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Stock market forecasting by using a hybrid model of exponential fuzzy time series

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ABSTRACT

The initial aim of this study is to propose a hybrid method based on exponential fuzzy time series and learning automata based optimization for stock market forecasting. For doing so, a two-phase approach is introduced. In the first phase, the optimal lengths of intervals are obtained by applying a conventional fuzzy time series together with learning automata swarm intelligence algorithm to tune the length of intervals properly. Subsequently, the obtained optimal lengths are applied to generate a new fuzzy time series, proposed in this study, named exponential fuzzy time series. In this final phase, due to the nature of exponential fuzzy time series, another round of optimization is required to estimate certain method parameters. Finally, this model is used for future forecasts. In order to validate the proposed hybrid method, forty-six case studies from five stock index databases are employed and the findings are compared with well-known fuzzy time series models and classic methods for time series. The proposed model has outperformed its counterparts in terms of accuracy.

1. Introduction

Stock market forecasting corresponds to determining the future value of a company stock traded on an exchange. The underlying assumption is that the more accurate the forecasting, the higher the profit can be. Accordingly, many forecasting methods have been developed during recent years, e.g., [1–6]. However, in the history of the development of prediction approaches, Fuzzy Time Series (FTS) methods have been standing out as a key solution for stock forecasting [7–13]. Since this study is focused on applying FTS to stock market data prediction, the following paragraphs provide a brief review of FTS models.

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Song and Chissom first introduced FTS model by using fuzzy relation equations and approximate reasoning [14,15]. Chen in 1996 presented a method to forecast student enrollment at the University of Alabama that takes less time computing max–min composition operations than Song and Chissom's model [16]. It is known that the length of intervals influences forecast accuracy in FTS. Consequently, determining the optimal length of intervals in FTS is the central issue in many subsequent studies. Along these lines, Huarng in 2001 proposed distribution-based and average-based length to determine the effective length of intervals in FTS [17]. Later, Yolcu and Egrioglu in 2009 proposed a method that applied a single-variable constrained optimization to determine the ratio for the length of intervals [18]. Recently, Javedani and Enayatifar have employed two Evolutionary Algorithms (EAs), specifically the Improved Harmony Search (IHS) and the Imperialist Competitive Algorithms (ICA), for determining optimal lengths of intervals to improve forecast accuracy in FTS [19,20].

EAs have been used recently in a lot of technical approaches. Two high speed EAs namely Particle Swarm Optimization (PSO) and Harmony Search (HS) are widely used in many different engineering application fields [21,20,22–27]. It is worth mentioning that the performance of PSO and HS algorithms is largely affected by fine-tuning of its operating parameters [21]. In this study, to tune the mentioned EAs parameters, a Learning Automata (LA) approach is employed as an effective tool which is introduced by Narendra et al. [28]. The LA can be described as an approach in which an optimal action from a set of actions is determined. The combination of EAs and LA leads to two improved EAs namely LAPSO [4] and LAHS [21]. When the EAs are enhanced with learning capability, it can adjust its parameters in each iteration based on the previous experience and current situation.

Although many optimization methods in FTS have been proposed to estimate optimal lengths, no single study exists which attempts to increase forecast accuracy by applying optimization methods for tuning other parameters. Therefore, this paper explores the way in which the optimization approach can be used in FTS models not only for determining optimal lengths but also other parameters as well. In fact, the proposed method contains two phases. In the first phase, the optimal lengths of intervals are estimated by applying LA based EAs in training set, using a conventional FTS method (here Chen's 1996 method is used). Subsequently, by using the obtained lengths, the second phase is established, with the aim of estimating certain adjusting parameters for minimizing errors in training set, by re-solving the same forecasting problem, and using the same settings. In this phase also LA based EA is employed. However, prior to starting the second phase, the conventional FTS employed in the first phase is replaced by a new parametric model of FTS, i.e., Exponential FTS (EFTS). The EFTS idea is based on another parametric FTS method, namely the Polynomial FTS (PFTS) proposed by Lee and Javedani in [12]. The main difference between the EFTS and the PFTS is that the former gives more weight to recent historical observation compared with the latter. This idea makes sense for stock market forecasting, because recent changes in stock indexes tend to have more degree of importance to traders and investors. This statement can be concluded from the outcome of this study.

The details of the proposed EFTS are given in Section 2 and Section 3. The fundamentals of FTS, PFTS, EFTS and LA based EAs are presented in Section 2. Section 3 discusses the proposed methodology. Section 4 explains the benchmarks and stock index databases. Subsequently, Section 5 is concerned with discussion and findings. Finally, Section 6 provides the conclusions resulting from this study.

2. Preliminaries

In this section the necessary concepts of LA based EAs, FTS, PFTS, and EFTS are presented. The first part of this section is about LA based approach for EAs while the next two subsections are HS and PSO, respectively. The subsequent parts are about the fundamentals of FTS, PFTS and EFTS respectively.

2.1. Learning automata based evolutionary algorithm

Learning Automata (LA) can be described as an approach in which an optimal action from a set of actions is determined. Learning automata at first is introduced by Narendra et al. [28] and recently has been used in many applications [29–32]. An automaton is an abstract object that can select from among a finite number of possible actions. An action from the finite set of actions is randomly chosen based on a specific probability distribution, and this action is then applied to an environment. The environment evaluates the selected action and sends back a reinforcement signal. This feedback is employed by the learning approach of the automata to update the probability distribution of the actions. The automaton learns the optimal action by repeating this process, which leads to favorable responses from the environment.

A learning automaton process can be implemented to automatically tune the parameters and/or operations of an EA regarding the environment feedback. This learning-based fine tuning mechanism not only solves the difficulties of parameter setting, but also enhances the local search abilities of the algorithm. The framework of learning automata based evolutionary algorithm is depicted in Fig. 1.

In the current study, the authors employ LAPSO and LAHS, following the general process of Fig. 1.

2.2. Particle swarm optimization (PSO)

Kennedy and Eberhart [33] in 1995 introduced an evolutionary algorithm named Particle Swarm Optimization (PSO), which is quite efficient for optimizing continuous non-linear functions. Basically, PSO is inspired by the birds flocking or