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Chaos Process Testing (Using Local Polynomial Approximation Model) in Predicting Stock Returns in Tehran Stock Exchange

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Abstract

Nowadays, the benefits of predicting are undeniably accepted in decision and policy making from different dimensions. Error in predicting makes a model unapplied and transient. Recently, structural models which were relatively successful in explaining the current situation have not been paid much attention in the field of forecasting. Thus, other tests such as local polynomial approximation model have been proposed. This model has introduced to test chaos processes in time-series of daily returns on Tehran Stock Exchange over a period from 2007 to 2013. The obtained findings prove the existence of such process in the evolution of this index.

Keywords: chaos, return on stock, local polynomial approximation model, time series.

1. Introduction

It is mainly believed that the analyzed variable has a linear procedure which is accompanies with a random process (White Noise). In sum, such models are called linear random models. Some researchers applied non-linear models such as ARCH and GARCH which simply use a non-linear model in residual variances with a random component. These models are called non-linear random models.

In mathematics, such non-linear random procedures are named chaos which cause chaotic events. By and large, a chaos 1) is non-linear, 2) dynamic, 3) causes complex procedures, and 4) is highly sensitive in a way that seems to be random. Based on chaos theory, new approaches such as Fractal market hypothesis were proposed. This hypothesis attempts to explain financial markets' phenomena against efficient markets hypothesis. Fractal market hypothesis can be confirmed if maximal and reverse Lyapunov exponential tests are accomplished. Maximal Lyapunov exponential (MLE) test is applied to ensure the predictability of analyzed series based on non-linear models, while reverse maximal Lyapunov exponential test is used to determine the predictable time. Mention must be made that if analyzed series are confirmed to be chaotic, they cannot be modelled or predicted on the basis of linear models anymore. In other words, linear models do not enjoy good results.

Edward Norton Lorenz, a pioneer of chaos theory, introduced the strange attractor notion and coined the term butterfly effect. He also applied chaos theory in the field of earth, planetary sciences, weather patterns, management, sociology, astrology, mechanics, physics, mathematics, biology and economics (Behdad Salami, 2003).

Chaos literally refers to the state of anarchy, bustle, confusion and disorder. Philosophically, chaos is a total lack of organization in which accident determines the occurrence of events. In theoretical discussions, chaos is considered as the order of seemingly disordered systems and derived from recognizing the existing secrets and regulations of the nature. Many interpretations have been utilized to conceptualize chaos theory. For instance, considering the smokes moving in ordered circles and gradually become disordered and fade, chaos theory can be understood. Chaotic systems are deterministic, meaning that their future behaviour is fully determined by their initial conditions, with no random elements involved. In other words, the deterministic nature of these systems does not make them predictable. But the analysts who are not aware of the nature of the system (or does not know it well enough), cannot distinguish between a chaotic and a random system (Haji Karimi, 2004).

2. Theoretical background and review of literature

Chaotic systems are nonlinear dynamic systems which (1) are highly sensitive to initial conditions; (2) have unusual complicated absorbents; (3) sudden structural breaks in their trajectory are distinguishable (Prokhorov, 2008). However, in order to perceive these systems deeply, it should be noted that:

1. The behaviour of chaotic systems though seems random, in essence can be theoretically explained by deterministic rules and equations. Nevertheless, even though we accept the existence of equations explains the source of their chaotic behaviour, proximity and inaccuracy (though very small) are inevitable due to measurement limitations.

2. Even very small inaccuracy in initial value (for instance 10^{-6} units), because chaotic system is highly sensitive to them, leads to huge differences between expected and realized values in the long term. In other words, as time passes, forecasted series and measured values of realized series totally diverge so much that previous forecasts are no longer reliable; a fact called unpredictability in the long run (Williams, 2005).

Recently, neural network and compound models have been applied to achieve more accurate results. GURESEN et al. (2011) conducted a research entitled "Using artificial neural network models in stock market index prediction" and attempted to improve traditional linear and non-linear models' performances. Ying Wei et al. (2011) assessed stock exchange of Taiwan through the application of fuzzy neural network model. They found that fuzzy neural network models are superior to artificial neural network models and statistical models such as time-series models. Esfahanipour and Aghamiri (2010) investigated and predicted price index of Tehran Stock Exchange through applying fuzzy neural network models.

Findings of this study indicated that the made predictions have been %97.8 consistent with the reality.

