International Journal of Digital Content Management (IJDCM)
Vol. 5, No. 9, Spring & Summer 2024; P 1-16
dcm.atu.ac.ir
DOI: 10.22054/dcm.2022.70147.1158

ATU PRESS

Original Research Submit Date: 14-09-2022 Revise Date: 07-10-2022 Accept Date: 19-11-2022
ISSN: 2717-3305 eISSN: 2717-3313

Prediction of Time Series of Financial Information Based on Lyapunov View of Information Using Chaos Theory

Mostafa Sohoulivahed — Ph.D.Candidate of Accounting, Department of Accounting, Yasuj Branch, Islamic Azad University, Yasuj, Iran

Mohammadali Aghaei – — Associate Professor, Department of Accounting, Tarbiat Modares University, Tehran, Iran

Fariborz Avazzadehfath — Assistant Professor, Department of Accounting, Gachsaran Branch, Islamic Azad University, Gachsaran, Iran

Ali Pirzad — Assistant Professor, Department of Management, Yasuj Branch, Islamic Azad University, Yasuj, Iran

Abstract

Purpose: The purpose of this research was to provide a model for predicting time series of financial information based on the Lyapunov representation of information using chaos theory.

Method: This research is applied in its purpose, which is conducted using a quantitative approach. The research ranks as descriptive-causal accounting research based on actual information in companies' financial statements. The research method is the "post-event" type and was carried out using chaos theory and Saida's method based on the Lyapunov view.

Findings: The findings showed that during the ADF test, the null hypothesis was rejected at a level of less than 5% type 1 error and 95% confidence, and it shows that the data is not static. During the substitution analysis test and its significance level, the behavior of the time series of the main financial

– Corresponding Author: aghaeim@modares.ac.ir

How to Cite: Sohouli Vahed, M., Aghaei, M.A., Avazzadeh Fath, F., Pirzad, A. (2024). Prediction of Time Series of Financial Information Based on Lyapunov View of Information Using Chaos Theory, *International Journal of Digital Content Management (IJDCM)*, 5(9), 1-16. DOI: 10.22054/dcm.2022.70147.1158

information is significantly different compared to their substitutes. The obtained value was calculated to describe the production process of all data sets for $\mu = 2$, ApEnMax equal to 0.65 and rMax equal to 0.32, and for $\mu = 3$, ApEnMax equal to 0.6 and rMax equal to 0.44. The value of the Lyapunov profile in stability at a certain point is less than zero and in the limited cycle of stability is equal to zero and in chaos, it is greater than zero and smaller than ∞, and in noise it is equal to ∞.

Conclusion: The results show that higher returns, encourage investors to invest and increase the flow of capital. It is believed that companies' stock returns are a function of systematic risk, and systematic risk represents the changes in the return rate of a share compared to the changes in the return rate of the entire stock market.

Keywords: Chaos Theory, Financial Information, Lyapunov View, Optimal Stock Portfolio, PSO Algorithm.

Introduction

Due to the importance of stock returns for investors, various models have been developed to estimate this variable, the most important of which are the Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), stock forecasting model based on O and Penman's financial statement items and Fama and French's three-factor model (FFM). The existence of an active and prosperous capital market is always recognized as one of the signs of the development of countries at the international level. In developed countries, most investments are made through financial markets. The active participation of people in the stock market guarantees the life of the capital market and the sustainable development of the country. The main problem that investors face in these markets is deciding to adopt the right security measures for investment and forming the optimal stock portfolio. The investment process in a coherent state requires the analysis of the main nature of investment decisions (Amiri & et al., 2019). Deciding to buy new shares or sell the existing shares requires obtaining information about the future state of the stock market price. Therefore, if it is possible to predict the future trends of the stock market price, economic decisions will be made based on information and as a result the loss or risk of investment will be reduced.

