of grey theory is the grey model which takes the grey generation function as its foundation, and differential fitting as the core. The grey theory shows that all the random variables are the gray variables and gray processes vary during a certain period of time within a certain range. Grey forecasting method neither emploies directly the raw data to model, nor finds the statistical laws and probability distribution of stochastic variables, but the generation operation on the raw sequence data is conducted to get new sequences with strong regularity in order to diminish the randomness and volatility of the raw data. Modeling and forecasting is based on the new sequences [14]. Utilizing the grey forecasting method to forecast elevator traffic demand needs neither to determine whether the passenger flow obeys a certain probability distribution, nor require a large number of observed samples.

1) Accumulating Generation Generator (AGO)

The sequence matrix of the raw data is constructed as follows.

$$X^{(0)} = \begin{bmatrix} X_1^{(0)} \\ X_2^{(0)} \\ \vdots \\ X_n^{(0)} \end{bmatrix} \tag{1}$$

Applying AGO to $X^{(0)}$ in (1) gives

$$X^{(1)} = \begin{bmatrix} X_1^{(1)} \\ X_2^{(1)} \\ \vdots \\ X_n^{(1)} \end{bmatrix} \tag{2}$$

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where $X_i^{(0)} = \{x_i^{(0)}(j) | i = 1, 2, \ldots, n, j = 1, 2, \ldots m\}$, and $X_i^{(1)} = \{x_i^{(1)}(j) | i = 1, 2, \ldots, n, j = 1, 2, \ldots m\}$, $x_i^{(0)}(j)$ is the observed number of passengers who arrive at the main terminal and go to the upper floors or who come from the upper floors to the main terminal by elevators within the ith Δt for the jth day and

$$x_i^{(1)}(j) = \sum_{k=1}^{j} x_i^{(0)}(k), \; i = 1, 2, \ldots, n, \;\; j = 1, 2, \ldots, m.$$

2) Modelling of Grey Multi- Model Method

This model is a time series forecasting model. The generated adjacent neighbor mean sequence $Z^{(1)}$ of $X^{(1)}$ is defined as follows

$$Z^{(1)} = \left[z_i^{(1)}(j) \right]_{n\times m} \qquad (3)$$

where $z_i^{(1)}(j)$ is the mean value of adjacent data, i.e. $z_i^{(1)}(j) = \alpha x_i^{(1)}(j-1) + (1-\alpha) x_i^{(1)}(j)$, i=1,2,…n, $j = 2,3,\ldots,m$, $Z_i^{(1)} = \{z_i^{(1)}(j) | j = 2,3,\ldots m, i = 1,2,\ldots,n\}$, usually α is set as 0.5 [10]. $x_i^{(1)}(j)$ approximately follows the exponential rule, in terms of $x_i^{(1)}(j)$, the whitenization differential equationcan is constructed as follows

$$\frac{dX_i^{(1)}}{dt} + a_i X_i^{(1)} = u_i \qquad (4)$$

Discretizing Eq. (4) yields grey differential equation as shown below

$$X_i^{(1)} - a_i Z_i^{(1)} = u_i \qquad (5)$$

Then the sequence parameters to be identified are $\mathbf{a}_i = [a_i \; u_i \;]^T$, where a_i is developing coefficient, u_i is grey influencing coefficient.

3) Find Parameters a_i and u_i

Applying the least squares method yieldsis

$$\mathbf{a}_i = [a_i \; u_i \;]^T = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T\mathbf{Y}_n \qquad (6)$$

where

$$\mathbf{B} = \begin{bmatrix} -z_i^{(1)}(2) & 1 \\ -z_i^{(1)}(3) & 1 \\ \vdots & \\ -z_i^{(1)}(m) & 1 \end{bmatrix}, \; \mathbf{Y}_n = \begin{bmatrix} x_i^{(1)}(2) \\ x_i^{(1)}(3) \\ \vdots \\ x_i^{(1)}(m) \end{bmatrix}, \; i=1,2,\ldots n.$$

4) Forecasting Results

According to Eq. (4), the solution of forecasted value $\hat{x}_i^{(1)}(j)$ of $x_i^{(1)}(j)$ is given as

$$\hat{x}_i^{(1)}(j+1) = \left[x_i^{(0)}(1) - \frac{u_i}{a_i} \right] \times e^{-a_i \times j} + \frac{u_i}{a_i} \qquad (7)$$

$$i = 0,1,\; 2,\ldots,n,\; j = 0,1,\; 2,\ldots,m$$

To obtain the forecasted value $\hat{x}_i^{(0)}(j)$ of the primitive data $x_i^{(0)}(j)$, the IAGO is used to establish the following grey model

$$\hat{x}_i^{(0)}(j+1) = \left(1 - e^{-a_i}\right) \times \left[x_i^{(0)}(1) - \frac{u_i}{a_i} \right] \times e^{-a_i \times j} \qquad (8)$$

$$i = 1,\; 2,\ldots,n,\; j = 0,1,\; 2,\ldots,m$$

The above shows that each observation period Δt which is set 5min corresponds to a forecasting model, therfore the method proposed here is called multi-model method.

