Proceedings of the 30th Chinese Control Conference
July 22-24, 2011, Yantai, China

Chaos Characteristics of Peak Elevator Traffic Flow

LI Jun-Fang[1,2], LENG Jian-Wei[2], ZHANG Jing-Long[1]

1. School of Electrical Engineering and Automation, Tianjin University, Tianjin 300072, P. R. China
E-mail: wendyljf@sina.com

2. School of Electrical Engineering, Tianjin University of Technology, Tianjin 300384, P. R. China
E-mail: wendyljf@sina.com

Abstract: In this paper, nonlinear time series techniques are applied to analyze the peak elevator traffic flow data. The phase space, which describes the evolution of the behaviour of a nonlinear system, is reconstructed using the delay embedding theorem suggested by Takens. The embedding parameters, e.g. the delay time and the embedding dimension are estimated using the mutual information of the data and the false nearest neighbor algorithm, respectively. Numerically the attractor of the elevator traffic flow from reconstruction is not necessarily sufficient indication of chaos, therefore we then calculate the correlation dimension of the resulting attractor and the largest Lyapunov exponent. It is demonstrated that the traffic flows of the up-peak and down-peak all exhibit low-dimensional chaotic behaviour. The result will help to adjust the group control scheduling methods according to the chaotic behaviour of the peak flow so as to increase the performance index.

Key Words: Elevator Traffic Flow, Chaos, Phase Space Reconstruction, Largest Lyapunov Exponent

1 Introduction

Characteristic analysis of Elevator Traffic Flow (ETF) is the key content to influence the energy losses of the Elevator Group Control System (EGCS). Because of the stochastic of the passenger's arrival and the uncertainty of the determination, this question becomes the difficult one of the EGCS[1,2]. Characteristic analysis of ETF affects the scheduling policy, start-stop times and the running status of the elevator and so on. Therefore, the exact characteristic analysis of traffic flow can explain some complex phenomenon of the ETF, and can provide useful guidance for elevator dispatching unit to improve the dispatching efficiency of the elevators.

But, many research results were about the predication and mode classification of the elevator traffic flow[3] in the past years. These studies can be help to the dispatching policy, but they still can't provide the straight analysis from traffic data. In recent years, mining useful information from the ETF have recently become a real challenge and hot subject of research. Most of researchers suppose that traffic flow has the characteristic of stochastic[4,5],and the traffic flow should obey Poisson Distribution or Homogeneous Distribution[6]. This assumption is considered from stochastic methods and Poisson Process assumption becomes incredible in other field with the flow's changes[7,8]. In the fact, the systems of the elevator traffic are complex nonlinear systems in which chaotic phenomenon have been reported[9,10]. So, maybe we can use chaotic theory to explain and understand the complexity of the ETF. At the same time, we wonder if the chaotic features also exist in the ETF. Till now, there is little research result in this point. We just refer to some results of the relevant domain, such as road traffic[11-15] and network traffic[16].

*This work is supported by National Natural Science Foundation (NNSF) of China under Grant 60874073, 91016018

In this paper, taking the up-peak traffic flow for example, we observed the chaotic features of the ETF from qualitative analysis and quantitative analysis. Firstly, continuous wavelet transform of the ETF is performed, which can smooth out the high frequency noisy and can construct a time-frequency representation of a signal that offers very good time and frequency analysis. Secondly, from the view of qualitative analysis, phase space reconstruction is used to obtain the reconstructed attractor of the original data set. And from the point of quantitative analysis, the invariant measures of correlation dimension and the largest Lyapunov exponent are calculated. At last, It is demonstrated that up-peak and down-peak traffic flow data exhibit similar low-dimensional chaotic behavior.

2 Analysis of Nonlinear Time Series of ETF

2.1 Continuous Wavelet Transformation

For these data, we conduct the wavelet analysis. Continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. In mathematics, the continuous wavelet transform of a continuous, square-integrable function $x(t)$ at a scale $a>0$ and translational value b is expressed by the following integral

$$X(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\psi(\frac{t-b}{a})dt \tag{1}$$

where $\psi(t)$ is a continuous function in both the time domain and the frequency domain. Here, we use the first derivative of the Gaussian function $g^{(0)}(x)=e^{-x^2/2}\big/\sqrt{2\pi}$, namely, $g^{(1)}(x)=dg^{(0)}(x)\big/dx$.

