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A differential harmony search based hybrid interval type2 fuzzy EGARCH model for stock market volatility prediction

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ABSTRACT

In this paper a new hybrid model integrating an interval type2 fuzzy logic system (IT2FLS) with a computationally efficient functional link artificial neural network (CEFLANN) and an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model has been proposed for accurate forecasting and modeling of financial data with changing variance over time. The proposed model denoted as IT2F-CE-EGARCH helps to enhance the ability of EGARCH model through a joint estimation of the important features of EGARCH like leverage effect, asymmetric shock by leverage effect with the secondary membership functions of interval type2 TSK FLS and the functional expansion and learning component of a CEFLANN. The secondary membership functions with upper and lower limits of IT2FLS provide a forecasting interval for handling more complicated uncertainties involved in volatility forecasting compared to type1 FLS. The performance of the proposed model has been observed with two membership functions i.e. Gaussian with fixed mean, uncertain variance and Gaussian with fixed variance and uncertain mean. The proposed model has also been compared with a few other fuzzy time series models and GARCH family models based on four performance metrics: MSFE, RMSFE, MAFE and Rel MAE. Again a differential harmony search (DHS) algorithm has been suggested for optimizing the parameters of all the fuzzy time series models. The results indicate that the proposed IT2F-CE-EGARCH model offers significant improvements in volatility forecasting performance in comparison with all other specified models over BSE Sensex and CNX Nifty dataset.

1. Introduction

Forecasting and modeling volatility with a reasonable accuracy plays a key role in achieving gain in different financial applications. Volatility provides a measure of fluctuation in a financial security price around its expected value. In recent years several time series models have been developed for financial data with changing variance over time. Among a number of time series models, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model provides a convenient framework for dealing with time dependent volatility. The GARCH model reflects the nonlinear dependence of the conditional variance of the time series, estimating jointly a conditional mean and conditional variance equation [1,2]. Irrespective of its simplicity and ability to capture the persistence of volatility, it does not recognize the transmission of volatility that comes from the input of positive or negative information. Therefore, this model is not appropriate when the market is asymmetric. To overcome these limitations, a class of asymmetric GARCH models like the GJR-GARCH, and EGARCH has been proposed.

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The GJR-GARCH model was developed by Glosten [3], while the exponential GARCH(EGARCH) was proposed by Nelson [4,5]. These models suggest that the negative relationship between volatility and stock prices can be understood by the fact that an increase in unexpected volatility will increase expected future volatility, assuming persistence. Some of these effects can be captured by modifications of linear models, while others demand nonlinear approaches. Although, many financial time series observations have nonlinear dependence structure, a linear correlation structure is usually assumed among the time series data. Thus GARCH type models alone may not be able to capture the nonlinear patterns in a highly volatile time series data except when hybridized with artificial intelligence (AI) based models [6]. Considering these difficulties, there is currently a demand for more flexible volatility forecasting models.