5) Limitations of the Traditional Grey Model in Practical Engineering Application

As stated earlier, grey forecasting is suitable for the situations in which the difficulty of incomplete or insufficient information is faced [16]. Since it can well reflecte the past state and future variation tendency, it has been widely used especially in short-term forecast. But like other methods, traditional grey forecasting method has its limitations [17]-[20], some of which are summarized as follows:

1. As the discrete degree of data increases, viz. the gray level increases, the forecasting accuracy becomes worse.

2. The forecasting result will be better, for a completely exponential growth sequence, and it is difficult to consider the situations where there exists outliers in the sequence, especially when the sample data growth deviates from

exponential rule, the forecasting accuracy will be getting worse.

3. Because the knowledge and rule are discovered on the raw sequence data taking no account or lacking of qualitative considerations and quantitative analysis for the objective factors which may impact the forecasting effect. Therefore, it is inferior in flexibility of application.

4. The growth rate of the raw data sequence $\lambda = \frac{dX_i^{(0)}}{dt} \Big/ X_i^{(0)} = \frac{d^2 X_i^{(1)}}{dt^2} = -a_i$ is a constant, but in general it is difficult to meet such implicit requirement. A slight change of a_i has little influence on forecasting accuracy, but a greater change of a_i will lead to the deterioration of forecasting accuracy.

5. Taking the primitive value $x^{(0)}(1)$ as the initial condition of the forecasting model casues that $\hat{x}^{(0)}(1)$ is irrelevant to the initial value of the raw data sequence. The information about $x^{(0)}(1)$ is overlooked, in this case, it is difficult to guarantee the minimum of the entire forecasting error.

Because of the reasons stated avove, to improve traditional grey forcasting method to increase forecasting accuracy concerning the specific engineering applications is of great significance.

3. Elevator Traffic Demand Forecasting for EGCS

3.1 The Processing of the Raw Data Sequence

The movement of people around a building is very complex, there is unpredictability in human behaviour. Due to some accidental or exceptional circumstances caused by the human occasionality and subjectivity, great random fluctuations of passenger traffic flow may occur during some specific time periods, which results in the outliers in the raw data sequence. Aside from the outliers processing, smoothing of the raw data sequence is needed for better forecasting results.

1) Outliers Discrimination

The outliers neither reflect nor represent the overall traffic characteristics, and will make the forecasting accuracy seriously deteriorate. Such outliers must be modified to refine the traffic models.

for all $\left\{x_i^{(0)}(j-1), x_i^{(0)}(i), x_i^{(0)}(j+1)\right\} \subset X_i^{(0)}$

If $x_i^{(0)}(i) > \gamma_1 \times \left(x_i^{(0)}(j-1) + x_i^{(0)}(j+1)\right)$

or $x_i^{(0)}(j) < \gamma_2 \times \left(x_i^{(0)}(j-1) + x_i^{(0)}(j+1)\right)$

Then $x_i^{(0)}(j)$ is called outliers, where $i = 1, 2, \ldots, n$, $j = 2, 3 \ldots m$, γ_1, γ_2 satisfies $\gamma_1 > 1$, $0 < \gamma_2 < 1$, the value of γ_1, γ_2 are determined by the specific circumstance.

2) Outliers Modification

The outliers should firstly be removed, and the related data point in $X_i^{(0)}$ will be empty, then empty data positions in $X_i^{(0)}$ will be updated with the new data which are generated by non-adjacent neighbor mean generation method given as follows.

$$x_i^{(0)}(j) = 0.5 \times x_k^{(0)}(j-1) + 0.5 \times x_i^{(0)}(j+1) \tag{9}$$

3) Smoothing Processing of the Raw Data Sequence

If the randomness of the raw data sequence is somehow smoothed, it will be easier to model and to forecast the expected performance of the system. Smoothing processing is to transform the raw data into an increasing sequence, which is intended for futher smoothing the randomness of the raw data sequence based on the above step 2).
for $2 \le j \le m-1$

$$x_i'^{(0)}(i) = 0.25 \times \left[x_i^{(0)}(j-1) + 2x_i^{(0)}(j) + x_i^{(0)}(j+1)\right] \tag{10}$$

and for $j = 1,\ m$

$$\begin{cases} x_i'^{(0)}(1) = 0.25 \times \left[3x_i^{(0)}(1) + x_i^{(0)}(2)\right] \\ x_i'^{(0)}(m) = 0.25 \times \left[x_i^{(0)}(m-1) + 3x_i^{(0)}(m)\right] \end{cases} \tag{11}$$

The above processing not only increases the weights of the current data, but avoid the value fluctuating excessively, and slowing the changing rate of the primitive sequence which tends to grew quickly to make the randomness of the new data sequence weaker than that of the raw data sequence. In this way, the application scope of the traditional grey model is expanded.

