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 for 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.
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                    |
|-------------|------------------------------|----------------------------------|
| ARMA/ARIMA  | Guo (2012)                   | Housing price                    |
|             | Widowat 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                         |
|             | Durud (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.

| Method | Author/References | Topic/Dataset |
|--------|------------------|---------------|
| Nonlinear Time Series Modeling | | |
| Threshold | Tong (1983) | threshold model |
| Autoregressive (TAR) | 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) | Duker and Neely (2007) | Portfolio returns |
| Markov Switching | Haas (2004) | Exchange rate return |
| | 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 |
| | Anggraini 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 | Gooijer and Hyndman (2006)                            | Large topic                            |
| Artificial Neural Network (ANN): FFNN, RNN, RBF, SOM, TLNN, SANN | Zhang, Patuwo, and Hu (1998)                        | Survey of ANN                          |
|                         | Ghunman 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                          |
|                         | Pindortiya et al. (2008)                              | Price in the electricity markets       |
|                         | Amjady and Keynia (2009)                              | Temperature                            |
|                         | Chen et al. (2010)                                    | Load                                   |
| Genetic Programming     | Beiki et al. (2010)                                   | Deformation modulus                    |
| Hybrid                  | 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                             |
|                         | Sarica 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             | 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 Chisso (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] introduced 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 Karagözoglu (2009) | Student’s academic performance |
| | 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) | Reinforced 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) | Business 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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References
[1] De Gooijer, J.G. and Hyndman R. J 2006 *Int. J. of Forecasting* vol 22(3) pp 443-473
[2] Widowati P S P, Koshio S and Oktanferdian V 2016 *Aquatic Procedia.* 7 pp 277-284
[3] Ruby F R, Saavedra J, Bahamonde, N and Cassano A 2017 *J. of Membrane Science* 524 pp 108-116
[4] He Z and Tao H 2018 *J. of Infectious Diseases* 74 pp 61-70
[5] Ohyver M and Pudjihastuti H 2018 *Proc. Computer Science* 135 pp 707-711
[6] Zhang L, Lin J, Qiu R, Hu X, Zhang H, Chen Q, …, Wang J 2018
[7] Ecological *Indicators* 95(1) pp 702-710
[8] Yantai Shu, Minfang Yu, Jiakun Liu and Yang O W W 2003 *IEEE Int. Conf. on Communications* 10 pp 1675-1679
[9] Durdu Ö F 2010 *Environmental Monitoring and Assessment* 169 pp 687-701
[10] Wang Y, Wang J, Zhao G and Dong Y 2012 *Energy Policy* 48 pp 284-294
[11] Arumugam P and Saranya R 2018 *Materials Today: Proc.* 5 pp 1791-1799
[12] Bivona S, Bonanno G, Burlon R, Gurreray D and Leone C 2010 *Acta Physica Polonica* B 41(5) pp 1083-1092
[13] Doornik J A and Ooms M 2004 *Studies in Nonlinear Dynamics & Econometrics* 8(2) pp 1-12
[14] Engle R 2001 *J. of Economic Perspectives* 15(4) pp 157-168
[15] Garcia R C, Contreras J, van Akkeren M and Garcia J B C 2005 *IEEE Transactions on Power Systems* 20(2) pp 867-874
[16] Zhou B, He D, Sun Z and Ng W H D 2005 Network Traffic Modeling and Prediction with ARIMA/GARCH Proc. 7(4) pp 1149-1156
[17] Jiang A W 2012 *Modeling and predicting of different stock markets with GARCH model* *Modeling and predicting of different stock markets with GARCH model* Master Thesis Uppsala University
[18] Alam M Z, Siddikee M N and Masukujjaman M 2013 *Volatility* 4(2) p 126
[19] Kronman S 2015 *The volatility of tomorrow—Comparison of GARCH and EGARCH models applied to Texas Instruments stock returns* Bachelor Thesis Stockholms universitet
[20] Hosseinipoor S, Hajirezaie S and Hadjiyousefzadeh N A 2016 Application of ARIMA and GARCH Models in Forecasting the Natural Gas Prices J. OKLAHOMA Univ.