Information is the main source of decision-making and its strategic importance is such that it is considered power. Correct and timely decision-making, and short-term and long-term planning in economic, political, cultural, social and otherwise matters related to an organization, company or at the national and international level depend on appropriate and correct information, and the lack of access to this information will cause great and irreparable economic and financial damages. The production and dissemination of scientific, technical, economic, statistical or otherwise required information and access to it is an integral part of the economic life of a country so that successful, international companies can compete in the market and produce a new product or optimize it. Billions of dollars are spent on research (Mitsa, 2010).

Every day, extensive efforts are made to enhance stock analysis methods in the world's financial markets. The endeavor to refine stock analysis methods, particularly in markets with a high number of stocks, has led to the emergence of new methods that, alongside existing approaches, aim to maximize profits in financial markets. However, these methods have not adapted well to the conditions of the Iranian capital market and have significantly influenced investors' choices. Conversely, recent clarifications in the stock exchange have provided access to a wealth of specialized information. This information is challenging for laypeople to utilize effectively and requires input from financial experts. The abundance of information and other influential factors have made individual decision-making and the evaluation of stock value and optimal portfolio models arduous, causing many individuals to base their stock selection decisions on cues for buying and selling, market news, rumors, and similar factors. Managing this vast amount of information and leveraging it effectively to enhance decision-making remains a contentious issue.

A critical challenge in forecasting financial time series data is constructing accurate models that capture subtle and precise data changes. Numerous studies have explored traditional statistical methods such as moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA) for forecasting financial time series data (Amiri et al., 2019). While these methods are statistically sound, they often fall short in accurately predicting experimental data. Subsequently, various intelligent computing techniques like artificial neural networks, fuzzy systems, and crowd intelligence-based models have been proposed for time series prediction (Mitsa, 2010).

Research indicates that hybrid models generally outperform individual models. Pioneers like Reid (1968) and Bates and Granger (1969) introduced composite time series models, concluding that combining various forecasting methods yields superior results compared to independent methods. Makridakis et al. (1982) further emphasized that integrating different models typically enhances forecasting accuracy. Pelikan et al. (1992) suggest that combining different artificial neural networks improves time series prediction accuracy. Coleman (1989) provides a comprehensive overview of diverse hybrid forecasting models. A well-constructed combined forecasting model can enhance performance, address limitations of independent models, and reduce uncertainties. Non-linearity and ambiguity in time series data may not solely stem from randomness but could also result from deterministic phenomena like chaos, which is highly sensitive to initial conditions. Economic, social, industrial, and geopolitical factors can influence financial time series data.

These series are vague, crowded and incomplete. Even so, time series forecasting of financial information has enormous practical potential in terms of large financial gains. Visually, a chaotic and a non-chaotic time series are similar, and therefore, traditionally, chaotic time series have been modeled like financial information time series to show the inherent randomness. Therefore, forecasting time series of financial information that are complex and important need more complex and powerful hybrid techniques to develop (Abbaszadeh & et.al.,2020)

Chaos theory pioneered by Poincker provides a new way to model the nonlinear dynamic behavior of a deterministic complex system by embedding an assumed numerical time series in its corresponding fuzzy space using parameters such as delay and embedded dimension, where the delay is the time delay and the embedded dimension refers to the number of variables required to present the nonlinear dynamics of the chaotic system. This research, aimed at predicting the time series of financial information using the hybrid model of the multi-layer perceptron chaos theory for the optimal selection of the stock portfolio for decision makers and investors. Therefore, we are trying to answer the following research question:

Can the time series of financial information be predicted using the hybrid model of multi-layer perceptron chaos theory?

Literature Review

In the review of research literature, the first principle is to find the theoretical foundations and backgrounds related to the research topic. This requires special accuracy and fussy exactitude in searching and citing scientific and research articles. To access the research background, databases and external sites such as Google Scholar, Emerald, Science Direct, Springer, ProQuest, etc.; were searched. The search results showed that few studies have been done on the subject of this research and there is an obvious study gap in the field of predicting time series of financial information using the hybrid model of multi-layer perceptron chaos theory for the optimal selection of stock portfolio for decision makers and investors in the country. Some related researches are mentioned below:

Pavlidis & et al. (2003) presented a hybrid technique for financial information time series forecasting that combines chaos theory and a neural network trained by the differential evolutionary (DE) PSO algorithm. This combination provides better results than independent neural networks for both DE and PSO in terms of average accuracy on daily yen-to-dollar and pound-to-dollar exchange rate data.