Al Wadia and Ismail (2011) accomplished a research entitled "selecting wavelet transforms model in forecasting financial time series data based on ARIMA model". They pointed to the application of wavelet transforms model in various fields such as physics, engineering, mathematics, and statistics (econometrics) and discovered the superiority of wavelet transforms model over time series data prediction. To achieve this result, they assessed stock data of Oman. Schwarcz (2010) applied a chaos test and examined various dimensions of financial markets and their effects on investing. Lento (2009) utilized Hurst chaos tests and investigated the relationship between long-term dependencies and interests and Canadian financial markets. By and large, different scholars such as Peters (1996), Mulligan and Lombardo (2004), Cornelis and Yalamova (2004), Onali and Goddard (2009), and Huang (2010) pointed out that economic policy makers pay increasing attention to non-linear models such as chaos tests and wavelet frequency analysis to model their stock markets, since they applied mathematics and physics to econometrics.

According to Abbasi Nezhad and Naderi (2012), Other important studies which were accomplished in this field can be named in the following manner: Naderi and Kamijani (2012); Heidari Zare and Kordloui (2010); Fahimifard et al. (2010); Moshiri et al. (2010); Monjemi et al. (2009); Fallah Shams and Delnavaz Asghari (2009); Moshiri and Morovat (2010); Azar and Afsar (2006); Moshiri and Morovat (2005); and Salami (2002).

3. Methodology

As it has been mentioned before, deterministic and random chaos are considerably different. This section deals with the fact that distinguishing between these two is so difficult. However, new studies have been accomplished in this field. Various tests have been discussed in the review of literature which make us capable of distinguishing a random system from a chaotic system. Some tests examine the random process, while others assess the chaotic characteristics of the process. Latter is called direct test, and the former is indirect. Indirect tests such as BDS examine the randomness of linear or non-linear residual regression; therefore, if this hypothesis that the process is random is rejected, it cannot be necessarily accepted that it is chaotic, since it can be rooted in the type of applied linear or non-linear model (Moshiri & Morovat, 2002).

The concept of Lyapunov exponential had been used before the emergence of chaos theory in order to recognize the consistency of linear and non-linear systems. Lyapunov exponential is calculated through assessing system skewness or flexture. Various methods exist to calculate Lyapunov exponential such as direct method or Jacobian Matrix method. In fact, Lyapunov exponential, which provide a qualitative and quantitative characterization of dynamical behavior, are related to the exponentially fast divergence or convergence of nearby orbits in phase space. A system with one or more positive Lyapunov exponential is defined to be chaotic. Reverse Lyapunov exponential shows the difference between deterministic and random process.

4. Maximal Lyapunov Exponential (MLE) test

Maximal Lyapunov exponential test, suggested by a Russian scholar, is applied to measure sensitivity to initial conditions through the following equation: ($du/dt = f(u), u \in D \subset R^n$). Lyapunov exponential are specific statistics of fixed points. Linear equation of $\frac{dy}{dt} = \frac{\partial f}{\partial u}\left(\Phi(u_0)\right)y$,where $u_0 = u(t = 0)$ and its answer can be written as $y(t) = U_{u_0}^t y_0$, where $U_{u_0}^t$refers to the main matrix of equation. This matrix is correct in the chain rule of $U_{u_0}^{t+s} = U_{u_0}^t \times U_{u_0}^s$. When $t \to \infty$, it can be stated that $\lambda(V^k, u_0) = \lim_{t\to\infty} \ln \frac{U_{u_0}^t e_1 \Lambda\, U_{u_0}^t e_2 \Lambda \ldots U_{u_0}^t e_n}{\|e_1 \Lambda\, e_2 \Lambda \ldots \Lambda e_k\|}$.

Assume that $m_n(t), \ldots, m_l(t)$ be eigen values of the answer of the following equation:

$$\begin{cases} \frac{dy}{dt} = A(x_0)y_0 \\ y(t) = e^{A(x_{.})t}, \end{cases}$$

Where $A(x_0) = \frac{\partial f}{\partial u}(x_0)$, so the Lyapunov exponents are $\lambda(x_0) = \lim_{t\to\infty} \frac{1}{t}\ln|m_i(t)|$, when limit exists.
Pay attention to the Lyapunov exponential of fixed point u^* in dynamic system of $du/dt = f(u)$. If $\hat{\lambda}_n \ldots, \hat{\lambda}_1$ be eigen values of the linear equation of $du/dt = A(u^*)$, then $m_i(t) = e^{\hat{\lambda},t}$ and $\lambda_i = \lim_{t\to\infty} \frac{1}{t}\ln\left|e^{\hat{\lambda},t}\right| = \lim_{t\to\infty} \frac{1}{t}Re[\hat{\lambda}_i]$.

