IMPROVED MODELS IN FUZZY TIME SERIES FOR FORECASTING

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To my wife

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ABSTRACT

The focus of this research is in the area of fuzzy time series. Such a study is important in order to improve the forecasting performance. The research approach adopted in this thesis includes introducing polynomial fuzzy time series, differential fuzzy logic relationships model, multi-layer stock forecasting model, data pre-processing approach, and k-step-ahead forecasting. The findings from this research provide evidence that integration of the polynomial concept and non-linear optimization transfer the fuzzy time series to a parametric model. By using polynomial fuzzy time series, 83% of experiments were improved significantly. Differential fuzzy logical relationships were defined to be used for establishing differential fuzzy logical relationship groups. By utilizing differential fuzzy time series in Taiwan Capitalization Weighted Stock Index (TAIEX) datasets, 90% of the results were improved and as for enrollment datasets this statistic was 100%. Data pre-processing approach managed to reduce the negative effects of noisy data by transforming the data into a new domain. By applying integrated data pre-processing fuzzy time series algorithm to short term load data and TAIEX, the average of Mean Absolute Percentage Errors (MAPEs) and Root Mean Square Errors (RMSEs) were reduced by 12.05 and 1.98, respectively. The multi-layer forecasting model enhances the performance of stock forecast values. Many experiments that were carried out on the forty years' stock data indicated that multi-layer fuzzy time series model could be considered as an advanced model for stock market forecasting. The one-day ahead forecasting was successfully employed to England and France 2006 half-hourly load data. The main conclusion drawn from this study suggests that the proposed methods were accurate compared to their counterparts. In addition, the functionality of the proposed methods was enhanced through the proposed algorithms which were tested to be robust and reliable. All of these findings were confirmed through various tests of the proposed methods on numerous case studies. The thesis also recommends that the fuzzy time series model should be considered in forecasting alongside with classical approaches.

ABSTRAK

Fokus kajian ini adalah dalam bidang siri masa kabur. Kajian sedemikian adalah penting dalam usaha untuk meningkatkan prestasi ramalan. Pendekatan penyelidikan yang disesuaikan dalam kajian ini termasuk memperkenalkan siri masa kabur polinomial, model hubungan perbezaan logik kabur, model ramalan saham pelbagai lapisan, pendekatan pra-pemprosesan data, dan ramalan k-langkah hadapan. Dapatan kajian ini memberikan bukti bahawa integrasi pengoptimuman polinomial konsep dan bukan linear memberi skim parametrik kepada model. Dengan menggunakan siri masa kabur polinomial, 83% daripada eksperimen telah meningkat dengan ketara. Perhubungan logik terbitan kabur telah ditakrifkan untuk digunakan bagi mewujudkan kumpulan hubungan kebezaan logik kabur. Dengan menggunakan perbezaan siri masa kabur dalam dataset TAIEX, 90% keputusan telah diperbaiki dan untuk dataset enrolmen, statistik ini adalah 100%. Data pendekatan pra-pemprosesan berjaya untuk mengurangkan kesan negatif data bising dengan mengubah data ke domain baru. Dengan menggunakan data bersepadu pra-pemprosesan siri masa kabur algoritma data beban jangka pendek dan TAIEX, peratusan ralat min mutlak (MAPEs) dan ralat min punca kuasa dua (RMSEs) masing-masing berkurang sebanyak 12.05 dan 1.98. Model ramalan pelbagai lapisan meningkatkan prestasi nilai ramalan saham. Banyak eksperimen telah dijalankan ke atas data saham untuk empat puluh tahun menunjukkan yang bahawa pelbagai lapisan model siri masa kabur boleh dianggap sebagai model lanjutan untuk ramalan pasaran saham. Ramalan satu hari ke hadapan telah berjaya digunakan untuk data beban setiap setengah jam England dan Perancis untuk tahun 2006. Kesimpulan utama yang dapat dibuat daripada kajian ini adalah kaedah yang dicadangkan lebih tepat berbanding dengan kaedah daripada kaedah lain yang setanding dengannya. Selain itu, fungsi kaedah yang dicadangkan ini telah dipertingkatkan melalui algoritma yang dicadangkan yang telah diuji kukuh dan boleh dipercayai. Semua penemuan ini telah disahkan melalui pelbagai ujian terhadap kaedah yang dicadangkan ke atas pelbagai kajian kes. Tesis ini juga mencadangkan bahawa model siri masa kabur perlu dipertimbangkan bersama-sama dengan pendekatan klasik dalam membuat ramalan.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
CPDA	-	Cumulative Probability Distribution Approach
DBFTS	-	Distance Based Fuzzy Time Series
DJI	-	Dow Jones Industrial average
DSL	-	Digital Subscriber Line
DVL	-	Deterministic Vector Long-Term forecasting
FL	-	Fuzzy Logic
FLR	-	Fuzzy Logical Relationship
FLRG	-	Fuzzy Logical Relationship Group
FOREX	-	FOReign EXchange market
FSFTS	-	Fuzzy Stochastic Fuzzy Time Series
FTS	-	Fuzzy Time Series
HHLD	-	Half Hourly Load Data
ICT	-	Information Communications Technology
KOSPI	-	Korea Composite Stock Price Index
MAPE	-	Mean Absolute Percentage Error
MSE	-	Mean Square Error
MaxAPE24	-	Maximum of Absolute Percentage Error for 24 steps ahead
MinAPE48	-	Minimum of Absolute Percentage Error for 48 steps ahead
MLR	-	Multiple Regression Model
NASDAQ	-	National Association of Securities Dealers Automated Quotations
NN	-	Nural Network
LHS	-	Left Hand Side

