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A survey of time series forecasting from stochastic method to soft computing

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Abstract. Forecasting is a part of statistical modelling that is widely used in various fields because of its benefits in decision-making. The purpose of forecasting is to predict the future values of certain variables that vary with time using its previous values. Forecasting is related to the formation of models and methods that can be used to produce a good forecast. This research is a survey paper research that used a systematic mapping study and systematic literature review. Generally, time series research uses linear time series models, specifically the autoregressive integrated moving average model that has long been used because it has good forecasting accuracy. The successfulness of the Box–Jenkins methodology is based on the reality that various models can imitate the behaviour of various types of series, usually without requiring many parameters to be estimated in the final choice of the model. However, the assumption of stationarity that must be met makes this method inflexible to use. With the advances in computers, forecasting methods from stochastic models to soft computing continue to develop and extend. Soft computing for forecasting can provide more accurate results than traditional methods. Moreover, soft computing has many advantages in terms of the amount of data that can be analysed and the time- and cost-effectiveness of the process.

1. Introduction

Time series data forecasting is a part of statistical modelling that is widely used in various fields because of its benefits in decision-making. Time series analysis has several objectives, namely, forecasting, modelling, and control. Forecasting is an element that is important in decision-making activities because whether or not an effective decision is made depends on several factors that influence, although unseen, when a decision is taken. The purpose of time series forecasting is to predict the future values of certain variables that vary with time using its previous values. Forecasting is related to the formation of models and methods that can be used to produce a good forecast. The use of time series data for forecasting is based on the behaviour of past events.

In time series data, the behaviour of past events can be used for forecasting because it is expected that, in the future, the influence of the behaviour of past events will still occur. The benefits of forecasting can be felt in many fields, including economics, finance, marketing, and production. Generally, time series research uses linear time series models, specifically the autoregressive integrated moving average (ARIMA) model. This method was first introduced by Box and Jenkins, and it has long been used because it has good forecasting accuracy and continues to develop. However, the assumption of stationarity that must be met makes this method inflexible to use. In addition to the ARIMA model, forecasting methods from stochastic models to soft computing continue to develop. The successfulness of the Box–Jenkins methodology is based on the reality that various models can imitate the behaviour of various types of series, usually without requiring many parameters to be estimated in the final choice of the model.

2. Methodology

The method used systematic mapping study and systematic literature review conducted by identifying and interpreting the findings in the literature review in accordance with the topic time series forecasting raised in this paper. Literature review related to the use and development of time series forecasting methods from various studies in various fields then studied to find newness and the latest developments from each method used. This paper produces clusters and classifications of various applications of forecasting methods from stochastic method to the development to soft computing method as artificial neural network, fuzzy logic, and its development in various fields and data cases. Based on the mapping results obtained identification of future research trends for forecasting time series.

3. Result and Discussion

3.1. Stochastic Method

In the 19th century, the time series analysis such as ARCH, Q-GARCH, ST-GARCH, ABS-GARCH, and exponentially weighted moving average (EWMA), are widely used foe series has been commonly described using the deterministic model. Yull in 1927 proposed the idea of stochasticity by suggesting that each time series can be considered a realization of a stochastic process [1]. Forecasting with a stochastic method will provide high accuracy when the behaviour of the time series data is not complex and the initial condition fulfils the assumption of stationary. The stochastic method used to forecast the time series can be distinguished as linear and nonlinear. Several linear stochastic models, such as autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), ARIMA, seasonal ARIMA (SARIMA), autoregressive fractionally integrated moving average (ARFIMA), autoregressive conditional heteroscedasticity (ARCH), and generalized ARCH (GARCH), as well as GARCH-M, E-GARCH, T-GAR forecasting.

For years, the ARIMA method has often been utilized for various types of univariate time series. The ARIMA method has been widely used in many areas, including business and industry, and has attracted the attention of and has been well developed by many statisticians. The ARIMA model as a useful prediction approach has a simpler idea than the other models because it only considers past data and does not require other information. The ARIMA model has good accuracy.in predicting. The latest ARIMA model has been applied by many researchers, among them, [2-5]. Time series data often have a certain pattern that tends to repeat in a certain period called a season. The SARIMA is an ARIMA model that can be used to handle data containing seasonal factors. [6-10] conducted an empirical study and determined that the SARIMA model provides an easy and flexible forecasting implementation, obtaining accuracy as well as other more complicated prediction methods. In addition to SARIMA, one method that can be used to forecast long-term time series data is the ARFIMA method. [11] and [12] have used ARFIMA to predict and examine data, that are indicated to have a long memory pattern.

