Engineering Applications of Artificial Intelligence 25 (2012) 295–308

Contents lists available at SciVerse ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

A new ARIMA-based neuro-fuzzy approach and swarm intelligence for time series forecasting

Chunshien Li *, Jhao-Wun Hu

Laboratory of Intelligent Systems and Applications, Department of Information Management, National Central University, Taiwan (R.O.C)

ARTICLE INFO

Article history:
Received 11 January 2011
Received in revised form
13 August 2011
Accepted 17 October 2011
Available online 8 November 2011

Keywords:
Time series forecasting
Hybrid learning
Neuro-fuzzy system (NFS)
Particle swarm optimization (PSO)
Recursive least-squares estimator (RLSE)
Auto-regressive integrated moving average model (ARIMA)

ABSTRACT

Time series forecasting is an important and widely interesting topic in the research of system modeling. We propose a new computational intelligence approach to the problem of time series forecasting, using a neuro-fuzzy system (NFS) with auto-regressive integrated moving average (ARIMA) models and a novel hybrid learning method. The proposed intelligent system is denoted as the NFS–ARIMA model, which is used as an adaptive nonlinear predictor to the forecasting problem. For the NFS–ARIMA, the focus is on the design of fuzzy If-Then rules, where ARIMA models are embedded in the consequent parts of If-Then rules. For the hybrid learning method, the well-known particle swarm optimization (PSO) algorithm and the recursive least-squares estimator (RLSE) are combined together in a hybrid way so that they can update the free parameters of NFS–ARIMA efficiently. The PSO is used to update the If-part parameters of the proposed predictor, and the RLSE is used to adapt the Then-part parameters. With the hybrid PSO–RLSE learning method, the NFS–ARIMA predictor may converge in fast learning pace with admirable performance. Three examples are used to test the proposed approach for forecasting ability. The results by the proposed approach are compared to other approaches. The performance comparison shows that the proposed approach performs appreciably better than the compared approaches. Through the experimental results, the proposed approach has shown excellent prediction performance.

1. Introduction

Using an intelligent modeling approach, a model can be set up for a target system, with which the relationship of input–output behavior can be approximated. This is known as system modeling. For function approximation, optimization, and forecasting, system modeling has been widely investigated for years. Time series forecasting is one of the momentous applications in system modeling. In a time series, time is usually a very important factor to make decision or prediction. Data in past history recorded in time sequence is called a time series. Managers usually use historical data to forecast various types of variables such as changes in stock, sales of products, population growth, and many others. The accurate and valuable prediction of these variables can assist managers to make a useful decision. For a more refined definition, time series is a group of statistics, according to the order which events are occurred in time sequence. For instances, daily average temperature or monthly rainfall at a place, daily stock market closing price, company's turnover, unemployment rate, economic growth rate, and total amount of national income and export. Modern business and economic activities, in essence, are dynamic, and they change frequently. How to make a reliable forecast is one of the most important issues for modern enterprises and organizations. The usage of time series to forecast the future tendency has to make use of detailed data, which were generated for some time past in the cause of understanding the trend of changes.

In the past four decades, various approaches have been presented for time series forecasting (Kim et al., 1997; Xiong, 2001; Box and Jenkins, 1976; Chen et al., 1991; Jang, 1993; Cho and Wang, 1996; Kasabov et al., 1997; Kim and Kasabov, 1999; Nauck and Kruse, 1999; Paul and Kumar, 2002; Sfetsos and Siriopoulos, 2004; Chen et al., 2005; Gao and Er, 2005; Chen et al., 2006; Rong et al., 2006; Herrera et al., 2007; Rojas et al., 2008; Sugiarto and Natarajan, 2007; Zounemat-Kermani and Teshnehlab, 2008; Deng and Wang, 2009; Graves and Pedrycz, 2009; Zhao and Yang, 2009), including powerful auto-regressive moving average (ARMA), fuzzy-based paradigm, neural-net computing model, neural fuzzy hybrid system, and others. In the recent twenty years, fuzzy system is one of the most frequently used methods (Kim et al., 1997; Xiong, 2001; Jang, 1993; Cho and Wang, 1996; Kim and Kasabov, 1999; Nauck and Kruse, 1999; Paul and Kumar, 2002; Rong et al., 2006; Herrera et al., 2007; Sugiarto and Natarajan, 2007; Zounemat-Kermani and Teshnehlab, 2008).

* Corresponding author.
E-mail address: jamesli@mgt.ncu.edu.tw (C. Li).

0952-1976/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2011.10.005

Many kinds of optimization algorithms have been used for fuzzy systems. The design of fuzzy systems to forecasting has been also proposed in related researches. For instance, Takagi and Sugeno (T–S) fuzzy model with fuzzy *C*-regression clustering model was used to determine number of fuzzy rules and gradient descent algorithm was applied for tuning the free parameters of T–S fuzzy model (Kim et al., 1997). A fuzzy model with genetic-based premise learning was proposed by Xiong (2001), for the well-known gas furnace time series dataset of Box and Jenkins. Hybrid neural fuzzy inference system (HyFIS) was developed by Kim and Kasabov (1999), for building and optimizing the fuzzy model. Adaptive-network-based fuzzy inference system (ANFIS) was proposed, where the backpropagation (BP) method and the recursive least-squares estimator (RLSE) were combined to adapt free parameters (Jang, 1993). Almost all of these studies used general T–S fuzzy model (Takagi and Sugeno, 1985) for system modeling and time series forecasting. Besides, neural networks are another major approach to time series forecasting in artificial intelligence field (Chen et al., 1991; Kasabov et al., 1997; Chen et al., 2005, 2006; Deng and Wang, 2009). Most of these studies focused on designing new structure of neural network and applying different learning methods to improve the accuracy of prediction. For example, Chen et al. (2006) presented local linear wavelet neural network (LLWNN). A hybrid training algorithm of particle swarm optimization (PSO) with both diversity learning and gradient descent method was introduced for the training of the LLWNN. Deng and Wang (2009) proposed a novel incremental learning approach (ILA) based on a hybrid fuzzy neural net framework.