Huang & et al. (2010) proposed a hybrid model that modeled the data based on chaos theory and with support vector regression predicted forex rates. They concluded that this combination performs better than the technique in terms of root mean square error (RMSE), MSE and mean absolute error (MAE) on daily data of exchange rates of Euro to USD, GBP, NZD, AUD, Japanese yen and Russian Ruble.

Li & et al. (2011) presented a new hybrid learning algorithm using PSO and Backward Least Squares Estimator (RLSE), that is, a hybrid PSO+RLSE+PSO algorithm was proposed for learning. The results showed that the neuro-fuzzy self-organization system of NFS, including the hybrid learning algorithm, works quite well in terms of fast learning convergence.

Aladag & et al. (2012) presented a time-invariant fuzzy model for forecasting based on PSO. Fuzzy average clustering method was used to fuzzify the time series. They concluded that the proposed method provides accurate predictions.

Ravi & et al. (2012) using a number of computationally intelligent techniques such as Back Propagation Neural Network (BPNN), Wavelet Neural Network (WNN), Multivariate Adaptive Regression Splines (MARS), Support Vector Regression (SVR), Neural Inference System - Dynamic Extended Fuzzy (DENFIS), Group Method of Working with Data (GMDH) and Genetic Programming (GP) proposed several forex forecasting models and concluded that the forecasting models are better than the experience of converting Dollars to yen, Pounds and Germany`s Mark.

Serempinis & et al. (2012) introduced a hybrid neural network architecture of PSO and adaptive radial basis functions (ARBF-PSO) to forecast the EUR to GBP exchange rate profit. The authors concluded that the proposed model outperformed MLP, Recurrent Neural Network (RNN) and PSI.

Donate & et al. (2013) presented the generalization of a balanced cross-validation evolutionary artificial neural network (EANN) that obtained better results compared to the unbalanced version of the same model.

Pulido & et al. (2014) proposed a PSO-based optimal structure of ANN with fuzzy integration of type one and two reactions. The authors concluded that this combination outperformed other fuzzy integrations.

Rout & et al. (2014) presented a hybrid forecasting model that combined an adaptive ARMA architecture with DE-based training of its pre-feed and post-feed parameters. DE optimization is used to achieve optimal training coefficients. This optimization strategy helps the hybrid prediction model to have better prediction accuracy than other hybrid models.

Serempinis & et al. (2015) extended the research of Serempinis & et al. (2012) by proving the efficiency of hybrid neural network architecture after testing on more data sets and comparing the results with more criteria. They introduced a Support Vector Regression – Hybrid Rotational Genetic Algorithm (RG-SVR) model and applied it to forecast and trade the exchange rates of Euro to Dollar, Euro to Pound, and Euro to Yen. The authors concluded that the proposed combination outperforms non-genetic and genetic optimal SVRs and SVMs.

Shen & et al. (2015) used Deep Belief Network (DBN) to predict the exchange rate. The authors applied the conjugate gradient method to speed up DBN learning. The authors concluded that the proposed pre-feed from neural network (FFNN) method provided more accurate forecasts in terms of RMW, MAE and MAPE after working with weekly data of Pound to Dollar, Brazilian Real to Dollar and Indian Rupee to Dollar.

Hussain & et al. (2016) forecast the time series of financial information including exchange rates of USD to EUR, USD to GBP, and JPY to USD using a novel self-organizing neural network inspired by the secure algorithm. The simulation results showed that the proposed neural network architecture provided more accurate predictions than SVM, RBFNN and BPNN

Svitlana (2016) discovered the use of neural networks in predicting the exchange rate of Euro to Dollar, Pound to Dollar and Dollar to Yen on a daily, monthly and quarterly basis. The author concluded that the short-term prediction method has good accuracy and can be used in practical systems and to predict the exchange rate one step ahead.