ARCH/GARCH is usually used to determine the volatility of data by analyzing the effect of the variances, errors, and squares from the data series. ARCH/GARCH is used if the selected ARIMA model does not meet the homoscedasticity assumption, which means that the model still contains heteroscedasticity. This method was first introduced by Engle [13], used for econometrics data, and focused on financial applications. Numerous studies applying GARCH and its expansion methods to various contexts aside from financial data have been conducted. Several researchers analyzed data with volatility using ARCH/GARCH, among them, [14-20] that obtained that ARCH/GARCH give better results than the ARIMA for data with volatility. One other approach that can be used to handle data with volatility and heteroscedasticity is the EWMA method developed by Morgan in 1994. The EWMA method is a step to estimate future volatility by giving greater weight to the latest observation

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data than the previous data. [21] and [22] used and analyzed the performance of EWMA and obtained promising forecast results. Table 1 up to 5, provides a list of studies that have been conducted related to the purpose of forecasting from traditional methods to methods that utilize the sophistication of computer technology. Several studies that developed new methods and techniques for forecasting are also summarized.

3.2. Nonlinear Time Series Modeling

[23] used the TAR to establish the threshold model and address the purchasing power parity issue, respectively. The four other researchers reviewed various areas using the nonlinear forecasting methodology such as TAR, STAR and SETAR, they are [24-27]. The latest study by Davies [28] developed a package and procedure for the identification, estimation, and forecasting of SETAR models. The results of the studies conducted by several experts showed that the nonlinear SETAR model provides more accurate forecasts than the AR model and yields smaller error than the linear model. The Markov switching model of Hamilton, which is also well-known as the regime switching model, is one of the most preferred nonlinear time series models in the literature. This model implicated substantial structures (equations), which can describe the characteristics of the time series. By enabling transitions between these structures, this model is able to capture more complex dynamic patterns. A novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable that follows the first-order Markov chain. The Markovian property specifies that the current value of the state variable depends on its immediate previous value. Thus, a structure may apply to a random period of time and will be replaced by another structure when a change occurs. In a simulation study, Haas [29] presented a new Markov switching GARCH model that copes with poor estimation problems or dynamic properties that are not well understood. Dueker and Neely [30] combined the literature on technical trading rules with the literature on Markov switching models that provide at least two marginal benefits compared with conventional MA rules to develop economically beneficial trading rules, where the models provide strong portfolio returns.

Table 1 A list of research areas in time series forecasting using stochastic method

	Method	Author/References	Topic/Dataset
Stochastic Method	ARMA/ARIMA	Guo (2012)	Housing price
		Widowati et al. (2016)	Microbenthic assemblages
		Ruby-Figueroa et al. (2017)	Permeate flux
		He and Tao (2018)	Epidemiology influenza viruses
		Ohyver and Pudjihastuti (2018)	Price of rice
		Zhang et al. (2018)	Environmental regulation
	SARIMA	Yantai Shu, Minfang Yu, Jiakun Liu, and Yang (2003)	Traffic
		Durdu (2010)	Boron concentration
		Wang et al. (2012)	Electricity demand
		Arumugam and Saranya (2018)	Rainfall data
	ARFIMA	Bivona et al. (2010)	Wind speed
		Doornik and Ooms (2004)	US and UK Inflation
	ARCH, ARCH(GARCH), GARCH-M, E-GARCH, T-GARCH, Q-GARCH, ST-GARCH, ABS-GARCH	Engle (2001)	econometrics and financial
		Garcia et al. (2005)	Electricity prices
		Zhou, He, Sun, and Ng (2006)	New network traffic prediction
		Jiang (2012)	Financial data
		Alam et al. (2013)	Daily data
		Kronman (2015)	Texas stock return
		Hosseinipoor et al. (2016)	Natural gas price
		Nieto and Carmona-Benítez (2018)	Airline industry
	EWMA	Staak and Berghaus (1982)	Software development
		Hunter (1986)	Quality control