According to the above method, first we use the continuous wavelet transform to perform a space-scale analysis of the data sequences of the ETF. A reasonable filtering scale has been chosen to smooth out the high frequency noisy fluctuations of the profile. The sequence of the elevator up-peak traffic flow is shown in Fig.1. The denoised sequence is shown in Fig.2, and then this sequence will be used to phase space reconstruction.

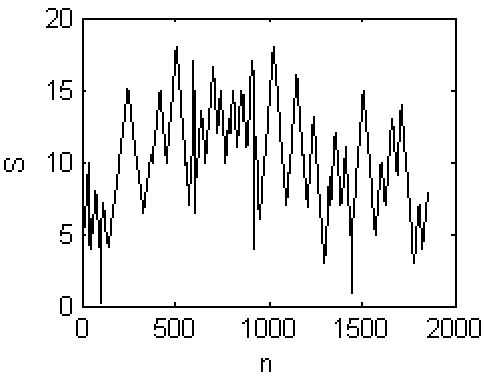


Fig. 1: Elevator traffic flow S of up-peak

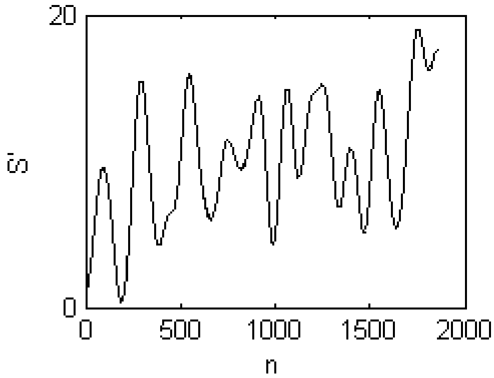


Fig. 2: Elevator traffic flow S' of up-peak after filtering.

2.2 Phase Space Reconstruction

Phase space reconstruction is a powerful technique to recover the topological structure of a dynamical system given by a scalar time series. Suppose a single variable time series $x_1, x_2, \cdots x_N$ of a dynamical system is observable, according to Taken's theorem[17] , the original phase space geometry of the system may be reconstructed in the m-dimensional phase space. The reconstructed attractor of the original system is given by the vector sequence:

$$P(i) = (x_i, x_{i+\tau}, x_{i+2\tau}, \ldots, x_{i+(m-1)\tau}) \tag{2}$$

where τ and m are the embedding delay and the embedding dimension respectively. In order to reconstruct the original phase space, we first estimate reconstruction parameters, the delay time τ and the embedding dimension m .

2.3 Time Delay

A reasonable time delay τ is very important for efficient phase space reconstruction because usually we have to deal with a finite amount of noisy data. Small delay will yield strongly correlated vector elements, while large delay leads to vectors whose components are almost uncorrelated. The time delayed mutual information method[18] suggested by Fraser and Swinney is commonly used to determine a reasonable delay. Unlike the autocorrelation function, the mutual information takes into account also the nonlinear correlations. We take time series of the ETF S as the primary data series $\{x(t)\}(t = 1, 2, \cdots, n)$,and Q as the delayed data series $\{x(t+T)\}$. A measure of mutual information between data of a time series is as follows:

$$I = (Q, S) = \sum_i \sum_j P_{sq}(s_i, q_j) \log_2 \left[\frac{P_{sq}(s_i, q_j)}{P_s(s_i) P_q(q_j)} \right] \tag{3}$$

where $P_s(s_i)$ is the probability to find a time series value in the ith interval, and $P_{sq}(s_i, q_j)$ is the joint probability that an observation falls into the ith interval and the observation time τ later falls into the jth interval. The first minimum of $I = (Q, S)$ is chosen as a delay time for the reconstruction of phase space.

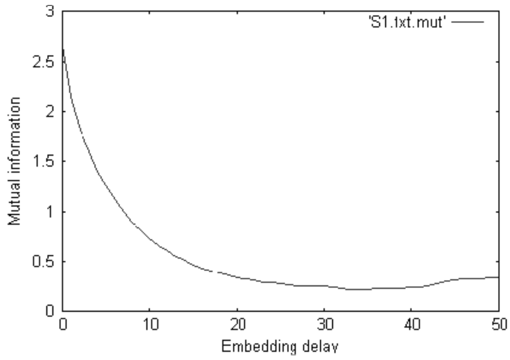


Fig. 3: Result of mutual information method for S'

From above analysis, mutual information method presents its first minimum at τ =35kb, which is chosen as the appropriate time delay for phase space reconstruction of the ETF.