Pradeepkumar and Ravi (2017) presented 2-stage hybrid models including Chaos Theory + CART (Classification and Regression Tree), Chaos + CART-EB (CART Generalization and Filler), Chaos + TreeNet, Chaos + MARS (Multiple Adaptive Regression Splines) variable), chaos + LASSO (minimum absolute value selection and contraction factor) and chaos + RFTE (total random forest tree). The results showed that chaos + MARS can perform better than other models and even the model of Pradeepkumar and Ravi (2017) after testing the daily exchange rate of yen to Dollar, Pound to Dollar and Euro to Dollar in terms of MSE and MAPE.

Method

The current research is practical in terms of purpose because it investigates the relationships of variables on the stock market and seeks to explain the relationships and provide suggestions to improve the efficiency of the market. It ranks as a descriptive-causal accounting research and was based on real information in financial statements of companies. Neural networks are used to predict the profits of companies admitted to the stock exchange in this research. The research method was "post-event". This type of method is used to conduct researches that aim to investigate the causes of certain relationships that came about in the past and ended. The statistical population of this research consisted of the companies admitted to the Tehran Stock Exchange during the years 2013 to the end of 2014. The obtained data was classified in the Excel software and analyzed using MATLAB software.

Chaos theory is an area of deterministic dynamics that proposes apparently random events can result from ordinary questions due to the complexity of the systems in which they are involved. Chaos in a time series is modeled by constructing the fuzzy space corresponding to the time series using lag (l) and embedded dimension (m). This process converts the assumed nonlinear one-dimensional time series into its equivalent multidimensional representation. This approach was originally proposed by Packard et al. and its mathematical model was explained by Tickens. If Y={y_1,y_2,…,y_k,y_(k+1),…,y_N } is a numerical time series, it can be fully represented in the m-dimensional fuzzy space represented by the vector P_j={y_j,y_(j+ l),y_(j+2l),...,y_(j+(m-1)l) } embedded so that j=1,2,...N-(m-1)l/Δt, m called embedded dimension becomes (m≥Θ where Θ is the capture dimension), 1 is the time delay and Δt is the sampling time.

In the present study, Saida's method was used based on Lyapunov view, which estimates λ as 1.

$$\lambda = \lim_{t\to\infty} \frac{1}{t} \ln \frac{|\Delta g(y_0,t)|}{|y_0|} \quad (1)$$

where y0 is a point in the state space that will produce an orbit in that space using a system of equations. A value of λ≥0 indicates that there is chaos; Otherwise, there is no chaos in the time series.

Findings

Stationary test of variables

According to the studies of content management specialists, the first method is differentiation to evaluate the stationarity in fixed time series of financial information, based on the assumption that distant observations should not be correlated. The results of the unit root tests in the present study are shown in Table 1:

Table 1. Results of unit root tests

Test	Data collection	significant level	Test statistics	Critical value		
				%1	%5	%10
ADF	At level **(1)(3)	0/009	-4/08	-3/41	-3/70	-3/57
ADF	First differentiation*** (2) (3) (4)	0/000	-9/58	-3/41	-3/70	-3/57
PP	at level*(5)	0/000	-3/90	|-3/41	-3/72	-3/58

* H0 is rejected at 90% confidence level, ** H0 is rejected at 95% confidence level, *** H0 is rejected at 99% confidence level (1) interval (1), (2) interval 1, 3, 9 and 11, (3) added intercept, (4) added intercept and trend, (5) constant deterministic component, (6) constant deterministic component with trend.

The findings show that during the ADF test, the null hypothesis was rejected at a level of less than 5% type 1 error and 95% confidence, and it shows that the data is not static. After the first-order differentiation, the test was repeated, and the null hypothesis was rejected, but the accuracy of the data was better than before the differentiation, and there was a possibility of rejection at the 99% confidence level, and after the second-order differentiation, the data was stationary again and so accepted. PP unit root test rejected the null hypothesis at 90% confidence level before first order differentiation. Therefore, during the ADF test and the PP unit root test to evaluate the stationarity in the fixed time series of financial information, the findings showed that the data is not stationary.

