A Review: Fuzzy Time Series Model for Forecasting

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ABSTRACT
This paper investigates predictive performance of hybrid fuzzy time series analysis methods and integration of neural network with fuzzy time series for forecasting market practice. Time series analysis is conventionally used for modeling univariate and multivariate data series. However, classical time series analysis has several limitations such as stationarity, normality etc. Particularly for non linear dataset, difficulties exist in time series practice. Fuzzy time series analysis is first suggested by Song and Chrisom (1993a, b) and it is a time invariant method for modeling. Rather than classical methods, there are no prerequisites like stationarity and normality, and there is no necessity for treatment of missing data.

KEYWORDS
Fuzzy Time Series, Neural, Forecasting, Classical

I. INTRODUCTION
Developments of computer science disclosed several new research fields and new scientific methods. Fuzzy numbers are one of the huge step ups of the uncertainty research. By the fuzzy numbers, automation and control studies gained crucial advances. Although, it is first presented 45 years ago (Zadeh, 1965), the importance and research boom rose in the last 20 years. Now, fuzzy studies are increasing day by day and application fields are various. Use of fuzzy numbers in economic modelling is also one of the substantial implementing areas. Fuzzy set theory defines how a linguistic value is distributed between quantitative boundaries and how is the most certain point(s) in the range.

Traditionally, time series forecasting problems are being solved using a class of Autoregressive moving average models. Being linear statistical models, they cannot build relationship among the nonlinear variables/factors. Calculating the parameters for multi-variables is another issue faced by them. The strong relationship among these variables may result in large errors. Furthermore a model cannot be estimated correctly if the historical data is less. Handling the irregularity and uncertainty of real data are some more issues concerning to this group of models. Several statistical nonlinear models have been developed to overcome these limitations of linear models [1]. Because these models are developed for specific nonlinear patterns, they are not capable of modeling other types of nonlinearity in time series [2]. Now to overcome these problem two methods has been adopted.

1. Hybrid approach (ARIMA)
Mixing of two or more than two models to improve the accuracy of the forecasted result. A hybrid approach of linear and nonlinear models was adopted in for taking benefits of both the models.

2. Neural network integration with fuzzy time series mode
Neural networks have been popular in their capabilities in handling nonlinear relationships. Hence, this study intends to integrate neural networks with a new fuzzy time series model to improve forecasting. Different from a previous study, the study includes all the degrees of membership in establishing fuzzy relationships, which assist in capturing the fuzzy relationships more properly.

II. LITERATURE SURVEY
Eollments of the University of Alabama is practiced in [14]. A heuristic model of fuzzy time series model has been developed to improve forecasting. The heuristic helped out the moving trend which supports forecasting without affecting the fuzzy relationships,i.e. the improvement in forecasting result is achieved by introducing heuristic rules. The model is applied on only one variable where it can be applied on more heuristic variables.
Weighted models are proposed in [11] to resolve the recurrence and weighting issues in fuzzy time series forecasting. These models demonstrate similarity to the weight functions in local regression models; though, both are dissimilar. The local regression models concentrated on fitting using a small portion of the data, whilst the weighted fuzzy time series models established fuzzy relationships using the promising data from the entire database.

Two new multivariate fuzzy time series forecasting methods are presented in [3]. These methods assume m-factors with one significant main factor. Stochastic fuzzy dependence of order k is presumed to define general methods of multivariate fuzzy time series forecasting and control.

A refined fuzzy time series model with improved defuzzification model is presented in [9] for stock exchange forecasting. Results with better accuracy were obtained by proposing a heuristic approach of fuzzy metric.

ARIMA, a popular statistical time series model is integrated with fuzzy regression model in [10] for forecasting the foreign exchange market. It is deduced from the results that it takes less observation to estimate a model than ARIMA. The forecasted results were made good by narrowing the fuzzy interval (Upper and lower bound). When fuzzy intervals were wide deleting its upper or lower bound the interval were made narrow. This gave better performance.

However deleting the bounds may cause incomplete or missing interval/data. T2-FLS is applied to forecast Mackay-Glass time series [19]. Using T1-FLS, a T2-FLS is formed by incorporating noise information. The FLSs were designed on a single realization for practice.