As it can be observed in the abovementioned model, Lyapunov exponential is equel to real part at eigen value of the critical points. They indicate the speed of contraction (when $\lambda_i < 0$) or expansion ($\lambda_i > 0$) near to fixed points. Spaces in which contraction or expansion occur are determined by suitable vectors of $A(\alpha)$. Positive one-dimensional Lyapunov exponential show that two close directions (for initial conditions with small difference) become divergent. Lyapunov exponential are directly defined based on calculating the integral of the following linear equation:

$$\frac{dy}{dt} = A(x_0)y \tag{4-1}$$

For $y(0) = (1,1, \ldots, 1)$, the equation is accompanied with equation of motion. If integral is calculated on a long time such as T, it can be said that $\lambda_i = \frac{1}{T}\ln[\, m_i(T)]$.
However, it is not very accurate, since when there is at least a positive Lyapunov exponential, $t \to \infty$ and severe problems will be caused by equation (4-1).
An appropriate method regards this reality that each initial disorder is averagely accompanied with the exponential growth. This study explains the calculation of one-dimensional maximal Lyapunov exponential. An initial value of x_0 and initial disorder of δx_0 are chosen. Let $y^{(0)} = y_0$ and, $u^{(0)} = \frac{y_0}{\|\delta y_0\|}$, linear equation's od U^0 is integrated over time T. Then, $y^{(1)} = y(T, u^{(0)}, y^{(0)}) = y(u^{(0)}, T)u^{(0)}$.

Let $u^{(1)} = y^{(1)} / \| \delta y^{(1)} \|$ is the normal value of $\delta y^{(1)}$, integral of linear equation of $u^{(1)}$ is calculated over time T, then the following equation is obtained:

$y^{(2)} = y\left(T, u^{(1)}, y^{(1)}\right) = y\left(u^{(1)}, T\right)u^{(1)}$

where $y^{(1)} = y(x^{(0)}, T)$.

Repeating the process for K times $y\left(KT, y_{0,}u_0\right) = \| y^{(x)} \| \cdots \| y^{(1)} \| u^{(k)}$ is obtained and when is large enogh, the following equation can be achieved:

$$\lambda_1 = \frac{1}{KT}\ln \| y(KT, y_{0,}u_0) \| = \frac{1}{KT}\ln\prod_{k=1}^{K} \| y^{(k)} \| = \frac{1}{KT}\sum_{k=1}^{K}\ln \| y^{(k)} \|.$$

Usually, T is 10 or 20 times bigger than system's natural period. If T is too larg or small, severe problems may be caused. Lyapunov exponential of can be evaluated through a similar approach. Since Lyapunov exponential can be used to assess the speed of contraction or expansion, they can be utilized to distinguish dissipative system from conservative system.

Phase space is maintained for $\sum_{i=1}^{n} \lambda_i = 0$. In such situations, a conservative system exists.

In dissipative systems, Phase space is contracted with $\sum_{i=1}^{n} \lambda_i < 0$.

It should be noted that a dynamic system has attractor only when $\sum_{i=1}^{n} \lambda_i \leq 0$, since when $\sum_{i=1}^{n} \lambda_i >$, the system is expanded and there is no attractor.

Lyapunov exponential help to recognize different attractors and dynamic systems. If there is a one-dimensional dissipative system, the only possible attractor is $\lambda_1 = (-)$ (which $(-)$ notation shows the sign of λ_i) by a fixed point in Phase space. For a dissipative system in two-dimensional Phase space, two Lyapunov exponential are regarded. The combination of $(\lambda_1, \lambda_2 = (-,-)$ indicates a quasi-point attractor, and $(\lambda_1, \lambda_2 = (\ ,-)$ shows a limit orbit in Phase space, which equals the equation. For a three-dimensional dissipative system, three types of answer are possible: $(-,-,-)$ quasi-point attractor, $(0,-,-)$ limit orbit, and $(0,0,-)$ central two-frequency quasi-periodic. Furthermore, nontrivial attractors with $(+,0,-)$ exist, when $\sum_{i=1}^{n} \lambda_i < 0$.