Many researchers, therefore, have taken the advantage of artificial intelligence techniques to process an extensive amount of informations to forecast financial markets leading to an increase in investment return. To enhance the predictive power of the financial time series models numerous computational intelligence based techniques like the Artificial Neural Network, fuzzy inference system, Support Vector Machine, Relevance Vector Machine hybridized with the financial time series models have been proposed in the literature [7–14]. Adaptive Neuro-Fuzzy system is one of the most popular hybrid models in stock time series prediction that provides the advantage of combining the rules in the fuzzy rule base to describe the complex relationships between the variables and the learning ability of neural network. A combination of wavelet neural networks with a fuzzy knowledge base (FWNN) optimized by using DE is proposed in [15] for financial time series prediction. The advantage of FWNN prediction system over other prediction systems is given in [16]. Two hybrid models based on EGARCH and Artificial Neural Networks are proposed to forecast the volatility of S&P 500 index in [17]. The attempt for using the hybrid system is to outperform the forecast results and overcome the shortcomings by extracting input variables from statistical methods and include them in ANNs learning process [18,19]. An adaptive fuzzy GARCH model comprising a functional type1 fuzzy inference system with a GARCH model optimized using genetic algorithm (GA) framework is presented in [20]. Another evolving fuzzy-GARCH model for financial volatility modeling and forecasting has been outlined in [21]. It combines both evolving fuzzy systems and the conditional variance GARCH model to deal with stylized facts such as time-varying volatility and volatility clustering. A new state space formulation of Fuzzy-GARCH model using Kalman filter is described in [22], where the Fuzzy-GARCH model analyzes the clustering properties and the Kalman filter deals with the problem of parameter estimation under fluctuating conditions. However, joining the parameters of the fuzzy membership functions and GARCH models in a state space formulation makes this problem highly nonlinear and complicated. An iterative algorithm based on particle swarm optimization (PSO) has been used to estimate parameters of the fuzzy membership functions and GARCH models. A Fuzzy GJR-GARCH model integrating both the concept of type1 fuzzy inference systems and GJR-GARCH modeling approach was proposed in [23] in order to consider the principles of time-varying volatility, leverage effects and volatility clustering. Again to handle more complicated uncertainties the extensions of classical fuzzy model is available in the literature. At present Interval Type2 Fuzzy logic Systems (IT2-FLS) are extensively used in different forecasting and classification [24–27] applications. In [28] an Interval type2 fuzzy model based on ARIMA has been proposed for forecasting. The proposed model used ARIMA to select appropriate coefficients from the observed dataset and IT2-FLS for handling the uncertainty in the time series data to yield a more accurate forecasting result. In [29] a PSO based integrated Functional Link Interval type2 Fuzzy Neural System is used to predict the chaotic financial time series data like the stock market indices. In this model the antecedent parts in each fuzzy rule are Interval type2 fuzzy sets and in the consequent part of the fuzzy rules, a Functional Link Artificial Neural Network is used which is a nonlinear combination of the input variables. The model parameters are optimized using PSO. In [51,52] Simulated annealing based parameter optimization method is used to optimize the parameters of the antecedent and the consequent parts of the type1 Takagi–Sugeno (TSK) fuzzy system in order to predict two well known time series data.

The motivation of this study is to enhance the ability of time series model in forecasting return volatility by integrating it with suitable machine learning approach. In the first step, the fitness of GARCH, EGARCH and GJR-GARCH models with different lag orders is evaluated and compared on two stock market indexes i.e. BSE SENSEX and CNX NIFTY indexes. The EGARCH$(1,1)$ model provides the best forecast when compared to the realized volatility. To enhance the ability of EGARCH model, a hybrid approach comprising an interval type2 Fuzzy logic system and computationally Efficient EGARCH (IT2F-CE-EGARCH(p,q)) model is proposed in forecasting highly nonlinear and complicated financial time series data. The IT2F-CE-EGARCH(p,q) model provides a joint estimation of interval type2 TSK FLS, the functional expansion and learning component of a CEFLANN along with the leverage effect, asymmetric shock by leverage effect of EGARCH model to handle the complicated uncertainties involved in volatility forecasting. The performance of the model is observed with two membership functions i.e. Gaussian with fixed mean and uncertain variance, and Gaussian with fixed variance and uncertain mean. The proposed model is also compared with an interval type2 fuzzy EGARCH(IT2F-EGARCH) model, type1 fuzzy EGARCH, type1 fuzzy-CE-EGARCH, EGARCH, GJR-GARCH and GARCH models based on three performance metrics: MSFE, RMSFE, MAFE and Rel MAE. Moreover, a differential harmony search (DHS) based parameter estimation algorithm is suggested to derive the optimal solution of the hybrid model.

The remainder of the paper is organized as follows: A detailed description of different GARCH family models is outlined in Section 2. Section 3 describes the theory of interval type2 fuzzy logic system. Detailed working principle of the proposed model is specified in Section 4 followed by the descriptions of interval type2 fuzzy EGARCH model, type1 fuzzy computationally efficient EGARCH model and type1 fuzzy EGARCH model in Sections 5, 6, 7, respectively. A detailed procedure for parameter optimization of the proposed model through differential harmony search algorithm has been described in