4) Elevator Traffic Demand Forcasting Results

Let the forcasting output of the accumulated sequence by the processed raw data sequence be

$$\hat{X}^{(1)} = \left\{ \hat{x}_i^{(1)}(m+1),\ \hat{x}_i^{(1)}(m+2), \dots \middle| i = 1, 2, \dots, n \right\} \quad (12)$$

where $\hat{x}_i^{(1)}(m+1), \hat{x}_i^{(1)}(m+2), i = 1, 2, \dots, n$, are respectively the forcasting output of the accumulated sequenc of the (m+1)th day, (m+2)th day, …. Employing IAGO to $\hat{X}^{(1)}$ yields the elevator traffic demand forcasting results

$$\hat{x}_i^{(0)}(m+1) = \hat{x}_i^{(1)}(m+1) - \hat{x}_i^{(1)}(m) \quad (13)$$

5) Model Accuracy Testing

The model accuracy is tested by error of residuals to check whether the the relative error meets the given requirements. Let the residual sequence be

$$E_i^{(0)} = \left\{ e_i^{(0)}(j) \middle| i = 1, 2, \dots, n,\ j = 1, 2, \dots m \right\} \quad (14)$$

where $e_i^{(0)}(j) = x_i^{(0)}(j) - \hat{x}_i^{(0)}(j)$

Define $\overline{\varepsilon}_i = \frac{1}{m}\sum_{j=1}^{m}\left| e_i^{(0)}(j) / x_i^{(0)}(j) \right| \times 100\%$ as the average relative error of model *i*, and $p^0 = (1 - \overline{\varepsilon}_i) \times 100\%$ is referred to as the accuracy of model *i*, which is the generally accepted criteria for evaluating the model evaluation grade whose values are set as shown in Table 1.

Table 1: Criteria for evaluating the model

Accuracy of model p^0	***Model evaluation grade***
$p^0 \leqslant 90\%$	excellent
$80\% \leqslant p^0 < 90\%$	good
$p^0 < 80\%$	poor or unacceptable

4. Simulation Experiments and Analysis

The simulation data are from an office block with a dining-hall in the first floor, the legal working time of the people in the block is from 7 :00 in the morning to 19:00 in the evening from Mon. to Fri. The time interval for observing traffic is Δt =5min, observations were made during 5 days from Mon. to Fri. between 7:00 and 19:00, 144 data were collected in a day. The observed data from Mon. to Thur. form the raw data sequence, and the Fri.'s observed data are taken as the comparison sample. i.e. using the raw data sequence from Mon. to Thur. to forecast the Fri.'s elevator traffic demand. Here γ_1, γ_2 are set as 2, 0.5 in up traffic and 2.4, 0.6 for down traffic, respectively. The accuracies of the models of the proposed method are shown in Table 2 indicating that both under up- and down traffic all the models meet the requirement of gry forcasting [10], where there are 132 models are with "excellent" level and 12 with "good" level for up traffic, and 134 with "excellent" level, and 10 with "good" level for down traffic.

Table 2: Model accuracy

Traffic patterns	***Model accuracy***	***Number of models***	***Model evaluation***
Up traffic	[0.8, 0.9)	12	Good
	[0.9, 1)	132	Excellent
Down traffic	[0.8, 0.9)	10	Good
	[0.9, 1)	134	Excellent

The simulation results are shown in Figure 1~ Figure 6, where Figure 1 and Figure 2, show the elevator traffic demand forecasting results of Fri., applying the raw data sequence from Mon. to Thur., compared with the obsvered data sequence on Fri. under up and down traffic patterns expectively. In order to compare the proposed method in this thesis with the traditional method, two types of error which are the mean square relative error (MSRE) and the mean relative error (MRE) are suggested. The forcasting err curves shown in Figure 3 and Figure 4 demonstrate that the proposed method performs better results than the traditional gry forcasting method under both up and down traffic in terms of forecasting errs as shown in Figure 5, Figure 6, whose MSRE and MRE are given by Table 2. The results in Table 2 suggest that both MSRE and MRE of the proposed method are much less than that of the traditional method, the reason for which is that there are some outliers in the raw data sequence created by human subjectivity and occasionality, which make the raw data sequence seriously deviate from the exponential growth rule resulting greater errors. After smoothing the randomness, the raw data become smoother, consequently, the forecasting accuracy is improved.