[21] Nieto M R and Carmona-Benítez R B 2018 *J. of Air Transport Management* 71 pp 1-8
[22] Staak M and Berghaus G 1982 *Archiv Fur Kriminologie* 169(5-6) pp 140-148
[23] Hunter J S 1986 *J. of Quality Technology* 18(4) ppv203-210
[24] Enders W and Falk B 1998 *Int. J. of Forecasting* 14 pp 171—186
[25] Clements M P, Franses P H, Smith J and Van Dijk D 2003 2(5) pp 359-375
[26] Boero G and Marrocucchi E 2004 Int. J. of Forecasting 20 pp 305-320
[27] Nieto F H 2008 *Statistical Methodology* 5(3) pp 263–276
[28] Umer U M and Sevil T Sevil G 2018 *The J. of Finance and Data Science* 4(2) pp 90–100
[29] Davies N, Pemberton J and Petruccelli J D 1988 *J. of the Royal Statistical Society Series D (The Statistician)* 37(2) pp 199-204
[30] Haas M 2004 *J. of Financial Econometrics* 2(4) pp 493-530
[31] Duiker M and Neely C J 2007 *J. of Banking and Finance* 31(2) pp 279-296
[32] Kunst R and Neusser K 1986 *Int. J. of Forecasting* 2(4) pp 447-456
[33] Lamy R 1986 Int. Journal of Forecasting 2(2) pp 201-216, 1986, 2.2: 201-216.
[34] Freeman J R, Williams J T and Lin TM 1989 American J. of Political Science 33(4) pp 842-877
[35] Holden K 1990 Int. J. of Forecasting 6 pp 11-23
[36] Karlsson S 1993 Int. J. of Forecasting 9 pp 61-76
[37] Weise C L 1999 J. of Money, Credit and Banking 31(1) pp 85-108
[38] Anggraeni W, Boga K and Mahananto F 2018 Procedia Computer Science 124 pp 189-196
[39] Dash P K, Ramakrishna G, Liew A C and Rahman S 1995 IEE Proc. Gener. Transm. Distrib 142(5) pp 535-544
[40] Zhang G, Patuwo B E and Hu M Y 1998 Int. J. of Forecasting 14(1) pp 35-62
[41] Ghumman A R, Ghazaw Y M, Sohail A R and Watanabe K 2011 Alexandria Engineering J. 50(4) pp 345-350
[42] Safi K 2013 J. of Natural and Engineering Studies 21(2) pp 1-22
[43] Liu H, Tian H Q, Li Y F and Zhang L 2015 Energy Conversion and Management 92 pp 67-81
[44] Lee K Y, Chung N and Hwang S 2016 Ecological Informatics 36 pp 172–180
[45] Tealab A, Hefny H and Badr A 2017 Future Computing and Informatics J. 2(1) pp 39–47
[46] Björklund S, Uhlin T, Blomvall J and Tang O 2017 Artificial neural networks for financial time series prediction and portfolio optimization Master of Science Thesis Industrial Engineering and Management Department of Management and Engineering, Linköping University
[47] Arino M A 1995 Time series forecasting via wavelets: an application to car sales in the spanish market 1 IESE UNIVERSIDADD E NAVARRA, Spain
[48] Zhang B L and Dong Z Y 2001 Electric Power Systems Research 59(2) pp 121-129