2.4 Embedding Dimension

The false nearest neighbor (FNN) algorithm suggested by Kennel[19] is the most commonly employed method to determine the minimal sufficient embedding dimension. The idea of the algorithm is as follows. For each point X_n in the time series, we look for its nearest neighbor X_t in an m-dimensional space. Calculate the separation between these two points

$$R_n(m) = \sqrt{(X_t - X_n)^2 + (X_{t-1} - X_{n-1})^2 + \cdots} \tag{4}$$

Then in an m+1-dimensional space, we can compute the separation $R_n(m+1)$. If $R_n(m+1)$ significantly exceeds $R_n(m)$, this point is marked as having an FNN. The criterion which the embedding dimension is high enough is that the fraction of FNN is zero or at least sufficiently small. From Fig.4. It can be clearly observed that the fraction of FNN convincingly drops to zero for m =8. So we take the minimal sufficient embedding dimension as 8.

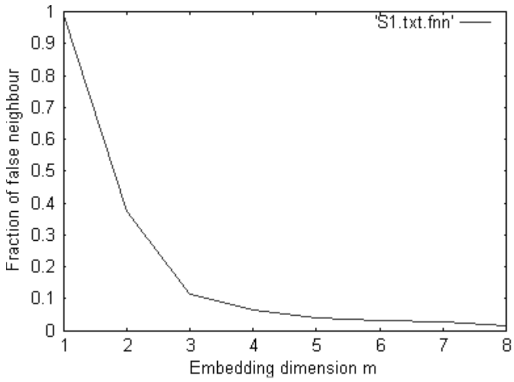


Fig. 4: Result of FNN method for ETF S'

With τ =35kb and m =8, the reconstructed attractor is shown in Fig. 5. And we can know the structure of the reconstructed attractor is very similar to the structure of the chaotic attractor. It shows that the time series of ETF has chaotic behavior.

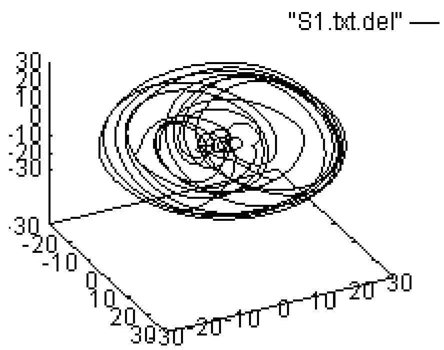


Fig. 5: Reconstructed attractors of ETF S'

2.5 Correlation Dimension

The correlation dimension method is used for detecting the possible presence of chaos. An algorithm suggested by Grassberger and Procaccia[20] is the most commonly employed method. Let $C(\varepsilon)$ be the number of points within all the sphere of radius ε. A plot of $\ln C(\varepsilon)$ versus $\ln \varepsilon$ should give an approximately straight line whose slope in the limit of small ε and large N is the correlation dimension

$$D_r(F) = \lim_{\varepsilon \to 0} \frac{\ln C(\varepsilon)}{\ln \varepsilon} \tag{6}$$

whether $D_r(F)$ can be got or not, it lies in the ε. One hand, if ε is large enough, then $C(\varepsilon)$=1. On the other hand, if ε is very small, then $C(\varepsilon)$=0. If the system is chaotic, the slope of $\ln C(\varepsilon)$ versus $\ln \varepsilon$ converges to m over an appropriate interval as m increases.

We use the TISEAN package and get the $D_2 \approx 1.55$ as shown in Fig.6. This value indicates the possible existence of low-dimensional attractor. Further, using TISEAN package we compute the LLE for elevator traffic flow.