3.3. Multivariate Time Series Method

The successful use of the univariate time series model for forecasting has motivated researchers to extend the use of models to multivariate cases. Several cases of time series forecasting depict the relationship between two or more variables. This is possible with the use of more information involving several related variables so that the precision of the data predicted by the model will increase. Several time series data forecasting models for multivariate time series data include vector autoregressive (VAR), vector moving average (VMA), and vector autoregressive moving average (VARMA). VAR is used to analyze the dynamic effect of interference factors contained in the model. VAR analysis is the same as the simultaneous equation model because it considers several endogenous variables together in a model. However, in the VAR, each variable, other than that explained by its previous value, is also affected by the previous values of other endogenous variables in the observation. The VARMA model is a generalization of the univariate ARIMA that can be used to predict multivariate data or data with more than one variable. The VARMA model has the condition that the data must be stationary. The VARMA model is the combination of the VAR and VMA models. This model has the advantage of not only being able to predict data but also being able to see the interrelationship between data. Different versions of the multivariate VAR model have been developed by [31-37] were implement VAR/VARMA to prediction various economic cases.

Table 2 A list of research areas in time series forecasting using nonlinear and multivariate method

	Method	Author/References	Topic/Dataset
Nonlinear Time Series Modeling	Threshold Autoregressive (TAR)	Tong (1983)	threshold model
		Enders and Falk (1998)	Purchasing power parity
		Nieto (2008)	Missing data
	Self-Exciting Threshold Autoregressive (SETAR)	Clements et al. (2003)	US GNP
		Boero and Marrocu (2004)	Euro effective exchange rate
		Society (2018)	Developed package & procedure
	Smooth Transition Autoregressive (STAR)	Dueker and Neely (2007)	Portfolio returns
		Haas (2004)	Exchange rate return
	Markov Switching	Umer, Sevil, and Sevil (2018)	Return, travel, leisure index
Multivariate Time Series Method		Freeman et al. (1989)	Political process
		Weise (1999)	Economics in monetary policy
		Kunst (1986)	Austrian macroeconomic
		Holden (1990)	UK economic variable
		Lamy (1986)	Canadian Composite Indicator
		Karlsson (1993)	Swedish unemployment rate
		Anggraeni et al. (2018)	Price of rice

3.4. Artificial Intelligence Method for Forecasting

Stationarity is the initial requirement of a time series analysis process that uses the ARIMA model. In practice in real cases, most time series data are nonstationary. The development of the artificial neural network (ANN) method facilitates time series analysis for cases of data that are nonstationary. However, a problem arises when the assumption of stationarity is not needed during the analysis of time series data. With the development of science, many new techniques and procedures have been developed. With the advancement of computational technology, new methods for time series prediction have also been developed. Artificial intelligence is a rapidly evolving method in forecasting. Forecasting with artificial intelligence methods has several advantages compared with stochastic methods, including (a) does not need to form a particular model, (b) is able to analyze the behavior of data without certain assumptions regarding the statistical distribution of data, (c) is able to process complex patterns and nonlinear data, and (d) provides more accurate prediction results. However, a disadvantage of using artificial intelligence methods is the possibility of getting stuck in optimum local value.

Table 3 A list of research areas in time series forecasting using artificial intelligence

Method		Author/References	Topic/Dataset
Artificial Intelligence	Artificial Neural Network (ANN): FFNN, RNN, RBF, SOM, TLNN, SANN	Gooijer and Hyndyman (2006)	Large topik
		Zhang, Patuwo, and Hu (1998)	Survey of ANN
		Ghumman et al. (2011)	Rainfall runoff
		Safi (2013)	Electricity consumption
		Liu, Tian, Li, et al. (2015)	Wind speed
		Lee et al. (2016)	Mosquito abundances
		Tealab et al. (2017)	Simulation data
		Björklund et al. (2017)	Expected return of financial ts
	Wavelet Transform	Arino (1995)	Monthly car sales
		Zhang and Dong (2001)	Electricity market
		Kim and Valdés (2003)	Droughts
		Jiang et al. (2005)	Traffic flow
		Mellit et al. (2006)	Solar radiation
		Partal and Kişi (2007)	Precipitation
		Pindoriya et al. (2008)	Price in the electricity markets
		Amjady and Keynia (2009)	Temperature
		Chen et al. (2010)	Load
	Genetic Programming Hybrid	Beiki et al. (2010)	Deformation modulus
		Nima Amjady (2007)	Bus load of power systems
		Aladag et al. (2009)	Canadian Lynx
		Shafie-Khah et al. (2011)	Electricity price
		Catalão et al. (2011)	Electricity price
		Khandelwal et al. (2015)	Lynx, exchange, mining, tempt
		Liu, Tian, Liang, et al. (2015)	Wind speed
		Sarıca et al. (2018)	BIST100, TAIEX
Support Vector Machines (SVM) Model		Lu' et al. (2002)	Pollutant concentrations
		Ahmad et al. (2014)	Building electrical energy
		Kaytez et al. (2015)	Electricity consumption
		Gui et al. (2015)	Stock price index
		Najafi et al. (2016)	Spark ignition engine
		Hong (2011)	Interurban traffic flow
		Li et al. (2015)	Vessel traffic flow