Attractors with positive Lyapunov exponential are called strange chaotic attractors, and equation (5-2) is strange if at least one of Lyapunov exponential is positive and one-dimensional. In strange chaotic attractors, positive Lyapunov exponential shows the expansion inside the attractor, while negative exponents indicate the contraction outside the attractor.

$$\frac{du}{dt} = f(u) \quad , \quad u(t_0) = u_0, \quad , \quad u \in D \subset R^n \quad , t \in R^+ \qquad (4-2)$$

5. Local Polynomial Approximation Model

The local polynomial approximation (LPA) of noisy data is considered with the new adaptive procedure for varying bandwidth selection. The algorithm is simple to implement and nearly optimal within In N factor in the point-wise risk for estimating the function and its derivatives. The adaptive varying bandwidth enables the algorithm to be spatial adaptive over a wide range of the classes of functions in the sense that its quality is close to that which one could achieve if smoothness of the estimated function was known in advance. It is shown that the cross-validation adjustment of the threshold parameter of the algorithm significantly improves its accuracy. In particular, simulation demonstrates that the adaptive algorithm with the adjusted threshold parameter performs better than the wavelet estimators.

Suppose that we are given by noisy samples of a signal $y(x)$,

$$z_\delta = y(x_\delta) + \varepsilon_\delta, \qquad \delta = 1,2,\dots,N \qquad (5-1)$$

where ε_δ independent identically distributed with, $E(\varepsilon_\delta) = 0$ and $E(\varepsilon_\delta^2) = \sigma^2$. It is assumed that $y(x)$ be longs to the nonparametric class of piecewise continuous m-differentiable functions.

$$\mathcal{F} = \left\{\left|y^{(m)}(x)\right| \le L_m\right\}$$

Our goal is to estimate $y_\delta = y(x_\delta)$ depending on observations $(z_\delta)_\delta^N = 1$ with a point-wise mean squared error (MSE) risk which is as small as possible. The following loss function is used in the standard linear LPA:

$$J_h(x) = \sum_{\delta=1}^{N} \rho_h(x_\delta - x)(z_\delta - C^T\phi(x_\delta - x))^2\,) \qquad (5-2)$$

$$\phi(x) = (1, x, x^2/2\,, \dots, x^{m-1}/(m-1)!)',$$

$$C = (C_0, C_1, \dots, C_{m-1})',$$

where x is the centre and m is the order of the LPA. The window $\rho_h(x) = \rho(x/h)/h$ is a function satisfying the convention properties of the “kernel” estimates, inparticular, $\rho(x) \ge 0$, $\rho(0) = \max_x \rho(x), \rho(x) \longrightarrow 0$ p(x) as $|x| \longrightarrow \infty$ and $\int_{-\infty}^{\infty} \rho(u)du = 1$. Here h is a window ‘size’ or a bandwidth. Then minimization of $J_h(x)$ with respect to C, obtained:

$$\hat{C}(x,h) = \arg\min_{C \in R^m} J_h \qquad (5-3)$$

$\hat{y}(x) \triangleq \hat{C}_0(x,h)$ is an estimate of $y(x)$, and $\hat{y_K}(x) \triangleq \hat{C}_k(x,h), k = 1, \dots m-1$, as estimates of the derivatives $y^{(k)}(x)$. These estimates can be represented in the form of linear filters

$$\hat{y}_k(x,h) = \textstyle\sum_\delta g_k(x, x_\delta, h) y_\delta \qquad (5\text{-}4)$$

where

$$\textstyle\sum_\delta g_k(x, x_\delta, h) x' = k!.\,\delta_{l,k}, \qquad k,l = 0.1, \dots, m-1 \qquad (5\text{-}5)$$

shows that the linear transforms (5-4) have accurate reproductive properties with respect to polynomial components of $y(x)$ up to degree $m - 1$.

The linear estimators (5-4) and (5-5) are a very popular tool in signal processing and statistics with application to a wide variety of the fields for smoothing, filtering, interpolation and extrapolation . It is wellknown that bandwidth selection is a crucial point of the efficiency of the LPA estimators. In particular, the essentially varying in x curvature of $y(x)$ requires a varying spatially adaptive bandwidth $h = h(x)$.