LHS	-	Left Hand Side
OL	-	Original Load data
PL	-	Processed Load data
RHS	-	Right Hand Side
RMSE	-	Root of Mean Square Error
S and P500	-	Standard and Poor's 500
SBI	-	State Bank of India
STLF	-	Short Term Load Forecasting
TAIFEX	-	Taiwan Futures Exchange
TAIEX	-	Taiwan Stock Exchange Capitalization Weighted Stock Index
UDM	-	Uniform Discretion Method
WCDT	-	Weighted C-fuzzy Decision Tree

CHAPTER 1

INTRODUCTION

1.1 The Background of Study

Time series are one of the efficient forecasting models among others which are tremendously used in real world applications. By emerging fast computers with high capacity memories and improving programming languages, however, there is a positive attitude toward using algorithm-based time series model (Gu *et al.*, 2011; Liao *et al.*, 2011; Ou, 2012; Wang *et al.*, 2012). In fact the algorithms could be transferred to computer codes easily. Additionally, the algorithm's performance itself could be in more convenient ways enhanced by researches in compared with classic time series models. Consequently, forecast accuracy is promoted by upgrading algorithms. However, Fuzzy Time Series (FTS) is one of the most important algorithm-based forecasting models. There is a large volume of published studies about FTS. Certain domains have applied FTS models to forecast events, including university enrollment (Chen, 2002; Jeng-Ren *et al.*, 1998a), stock index forecasting (Chen *et al.*, 2007; Huarng, 2001; Huarng and Yu, 2005; Kunhuang, 2001), and temperature prediction (Hsu *et al.*, 2010; Wang and Chen, 2009). There are considerable variations in the pattern of FTS algorithms in recent years. Since every FTS model is algorithm-based, the performance of FTS can be affected by the improvement of their steps. For instance, after proposing first definitions and algorithm by Song and Chissom (1994, 1993), later Shyi-Ming (1996) proposed a novel algorithm by revision of certain steps of Song and Chissom model. Subsequently, Huarng (2001) refined Chen's model to produce more accurate forecasts. From FTS studies it was concluded that attempts for enhancing performance of FTS algorithms could be classified in five groups. The first group which is also included major studies are concentrated to enhancing certain steps of FTS. In common the every FTS algorithm must include at least six steps. First section is about to define the universe of discourse and portioning universes of discourse, the second is defining fuzzy sets, the third one is fuzzifying observed values, the fourth one is establishing fuzzy logical relationships and fuzzy logical relationship groups, the fifth one is forecasting and the last section is defuzzifying forecasts. However, the main concerns have been about first step i.e. defining the universe of discourse and portioning it (Huarng, 2001; Yolcu *et al.*, 2009). Huarng showed in his study that the different length of intervals produced different forecasts. So, he concluded that the effective length of intervals must be recognized. Therefore, in this step the main problem is how it is possible to portion universe of discourse to reflect the relationship of data further and consequently promote a better forecast. Certain studies also focused on enhancing defuzzification and forecasting steps. For instance (Yu, 2005) proposed weighted FTS models to give more weight to the recent observations during forecast step. The second group is related to forecasting when data have trend with no specific pattern. Just few studies have been found in this issue (Cheng *et al.*, 2006b). These models follow the trend inside data. Data which includes upward mutations and downward mutation trends were supposed to be settled with his type of models. The forecasts when applying for instance conventional FTS model which is proposed by Chen's always lie inside the universe of discourse, therefore, Chen's algorithm is not suitable for forecasting trend data. Since, for trend data it is sometimes expected that forecast lie apart from the universe of discourse, proposing advanced FTS algorithm to be suitable for this kind of data is required. The third attempt for enhancing FTS algorithms is a hybridization of other techniques with FTS algorithms. For instance, certain studies in this field employed NN inside FTS algorithm (Egrioglu *et al.*, 2012) or utilized GA for enhancing FTS algorithm performance (Ou, 2012; Chen and Chung, 2006). According to a review of literature about 24% of important FTS studies were connected to this approach. The fourth groups tried to propose a specific FTS algorithm to be more suitable for specific applications. For instance, for stock market forecasting, there are specific FTS algorithm. For stock market forecasting, since the pattern of stock market forecasting was different with other type of data, the difference must be reflected in their algorithms. Thus, the author proposed a FTS algorithm which includes the adaptive expectation model into forecasting processes to adjust forecasting errors (Cheng *et al.*, 2008a; Chen *et al.*, 2007). The last group effort is restricted to proposing computational procedures rather than pure algorithm. That means they propose the such algorithm to be more appropriate to transfer to computer programs. Then these models could be used in the real world in a conventional way. For instance, a computational method of predicting based on FTS had been advanced to offer improved forecasting results to contend with difficulties up the situation containing higher uncertainty due to large noisy in consecutive year's values in the time series data and having no imagining of trend or periodicity (S.R, 2008).

