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Elevator Traffic Pattern Recognition Based on Fuzzy BP Neural Network with SOM Algorithm

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Abstract

Elevator traffic pattern recognition (ETPR) is the prerequisite for effectively implementing the strategies of elevator group control system (EGCS). In view of the time-varying, nonlinear and uncertain characteristics of elevator traffic, an ETPR method based on fuzzy BP neural network with self-organizing map (SOM) algorithm is proposed, in which the fuzzy logic (FL) is introduced into BP neural network and, the SOM algorithm is employed to both determine the membership functions and merge the fuzzy rules. Thus as a result, the network structure is optimized, at the same time, the self-learning function of BP neural network enables the weighting coefficients of the FL membership functions to vary with different traffic patterns (TPs) and, the elevator traffic demand information is processed by fuzzy reasoning to realize ETPR and, therefore, to provide effective support to scheduling EGCS. Simulation experiments show the validity of the proposed method.

Key words

Elevator traffic demand, elevator traffic pattern recognition (ETPR), fuzzy neural network, expert experience, self-organizing map (SOM) algorithm

1. Introduction

EGCS is the core in transporting passengers efficiently and conveniently, in order to perform optimal quality and quantity of passenger service, the sophisticated control is required. It is generally aware that the elevator traffic demand is time-varying, presenting different TPs, and different TPs need respective control strategies of EGCS to deal with [1]. Therefore, the pattern recognition of elevator traffic demand is the essential prerequisite for effectively implementing the strategies of EGCS [2, 3], which has become an important research issue in the field of elevator group control technologies. Different ways have been employed to solve the problem [4-8], including the technologies of fuzzy reasoning, neural network, machine learning (e.g. SVM technique) and statistical pattern recognition (e.g. Bayesian decision), etc. These methods have made contributions in different levels to elevator group control under specific conditions. But it is very difficult for the single neural network method to determine the training samples and the network structure, besides, the long time offline learning for the optimal in-out mapping is an insurmountable drawback for the network training. In addition, the lack of learning ability is a major disadvantage for the FL to satisfy to varying elevator traffic demand. Therefore, further research of this problem is of indispensable significance. In essence, as stated above, elevator traffic system is a time-varying discrete system, different traffic demands will lead to different TPs, based on which the control strategies of EGCS are conducted respectively. As a result, to effectively identify the TPs will directly affect the total service level of EGCS.

In accordance with the preceding analysis, an ETPR method based on fuzzy BP neural network with SOM algorithm is proposed for the following reasons.

1) There exist a lot of uncertainties and fuzziness in elevator traffic system [9,10], including the indeterminate waiting floors for passengers to board the elevators, the indeterminate destination floors for passengers to leave the elevators and, the uncertain time for passengers to arrive at the destination floors, which make the elevator traffic system become exceptionally complex. Meanwhile, the dynamic and discrete characteristics of elevator traffic flow make the accurately predicting of elevator traffic demand extremely complicated. Hence, it is hard to establish the accurate mathematical model to identify the elevator traffic pattern.

2) Production rule based FL theory provides an effective way to solve the control system both with high complexity, and the state of which is not easy to accurately predict. The FL method has strong robustness and don't need precise mathematical model, but the problem is that both the construction of membership functions and the determination of fuzzy rules are difficult to achieve accurate and reasonable levels. Especially when the elevator traffic changes, the method is difficult to adapt to the changing traffic modes because of lacking self-learning ability. However, compared with the FL method [11], the neural network technique has stronger self-learning ability which is suitable for dealing with nonlinear and uncertain dynamics of elevator traffic, but the deficiency of which lies in that the property of multi-state of the system will bring

about the huge structure of the neural network, furthermore, the difficulty of knowledge representation and the slow learning speed will result in the undesirable effects of ETPR.

Therefore, to combine the two methods properly to constitute the fuzzy neural network, will not only makes up for the defects of lacking self-learning ability of the fuzzy technology, but also solve the problem that the neural network structure is difficult to determine.

3) SOM algorithm is a kind of feed-forward unsupervised learning network algorithm [12], the idea of which is to cluster the similar inputs on the same output in order to generate better clustering center over an enough number of iterations. The SOM algorithm is employed to obtain the membership functions in the network input/output space, which enables the membership functions to accurately reflect the distribution of samples and to merge the fuzzy rules to avoid the duplication, contradiction or redundancy of the fuzzy rules, and then the computational complexity is reduced to ensure the stability of the output and to optimize the structure of the network.