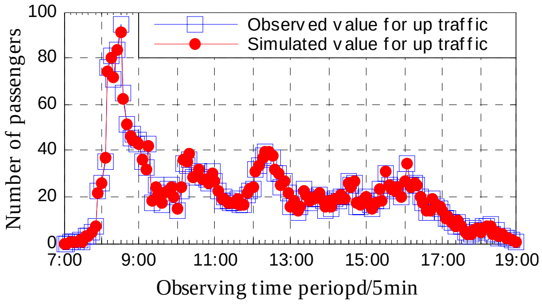

Fig.1. Simulated result for up traffic on friday by improved method

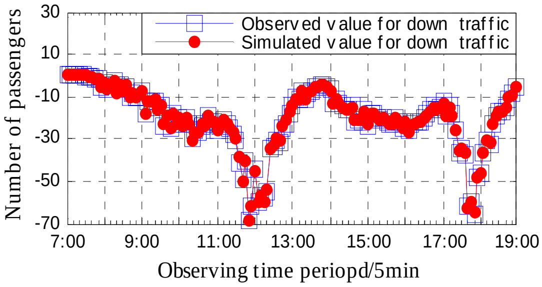

Fig.2. Simulated result for down traffic on friday by proposed method

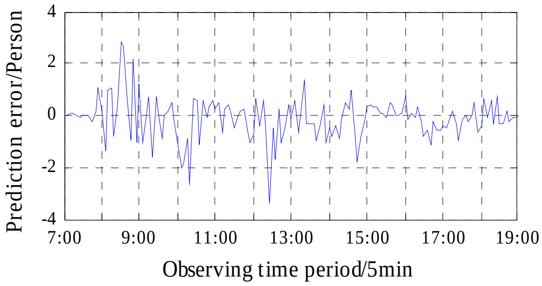

Fig.3. Forecasting error for up traffic by improved method

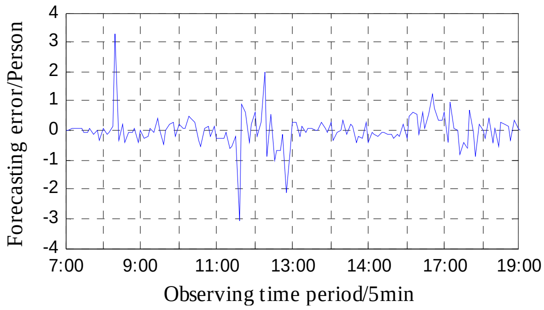

Fig.4. Forecasting error for down traffic by improved method

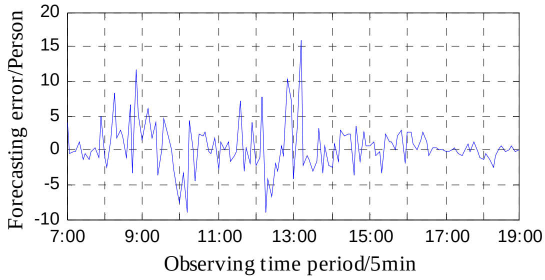

Fig.5. Forecasting error for up traffic by traditional method

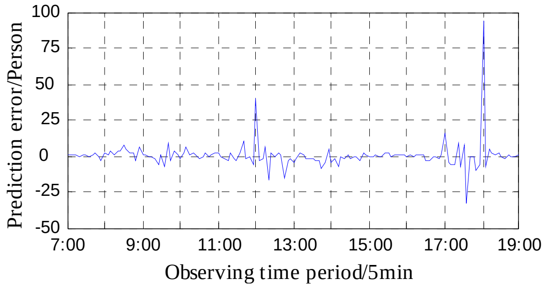

Fig.6. Forecasting error for down traffic by traditional method

5. Conclusions

In reguard to the strong grey characteristics of elevator traffic demand, a grey thoery based multi- model method to forecast the elevator traffic demand for EGCS is proposed in this thesis. Taking full advantage of the grey forecasting, the method is suited to the EGCS with limited number of samples and the incomplete information, on the other hand, for futher smoothing the randomness of the raw data sequence and weakening the influence of abnormal information caused by human subjectivity and occasionality, the raw data sequence is processed by comparing real time traffic data with the historical ones to modify the outliers to refine the traffic models, which effectively decrease the model error of the gry forcasting to reduce the impact of randomness on accuracy of modeling shch that the forecasting errs can be controled within the acceptable range for engineering problems, and consequently, making up for the deficiency of the grey forecasting method in theory. The simulation experiment indicates that the proposed method performs better results than the traditional gry forcasting method in forecasting auucracy, quite proximating to practical situation. The proposed method needs limited number of samples, especialy, it is suitable for short-term prediction of elevator traffic demand, providing the essential prerequisite for effectively implementating the EGCS.

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