Placement analysis test

Substitution analysis test is an important method to determine the non-linearity of time series, which can differentiate between a linear stochastic process and a non-linear process by evaluating the nature of fluctuations. The findings of the substitution analysis test of financial information values and their significance level are shown in Table 2:

Table 2. Substitution analysis of values and significance level

meaningful level		Original data		Alternative data			
Percentage	$erfc(\delta/\sqrt{2})$	δ	QD	The first century	σH	νH	Number
0/03	0/019	3/4896	-0/08775	-0/0629	0/0274	-0/0007	189

During the substitution analysis test and its significance level, the behavior of the time series of the main financial information is significantly different compared to their substitutes. Therefore, the findings show that the long-term series of stock prices does not belong to the family of Gaussian linear random signals and the possibility of using a chaotic process can be effective in simulating its behavior.

Measuring complexity and entropy

The limitations related to the length of the investigated time period have limited the evaluation and representation of the nonlinear dynamic behavior of signals produced by biological and social systems . ApEn and SampEn algorithms evaluate the complexity (or regularity) of the system by measuring the repeatability or predictability in a time series.

Table 3. Entropy analysis

	Data series	Threshold r							
Data collection	Real Data	0/1	0/15	0/2	0/25	0/3	0/32	0/35	0/4
	Experimental-Random 01	1/766	1/330	1/086	0/893	0/755	0/736	0/696	0/632
	Experimental-Random 02	3/497	2/565	2/157	1/693	1/745	1/598	1/482	1/366
	Logistic = Periodic (α=3.4)	2/565	2/398	1/936	1/856	1/695	1/614	1/419	1/316

	Logistic = Chaos (α=4)	0/00 1	0/00 1	0/00 1	0/00 1	0/00 1	0/00 1	0/00 1	0/00 1
	Real Data	0/72 8	0/76 9	0/69 6	0/69 5	0/70 8	0/69 5	0/67 2	0/66 4

Based on the calculations, the value obtained to describe the production process of all data sets is for μ = 2, ApEnMax is equal to 0.65 and rMax is equal to 0.32, and for μ = 3, ApEnMax is equal to 0.6 and rMax is equal to 44. 0/ was calculated. Values higher than 3 were excluded from the study due to questionable output for evaluating the dataset. The evaluation results showed that ApEn and SampEn are periodic and chaotic systems and supported the findings of previous researches and remained stable at the level of different values (Ferrario et al. It provides a basis for comparison.

For μ = 2, while the stochastic time series diverge and show chaotic behavior, the original data set gives closer values for ApEn with r ≤ 0.5 ≥ 0.3 and SampEn with r ≥ 0.45 ≤ r indicates 0.3. Also, an important point is that the range of r values is consistent with the selection of rmax. Although the substitution curve mimics the pattern of the original time series, the values of ApEn and SampEn are larger.

For μ = 3, the ApEn values of the random time series differ from chaotic behavior and the SampEn values describe an unusual shape that moves from infinity at small values of r, which is a characteristic feature of random systems. The values of ApEn and SampEn from the original data set have an almost chaotic behavior at r ≤ 0.3 ≥ 0.5 and r ≤ 0.3 ≥ 0.45, respectively.

Average replacement curves continue to imitate the original time series pattern, but in larger values. However, ApEn values with ≥ 0.5 r ≤ 0.3 are closer to chaotic time series. However, fixed surrogate analysis (described further in this section) rejected the null hypothesis for ApEn and SampEn at (μ = 2, 3, rmax) at the 95% confidence level. These results confirm the random linear nature of the substitutions; hence any disorderly chaotic behavior is discarded.

The accuracy of both algorithms has been evaluated by comparing the values of ApEn and SampEn for μ = 2 and 3 reduced in the respective rmax, respectively, SampEn is more reliable for evaluating small data sets. Since this algorithm also provides a consistent output, it was chosen for entropy analysis.

Table 3 summarizes the values of SampEn for $\mu = 2$ and $r \geq 0.4 \leq r$ 1.0, and in comparison, rmax values from the original and chaotic time series are marked with blue color and random time series values are distinguished with color green from other values.