In consequence, the fuzzy BP Neural Network is constructed by employing the SOM algorithm, based on the self-learning function of neural network, the weighting coefficients of FL membership functions vary with the changing of different TPs, the ETPR is conducted by fuzzy inference to process elevator traffic demand information.

The remainder of this thesis is organized as follows. In Section 2, the classification of elevator TP is elaborated. In Section 3, construction of the fuzzy neural network is discussed in detail. In Section 4, the implementation of ETPR is conducted. In Section 5, results and discussions of the simulation are presented. And conclusions are drawn in Section 6.

2. Classification of Elevator TP

In every type of building, the residential or working population will want to enter or leave the building at various times during the day. There is a critical elevator traffic period, the type, direction, and intensity of elevator traffic during this period determine the quantity of elevator service for the building [13-15]. As per the size and direction of traffic flow in different types of building during different time periods in a day, the elevator traffic mode may be divided into the following main four categories.

2.1 Up-peak TP

An up-peak traffic mode exists when the dominant, or only, traffic flow is in an upward direction, with all, or the majority of, passengers entering the elevator system at the main terminal (MT) floor of the building. The major feature of this traffic mode is that the vast majority of passengers arriving at the lobby or MT floor seeking transportation to upper floors, and the minimum down traffic and inter-floor traffic are expected during this period.

Occurrence period: The up-peak traffic period is often the morning in-rush when everyone is leaving for work. Therefore, there are usually one starting floor and multiple random upper destination floors. The passenger arrival rate in this period is bigger than that in other traffic modes. In addition, in the moment after the lunch break, the up peak traffic may possibly happen for short duration.

2.2 Down-peak TP

A down-peak traffic condition exists when the dominant, or only, traffic flow is in a downwards direction with all, or the majority of, passengers leaving the elevator system at the MT floor of the building. There are usually one destination floor, and multiple starting floors. The profile of the down-peak traffic is larger in size and longer in duration than that of the up-peak traffic.

Occurrence period: It mainly occurs during the off hours at the end of the working day, and to a lesser extent at the start of the midday break, besides, there will be a down-peak traffic condition after the lunch break starts.

2.3 Inter-floor TP

The inter-floor traffic mode is caused by the normal circulation of people around a building during the course of their business. The major feature of this traffic mode is that there coexists the similar up and down traffic demand and, passengers usually return to their original floor after moving about the building. Therefore, over a period of time they balance out. Random inter-floor traffic can be said to exist when no discernable pattern of calls can be detected. The passenger traffic intensity may be in middle or relatively busy level.

Occurrence period: This type of TP exists for most of the working day and is a very important traffic demand, mainly occurs during the office hours both in the morning and in the afternoon.

2.4 Idle-TP

The idle-TP exists when there are a small number of passengers in the building and, the interval between successive passenger arrivals is relatively long. The total traffic volume of all the floors in the building in a certain period of time is very small.

Occurrence period: This type of TP exists for most of the holiday, late at night and dawn or before working start in the morning when the passenger traffic flow may be very few and inconsecutive.

3. Construction of the Fuzzy Neural Network

3.1 Network Architecture Design

The architecture of fuzzy neural network is shown in Fig.1. as a five-layer network, in which the normal signal propagation direction is from left to right layer by layer, but in the network training, the direction is from right to left called back propagation.

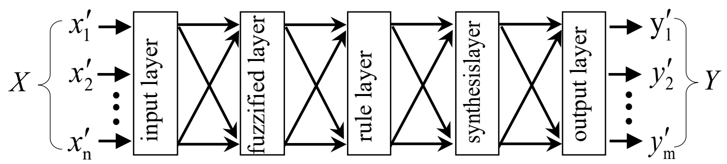

Fig.1. Architecture of Fuzzy Neural Network

where,

1) The first layer is the input layer whose nodes represent the input variables as crisp values of the input X.

2) The second layer is the fuzzified layer which performs fuzzification whose nodes represent the membership functions corresponding to the input variables.

3) The third layer is the fuzzy rule layer. The fuzzy rules are represented by the nodes of this layer and, the pre-conditions of the input fuzzy rules are related to the nodes of input fuzzy subsets and, the conclusions of the rules are related to the nodes of output fuzzy subsets. In rule layer each node represents a single fuzzy rule and fuzzy sets are converted as fuzzy connection weights.