One method for estimating future value using time series data is the ANN method. Currently, the ANN, which is better known as neural network (NN), has attracted considerable attention. The NN is one of supervised machine learning methods that can represent data relationships, including time-related data. The NN is able to solve nonlinear problems in various fields, including pattern recognition, portfolio management, medical diagnosis, credit ratings, targeted marketing, voice recognition, financial forecasting, quality control, and intelligent search, that are difficult to solve with classical models. The feedforward neural network (FFNN) model, which is also known as backpropagation, is one of the most flexible forms of NN models that can be used for various applications, including forecasting. Compared with other algorithms, NN has better adaptive capability, training, and nonstationary-signal-processing capability [1]. NN is able to solve nonlinear problems that are difficult to resolve with the classical models. Furthermore, NN for time series forecasting has undergone considerable model development. The FFNN, recurrent neural network (RNN), radial basis function (RBF), self-organizing map (SOM), time-lagged neural network (TLNN), and seasonal artificial neural network (SANN) are several NN models used for time series prediction.

Many researchers have developed nonlinear methods with artificial intelligence. [38], [39], [40], [41]. Numerous variations of classical NN methods have been proposed by [42], [43], [44], and [45]. Several experimental simulations with different training algorithms were conducted to select the best training algorithm for ANN models. The main findings indicate that the ANN is superior had high accuracy and better at selecting the most appropriate forecasting model than the ARIMA. In addition, several artificial intelligence techniques, such as wavelet transform, genetic algorithm (GA), simulated annealing, genetic programming, and hybrid methods, have been developed and widely utilized for time series forecasting. The application of wavelet transform to forecasting cases has been implemented for a long time. [46], [47] proposed and applied wavelet transform to forecasting that are applied to real life. Further developments were made by several experts. [48], [49], [50], [51], [52], [53], and [54] proposed an adaptive wavelet model for predicting and applied a new hybrid forecasting method consisting of wavelet transform, NN, and evolutionary algorithm (EA).

In a simulation study, [55] implemented a novel and efficient using the concept of genetic programming. Numerous variations of original methods have been proposed. For instance, [56], [57], [58], [59], [60], [61] proposed the modification of a new hybrid combining several method such as ARIMA, NN, RBFN, GA, wavelet transform, PSO, and adaptive neuro-fuzzy inference system (ANFIS). In latest research, [62] proposed a new hybrid method for time series forecasting called AR–ANFIS, which is trained using PSO, and conducted fuzzification using the fuzzy C-means method. Their hybrid method provided considerable improvement, produced accurate forecasts, and exhibited better prediction accuracy than conventional method.

3.5. Support Vector Machines

Support vector machine (SVM) is a technique for making predictions, both in the case of classification and regression. SVM included in supervised learning class and same as Artificial Neural Network (ANN) in terms of functions and problem conditions that can be solved. The purpose of using support vector machines (SVM) is to make decisions with good generalization capabilities through the selection of certain parts of the training data. Several methods of SVM models that can be used for predicting/forecasting time series data are: support vector kernel, SVM for regression, LS-SVM, and DLS-SVM. some researchers who have promoted and developed SVM for predictions, such as [63], [64], [65], [66], [67], [68], and [69]. Experimental research conducted by several researchers obtained satisfactory prediction results using the SVM method and its development.