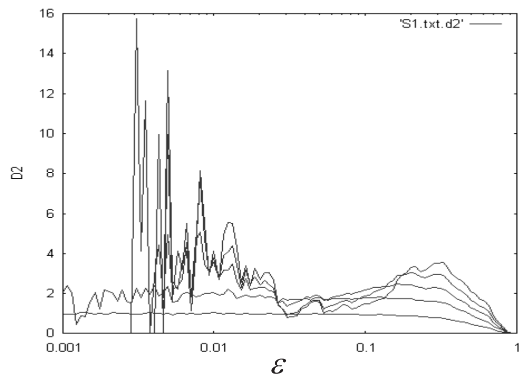


Fig. 6: Estimation the correlation dimension of ETF S'

2.6 Largest Lyapunov Exponent (LLE)

The Lyapunov exponent shows how predictable or unpredictable the system is. For a chaotic system, there is at least one positive Lyapunov exponent. According to the methodology of Kantz[21], we consider the representation of the time series as a trajectory in the embedding space. Assume that we observe a close return $s_{n'}$ to a previously visited point s_n. Then we can consider the distance $d_0 = \|s_n - s_{n'}\|$ as a small perturbation, which should grow exponentially in time. At time *t*, for a chaotic system, one obtains $|d_t| \approx d_0 e^{\lambda t}$,

$$S(\varepsilon, m, t) = \left\langle \ln\left(\frac{1}{|u_n|} \sum_{s_{n'} \in u_n} |s_{n+t} - s_{n'+t}| \right) \right\rangle_n \tag{1}$$

If $S(\varepsilon, m, t)$ exhibits a linear increase with identical slope for all m larger than some m_0 and for a reasonable range of ε, then this slope can be taken as an estimate of the LLE.

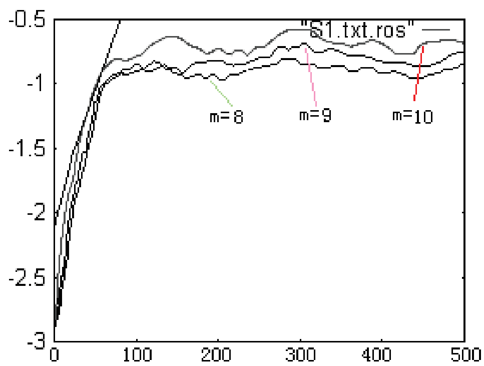
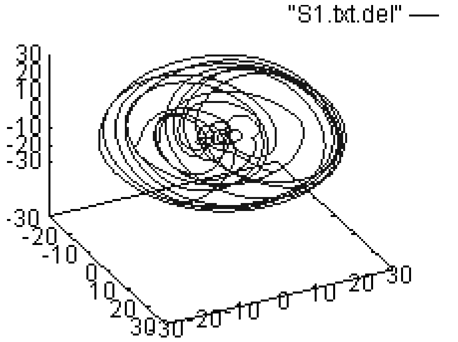
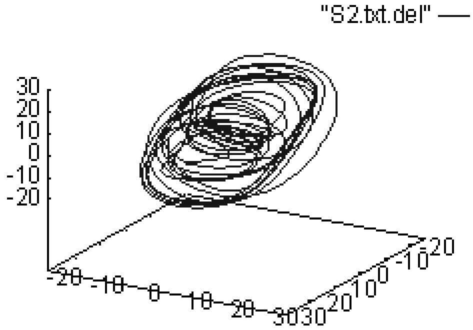


Fig. 7: Estimation the LLE of ETF S'

In Fig. 7, the computed LLE is the mean value of local slopes gathered from the linear regime when m = 8 ,9,10 and converges to 0.00725. This positive value indicates the existence of chaotic behavior is consistent with the estimation from the correlation dimension method and the FNN method as discussed above. Finally, we analyze the elevator down-peak traffic flow with the same method.



(a) Up-peak



(b) Down-peak

Fig. 8: Reconstructed attractors of elevator traffic flow.

Table 1: Computation of the Largest Lyapunov Exponents and D_2 of Elevator Traffic Flow

Traffic Mode	Largest Lyapunov Exponents (λ)	Correlation Dimension (D_2)
Up-peak	0.02	1.55
Down-peak	0.0275	1.65

Figure 8 shows the reconstructed attractors of up-peak and down-peak. We can see that the attactors share the similar shape. They look like two strands of intersecting rings. The values of the LLE and correlation dimension of these ETF sequences are shown in Table.1 It is shown that the LLE of these samples are very close to each other and are in the range of [0.02,0.03].The values of correlation dimension are in the range of [1.50, 1.65]. Thus these ETF sequences exhibit similar low-dimensional chaotic behaviour.