4) The fourth layer is the synthesis layer. There are two kinds of operation modes for this layer, one is normal signal propagation from left to right, the other is from right-left propagation which executes the "OR"operation to realize the rule synthesis, viz. synthesizing the rules which have the same results, where the number of neurons equals to the number of fuzzy subset of all the output variables.

5) The fifth layer is the defuzzification layer. The nodes of which represent the output variables of the output Y, the crisp values of Y are calculated based on the weighted average method according to each of the membership grade of the fuzzy subset for each of the output variables.

3. 2 Network Parameters Setting

1) Determination of the Input/Output Variables

The network input: In conducting ETPR, the features of elevator TP should be reflected by the network model input variables. As a result, the elevator traffic volume over 5minutes interval is taken as the characteristic values of TP, but considering the difference effect of dimensional quantities on the accuracy of ETPR, characteristic values x_1, x_2, x_3, are normalized as $x_1' = x_1/x_{\max}$, $x_2' = x_2/x_{\max}$, $x_3' = x_3/x_{\max}$, so, the network input is constructed as below:

$$X = \{x_1', x_2', x_3'\} \qquad (1)$$

Where, x_1 is the total traffic volume, x_2 is the traffic volume entering the MT floor, x_3 is the traffic volume leaving the MT floor, $x_{\max}$ is the maximum number of passengers over a 5minutes interval, $x_1' \geq x_2' + x_3'$, $x_i' \subset (0,\ 1)$, $i = 1,2,3$. All the three characteristic values are employed to describe the traffic feature over a certain time interval and based on which the elevator TPs are recognized. The network output is given as:

$$Y = \{y_1, y_2, y_3, y_4\} \qquad (2)$$

where, y_1、y_2、y_3、y_4 denote respectively the proportion of up peak TP, down-peak TP, inter-floor TP and idle-TP, to the total traffic volume.

2) Determination of the Membership Functions

The membership functions are obtained in the input/output space with SOM algorithm, namely, that the training data are clustered and, each class corresponds to a fuzzy subset. Therefore, the input and output variables are evenly divided corresponding to seven fuzzy subsets respectively. In the self-organizing process of SOM algorithm, after entering sample data, the output neurons of the network will output different values by training the SOM network, and then the winning neurons with the largest output value will be selected to denote the category of the input data. The steps of the algorithm are given as follows [16]:

Step 1. Initialization. Randomly assign weights to the network, and obtain $M_l (l = 1,2,..,7)$, reset counter $t = 0$.

Step 2. Receive inputs. Input the sample one by one as the network input nodes (neurons), there exist

$$X^{p}=\left(x_{1}^{\prime p},x_{2}^{\prime p},x_{3}^{\prime p}\right) \quad (3)$$

where, $p=1,2,..,r$ (r is the number of training sample).

Step 3. Select the winning neurons, firstly, calculate the distance between the X^p and l, viz,

$$d_{l}=\left\|X^{p}-M_{l}\right\|=\sqrt{\sum_{i=1}^{3}\left[x_{i}^{\prime p}(t)-m_{il}(t)\right]^{2}} \quad (4)$$

Then select the neuron c as the winning neuron, that is

$$\left\|X^{p}-M_{c}\right\|=\min\left\{d_{l}\right\} \quad (5)$$

where， $l=1,2,..,7; p=1,2,..,r$.

Step 4. Adjust parameters. Update the wining neuron c and connection weights of its' neighbourhood neurons, there exit

$$w_{il}\left(t+1\right)=w_{il}\left(t\right)+\eta\left(t\right)\left[x_{i}^{\prime p}\left(t\right)-w_{il}\left(t\right)\right] \quad (6)$$

where $\eta(t)$ denotes the learning rate at time t, $\eta(t)$ is generally set as t^{-1} , $i=1,2,3,\ l=1,2,..,7,\ p=1,2,..,r$

Step 5. Calculate the output O_c , viz,

$$O_{c}=f\left(\min_{l}\left\|X^{p}-W_{l}\right\|\right) \quad (7)$$

where $f(\bullet)$ is set as Gaussian function, $l=1,2,..,7,\ \ p=1,2,..,r$

Step 6. Go to Step 2 for various $t=1,2,..,z$ $(100\le z\le 1000)$, repeat the afterwards steps till the termination condition is satisfied.

3) Generate and merge fuzzy rules based on SOM algorithm.

