ABSTRACT

Statistical models have been widely used for the purpose of forecasting. However, it has some limitations regarding its performance, which prevents an automatic forecasting system development. In order to overcome such limitations, Artificial Neural Networks (ANNs), Evolutionary Algorithms (EAs) and Fuzzy Systems (FSs) based approaches have been proposed for nonlinear time series modeling. However, a dilemma arises from all these models regarding financial time series, which follow a Random Walk (RW) model, where the forecast of such time series exhibits a characteristic one step shift regarding original data. In this way, this work presents a new approach, referred to as Increasing Translation Invariant Morphological Forecasting (ITIMF) model, to overcome the RW dilemma for financial time series forecasting, which performs an evolutionary search for the minimum dimension to determining the characteristic phase space that generates the financial time series phenomenon. It is inspired on Takens Theorem and consists of an intelligent hybrid model composed of a Modular Morphological Neural Network (MMNN) combined with a Modified Genetic Algorithm (MGA), which searches for the particular time lags capable of a fine tuned characterization of the time series and estimates the initial (sub-optimal) parameters (weights, architecture and number of modules) of the MMNN. Each individual of the MGA population is trained by the Back Propagation (BP) algorithm to further improve the MMNN parameters supplied by the MGA. After adjusting the model, it performs a behavioral statistical test and a phase fix procedure to adjust time phase distortions observed in financial time series. Furthermore, an experimental analysis is conducted with the proposed model using ten real world financial time series. Five well-known performance metrics and an evaluation function are used to assess the performance of the proposed model and the obtained results are compared to classical models presented in literature.

DOI: 10.4018/978-1-61520-629-2.ch010
1. INTRODUCTION

The development of solutions for stock market forecasting is considered a rather difficult problem, due to many complex features including irregularities, volatility, trends and noise. Some different paradigms have been studied for the development of predictive models which are able to determine the future behavior of a given phenomenon, or a time series, based on its past and present data.

A wide number of linear statistical models were proposed. Among them, the popular linear statistical approach based on Auto Regressive Integrated Moving Average (ARIMA) models (Box, Jenkins, and Reinsel, 1994) is one of the most common choices for stock market forecasting. However, since the ARIMA models are linear and most real world applications involve nonlinear problems, this can introduce an accuracy limitation of the generated forecasting models.

In order to overcome such limitations, other nonlinear statistical approaches have been developed, such as bilinear models (Rao and Gabr, 1984), threshold autoregressive models (Ozaki, 1985), exponential autoregressive models (Priestley, 1988), general state dependent models (Rumelhart and McClela, 1987). The drawbacks of those nonlinear statistical models are the high mathematical complexity associated with them (resulting in many situations in similar performances to the linear models) and the need, most of the time, of a problem dependent specialist to validate the predictions generated by the model, limiting the development of an automatic forecast system (Clements, M. P., Franses, P. H., and Swanson, 2004).

Alternately, approaches based on Artificial Neural Networks (ANNs) have been successfully applied for nonlinear modeling of time series in the last two decades (Crottel, Girard, Girard, Mangeas, and Muller, 1995; Hocevar, Sirok, and Blagejevic, 2005; Khotanzad and Elraga, 2000; Myhre, 1992; Preminger, and Franck, 2007; Sitte and Sitte, 2002; Zhang and Kline, 2007; Zhang, Patuwo and Hu, 1998). However, in order to define a solution to a given problem, ANNs require the setting up of a series of system parameters, some of them are not always easy to determine. The ANN topology, the number of processing units, the algorithm for ANN training (and its corresponding variables) are just some of the parameters that require definition. In addition to those, in the particular case of time series forecasting, another crucial element necessary to determine is the relevant time lags to represent the series (Ferreira, Vasconcelos and Adeodato, 2008). In this context, evolutionary approaches for the definition of neural network parameters have produced interesting results (Ferreira, Vasconcelos and Adeodato, 2008; Leung, Lam, Ling and Tam, 2003; Matilla-Garcia and Arguello, 2005). Some of these works focused on the evolution of the network weights whereas others aimed at evolving the network architecture.

A relevant work was presented by Ferreira (Ferreira, Vasconcelos and Adeodato, 2008), consisting of the Time-delay Added Evolutionary Forecasting (TAEF) method definition, which performs a search for the minimum number of necessary dimensions (the past values of the series) to determine the characteristic phase space of the time series. The TAEF method finds the most fitted predictor model for representing a time series, and then performs a behavioral statistical test in order to adjust time phase distortions that may appear in the representation of some series.

Nonlinear filters, on the other hand, have been widely applied to signal processing. An important class of nonlinear systems is based on the framework of Mathematical Morphology (MM) [Maragos, 1989; Serra, 1982]. Many works have focused on the design of morphological systems (Davidson and Hummer, 1993; Herwing and Shalkoff, 1994; Loce and Dougherty, 1992; Maragos, 1989; Wilson, 1989; Yang and Maragos, 1998). An interesting work was presented by Salembier (Salembier, 1991; Salembier, 1992), which designed Morphological/Rank (MR) filters via gradient-based adaptive optimization. Also,