Time Series Analysis on Univariate and Multivariate Variables: A Comprehensive Survey

Satyanarayana Reddy Beeram and Swarna Kuchibhotla

Abstract Time series analysis and forecasting have become an active research area for a couple of years in various domains like signal processing, weather forecasting, earthquake prediction, communication engineering, and any domain which involves temporal measurements. These domains raise important challenges and making it to devise new approaches to accurately predict or forecast into future. This paper surveys the comprehensive studies on different time series analysis, viz., univariate and multivariate and also demonstrates various practical predictions and forecasting models. Furthermore, it proposes some possible research paths that can be explored by active researchers in the area for designing more efficient models for forecasting in time series applications.

1 Introduction

A time series, viewed as a sequence of data points that are collected over a period of time, has wide range of many different domain scientific fields from economics to engineering. In the engineering literature, state-space methods have been developed for the sequential analysis of data [1]. Time series analysis involves to extract the meaningful information or patterns or characteristics from the given raw data to understand the behavior. On the other hand, time series predictions are involved in building a model that can forecast into the future based on available observed data. The fundamental time series model is the regression analysis, which constructs a model by considering one or more independent variables to predict the outcome on continuous variables. The analysis of time series has some pattens involved, which can be discovered. Time series analysis can be further classified into univariate and multivariate based on the number of variables available for observation.

S. R. Beeram (✉)
Kallam Haranadhareddy Institute of Technology, Guntur, AP, India
e-mail: snreddy.beeram@gmail.com

S. Kuchibhotla
Koneru Lakshmaiah Education Foundation (KLEF), Vijayawada, AP, India
e-mail: drkswarna@kluniversity.in

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The univariate time series consists of a single observation over a time period. The multivariate time series consists of more than one observations collected over time.

Multivariate time series analysis research is more challenging compared to univariate time series analysis. To design and correlation of multivariate across hierarchical levels vary from "system-to-system". To handle multivariate time series, uses factor analysis which reduces the attribute space from large numbers to smaller numbers of factors. Various prediction and forecasting machine learning models have been proposed in [2–6].

2 State-of-the-Art in Time Series on Various Domains

This section describes the detailed survey of various time series methods proposed by research communities that forecasting various application domains. More than two decades, the BOX-Jenkins method for time series forecasting using ARIMA model treated as benchmark to evaluate some of new methods.

The nonlinear Taylor rule-based exchange rate system has been analyzed by [7], complementing latest studies that discovered that the linear variant of this system outperforms a random walk method. It is found that, with respect to several macroeconomic determinants, the evidence of nonlinearities in the exchange rate suggests that the Taylor rule exchange rate models can in some cases be improved by considering regime changes. Future study in this region might consider alternative nonlinear modeling methods and a broader range of prospective factors for transformation.

Multiple sophisticated time series models have been suggested to forecast forex up to 30 pairs by [8]. Based on the Augmented-Dickey Fuller Test (ADF-test), each forex was converted to be stationary. It is discovered that the enormous benefit of using BCVAR and TVP-BCVAR to estimate EUR-DKK for all forecasting activities compared to the typical Bayesian Auto Regression (AR)(4).

Veraart [9] proposed a new methodology to investigate the connection between the amount of limited order entries and deletions in a limited order book relies on a blended moving average method powered by Levy Noise, called a trawl method. The methodology can be extended to four dimensions to get more accurate predictions.

Phan et al. [10] proposed a new method for filling missing values in the time series which resulted a better prediction accuracy.

The GRU-D model of [11] proved that the model with trainable decays has same time and space complexity to the existing RNN models, but is ahead of non-deep learning methods.

The MTS Networks proposed by [12] facilitates an easy interpretation of dynamics of multivariate time series.

The SFM recurrent neural network developed by [13] is tested on real-time trading data and the accuracy of trading patterns predicted is better than AR model and LSTM.

Ma et al. [14] proposed a new approach for predicting solar flares based on the past data available. Though the approach requires expensive clustering time, guarantees satisfiable prediction accuracy.

Nayak [15] has developed a hybrid system by considering the base system of four higher order neural networks. The performance of these hybrid designs is assessed by predicting some actual stock market's one-step-ahead exchange prices. The efficiency and superiority of the models are established by comparing the results with other models.

Dasgupta and Osogami [16] extended to Gaussian DyBM the dynamic Boltzman Machine (DyBM), which deals with true valued information. The design has also been expanded to a recurrent neural network (RNN) that regulates the DyBM units preference entry. Experiments with synthesized datasets demonstrate that the RNN-Gussian DyBM increases predictive precision by up to 35 percent with normal VAR.

The adaptive inferential model learning design of neuro-complex fuzzy has been expanded by [17] to the multivariate time series data. The writers explored the scheme with design variants of single-input-single-output, multi-input-single-output, and multi-input-multiple-output, testing its efficiency on four multivariate trigger levels. It was evident that the drawings on these datasets are inferior to the published results, and at least as precise as filters based on kernel-based forecasting methods.

The IFS-based technique suggested by [18] utilizes a straightforward max-min synthesis operator for IFSs, making the technique easy and less complicated. Not only does the suggested technique outperform the techniques proposed by different scientists, but it is also sufficiently effective to predict in near line with real-time series data in the hesitation environment.

According to [19], the performance of Functional Link Radial Basis Function method seems better compared to Functional Link method and Radial Basis Function alone.

Opare [20] studied the mortality rate under 5 years using ARIMA model. The study used time series data from 1961 to 2012. The dataset is partitioned into train data from 1961 to 2000 and test data from 2001 to 2012 for each model.