After the membership functions are determined, the fuzzy rules need to be generated and merged based on SOM algorithm, the competitive algorithm is employed to adjust the interconnection weightings between the third layer and fourth layer. After competition learning, the maximum one of all the weights of the network layer is retained, the corresponding output linguistic variable is the output of fuzzy rules.

After the rule nodes are determined, the fuzzy rules are optimized by merging the similar rules to avoid the duplicated, redundant rules and rule contradiction, and thereby, the system calculation is decreased, the generalization ability of the system is improved to ensure the stability of the output. The principle of merging multiple rule nodes into one node is given below:

- They have the same conclusions.
- Some certain prerequisites of these nodes are the same.
- The merging of the prerequisites of these nodes, forms an input of each different language variables.

4) Principle of network training.

The network training is done after the network architecture optimization is conducted. In this thesis, the improved BP algorithm is employed to the neural network training and learning [17]. The main idea of this algorithm is: For training samples $X^1, X^2, \ldots$, it is known that the desired corresponding output samples are $Y^1, Y^2, \ldots$, the actual outputs of network are $\hat{Y}^1, \hat{Y}^2, \ldots$, the purpose of training the network is to narrowed down the error between the actual and desired outputs, the error function is usually set as a square type function:

$$E = \frac{1}{2}\sum_{p=1}^{r}\left(Y^p - \hat{Y}^p\right)^2 \qquad (8)$$

where, $\hat{Y}^p$ and Y^p represent the actual calculated outputs and desired outputs respectively, $p = 1, 2, .., r$, r is the number of training samples. The output of equation (8) is the training error which is expressed by the training error curve.

4. Implementation Procedures of ETPR

4.1 Acquisition of the Training Samples

The network training samples are determined as per the feature of the corresponding TPs. Findings show that [18, 19]: The expertise of elevator traffic can reflect the relationship between the current actual traffic situation in buildings and the main TPs of elevator traffic in theoretical meaning. Therefore, the training samples are defined mainly on expertise by successively determining the relationship between the traffic information and TPs. The expertise is generally obtained through interaction with individuals or observation in the workplace.

1) Input samples: After the normalization of the primitive characteristic values of traffic demand, the scope of the network input values are limited to [0, 1]. As thus, the principle to set the network inputs is given as: The three inputs of the network are selected in the range of [0, 1] with the increment of 20%, where the outliers are ruled out based on the constraint condition $x_1' \geq x_2' + x_3'$, and the sample set with 56 training samples is acquired at last according to the aforementioned method.

2) Output samples: The output samples are determined in the same way as that of determining the input samples as per the feature of the corresponding TPs, viz, the network outputs y_1, y_2, y_3, y_4 are given, respectively, as the percentages of the up peak traffic, down-peak traffic, inter-floor traffic and idle-traffic, to the total traffic volume. So, the percentage based traffic modes which are the network outputs can be descripted as follows:

- If the number of passengers entering the MT floor of the building accounts for a very large proportion of the total traffic, then the up-peak TP occupies a large percentage of all the traffic modes as the predominating TP.
- If the number of passengers leaving the MT floor accounts for a very large proportion of the total traffic, then the down-peak TP occupies a large percentage of all the traffic modes as the predominating TP.
- If there is a large traffic percentage in between the top floor and the MT floor, then the inter-floor TP occupies a large percentage of all the traffic modes.
- If there are very few passengers in the building, then the idle-floor TP occupies a large percentage of all the traffic modes.

4.2 Parameter Determination of Fuzzy Neural Network Architecture

After the training sample set is determined, the training of the network is conducted, to determine the parameter of FNN architecture, as follows:

Step 1. Cluster the training samples into different categories by SOM algorithm, and then, to determine the center and width of membership functions.

Step 2. Adjust the interconnection weightings between the third and fourth layer based on the learning strategies of SOM algorithm and, optimize the fuzzy rules according to the weights.

Step 3. The improved BP algorithm is employed to train the network till the desired training error to determine the structure parameters.

The architecture parameter of the network model is obtained as shown in Table 1.

Table 1. The architecture parameter of the network model

Number of inputs	Number of outputs	Number of input fuzzy subsets	Number of output fuzzy subsets	Number of nodes of each layer
3	4	7	7	3-21-343-28-4

5. Simulation Experiment

5.1 Simulation Samples

The elevator traffic samples are collected from a real high-rise office block in Guangzhou. The statistical time is from 7:00~19:00 for a working day which lasts 12 hours in total, the sampling interval is 5 minutes. The samples include respectively x_1, x_2 and x_3 as shown in Fig. 1. As thus, there are 144 traffic sampling time points. x_1 , x_2 , x_3 are taken as the three input feature values to the fuzzy neural network.