However, for different realizations of same data set, different FLSs parameters must be choose to obtain improved forecasting [19]. A novel hybridization model based on ARIMA and of soft computing methods such as Neural networks and evolutionary algorithm is explored in [26]. Fuzzy IF-THEN rules were evaluate by mamdani-Assilian technique and implemented by an evolutionary algorithm to determine the model structure. Unusually this attention grabbing technique used the rules to select the best method instead of time series forecasting.

Reference [6] integrated ANFIS and an Evolution Optimizer to synchronize a First-order Interval Type

2 Takagi- Sugeno-Kang (IT2TSK) Fuzzy Logic System (FLS) to a hybrid model. Neuro-Evaluative IT2 TSK model has independent, normal distributed, uncorrelated and smaller residuals than other methods. It is observed as a good forecaster but in-depth search is required for replacing the worst data set with new ones. The developed Neuro-Genetic structure involves complex computation and to attain simplicity in such a model, an efficient algorithm(s) should be explored.

III. FUZZY TIME SERIES

The fuzzy time series were firstly defined in Song and Chissom. Many time series in the real life have uncertainty observations. This kind of the time series is called fuzzy time series. For example, some of these time series are stock index data, air pollution data, enrollment data, and temperature data. The observations of these time series are convertible to fuzzy sets. The fuzzy time series separate two classes which are time-variant and time-invariant. The time-invariant fuzzy time series have time-invariant relationship of lagged fuzzy time series variables. This relationship is proved from an "*" matrix, which is invariant in the time space. The first method for forecasting time-invariant time series is proposed in Song and Chissom, in which the membership of observations is determined, subjectively.

The time-variant and time-invariant fuzzy time series definitions are given below.

Definition 1. Let $Y(t)$, a subset of real numbers, be the universe of discourse on which fuzzy sets $f(t)$ are defined. If $F(t)$ is a collection of $f1,f2$, then $F(t)$ is called a fuzzy time series defined on $Y(t)$.

Definition 2. Suppose $F(t)$ is implied by $F(t-1)$ only, that is, $F(t-1)$ $F(t)$. Then this relation can be expressed as $F(t) = F(t-1) * R(t-1)$, where $R(t-1)$ is the fuzzy relationship between $F(t-1)$ and $F(t)$ and is called the first order model of $F(t)$.

IV. NEURAL NETWORKS MODEL

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output as shown in the graphic below.
Most ANNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. In a sense, ANNs learn by example as do their biological counterparts; a child learns to recognize dogs from examples of dogs. Although there are many different kinds of learning rules used by neural networks, this demonstration is concerned only with one; the delta rule. The delta rule is often utilized by the most common class of ANNs called 'backpropagational neural networks' (BPNNs). Backpropagation is an abbreviation for the backwards propagation of error. With the delta rule, as with other types of backpropagation, 'learning' is a supervised process that occurs with each cycle or 'epoch' (i.e. each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. More simply, when a neural network is initially presented with a pattern it makes a random 'guess' as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights.

V. ARIMA TIME SERIES

In statistics and econometrics, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). They are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to remove the non-stationarity. The model is generally referred to as an ARIMA(p,d,q) model where parameters p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. ARIMA models form an important part of the Box-Jenkins approach to time-series modelling. When two out of the three terms are zeros, it is a common mistake to refer to the model as ARIMA. The model should be referred to as defined in the parameters, dropping "AR", "I" or "MA" from the acronym describing the model. For example, ARIMA(0,1,0) is I(1), and ARIMA(0,0,1) is MA(1).

VI. CONCLUSION AND FUTURE SCOPE

In this paper fuzzy time series model has been analyzed along with ARIMA and neural network, as it has been discussed traditional time series does not provide good results, so methods based on neural or fuzzyfication are achieving good results in forecasting. It has been also concluded that Uses of fuzzy models are more transparent than neural networks, which make them useful in applications where transparency is required. The future lies in the use of Particle Swarm Optimization algorithm to improve more accuracy.

REFERENCES