3.6. Fuzzy Logic for Forecasting

Fuzzy logic is the development of an artificial intelligence expert system that can process a large amount of data by forming data in range to simplify the calculations to obtain results. Fuzzy logic is also flexible, that is, it is able to adjust to the changes of and uncertainties in the problem, model complex nonlinear functions, and construct and apply expert experiences immediately without having to go through the training process. Fuzzy logic methods for time series forecasting that have been used for forecasting include fuzzy time series (FTS; time variant and time invariant), FNN (fuzzy neurons), neural fuzzy system or neuro-fuzzy, fuzzy ARMA, fuzzy inference system, and ANFIS. In increasingly complex systems, fuzzy logic is usually difficult and needs a long time to set the right rules and membership functions. In NN, the combined approach must be methodical when employing the Yu and Chen models in fuzzy logic. Several empirical studies showed that the combined model has good applications.

Several researchers conducted forecasting using fuzzy logic and fuzzy combinations with other methods. For instance, [70], [71], and [72] proposed and combine a new hybrid ANN with fuzzy that can be a potential method to improve forecasting accuracy because the benefits of ANN and fuzzy are combined to overcome the limitations of both models. The development of computing also supports the development of forecasting using fuzzy system. [73] proposed a method to simplify the computational approach that can minimize the complicated calculations of fuzzy relational matrices, identify appropriate defuzzification processes, and achieve better forecasting accuracy. Furthermore, [74], [75], and [76] proposed FTS for forecasting. Several researchers further developed the FTS, which is an expansion of fuzzy logic used for predicting time series data. [77] first showed forecasting procedures using FTS. Other researchers who used FTS for various case studies include [78], [79], [80], [81], [82] and [83]. Furthermore, FTS is increasingly developing, with several new methods being integrated. [84] and [85] proposed a new FTS forecasting technique, which are more accurate than traditional FTS models. Other than that [86] and [87] developed a hybrid model based on FTS with a combination of other methods that show promising accuracy and performance.

Table 4 A list of research areas in time series forecasting using fuzzy logic

Method		Author/References	Topic/Dataset
Fuzzy Logic	Fuzzy Logic	Rojas et al. (2008)	Macroeconomic data
		Chou (2013)	Stell price index
		Cai et al. (2013)	Stock price
		Bas et al. (2015)	Index 100 Istanbul stock market
		Bisht and Kumar (2016)	Enrollment Univ of Alabama
		Cagcag Yolcu and Lam (2017)	TAIEX
		Dash, Ramakrishna, Liew, and Rahman (1995)	Electrical load
		Singh (2007)	Enrollment Univ of Alabama
		Zhang and Wan (2007)	Exchange rate
		Khashei et al. (2008)	Gold price
	Fuzzy Time Series	Hosseini, Fard, and Baboli (2011)	Stock price
		Maman Abadi et al. (2008)	Inflation rate in Indonesia
		Chen and Hsu (2004)	Numbers of enrollment of the University of Alabama
		Chou (2013)	Global steel price index
		Huarng and Yu (2005)	Taiwan stock index
		Song and Chissom (1993)	Forecasting procedures
		Stevenson and Porter (2009)	Numbers of enrollment of the University of Alabama
		Jiang, Dong, Li, and Lian (2017)	Numbers of enrollment of the University of Alabama, TAIEX, and electricity load demand
		Ye et al. (2016)	Exchange rate & stock price
		Silva et al. (2017)	Enrollment Univ of Alabama

3.7. Adaptive Neuro-fuzzy Inference System

Many studies have implemented the ANFIS methods in all kinds of contexts. For instance, [88] and [89] discussed the issues in the hydrological applications of ANFIS. [90] utilized ANFIS for electricity load forecasting. [91] presented ANFIS and showed its excellence in terms of minimizing errors, robustness, and flexibility compared with the Sugeno–Yasukawa, ANN, or multiple regression approaches for forecasting USD/JPY exchange rates. [92] introduced new trends in the soft computing technique, with model development of fuzzy systems, integration, hybridization, and adaptation. Many other experts, such as [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], and [103], have also used ANFIS for prediction purposes. Their empirical results showed that the performance of ANFIS is better, with a high correlation coefficient value, than that of ANN and ARIMA during the training and validation phases.