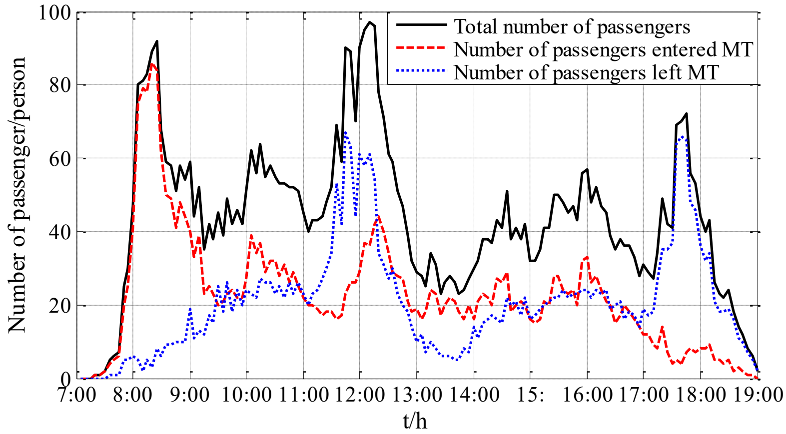

Fig.2. Passenger demand for the high-rise office block over a working day

It can be seen from Fig. 2. that the maximum value obtained from every 5 minutes approaches 100, so the maximum passenger traffic volume can be set as 100 which is used to normalize the input feature values.

5.2 The Network Training

The network training is conducted by the algorithm given in the **appendix**, the training error curve of the network is given below (see Fig. 3), the root mean square training error is 9.73295×10^{-4}.

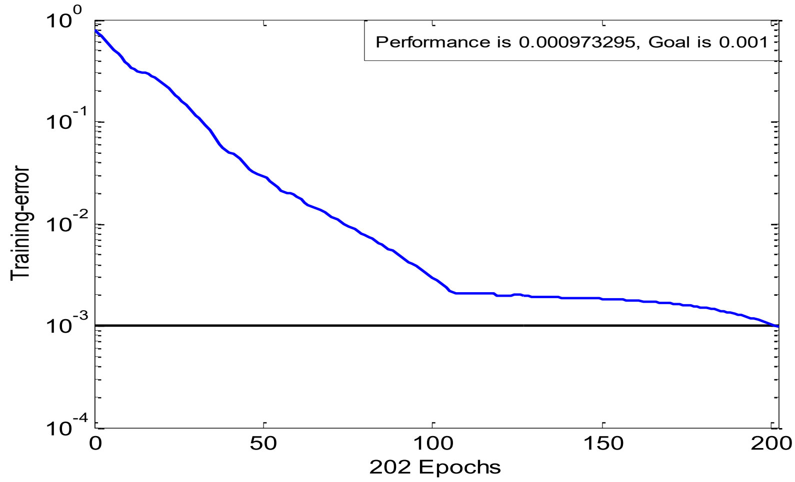

Fig.3. Training Error Curve of FNN for ETPR

5. 3 Simulation Results of the ETPR

Based on the trained fuzzy neural network model, the percentage of each traffic mode is obtained respectively as shown in Fig. 4 through Fig.7. The results of the up-peak ETPR as shown in Fig. 4 show that: There are two typical up-peak TPs in a day, one is from 8:00 to 9:00 in the morning, the other is from 12:10 to 12:30 in the afternoon, in which the up-peak traffic accounts for relatively bigger percentage.