Adaptive bandwidth possesses simultaneously many attractive asymptotic properties, namely, 1). It is nearly optimal within in N factor in the point-wise for estimating the function and its derivatives; 2). It is spatial adaptive over a wide range of the classes of $y(x)$ in the sense that its quality is close to that which one could achieve if smoothness of $y(x)$ was known in advance.The intersection of the confidence intervals (ICI) of the estimates with different bandwidths is proposed in (5-4)for bandwidth selection.

The multi-window LPA with the data-driven adjustment of the threshold parameter of the ICI bandwidth selection is developed in this paper. It is shown that this adjustment results in a very valuable accuracy improvement of the adaptive estimates of $y(x)$. The R statistical software is used.

6. Local polynomial prediction

Presume that the state vector of time T is:

$$\mathbf{x}_T = (\mathbf{x}_T, \mathbf{x}_{T-\tau}, \dots, \mathbf{x}_{T-(m-1)\tau})$$

The parameters are obtained by fitting curves in a small zone with the local polynomial method, and then predicting the data $\mathbf{x}_{T+p}$ after p step using *s*-order polynomial:

$$\hat{\mathbf{x}}_{T+p} = F(\mathbf{x}_T) = f_0 + \sum_{k_1}^{m-1} f_{1k_1}\mathbf{x}_{T-k_1\tau} + \sum_{\substack{k_2=k_1\\k_1=0}}^{m-1} f_{2k_1k_2}\mathbf{x}_{T-k_1\tau}\,\mathbf{x}_{T-k_2\tau}$$

$$+\cdots+ \sum_{\substack{k_s=k_{s-1},\dots,k_2=k_1\\k_1=0}}^{m-1} f_{sk_1k_2}\,\mathbf{x}_{T-k_1\tau}\,\mathbf{x}_{T-k_2\tau}\cdots\mathbf{x}_{T-k_s\tau} \qquad (6-1)$$

K neighboring points $\mathbf{x}_T$ are $\mathbf{x}_{a_1}, \mathbf{x}_{a_2}, \dots, \mathbf{x}_{a_k}$, and if thesystem is stable, when $\mathbf{x}_T$ comes near $\mathbf{x}_{a_k}$, $\mathbf{x}_{T+p}$ also comes near $\mathbf{x}_{a_{k+p}}$.

Then, the problem is transformed to solve the coefficients of $f_0, f_{10}, \dots, f_{1(m-1)}, f_{200}, \dots, f_{s(m-1)\dots(m-1)}$ using weighted least square principal, just make:

$$\sum_{k=1}^{k} P_k\,|\mathbf{x}_{a_k+P} - \hat{\mathbf{x}}_{T+p}|^2 = \sum_{k=1}^{k} P_k\,\left|\mathbf{x}_{a_k+P} - F(\mathbf{x}_T)\right|^2 = \min \qquad (6-2)$$

note:

$$y = [\mathbf{x}_{a_1+P}, \mathbf{x}_{a_2+P}, \cdots, \mathbf{x}_{a_k+P}]^T \in R^K$$

$$f = [f_0, f_{10}, \dots, f_{1(m-1)}, f_{200}, \dots, f_{s(m-1)\dots(m-1)}]^T \in R^J$$

$$X = \begin{bmatrix} 1 & P_1 x_{a_1} & \cdots & P_1 x_{a_{1-(m-1)\tau_1}} & P_1 x_{a_1}^2 & \cdots & P_1 x_{a_{1-(m-1)\tau_1}}^s \\ 1 & P_2 x_{a_2} & \cdots & P_2 x_{a_{2-(m-1)\tau_1}} & P_2 x_{a_2}^2 & \cdots & P_2 x_{a_{2-(m-1)\tau_1}}^s \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & P_k x_{a_k} & \cdots & P_K x_{a_{k-(m-1)\tau_1}} & P_K x_{a_k}^2 & \cdots & P_K x_{a_{k-(m-1)\tau_1}}^s \end{bmatrix} \in R^{K \times J}$$

The required coefficient J is $(m + s)!/ m! s!$, P_i is the weight of neighboring point in Section 3.2. Coefficients $f_0, f_{10}, \dots, f_{1(m-1)}, f_{200}, \dots, f_{s(m-1)\dots(m-1)}$ satisfy the following matrix equations:

$$y = Xf$$

In order to obtain a stable result, it is required that $K \geq J$. If matrix $X^T X$ can be inversed, then

$$f = (X^T X)^{-1} X^T y$$

Where T is a notation for transposed a matrix.