[49] Kim T W and Valdés J B 2003 J. of Hydrologic Engineering 8(6) pp 319-328
[50] Jiang X and Adeli H 2005 J. of Transportation Engineering 131(10) pp 771-779
[51] Mellit A, Bengham M and Kalogirou S A 2006 Applied Energy 83(7) pp 705-722
[52] Partal T and Kisi Ö 2007 J. of Hydrology 342(1–2) pp 199-212
[53] Pindoriya N M, Singh S N and Singh S K 2008 IEEE Transactions on Power Systems 23(3) pp 1423-1432
[54] Amjady N and Keynia F 2009 Energy 34(1) pp 46-57
[55] Chen Y, Luh P B, Guan C, Zhao Y, Michel L D, Coolbeth M A, … Rourke S J 2010 IEEE Transaction on Power Systems 25(1) pp 322-330
[56] Beiki M, Bashari A and Majdi A 2010 Int. J. of Rock Mechanics and Mining Sciences 47 pp 1091-1103
[57] Amjady N 2007 IEEE Transaction on Power Systems 34(1) pp 333-341
[58] Aladag C H, Egrioglu E and Kadilar C 2009 Applied Mathematics Letters 22(9) pp 1467-1470
[59] Shafie-Khah M, Moghaddam M P and Sheikh-El-Eslami M K 2011 Energy Conversion and Management 52(5) pp 2165-2169
[60] Catalaio J P S, Pousinho H M I and Mendes V M F 2011 IEEE Transactions on Power Systems 26(1) pp 137-144
[61] Khandelwal I, Adhikari R and Verma G 2015 Procedia Computer Science 48(C) pp 173-179
[62] Liu H, Tian H, Liang X and Li Y 2015 Renewable Energy 83 pp 1066-1075
[63] Sarcar B, Eğrioglu E and Aşıkgil B 2018 Neural Computing and Applications 29(3) pp 749-760
[64] Lu’ W, Wan W, Tileungl A Y, Lo’ S M, Kyued R K, Xu Z and Fan’ H 2002 Proc. of the Int. Joint Conf. of Neural Network pp 630-635
[65] Hong W C 2011 Neurocomputing 74(12-13) pp 2096-2107
[66] Li M W, Han D F and Wang W 2015 Neurocomputing 157 pp 243-255
[67] Ahmad A S, Hassan M Y, Abdullah M P, Rahman H A, Hussein F, Abdullah H and Saidur R 2014 Renewable and Sustainable Energy Reviews 33 pp 102-109
[68] Kaytez F, Taplamacioglu M C, Cam E and Hardalac F 2015 Int. J. of Electrical Power and Energy Systems 67 pp 431-438
[69] Gui B, Wei X, Shen Q, Qi J and Guo L 2015 Proc. 10th Int. Conf. on Computational Intelligence and Security, CIS 2014 55(1-2) pp 307-319
[70] Najafi G, Ghobadian B, Moosavian A, Yusaf T, Mamat R, Kettner M and Azmi W H 2016 Applied Thermal Engineering 95 pp 186-203
[71] Zhang Y Q and Wan X 2007 Applied Soft Computing J 7(4) pp 1149-1156
[72] Khashei M, Reza Hejazi S and Bijari M 2008 Fuzzy Sets and Systems 159(7) pp 769-786
[73] Rojas I, Valenzuela O, Rojas F, Guillen A, Herrera L J, Pomares H, … Pasadas M 2008 Neurocomputing 71(4-6) pp 519-537
[74] Singh S R 2007 Applied Mathematics and Computation 186(1) pp 330–339.