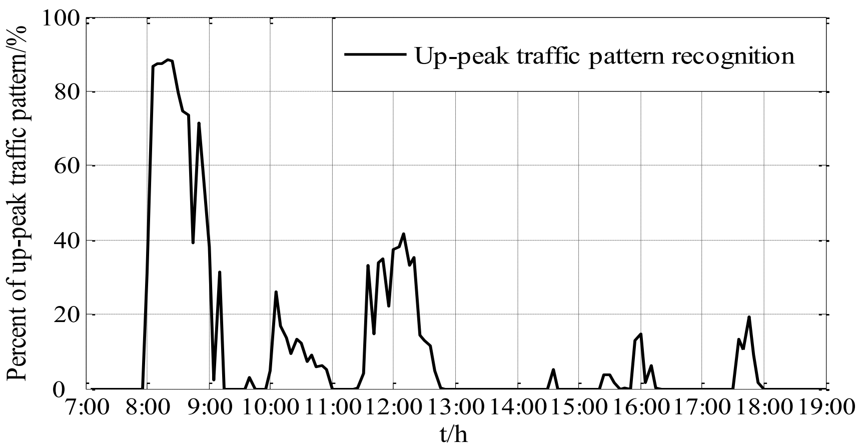

Fig.4. Percentages that the up-peak TPs occupy

Most of the passengers go upper floors from the main terminal, in addition, since there are only part of the staff leaving the building, the intensity of up-peak traffic is bigger than that of the midday up-peak traffic.

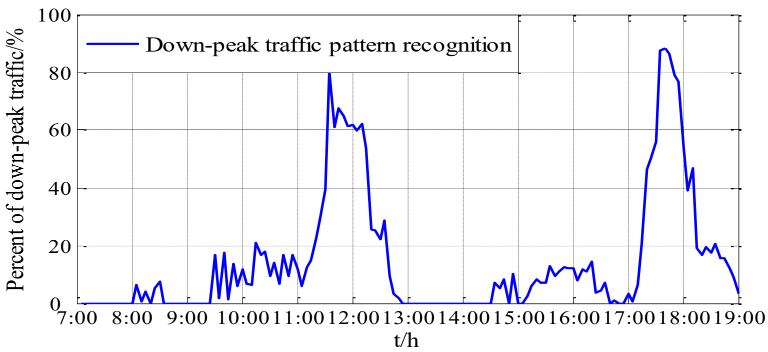

Fig.5. Percentages that the down-peak TPs occupy

It can be seen from the results of the down-peak ETPR as shown in Fig. 5 that: There are two typical down-peak TPs in a day, one is from 11:30 in the morning to 12:05 at midday, the other is from17:30 to18:10 in the afternoon, in which most of the passengers at various upper floors waiting to go down to the lobby or the MT floor, the down-peak traffic accounts for relatively bigger percentage, and the intensity of morning down-peak traffic is bigger than that of the midday down-peak traffic.

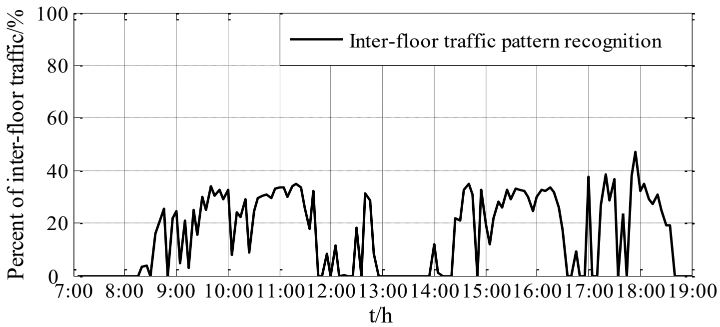

Fig.6. Percentages that the Inter-floor TPs occupy

It can be seen, from the results of the inter-floor ETPR as shown in Fig. 6, that the inter-floor TPs between 9:00 and 11:40, 14:20 and 18:20 account for bigger percentage. It is generally recognized that this is a very traffic mode which lasts the longest in the vertical building traffic system.

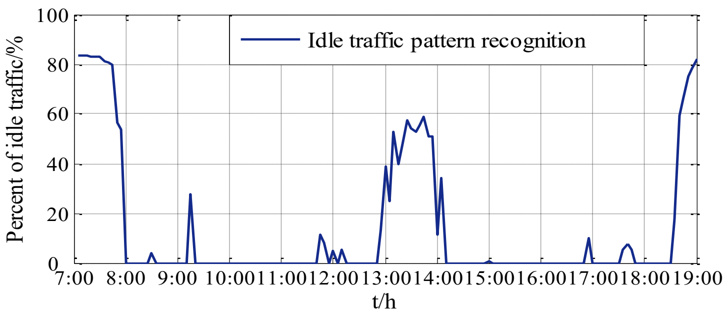

Fig.7. Percentages that the idle-TPs occupy

It is shown by the idle-traffic recognition results in Fig. 7 that the idle-TP occupies a relatively large percentage of all the traffic modes, before 8:00 when most of the people hurry to work and after 18:30 in the afternoon when people are usually more anxious to get off work. The number of passengers involved in this traffic mode is less and the interval between successive passenger arrivals is longer than usual, and that almost no passengers taking elevators in the period of 12:50 to 14:10, idle-traffic mode accounts for a large proportion.