The remarkably good forecasting performance of ANFIS combined with various other methods and approaches has been reported by several researchers. [104] isntroduced the combination of ANFIS and rough set to minimize the number of fuzzy rules and employed the simpler structure of ANFIS and PSO to determine the parameter. [105] conducted experiments that compared the performance of the combination of firefly algorithm and ANFIS with that of other methods. [106] proposed the ANFIS modelling procedure for selecting input variables based on the pre-processing of original data using the subset ARIMA model. Three important concepts, namely, selection of the input variables, specifying the number of clusters, and selection of the membership functions, need to be considered in developing a good model. [107] applied the subtractive clustering procedure to clustered data to help streamline the fuzzy rules.

Table 5 A list of research areas in time series forecasting using anfis

Method	Author/References	Topic/Dataset
Adaptive Neuro-fuzzy Inference System (ANFIS)	Wang, Chau, Cheng, and Qiu (2009)	River flow
	Ucenic and George (2006)	Electrical load
	Pramanik and Panda (2009)	Hydrological applications
	Alizadeh et al. (2009)	USD/JPY exchange
	Yazdani-Chamzini, Yakhchali, Volungevičienė, and Zavadskas (2012)	Gold price
	Loganathan and Girija (2013)	Simulation data
	Nhu, Nitsuwat, and Sodanil (2013)	Vietnam stock market
	Bushara and Abraham (2015)	Weather
	Mathur, Glesk, and Buis (2016)	Limb temperature
	Tan, Shuai, Jiao, and Shen (2017)	Country sustainability
	Taylan and Karagözoğlu (2009)	Student's academic performa
	Wei, Chen, and Ho (2011)	Stock price trends
	Kisi, Shiri, and Nikoofar (2012)	Daily lake-level variations
	Singh Saroa, Waleed Hndoosh, Saroa, and Kumar (2012)	Washing machine
	Jiin-Po Yeh and Chang (2012)	Chaotic traffic volumes
	Tarno et al. (2013)	Indonesian inflation
	Jiang, Kwong, Law, and Ip (2013)	Customer satisfaction
	Yeh and Yang (2014)	Reinfored concrete beams
	Loganathan and Girija (2014)	Simulation data
	Vaidhehi (2014)	Student's course req
	Rezaei and Fereydooni (2015)	Suspended sediment
	Wang and Ning (2015)	Bank cash flow
	Bhatnagar, Chopra, Bhati, and Gupta (2015)	Simulation data
	Kaveh, Bui, and Rutschmann (2015)	Contraction scour depth
	Najib, Salleh, and Hussain (2016)	Bussines and economic
	Adyanti, Asyhar, Novitasari, Lubab, and Hafiyusholeh (2017)	Marine weather

[108] designed a fuzzy system with RKLM to adapt its membership functions and parameters to increase system performance. [109] used ANFIS with grid partitioning technique. [110] proposed a hybrid learning method based on the adaptive population activity PSO algorithm merged with the least squares method to optimize the ANFIS model. [111] introduced the application of new hybrid learning rules merged with the Levenberg–Marquardt and gradient methods to the ANFIS technique as an alternative to the general hybrid learning methods. [112] reviewed metaheuristic algorithms, such as GA, PSO, ABC, CSO, and their variants, to train ANFIS to overcome computationally expensive problems and reduce the number of rules in the ANFIS rule base. [113] presented prediction system using the TS–ANFIS hybrid method. The proposed ANFIS hybrid method exhibited a better performance and was more efficient than the classical methods. Moreover, the experimental results showed that the optimization speed is fast and the prediction accuracy is high.

4. Conclusion: The Future of Forecasting Development

When referring to the development of technology and user institutions in the future, two things are predicted to occur. First, the development of computerization with its increasingly sophisticated capabilities coupled with the development of software will be a strong combination in terms of forecasting. Various methods and techniques that are complex that can only be imagined at this time will soon be realized and used in practice in real cases. Second, in relation to the amount of data, the variations and levels of difficulty are also increasing. Institutions that have the need for forecasting with large amounts of data will also increase in number. These two combinations of computer development and large amounts of data that involve forecasting and data mining will grow rapidly in the future and will become a common thing. Thus, it is important to develop new forecasting methods and techniques using soft computing methods that can not only provide forecasting results that are more accurate than those of traditional methods but also have many advantages in terms of the amount of data that can be analysed and the time- and cost-effectiveness of the process.

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