Swarm and Evolutionary Computation 36 (2017) 136–149

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

# Financial time series prediction using hybrids of chaos theory, multi-layer perceptron and multi-objective evolutionary algorithms

Vadlamani Ravi[a,*], Dadabada Pradeepkumar[a,b], Kalyanmoy Deb[c]

[a] Center of Excellence in Analytics, Institute for Development and Research in Banking Technology (IDRBT), Castle Hills, Masab Tank, Hyderabad 500057, India

[b] School of Computer and Information Sciences (SCIS), University of Hyderabad, Hyderabad 500046, India

[c] Koenig Endowed Chair Professor, Electrical and Computer Engineering, Michigan State University, East Lansing, MI 4882, USA

ARTICLE INFO

*Keywords:*
Financial time series prediction
Multi-objective optimization
Chaos theory
MLP
MOPSO
NSGA-II

ABSTRACT

Financial Time Series Prediction is a complex and a challenging problem. In this paper, we propose two 3-stage hybrid prediction models wherein Chaos theory is used to construct phase space (Stage-1) followed by invoking Multi-Layer Perceptron (MLP) (Stage-2) and Multi-Objective Particle Swarm Optimization (MOPSO) / elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) (Stage-3) in tandem. In both of these hybrid models, Stage-3 improves the prediction yielded by stage-2. The effectiveness of the proposed models is tested on financial datasets including the exchange rates data of US Dollar (USD) versus Japanese Yen (JPY), British Pound (GBP), Euro (EUR), and Gold price in terms of USD. From the results, it is concluded that Chaos+MLP +NSGA-II hybrid yielded better predictions than the other three-stage hybrid models: Chaos+MLP+MOPSO and Chaos+MLP+PSO, and Two-stage hybrid models: Chaos+PSO, Chaos+MOPSO and Chaos+NSGA-II in terms of both Mean Squared Error (MSE) and Directional Change Statistic (Dstat). Theil's inequality coefficient computed also confirms the superiority of the Chaos+MLP+NSGA-II hybrid over the Chaos+MLP+MOPSO across all datasets. Finally, Diebold-Mariano test indicates that the performance of Chaos+MLP+NSGA-II hybrid is statistically significant than the Chaos+MLP+MOPSO and other hybrids across all datasets. The results of these models are also compared with the two-stage hybrids found in literature [1,2] (Pradeepkumar and Ravi, 2014, 2017). These results are encouraging and suggest further application of these hybrids to other financial and scientific time series prediction problems in the future.

## 1. Introduction

A Time series is a set of chronologically recorded observations of one variable (Univariate) or multiple variables (Multivariate). In general, the Time series data is continuous, substantial in its size and high dimensional [3]. *Time series prediction* is a popular Time series data mining task [4]. In univariate time series forecasting, the problem is to predict the value of a variable at discrete times. It involves predicting the future given the past and present values. Note that the terms *prediction* and *forecasting* will be used interchangeably in the paper. Mista [5] describes various diverse applications of prediction found in Finance (e.g., exchange rate prediction, gold price prediction, stock price prediction, demand forecasting and volatility forecasting), Medicine (e.g., disease prediction, heart diagnosis prediction) and Business (e.g., demand forecasting, monthly sales forecasting).

Financial time series is a collection of chronologically recorded observations of the financial variable(s). For example, the daily exchange rate of a currency pair is a univariate financial time series. The financial time series are non-stationary and chaotic [6]. A time series is said to be chaotic if and only if it is nonlinear, deterministic and sensitive to initial conditions [7]. The prediction of a chaotic time series engages with the prediction of future behavior of the chaotic system by utilizing the current and past states of that system.

In addition to these, the Financial Time Series Prediction is a highly complicated task as a typical financial time series exhibits the following characteristics:

1. Financial time series often behave nearly like a random-walk process, making the prediction impossible (from a theoretical point of view) [8].
2. Financial time series are usually very noisy and chaotic [9,6].
3. Statistical properties of the financial time series are different at different points in time as the process is time-varying [8].

* Corresponding author.
*E-mail addresses:* rav_padma@yahoo.com (V. Ravi), dpradeepphd@gmail.com (D. Pradeepkumar), kdeb@egr.msu.edu (K. Deb).

http://dx.doi.org/10.1016/j.swevo.2017.05.003
Received 31 January 2017; Received in revised form 10 April 2017; Accepted 13 May 2017
Available online 17 May 2017
2210-6502/ 

The challenging task in Financial Time Series Prediction is building the right forecasting model that captures the subtle and obvious changes in the data. Literature abounds with various traditional statistical methods such as Moving Averages, Exponential Smoothing, Auto-regressive Integrated Moving Averages (ARIMA) [10–12], etc. for financial time series prediction. While these methods are statistically powerful, they failed to yield accurate predictions on the test data. Later, various computational intelligent techniques such as Artificial Neural Networks, Fuzzy Systems, Swarm Intelligence based model, etc. have been proposed for time series prediction. Often, they tended to yield more accurate predictions. However, these are not without demerits [5]. In this context, the hybrid forecasting models (in short, hybrids) in the paradigm of Soft Computing, which combine different prediction models in various permutations and combinations found traction by demonstrably yielding superior predictions compared to their stand-alone counterparts.