Conclusion and Discussion

There are two important measures in conducting the ETPR with the fuzzy neural network technology, one is to simplify the fuzzy rules by determining the membership functions based on SOM and, the other is to couple the neural network with the FL which enables the FL adaptively handle the changing elevator traffic conditions. Simulation experiment suggests that the results of ETPR based on fuzzy BP neural network with SOM basically match with the actual traffic condition showing the validity of the proposed method and, based on which, the control strategies of EGCS can be conducted effectively as follows:

• **The up-peak traffic strategy**: The incoming traffic of passengers from the MT floor to the upper floors is very crowded in up-peak TP, therefore, 1) The MT floor calls are given priority over the upper floor calls. 2) Cars are usually scheduled to wait at the MT floor and selected according to their arrival sequence to attend the MT floor calls. 3) The cars loaded with the passengers from the MT floor travel upward and drop off passengers until its highest destination is reached. Then the car will pick up passengers, if any, at that floor, reverse direction and travels toward the lobby. During the return trip, the car will stop at a floor only if there is at least one other car located at the lobby, not more than a full load car of passengers is waiting at the MT floor, its contract capacity is not reached, and there is a landing request at that floor. 4) When a loaded car arrives at the MT, it drops off all passengers. If no passenger is located at the MT, the car waits at least 3 seconds or so. If no passenger shows up, the car is free to answer an upper landing call, on a longest waiting time basis.

The switching condition of such strategy is that if there are two consecutive cars travelling up from the MT with full load, then the up peak traffic strategy will be automatically selected. Otherwise, if the consecutive car load is less than a predefined level, say 60%, of its rated load, the up peak traffic strategy will be switched off.

• **The inter-floor traffic strategy:** This strategy has no preference between the MT floor and the upper floors hall calls. Passengers enter a car at the MT floor and leave at various floors during the up trip. On its down trip the elevator picks up passengers at various floors and lets them out at the MT floor. Once a car is free, it will respond to the landing call that waited the longest. When a hall call at the MT floor is responded, the car will pick up passengers to its capacity. The car will travel and stop only at the passengers destinations, and unload passengers until everybody is out. When a hall call at an upper floor is responded, the car will pick up passengers to its capacity. The car travels to the MT floor and answers a landing call in its way only if its maximum capacity is not reached yet, and no other car is located at that floor.

• **The down peak traffic strategy:** 1) The hall calls of upper floors are given priority over the MT calls. 2) The intensity of passenger flow is intense with lots of descending passengers from the upper floors who will go to the MT floor, while the inter-floor and ascending traffic is few and far between. Therefore, it usually occurs that the descending cars are often fully loaded at upper floors, which makes the passengers' waiting time of the lower floors increase. 3) On account of the above reasons, the building is usually divided into zones, cars are usually grouped into zoning operation mode. Each car serves a specific zone: This means that a car can respond only to the calls registered within its zone. Passengers at the lobby can travel to any floor.

• **The idle traffic strategy:** Passenger traffic is tiny and intermittent. Cars at the MT are dispatched according to the "first come, first work" principle. under the condition of satisfying the service performance figure (such as the average passenger waiting time which is accepted as less than 60s), the number of elevators may be adjusted with the varying of the traffic intensity. From the average waiting time point of view, arranging a few elevators to attend hall calls will satisfy the service requirements to avoid empty driving of cars, which greatly reduce the energy loss and equipment depreciation of the elevator system.

The switching condition of such strategy is that when EGCS works in the none up-peak strategies, if there are neither hall calls appeared in 90-120s, nor the load of cars is less than 40% of the rated load, the idle traffic strategy will automatically selected. If there appears one hall call in 90s, or two hall calls in a relatively short time (about 45s) or three hall calls in a shorter period of time (about 30s) , then such strategy will be terminated.

Therefore, it goes without saying that the traffic pattern recognition of elevator traffic demand is of great importance and plays an irreplaceable role in elevator group control strategies.

References

1. Zhenshan Yang, Cheng Shao, Guizhi Li, Multi-objective optimization for EGCS using improved PSO algorithm, American Control Conference, ACC' 2007, New York, USA, July, 2007, Proc. pp. 5059-5063.