1.2 Problem Statement

As it was noted in the former section, FTS is an algorithm-based model which can be improved by modification in its steps. While different basic approaches were made by researchers to enhance FTS algorithms, still there are other serious problems about enhancing FTS algorithms. By resolving these shortcomings it is possible to propose new refined FTS algorithms. However due to limitation in space, the author limits his concern just into five major recognized problems as follows: The first recognized problem was about the role of Fuzzy Logical Relationship Groups (FLRGs) in fuzzy time series algorithm. To date, for establishing FLRGs, partial information from historical datasets had been used and there had been little effort for using thorough information that hides inside a historical data for establishing them. To reconcile this problem author was thinking about using optimization approaches within FTS algorithm. However, in most FTS studies, the optimization approach which is integrated with FTS was mainly concentrated on finding optimal length by minimizing error between fitting and actual values in the training set (Hsu *et al.*, 2010; Yolcu *et al.*, 2009; Egrioglu *et al.*, 2010). Therefore, to enhance the role of FLRGs through forecasting process it was needed to give a parametric scheme to FTS algorithms then by minimizing error between fitting and actual values in training dataset and estimating related parameters the goal was achieved. The output of this attempt was proposed by the author as polynomial FTS which is discussed in the methodology chapter by details. One of the limitations with using fuzzy time series models was present here is dealing with the trend of the data. In this case, the key problem with using fuzzy time series was that they failed to take the pattern of trend data into account in the forecasting process. Although there were few studies about this issue (Cheng *et al.*, 2008a; Ching-Hsue and You-Shyang, 2007) , their works would have been far more persuasive if the results were more accurate and their methodology was more applicable. Because applicants and people in the mission area who are involved in business, investing or other relevant fields expect a new trend FTS algorithm if applicable. These methods must produce further precise results and promote quick-outcome and include straightforward concepts to understand. To reconcile this shortcoming, this study proposes a different fuzzy time series algorithm for data with various increasing or decreasing trends, which are appearing between dataset. Therefore, in this case, a new algorithm will be proposed in the methodology chapter by details. Data pre-processing is a preference, which contributes to remove certain negative effects of noisy data and fluctuation in time series. So far, different techniques of data pre-processing, which are utilized in time series area of study e.g. seasonality differencing, data normalization, data transformation, data cleaning, data smoothing, and other techniques, have been introduced. For instance, for detrendization of data, researchers apply some order of difference on data(Gonedes and Roberts, 1977a). Likewise, Nelson and Granger(1979) used variable transformation to remove trend, non-stationery patterns, seasonality and other features that make the analysis of data problematic. In the same venue, certain research has been conducted to propose specific data pre-processing to carry out accurate prediction in particular application(Cannas *et al.*, 2006; Cao and Cao, 2006). Although there has recently been an increasing interest in using Fuzzy Time Series in several applications, far too little attention has been paid to propose an appropriate data pre-processing whereby FTS promotes better forecasts. Considering our pervious unpublished works and experiences on improving FTS performance and having a huge volume of experiments, in this thesis, the author presents a kind of proper seasonal data pre-processing technique together with a simple formula to recognize appropriate length of the intervals to improve FTS algorithm for noisy data. Considering the reviewed studies, in stock market forecasting which were almost included in half of all case studies in this field, most of forecasting literature to date have focused on the proposing new algorithms. In this way, one criticism of much of the literature on using fuzzy time series algorithms was the absence of any standard model to facilitate making a forecasting system, however, in this research, the approach differs from those earlier studies were tied to propose a particular algorithm. However, here, the aim is not just to propose a new algorithm; instead, a systematic, descriptive and well-structured framework model, which is constructed of some meaningful layers that play an independent role throughout the forecast process will be proposed. Perhaps the most serious disadvantage of fuzzy time series methods is that they were not designed for k-step-ahead forecasting. Up to date every FTS model just discussed for one-step-ahead forecasting purposes, since the nature of FTS is different with other type of time series, because of using fuzzy logic, it is not very easy for users to convert FTS algorithm for k-step-ahead forecasting usage. Therefore, the lack of such models is a serious problem. Here a kind of computational FTS algorithm called k-step-ahead FTS forecaster is introduced whereby every FTS algorithm can be transformed to be suitable for k-step-ahead forecasting.