[75] Bas E, Yolcu, U, Egrioglu E and Aladag C H 2015 American J. of Intelligent Systems 5(3) pp 81-91
[76] Bisht K and Kumar S 2016 Expert Systems with Applications 64 pp 557-568
[77] Cacag Yolcu, O and Lam H K 2017 Neurocomputing 247 pp 87-101
[78] Song Q and Chissom B S 1993 Fuzzy Sets and Systems 27 pp 269-277
[79] Huarng K and Yu H K 2005 Physica A: Statistical Mechanics and Its Applications 353(1) pp 445-462
[80] Maman Abadi, A and Saleh S 2008 The First Int. Conf. on Science and Technology Islamic Uniniversity of Indonesia Yogyakarta
[81] Stevenson M and Porter J E 2009 World Academy of science, Engineering and technology 55 pp 154-157
[82] Hosseini S M, Fard M Y and Baboli S M 2011 Australian J. of Basic and Applied Sciences 5(12) pp 894-898
[83] Chou M T 2013 Rev. of Economics & Finance pp 90-98
[84] Jiang P, Dong Q, Li P and Lian L 2017 Applied Soft Computing 55 pp 44-62
[85] Chen S M and Hsu C C 2004 Proc. of the Eighth Int. Conf. on Machine Learning and Cybernetics pp 3026-3029
[86] Cai Q Sen, Zhang D, Wu B and Leung S C H 2013 Procedia Computer Science 18 pp 1155-1162
[87] Ye F, Zhang L, Zhang D, Fujita H and Gong Z 2016 Information Sciences 367-368 pp 41-57
[88] Silva P C L, Sadaei H J and Guimaraes F G 2017 IEEE Symposium Series on Computational Intelligence
[89] Wang W C, Chau K W, Cheng C T and Qiu L 2009 J. of Hydrology 374(3-4) pp 294-306
[90] Pramanik N and Panda R K 2009 Hydrological Sciences J. 54(2) pp 247-260
[91] Uncenic C and George 2006 Proc. of the 2006 IASME/WSEAS Int. Conf. on Energy & Environmental Systems pp 299-304
[92] Alizadeh M, Khaleghie A, Esfahani M S, Rada R, Balagh G, Mehdi M and Esfahani S 2009 IFSA-EUSFLAT pp 1745-1750
[93] Taylao O and Karagözoglu B 2009 Computers and Industrial Engineering 57(3) pp 732-741
[94] Wei L Y, Chen T L and Ho T H 2011 Expert Systems With Applications 38 pp 13625–13631
[95] Yeh Jiin and Po and Chang Y C 2012 J. of Intelligent Learning Systems and Applications 4 pp 247-254
[96] Singh Saroa M, Waleed Hndoos R, Saroa M S and Kumar S 2012 European J. of Scientific Research 86(3) pp 443-459
[97] Yazdani-Chamzini A, Yukhchali S H, Volunegvečienė D and Zavadskas E K 2012 J. of Business Economics and Management 13(5) pp 994-1010
[98] Kisi O, Shiri J and Nikoofar B 2012 Computers and Geosciences 41 pp 169-180
[99] Loganathan C and Girijia K V 2013 Int. J. of Engineering And Science 2(1) pp 6-13
[100] Bushara N O and Abraham A 2015 J. of Network and Innovative Computing 3 pp 146-158
[101] Rezaei M and Ferreydooni M 2015 Indian J. of Fundamental and Applied Life Sciences 5(S1) pp 3598-3606
[102] Bhatnagar S, Chopra S, Bhat S and Gupta N K 2015 Int. J. of Electricaland Electronics Engineers 7(1) pp 98-104
[103] Mathur N, Glesk I and Buis A 2016 Medical Engineering and Physics 38(10) pp 1083-1089
[104] Tan Y, Shuai C, Jiao L and Shen L 2017 Environmental Impact Assessment Rev. 65 pp 29-40
[105] Jiang H, Kwong C K, Law M C and Ip W H 2013 Procedia Computer Science 22 pp 104-112
[106] Nhu H N, Nitsuwat S and Sodanil M 2013 Int. Computer Science and Engineering Conf ICSEC 2013
[107] Tarno, Subanar, Rosadi D and Suhartono 2013 Int. J. of Computer Science Issues (IJCSI) 10(2(1) pp 491-496
[108] Yeh J P and Yang R P 2014 J. of Intelligent Learning Systems and Applications 6 pp 162-175
[109] Loganathan C and Girija K V 2014 J. of Engineering Research and Applications 4(10) pp 31-37
[110] Vaidhehi V 2014 Int. J. of Innovative Research in Advanced Engineering (IJIRAE) 1 pp 249-253
[111] Wang J S and Ning C X 2015 Information 6 pp 300-313
[112] Kaveh K, Bui M D and Rutschmann P 2015 Proc. of the 14th International Conference on Environmental Science and Technology pp 3-5
[113] Najib M, Salleh M and Hussain K 2016 Int. J. of U-and e-Service 9(7) pp 165-1721
[114] Adyanti D A, Asyhar A H, Novitasari D C R, Lubab A and Hafiyusholeh M 2017 Int. Conf. on Electrical Engineering, Computer Science and Informatics (EECSI) Yogyakarta