Lyapunov view

The Lyapunov exponent (λ) determines the system's chaotic level by measuring the sensitivity of the system to changes in the initial conditions by quantifying the exponential divergence of the near paths between nearby spatial states. Table 6 shows the types of possible movement of the system and the corresponding value of maximum λ in the systems:

Table 4. The type of possible movement and the value corresponding to the maximum Lyapunov view

Type of movement	Maximum Lyapunov view
Stability at a certain point	$\lambda<0$
Limited cycle stability	$\lambda=0$
chaos	$0<\lambda<\infty$
noise	$\lambda=\infty$

The positive value of the Lyapunov exponent (λ) proves the state of chaos in dynamic systems. The findings showed that the value of the Lyapunov exponent in stability at a given point is less than zero and in the limited cycle of stability it is equal to zero and in chaos it is greater than zero and less than ∞ And it is equal to noise.

Table 5. Maximum Lyapunov view for time series

time interval (τ)	Series	Dimension reduction (m)					
	1	3	4	5	6	7	8
	2	0/434	0/543	0/387	0/309	0/298	-
	3	0/603	0/489	0/328	0/308	0/573	-
	4	0/856	0/890	0/651	0/865	-	-
	5	0/867	0/634	0/679	-	-	-

Using the built-in parameters $7 = m$ and $2 = \tau$, the optimal value of λ equal to 0.573 has been calculated. For $m = 8$ and a combination of large m, the calculation of λ was not possible due to the lack of neighbors. This indicates the loss of sensitivity of the systems in the dimension of high embedding and long delay.

Conclusion

The most important criterion for evaluating the performance of institutions is the rate of return on shares. This criterion alone contains information for investors and is used to evaluate performance. Risk and return are the two main elements of investing in stocks. Efficiency in the investment process is a driving force that motivates and is considered a reward for investors. Therefore, this research has sought to predict the efficiency of companies present in the Tehran Stock Exchange.

During the ADF test and the PP unit root test in evaluating the stationarity in fixed time series of financial information, the results showed that the data is not stationary. During the substitutability analysis test, the behavior of the time series of the main financial information is significantly different compared to their substitutes. Therefore, it can be concluded that the long-term series of stock prices does not belong to the family of Gaussian linear random signals and it is possible to use the chaotic process in simulating its behavior. The results of evaluation and measurement of system complexity and entropy showed that ApEn and SampEn are periodic and chaotic systems and supported the findings of previous researches and remained stable at the level of different values (Abbaszadeh & et al., 2020; Hussain & et.al,2016; Sermpinis & et.al, 2015), thus providing a solid basis for comparison.

The positive value of the Lyapunov exponent (λ) proves the state of chaos in dynamic systems and the analysis may be limited to finding of this value only (Amiri & et al. ,2019). To overcome the data set size limitation, Pradeepkumar & Ravi,2017) developed a reliable method for calculating λ from a small data set during an evidence-based study that, when faced with changes in the embedding dimension, set size data, reconstruction delays and noise levels are also strong.

Risk is the main factor that determines return. Higher returns encourage investors to invest and increase capital flow. It is believed that companies' stock returns are a function of systematic risk, and systematic risk represents the changes in the return rate of a share compared to the changes in the return rate of the entire stock market.

Therefore, it is suggested that the authorities of the stock exchange, by requiring timely reporting of information by companies, should provide alternative information and appropriate information for investment risk to investors for economic decisions. Also, potential and actual investors in Tehran Stock Exchange are recommended to pay attention to the accounting variables affecting stock returns in their decisions.

CONFLICT OF INTEREST: The authors declare that they have no conflicts of interest regarding the publication of this manuscript.

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How to Cite: Sohouli Vahed, M., Aghaei, M.A., Avazzadeh Fath, F., Pirzad, A. (2024). Prediction of Time Series of Financial Information Based on Lyapunov View of Information Using Chaos Theory, *International Journal of Digital Content Management (IJDCM)*, 5(9), 1-16. DOI: 10.22054/dcm.2022.70147.1158