7. Results

This study aimed to assess daily returns in listed companies on Tehran Stock Exchange. Days in which no transaction has happened or whose return was zero were omitted from the model. Table 1 demonstrates the descriptive statistics of the returns on Tehran Stock Exchange in daily time-series based on annual periods.

Table 1. Descriptive Statistics of The Stock Returns

Year	Mean ± SD
2007	0.02879 ± 3.811676
2008	0.03564 ± 0.169521
2009	0.971213 ± 98.3987
2010	0.002781 ± 0.014956
2011	0.038487 ± 9.53924
2012	0.000537 ± 0.056608
2013	0.008495 ± 0.163849
Total	0.005621 ± 0.089242

In the present study, chaos was analyze and different chaotic models were evaluated to predict returns on Tehran Stock Exchange through the application of local polynomial approximation model. The achieved results showed error level of %5 for the existence of chaotic process in return series on Tehran Stock Exchange. Furthermore, predictability, martingale process and non-linearity of the series were confirmed. Therefore, the efficient market hypothesis of the series cannot be confirmed. This conclusion could be also drawn that the studied series are chaotic and Fractal market hypotheses about the stock returns are confirmed.

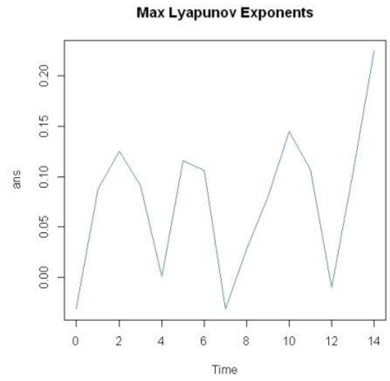

Fig.1- Maximal Lyapunov Exponential

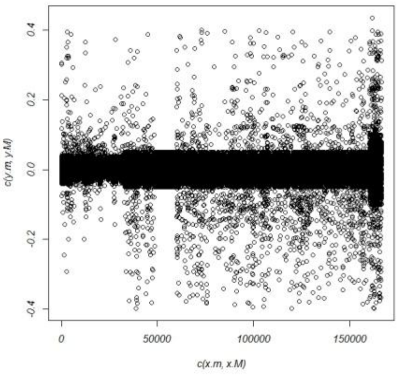

Fig.2- Weighted first-rank local-region

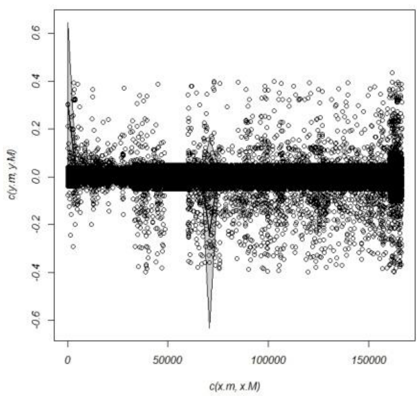

Fig.3- Local polynomial

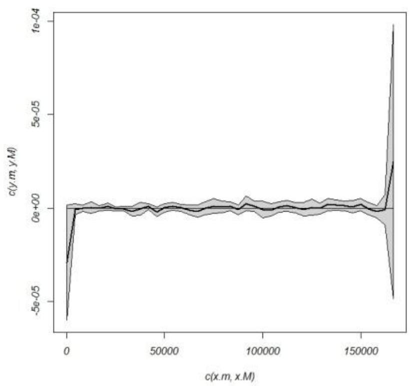

Fig.4- Improved local polynomial

Table 2. Comparison of Prediction Performance

Prediction methods	RMSE (root-mean-square error)
Weighted first-rank local-region	0.02816715
Local polynomial	0.053572912
Improved local polynomial	0.0281774

The weighted first-rank local-region and improved local polynomial method have a better RMSE rather than the local polynomial. Since using weighted first-rank local-region and improved local polynomial method are suggested.

8. Conclusion and suggestions

Time-series tests of local polynomial approximation model were applied in the current study, and with a high level of confidence confirmed the chaotic process among listed companies on Tehran Stock Exchange over a period from 2007 to 2013. On the achieved results of this study, it can be suggested to generate efficient processes in order for more appropriate models, and complex and volatile predictions. Using time-series tests of local polynomial approximation model can improve predictable results of the series whose chaotic process had been previously confirmed. Technically, models that are based on genetic algorithm, non-linear regression and Fractal models, which are the most useful non-linear models, can be employed to test chaotic series.

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