Journal of Applied Economics and Business

OPEN ACCESS ARTICLE

FINANCIAL-ECONOMIC TIME SERIES MODELING AND PREDICTION TECHNIQUES – REVIEW

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Abstract

Financial-economic time series distinguishes from other time series because they contain a portion of uncertainity. Because of this, statistical theory and methods play important role in their analysis. Moreover, external influence of various parameters on the values in time series makes them non-linear, which on the other hand suggests employment of more complex techniques for ther modeling. To cope with this challenging problem many researchers and scientists have developed various models and techniques for analysis of financial-economic time series and forecasting of the future trends, both linear and non-. This paper aims at reviewing current state-of-the-art techiques for financial-economic time series analysis and forecasting.

Keywords

Prediction; Time Series; Data Mining; Stock Market Prediction; Forecasting Techniques.

INTRODUCTION

Simulation models could be considered as digital prototypes and abstractions of reality to which experiments can be applied to improve our understanding of objects or phenomena in the real world. Simulation models are the basis of various scientific disciplines including economics, engineering, medicine, politics, sociology and data management in general. They also play fundamental role in humans' everyday live. Simulation models are often used to predict the performances in the real world, to predict future events or to organise data in ways that allow information to be extracted from it. More accurate the model is, better the prediction will be.

Creation and application of models to economic and finantial data has gathered increasing interest in the last two decades. The common approach to construct this kind of model is the inductive one i.e. estimating model from measured data. This estimation process is nothing else but, learning from previously collected (historical) data. In this context, learning implies finding patterns in the data or obtaining a parsimonious representation of data that can then be used for several purposes such as forecasting.

Forecasting a financial series, such as a stock market index or an exchange rate, using created model is very specific task, which aims at supporting key financial decisions such as selling and hedging. Because of the market volatility, market indices are highly fluctuating and they are affecting the investor's belief. Therefore, building an accurate model that will enable effective stock market index prediction is important for stock market investor in order to make more informed and accurate investment decisions. To cope with this challenging problem many researchers and scientists have developed various models and techniques for analysis of financial-economic time series and forecasting of the future trends. This paper aims at reviewing current state-of-the-art techiques and it is organized as follows: section 2 describes the nature of financial time series, section 3 presents various methodologies for prediction from these time series (both linear and non-linear) and the final section presents the conclusions drawn from the previous analysis.

Financial-ecnonomic time series - nature and problems

Analysis of financial-economic systems and prediction of their future behaviour is usually based on historical raw data. This data is usually composed of a series of values influenced by some external factors and collected at regular time intervals. Since the external (exogeneous) influencing factors are usually unknown, the model of financial-economic system is constructed in the form of a mathematical function, taking into account past values of the series, as in (1).

$$x(t+1) = F_{\varphi}(x(t), x(t-1), x(t-2), \ldots\ldots, x(t-m+1)) \quad (1)$$

The new forcasted value x(t+1) is estimated from the known current and past values of x (Ljung, 1987; Weigend et al, 1994). The parameter φ of the model F_{φ} is chosen according to the information available, i.e . to all known values of x; this step if called learning.

When other exogeneous information, which is influencing the system, is available, it could be included in the model, usually in the form (2)

$$x(t+1) = F_{\varphi}(x(t), x(t-1), \ldots\ldots, x(t-m+1), y_t^1, y_t^2, \ldots, y_t^L) \quad (2)$$

where the values at time t of L external variables are used in the model.

Many reasearchers and practitioners have tried to develop and apply linear models for capturing certain types of economic behavior, or economic performance. However, due to the nature of these processes non-linear models could be best fitted to model the financial-economic data series.

Given the wide range of nonlinear time series models available and the inherent flexibility of these models, the possibility of getting a spuriously good fit to any time series data set is very high. Therefore it is usually recommended to perform a test of linearity against nonlinearity before building a possibly complex nonlinear model. In this context, one of the most popular tests for non-linearity is the BDS test published by Brock et al, (1996).

The idea behind the BDS test is the correlation integral, which is a measure of the frequency with which temporal patterns are repeated in the data. Consider a time series of financial data defined as in (1), and define its m-history. Than, the correlation integral at embedding dimension *m* can be estimated by (3):

$$C_{m,e} = \frac{2}{T_m(T_m - 1)} \sum \sum_{m=s<t=T} \mathrm{I}(x_t^m, x_s^m, \varepsilon) \tag{3}$$

Where Tm=T-m+1 and $\mathrm{I}(x_t^m, x_s^m, \varepsilon)$ is an indicator function which is equal to one if $|x_{t-i} - x_{s-i}| < \varepsilon$ for i=0,1,2…, m-1 and zero otherwise.