3 Conclusion

In this paper, we have investigated the ETF sequences of up-peak and down-peak. After denoising with continuous wavelet transformation, these ETF sequences are analyzed by phase space reconstruction method. Correlation dimension and the LLE indicate low-dimensional chaotic behaviour in both of the sequences. Furthermore, the sequences have similar attractor shape. We suggest that chaotic properties may be ubiquitous in the ETF sequences of all peak modes. But we need to build the traffic model to analyze the influence of the reference (such as, the arrival rate) to chaos characteristic. This study will help to the regulation of the scheduling method of the group control system aiming at the traffic flow character.

References

[1] Zhou, J, L. Yu, et al. Double-deck elevator systems adaptive to traffic flows using genetic network programming. *Congress on Evolutionary Computation*.2008:773-778.

[2] Nagatani T. Complex behavior of elevators in peak traffic. *Physica a-Statistical Mechanics and Its Applications*,326(3-4): 556-566,2003.

[3] Zong Qun, Zhao Zhan Shan,and Shang An-Na. Recursive forecasting method for elevator traffic flow based on SARIMA.*Tianjin Daxue Xuebao*, 41(6):653-659,2008.

[4] Benmakhlouf S M, Khator, S K. Smart lifts: Control design and performance evaluation. *Computers and Industrial Engineering,* , 25(1-4): 175-178, 1993.

[5] Siikonen. M J. Elevator traffic simulation. *Simulation*, 61 (4): 257-267,1993.

[6] Barney G C. Traffic design. *Elevator Technology. Ellis Horwood: Chi Chester,* 1986.

[7] Bigdeli, N. and M. Haeri. Time-series analysis of TCP/RED computer networks, an empirical study. *Chaos Solitons & Fractals,* 39(2): 784-800,2009.

[8] Paxson V. Fast. Approximate synthesis of fractional Garssian noise for generating self-similar network traffic]. *Computer Communication Review,* 5(3):5-18,1997.

[9] Nagatani T. Dynamical behavior in the nonlinear-map model of an elevator. *Physica a-Statistical Mechanics and Its Applications,* 310(1-2): 67-77,2002.

[10] Nagatani T. Dynamical transitions in peak elevator traffic. *Physica a-Statistical Mechanics and Its Applications* 2004,333: 441-452.

[11] Nagatani T. Chaos and dynamical transition of a single vehicle induced by traffic light and speedup. *Physica a-Statistical Mechanics and Its Applications,*2005,348: 561-571.

[12] Nagatani T. Chaos control and schedule of shuttle buses. *Physica a-Statistical Mechanics and Its Applications,* 371(2): 683-691, 2006.

[13] Low D J, Addison P S. Chaos in a car-following model with a desired headway time, in *Proceedings of the 30th ISA-TA Conference.Florence,Italy,*1997:175-182.

[14] Nagatani T , Nagai R. Chaotic and periodic motions of two competing vehicles controlled by traffic lights. *Chaos Solitons & Fractals,*2005, 25: 245-253.

[15] Lo S C , H J Cho. Chaos and control of discrete dynamic traffic model. *Journal of the Franklin Institute-Engineering and Applied Mathematics*,342(7): 839-851,2005.

[16] Nagatani J H C, H H C Iu, et al. Analysis and control of bifucation and chaos in average queue length in TCP/RED model. *International Journal of Bifurcation and Chaos*,18(8): 2449-2459,2008.

[17] Takens F. Detecting Strange Attractors in Turbulence. *Berlin Springer:* 1981

[18] Frazer A M, Swinney H L. Independent coordinates for strange attractors from mutual information. *Physics Review A,* 1986, 33: 1134~1140

[19] Kennel M, Brown R, and Abarbanel H. Determining embedding dimension for phase-space reconstruction using a geometrical construction. *Physics Review A,* 1992, 45: 3403-3411

[20] Grassberger, P. and Procaccia, I. Measuring the strangeness of strange sttractors. *Physica D9*, 1983:189-208.

[21] Schreiber T, Kantz H. Practical implementation of nonlinear time series methods: The TISEAN package . *Chaos*, 1999, 9: 413-43