2. J. Fernandez, P. Cortes A Survey of elevator group control systems for vertical transportation, a look at recent literature, IEEE Control Systems Magazine, vol.35, no.4, pp.38-55, 2015,
3. Zhenshan Yang, Yunli Zhang, Dewen Zhu, Research on elevator traffic dispatching using genetic algorithms, AMSE conference, MS’2002, Girona, Spain, Jun 2002, Proc. pp. 627-634.
4. Pablo Cortés, R.F. Joaquín, José Guadix, *et al.*, Fuzzy logic based controller for peak traffic detection in elevator systems, Journal of Computational and Theoretical Nanoscience, vol. 9, no. 2, pp. 310-318, 2012.
5. Zhenshan Yang, Cheng Shao, Haifeng Ma, LS-SVM base determination of critical time ranges for elevator TPs, Elevator World, vol. 56, no. 5, pp. 110-115, 2008.
6. Fujun Ma, Traffic pattern identification of elevator group control based on Bayes decision theory, Mechanical & Electrical Engineering Magazine (in Chinese), vol. 26, no. 9, pp. 104-107, 2009.
7. Albert T P So, J R Beebe, W L Chan, et a1., An artificial neural network based traffic pattern recognition system, Int. Journal of Elevator Engineering, vol. 1, no. 1, pp. 35-46, 1996.
8. 岩田稚史, 匹田志朗, 駒谷喜代俊, ニューラルネットワークによるエレベータ交通流の検出, 計測自動制御学会論文集. 1997, vol. 33, no. 3, pp. 210 – 215, 1997.
9. Zhenshan Yang, Cheng Shao, A new method for multi-objective control of elevator group in high-rise building, AMSE Journals, Series Advances D, vol. 13, Nº 2, pp. 15-27, 2008.
10. G C Barney, Lutfi Al-Sharif, Elevator Traffic Handbook: Theory and Practice, Taylor & Francis Ltd., 2016.
11. James C. Bezdek, James Keller, Raghu Krisnapuram, Fuzzy models and algorithms for pattern recognition and image processing, Springer Science+Business Media, Inc., 2005.
12. Buyun Xu, He Ni, Comparative analysis of SOM and K-means clustering, The Journal of New Industrialization (in Chinese), vol. 4, no. 7, pp. 63-69, 2014.
13. George R. Strakosch, Robert S. Caporale, The vertical transportation handbook (4th ed.), John Wiley & Sons, Inc., 2010.
14. CIBSE, Transportation system in buildings, GIBSE Guide D 2010 (4th ed.), Page Bros. (Norwich) Ltd., 2010.
15. Zhenshan Yang, Yunli Zhang, Traffic demand forecasting for EGCS with grey theory based multi- model method, Int. Journal of Computer Science Issues, vol. 10, no. 1, pp. 61-67, 2013.

16. Yuanli Gu, Xingchuan Wang, Jianxiang Xu, Traffic data fusion research based on numerical optimization BP neural network, Applied Mechanics and Materials, vol. 513-517, no. 1, pp. 1081-1087.
17. Alexander I. Galushkin, Neural networks theory, Springer-Verlag Berlin Heidelberg, 2010.
18. P. Cortés, J. Fernández, J. Guadix et al., Fuzzy logic based controller for peak traffic detection in elevator systems, Journal of Computational and Theoretical Nanoscience, vol. 9, no. 2, pp. 310-318, 2012.
19. Zhenshan Yang, Wei Ren, Elevator traffic planning under complex building conditions, Journal of Bohai University (in Chinese), vol. 35, no. 1, pp. 17-22, 2014.

Appendix: Algorithm Implementation of ETPR

Step 1. Input the training samples which have been normalized $X=\{x_1',x_2',x_3'\}$ as the network input, and the $Y=\{y_1,y_2,y_3,y_4\}$ is taken as the network output.

Step 2. Conduct the clustering analysis based on self-organization algorithm and construct the SOM network.

Step 3. Initialize the SOM network and set it's network parameters.

Step 4. Train the SOM network, preliminarily determine the membership functions and simplify the fuzzy rules.

Step 5. Employ the improved BP algorithm to train the fuzzy neural network to construct the BP network, where there consists respectively of 21, 343, 28 neurons number, and 4 outputs in the three hidden layers of the network structure determined in the previous step.

Step 6. Determine the parameters of the BP network, learning rate η is set as 0.01, the limit of error ep = 0.001, training epochs = 500.

Step 7. Input the test samples into the trained network model to realize TP recognition.