Intuitively the correlation integral estimates the probability that any two m-dimensional points are within a distance of ε of each other. That is, it estimates the joint probability:

$$P_r(|\, x_t - x_s\, |) < \varepsilon, |\, x_{t-1} - x_{s-1}\, | < \varepsilon, \ldots, |\, x_{t-m+1} < x_{s-m+1}\, | < \varepsilon) \tag{4}$$

If x_t are iid, this probability should be equal to the following in the limiting case:

$$C_{1,\varepsilon}^{m} = P_r(|\, x_t - x_s\, | < \varepsilon)^m \tag{5}$$

Brock, Dechert, Scheinkman and LeBaron (1996) define the BDS statistic as follows:

$$V_{m,\varepsilon} = \sqrt{T}\, \frac{C_{m,\varepsilon} - C_{1,\varepsilon}^{m}}{s_{m,\varepsilon}} \tag{6}$$

Under fairly moderate regularity conditions, the BDS statistic converges in distribution to N(0,1):

$$V_{m,\varepsilon} \xrightarrow{d} N(0,1) \tag{7}$$

so the null hupothesis of iid is rejected at the 5% significance level whenever $|V_{m,\varepsilon}| > 1.96$.

METHODOLOGIES FOR FINANCIAL-ECONOMIC TIME SERIES

An interesting application of time series modelling and analysis in the field of finance is the stock market index forecasting. Traditionally, autoregressive integrated moving average (ARIMA) models are considered as one of the most popular linear models in time series forecasting mainly because of their theoretical elaborateness and accuracy in short-term forecasting (Jhee & Shaw, 1996).

Since ARIMA models can't cope with non-linearities in financial markets originating the existence of a bounded rationality assumption (McNelis, 2005), recently the artificial neural networks (ANNs) have gained rising popularity for forecasting and time series prediction (Zhang et al, 1998).

Yao and Tan (2001) used artificial neural networks for classification, prediction and recognition. They have elaborated an approach for neural network training as well as trading based on neural network outputs, or trading strategy. Authors discuss a seven - step neural network prediction model building approach.

Recently, hybrid techniques, which decompose a time series into its linear and nonlinear components, have been shown to be successful for single models, but they show to have many disadvantages. In this context, a novel hybridization of artificial neural networks and ARIMA model has been proposed by Khashei and Bijari (2011) in order to overcome limitation of ANNs and yield more general and more accurate forecasting model than ANNs models. The proposed model uses the unique advantages of ARIMA models in linear modeling in order to identify and magnify the existing linear structure in data, and then a neural network is used in order to determine a model to capture the underlying data generating process and predict, using preprocessed data.

Although various neural network models have been developed and applied to financial time series forcasting, little or no attention has been paid to selecting the input features for training these networks. Wong and Versace (2012) have proposed a novel CARTMAP neural network model based on Adaptive Resonance Theory that incorporates automatic, intuitive, transparent, and parsimonious feature selection with fast learning. The model first clusters all correlated features together and then chooses at most one feature per cluster for training with ARTMAP network, which ensures that the selected features will be uncorrelated. The presence of low-dimensional deterministic chaos increases the complexity of the financial time series behavior. Shahwan and Said (2012) proposed the Generalized Multilayer Perceptron (GMLP), and the Bayesian inference via Markov Chain Monte Carlo (MCMC) method for parameter estimation and one-step-ahead prediction.

Hsieh et al, (2005) used data mining methods i.e. association rule and sequential pattern mining. Association rule was used to analyze the customer consumption behaviors and find the patterns of buying habits in the retailer business. The sequential pattern was used to help web viewers match their needs quickly but it will not know when to buy or sell and it does not include time interval dimension.

Yu and Huarng (2010) used neural network because of their capabilities in handling nonlinear relationship and also implement a new fu zzy time series model to improve forecasting. In the neural network fuzzy time series model input sample observations are used for training and output sample observations are used for forecasting. The drawback of taking all the degree of membership for training and forecasting may affect the performance of the neural network. To avoid this the difference between observations have been proposed which on the other hand reduces the range of the universe of discourse. They have evaluated the proposed method to forecast the Taiwan stock index, and obtained good results.

Hassan and Nath (2005) used Hidden Markov Models (HMM) approach to forecasting stock price for interrelated markets. HMM was used for pattern recognition and classification problems because of its proven suitability for modeling dynamic system. The authors summarized the advantage of the HMM was strong statistical foundation. It's able to handle new data robustly and computationally efficient to develop and evaluate similar patterns. The author decides to develop hybrid system using AI paradigms with HMM improve the accuracy and efficiency of forecast the stock market.

Cheng et al, (2010) proposed a hybrid forecasting model using multi-technical indicators to predict stock price trends. There are four procedures described such as select the essential technical indicators, the popular indicators based on a correlation matrix and use CDPA to minimize the entropy principle approach. They used RST algorithm to extract linguistic rules and utilized genetic algorithm to refine the extracted rules to get better forecasting accuracy and stock return. Production of more reliable and understandable rules and forecasting rules based on objective stock data rather than subjective human judgments have been considered as a main force point of the proposed method.

CONCLUSIONS

Many reasearchers and practitioners have tried to develop and apply linear models for capturing certain types of economic behavior, or economic performance. However, due to the nature of these processes non-linear models could be a better alternative to model the financial-economic data series and make more accurate forecasting further. However, according to the results of empirical evaluation of various proposed solutions one may draw-out a conclusion that hybrid models are the best fitted ones for making most accurate forcasting.

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