Several researchers demonstrated that hybrid or ensemble models do yield better results compared to stand-alone models. Reid [13] and Bates and Granger [14] laid the foundation for proposing various hybrid time series models. Bates and Granger [14] concluded that suitably combining different forecasting methods can yield better predictions than the stand-alone methods. Similarly, Makridakis et al. [15] reported that a hybrid or an ensemble of several models is commonly needed to improve forecasting accuracy. Pelikan et al. [16], and Ginzburg and Horn [17] reported that the combination of several ANNs improved time series forecasting accuracy. An excellent comprehensive review of various hybrid prediction models and annotated bibliography can be found in [18]. Usually, a good hybrid prediction model can:

1. Improve the forecasting performance.
2. Overcome deficiencies of stand-alone models.
3. Reduce the model uncertainty [19].

Uncertainty and nonlinearity in a time series need not be caused by randomness alone always. It can be due to deterministic phenomena, labeled as chaos, which is highly sensitive to initial conditions. A financial time series can be affected by economical, social, industrial and geo-political factors. It is uncertain, noisy and incomplete. Despite this, the prediction of financial time series has tremendous practical potential in terms of huge financial gains. Visually, a chaotic and non-chaotic time series look alike and hence, traditionally, chaotic time series such as financial time series have been modeled to account for the inherent randomness. Therefore, prediction of financial time series, being complex and important, it calls for the development of more sophisticated and powerful hybrid techniques.

Chaos theory, pioneered by Poincare [20,21] offers a new way to model the underlying nonlinear dynamic behavior of a deterministic complex system by embedding a given scalar financial time series in its corresponding phase space using parameters such as lag and embedding dimension, where lag is the time delay and embedding dimension signifies the number of variables needed to represent the nonlinear dynamics of the chaotic system.

In general, Artificial Neural Networks (ANNs) including Multi-Layer Perceptron (MLP) can capture complex nonlinear relationships very well. They can generalize well and are good universal approximators [22]. However, in MLP, convergence is slow, local minima can affect the training process, and it is hard to scale. Multi-objective evolutionary algorithms (MOEAs) including Multi-objective Particle Swarm Optimization (MOPSO) and elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) are good at solving Multi-objective optimization problems [23]. NSGA-II improves the nondominated sorting algorithm and reduces the computational complexity. It sorts the combination of parents and children population with elitist strategy, introduces the crowded comparison operator to improve diversity of solutions, and avoids the use of niched operators.

This paper proposes two 3-stage hybrid financial time series prediction models. Both of these models check for the presence of chaos at both stages. In the Hybrid Model-1 (Chaos+MLP+MOPSO), chaos in the dataset is first modeled using minimum lag and minimum embedding dimension (Stage-1). The resultant multivariate time series is fed to MLP in Stage-2. Stage-3 tests for the presence of chaos in the residuals. If chaos is present, then it is suitably modeled and the resultant multivariate time series of the residuals is fed to MOPSO-trained auto-regression model; otherwise, polynomial regression is employed to model the residuals. The predicted values in the Stage-3 and the predicted values in the Stage-2 are algebraically summed up to obtain the final optimal predictions. The Hybrid Model-2 (Chaos+MLP+NSGA-II) is the same as Hybrid Model-1, except that the MOPSO-trained auto-regression is replaced with NSGA-II-trained auto-regression model in Stage-3.

The contributions of this paper are:

1. Two 3-stage hybrids including Chaos+MLP+MOPSO and Chaos+MLP+NSGA-II are proposed and these are applied to predict financial time series including exchange rates of JPY/USD, GBP/USD, EUR/USD and Gold price (USD).
2. The financial time series prediction problem is formulated as a bi-objective optimization problem in the Stage-3. Apart from MSE value, Directional change statistic (Dstat) [6] was also accorded importance, thereby considering both of them as two objective functions for the problem.
3. Thiel's inequality coefficient [24] was computed to determine the closeness of the predictions yielded by the hybrids. The results of proposed hybrids are tested whether they are statistically significant or not using Diebold-Mariano (DM) test [25].

The rest of this paper is structured as follows: Section 2 presents various hybrid models proposed for financial time series prediction. Later, various techniques used are described in Section 3. The proposed hybrid models are presented in Section 4. The Section 5 highlights the experimental methodology and the results obtained are discussed in detail in Section 6. Finally, the paper is concluded in Section 7.

## 2. Literature review

It is well known that hybrids of time series forecasting models yield better predictions than a single time series model [26]. In the following, a few relevant hybrid financial time series prediction models are reviewed. First, we present various Chaos-based hybrid forecasting models, second, we present various hybrid forecasting models involving MLP and PSO and finally, we present the forecasting models involving MOEAs.

The chaos-based hybrid forecasting models reviewed are as follows. Pavlidis et al. [27] proposed a hybrid technique for predicting financial time series involving pre-processing to account for chaos and a neural network trained by PSO/Differential Evolution (DE). The hybrid yielded promising results for both DE and PSO than the stand-alone neural network on the daily exchange rate data of JPY/USD and GBP/USD in terms of mean accuracy. Then, Huang et al. [28] proposed a hybrid model that models the Chaos in the data followed by prediction by support vector regression to predict FOREX Rates. They concluded that the hybrid outperformed the stand-alone techniques on the daily exchange rate data of EUR/USD, GBP, NZD, AUD, JPY and RUB in terms of Root Mean Squared Error (RMSE), MSE and Mean Absolute Error (MAE). Pradeepkumar and Ravi [1] proposed 3-stage hybrid models in the paradigm of soft computing for FOREX Rate prediction. They are Chaos+ANN (MLP/General Regression Neural Network (GRNN)/ Group Method of Data Handling (GMDH)) + PSO/Polynomial Regression (PR) and Chaos+PSO+ANN/PR. In these models, the Stage-3 refines the initial predictions yielded by Stage-2.