However, most of these researches used stationary time series to verify the forecasting performance of their approaches or models. Basically, a time series can be viewed as a set of observations from a stochastic process. A time series is considered stationary if the stochastic process is with the property that probability distribution does not change with time shift, so that the statistics such as mean, variance, and covariance of the time series are of finite constant. In contrast, a non-stationary time series whose probability distribution is changing with time. Thus, the mean, variance and covariance vary with time. This class of time series is usually hard to find the regularity for a prediction model. Traditional mathematical approaches to non-stationary time series are usually feeble and hard to attack such problems with satisfactory performance. Practically, time series in real world usually are non-stationary, especially in economic and finance field. The fluctuations and changes of these non-stationary time series are quite enormous, such as daily closing stock price. Accordingly, the prediction by forecasting models may deviate from the future value easily. For non-stationary time series, the auto-regressive integrated moving average (ARIMA) model, first proposed by Box and Jenkins, has been used in order to make forecasting more accurate. For ARIMA process, models that describe homogeneous non-stationary behavior can be obtained by supposing some suitable difference of the process so that the differenced version of the time series may become stationary (Box and Jenkins, 1976). An ARIMA model combines three different processes including an auto-regressive (AR) process, integration part, and a moving average (MA) process. In previous researches, the concept of ARMA model was used in the fuzzy inference system or neural network. Gao and Er (2005) proposed a ARMA-like model using fuzzy neural network method , called the nonlinear autoregressive moving average with exogenous inputs (NARMAX). They used TSK-type weight vector to mimic ARMA model with exogenous inputs, and cast the NARMAX model into a fuzzy neural network (FNN). Basically, the NARMAX approach is based on the so-called G-FNN framework, whose functionality is equivalent to a TSK-type fuzzy inference system. A hybrid methodology combining an artificial neural network (ANN) and ARMA models was proposed (Rojas et al., 2008) to investigate time series forecasting. However, the forecasting performance and accuracy were not good enough in these previous works. In our study, we propose an innovative hybrid computing paradigm, integrating both neuro-fuzzy system (NFS) and ARIMAs together to achieve ARIMA-based neuro-fuzzy nonlinear-mapping ability for accurate forecasting. Our approach expands ARIMA from its linear modeling ability to the horizon of nonlinear modeling by neuro-fuzzy method, so that excellent performance for accurate forecasting can be achieved. With the neuro-fuzzy system (NFS) theory, ARIMA models are embedded into fuzzy If-Then rules to construct a new NFS–ARIMA predictor to the problem of time series forecasting, equipped with a novel hybrid learning ability. NFS has been a useful modeling tool to represent and process linguistic information and to deal with uncertainty and imprecision (Jang et al., 1997). In fuzzy theory, fuzzy sets can be used to reflect human concepts and thoughts, which tend to be incomplete and vague (Zadeh, 1965, 1975; Fukami et al., 1980; Klir and Yuan, 1995). Besides the viewpoint of learning and adaption, there are perspectives for the use of neuro-fuzzy framework. Basically, neural networks (NNs) and fuzzy systems (FSs) have been proven universal approximators, which can theoretically approximate any function to any degree of accuracy on a compact set. Neuro-fuzzy systems have been successfully applied in various applications. The integration of them tends to adopt their merits to become a unified framework of computing model for information processing, where NN can provide capability for flexible adaptive low-level structure for learning from examples and pattern recognition, and FS can provide high-level comprehensive rule inference for imprecise information processing and decision-making. In this paper, the basic idea of combining fuzzy system and neural network is to design a neuro-fuzzy framework that uses a fuzzy inference system to represent knowledge in an interpretable manner, embedded in the adaptive distributed structure of a neural network. Although the PSO method does not need the support of NN, we think this neuro-fuzzy integration can augment the value of fuzzy system in the perspective of neural network. They complement to one another. Through the connectionist structure by NN, FS can be transformed into a neuro-fuzzy system, providing an insight to the formation of knowledge-base structure and possible design types for FS in the view point of neural network. Therefore, we adopt the participation of NN that can positively provide adaptive flexibility and unified model framework to the proposed approach.

In this paper, a novel intelligent approach is presented for time series forecasting, using Takagi–Sugeno (T–S) neuro-fuzzy model (Jang et al., 1997; Sugeno and Kang, 1988) and ARIMAs. The implementation of a T–S neuro-fuzzy model is very similar to that of a fuzzy logic inference system, except the consequents are described by functions of crisp inputs. An appropriate neuro-fuzzy model for prediction is very important to forecast time series accurately. How to design and adjust fuzzy sets and fuzzy rules in an NFS is significantly critical to forecasting. The proposed neuro-fuzzy approach is denoted as NFS–ARIMA, where ARIMA models are embedded in the fuzzy rules. For different time series, different order of NFS–ARIMA can be conducted to make forecasting as good as possible. Furthermore, because there are usually many unknown parameters in the NFS–ARIMA, the selection of learning algorithm plays an extremely pivotal position. In order to adapt the free parameters, a hybrid learning algorithm is proposed in this paper, using both the particle swarm optimization (PSO) (Kennedy and Eberhart, 1995) and the recursive least-squares estimator (RLSE) (Jang, 1993; Jang et al., 1997). The PSO is used for the update of the premise parameters of the NFS–ARIMA; the RLSE for the consequence parameters; they work together in a hybrid way. The focus is to find the optimal or near-optimal