1.3 The Significance of the Research

By this research some refined algorithms were proposed. Since in each proposed algorithm the main aim has improved forecast accuracy then it is justifiable for who which looking for more forecast accuracy to apply these refined algorithms. In particular, in this section the importance of each refined algorithm discusses one by one. The importance of the first proposed algorithm i.e. polynomial fuzzy time series is highlighted when training dataset is huge. Always the optimization can find the best weights in this method in training, therefore, forecast will be accurate. In the case that noisy data are employed, this method will not produce good results. If this method combined with k-step-ahead forecaster algorithm can be useful for power managers when STLF is in the case. Concerning differential fuzzy time series, this method work on trend data well. For instance, the application like financial time series that contain differently upwards and downwards trends through their life cycle can be forecasted by this method well. It is good to use by financial managers to predict financial time series. The reputation of third method i.e. revised fuzzy time series model for noisy data will be appearing when a data contains a seasonality pattern with noise. In stock market for prediction, this method will promise the accurate forecast. The application of this method is tested on stock amount forecasting and STLF. Multilayer forecasting model, which is a fourth refined method in this thesis, is very used full typically for stock market and financial time series forecasting. In this study the performance of this method is tested in frothy stock market case studies. It's also very elastic and can be combined with other FTS algorithms to be better. Finally, k-step-ahead forecaster is useful for when in FTS applications, k-step-ahead forecast is required. The algorithm is generalized and tested for STLF but not limit too. Any application which required to perform k-step-ahead forecasting using fuzzy time series can use this method.

1.4 Research question

The objectives of this study are to determine five gaps in fuzzy time series literature, to propose and improve novel algorithms which deal appropriately with these shortcomings and to evaluate and validate the performance of the proposing algorithms by applying different appropriate case studies.

1.5 Objective of study

The main goal of this research is to enhance the fuzzy time series algorithm by revision techniques through new algorithms. In order to attain research aim the following research objectives are recognized:

1. To propose polynomial fuzzy time series, to enrich the role of FLRGs in fuzzy time series algorithms.
2. To propose differential fuzzy time series to deal with trend of data appropriately.
3. To present revised fuzzy time series model for noisy data to propose the way of integrating fuzzy time series model together with data pre-processing.
4. To propose a multi-layer fuzzy time series model for stock market forecasting. While forecasting the stock market was one of the main application in fuzzy time series researches, absence of any standard model to facilitate making a stock forecast system was a considerable problem.
5. To propose a modified fuzzy time series model for k-step-ahead forecasting.
6. To validate the performance of proposed methods and algorithms by evaluating the results which are obtained by different experiments.

1.6 Scope of study

This study is limited to resolving five shortcomings in univariate fuzzy time series by revising certain steps of basic algorithms or proposing new approaches. The datasets that used through this research for validation of the proposed models are half-hourly load data of different sources i.e. France, England, and Malaysia, and stock data such as forty years of Taiwan Capitalization Weighted Stock Index (TAIEX), National Association of Securities Dealers Automated Quotations (NASDAQ), Dow Jones Industrial Average (DJI) and S&P500. In addition, a benchmark dataset in fuzzy time series studies, namely the number of enrollments of Alabama University is also applied.

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