Aboagye-Sarfo et al. [21] presented a paper on the comparison of time series models of univariate and multivarite. The paper demonstrated the comparative performance of VARMA and ARMA models applied to predict the demand for strategic planning and resource allocation from the Emergency Department (ED). The study concluded the superiority of VARMA model.

A mixed regression model for mortality data was proposed by [22].

A hybrid prediction method for the Foreign Exchange Market was proposed by [23]. The findings show that the hybrid technique described is a very helpful and efficient technique for forecasting economic prices and extracting economic patterns.

Adhikari and Agrawal [24] proposed a combined approach to exploit the strengths of the systems Random Walk (RW) and Artificial Neural Network (ANN). The strategy utilizes the RW system to process the linear part of a monetary dataset and the remaining discrete residuals are handled with neural models. Predictive capacity of suggested system is examined in light of three common error stats on four real-world economic time series. The findings acquired obviously show that the combined technique achieves predictive accuracies fairly better than each of the designs RW, FANN, and EANN.

Khashei and Bijari [25] submitted a new hybrid model for time series which is tested on three real datasets. The final extracted results indicate that the model proposed produces higher prediction accuracy.

The authors [26] have proposed an ANN-based naive method to forecast the financial time series.

The time series prediction of electric prices based on asymmetric subset hood product fuzzy neural inference system was proposed by [27]. Authors suggested a better approach for predicting the time series into future with neuro-fuzzy inference system.

Authors proposed in [28], a hybrid approach that combines linear ARMA and Artificial Neural Networks. To reduce the error rate the proposed method used artificial neural network to forecast the time series. This hybrid approach achieves less error rate for real datasets and synthetic time series.

Summary of all the research papaers studied is given in Table 1.

3 Conclusion

The growth of the time series applications enables many services in real time. As the time series data increases, it leads to many challenges. In order to guarantee the accurate forecast need an efficient mechanisms for time series analysis. Even though the AR, MA, ARMA, and ARIMA methods have their advantages and disadvantages that impact to analyze the time series, they can only be applied on univariate time series data.

This paper provides a study of projections of univariate and multivariate time series that closely defines current methods. A comprehensive literature assessment was given, highlighting each study's accomplishments and its primary objectives. Researchers have a strong stake in analyzing the literature proof in time series forecasting over the previous few years, driven by the difficulties generated by the new algorithms. In addition, the evolution of time series demonstrates a growing interest for univariate and multivariate factors. Furthermore, the research continues to explore time series information using sophisticated processes to correctly predict profound training in real time.

4 Suggested Future Research

The comprehensive review suggests the below methods as future research directions.

- It is possible to explore the hybridization of Fuzzy regression and fuzzy support vector regression to see if the stronger time series prediction can be achieved.

Table 1 Summary of time series analysis and fore casting models state of the art

Studies	Approach	Compared with	Winner	Dataset
Lin [29]	Box-Jenkins + Tiao-Box	AR	Box-Jenkins + Tiao-Box	Medical dataset
Watanabe et al. [30]	Rough set + NN	ARIMA models	Rough set theory + NN	Stock price
Rojas et al. [28]	ARMA + NN	ARMA	ARMA + NN hybrid	General time series
Lee and Roberts [1]	Dynamic multi AR	AR	Dynamic multi AR	Global temperature TS data
Narayan et al. [27]	Neuro-fuzzy	General fuzzy inference system	Neuro-fuzzy inference system	Electricity data
Bagheri et al. [23]	ANFIS	Fuzzy models	ANFIS	FOREX dataset
Adhikari and Agrawal [24]	Random walk (RW) + ANN	RW, EANN, FANN	RW + ANN	Real world financial TS data
Ekheden and Hössjer [22]	Mixed regression model	Autoregression models	Mixed-regression model	General TS data
Aboagye-Sarfo et al. [21]	VARMA	ARMA	VARMA	Emergency department demand
Rout and Dash [19]	Functional link RBF neural network	Linear, nonlinear and hybrid neural networks	FLRBFNN	Exchange rates dataset
Zhang and Aggarwal [13]	State frequency memory RNN	AR, conventional LSTM Model	State frequency Memory RNN	Real-time stock price data
Ma et al. [14]	Decision trees	ANN, ARIMA	Decision tree model, but requires extra time for clustering	Sunspots dataset
Yang and Lin [31]	EMD + PSR + ELM	Existing state-of-art models	The Hybrid model of EMD, PSR, ELM	FOREX rates dataset
Nayak [15]	Higher order NN (HONNs)	RBFNN, multilayer perceptron NN, multi-linear regression method	HONNs	Real stock market data
Dasgupta and Osogami [16]	RNN-Gaussian DyBM	DyBM, Gaussian DyBM	RNN-Gaussian DyBM	Synthetic dataset

(continued)

Table 1 (continued)

Studies	Approach	Compared with	Winner	Dataset
Yazdanbakhsh and Dick [17]	Neuro-complex fuzzy inferential system	Kernel-based prediction algorithms (KBPA)	Neuro-complex fuzzy inference system is as accurate as KBPA	General time series data
Che et al. [11]	Deep learning model based on GRU-D	Non-deep learning models	Proposed deep learning model	Synthetic and real-time healthcare dataset
Phan et al. [10]	Novel fuzzy similarity-based measure	General multivariate time series models	Fuzzy similarity-based model	General Non-correlated dataset
Veraart [9]	Mixed moving average model	Moving averages model	The mixed moving averages model	Limit order book dataset
Kumar and Gangwar [18]	Intuitionistic fuzzy time series (IFS) model	Intuitionistic fuzzy set-based model	Intuitionistic fuzzy time series (IFS) model	University of Alabama enrollments, SBI market Price
Wang et al. [7]	Nonlinear Taylor rule-based exchange rate model	Random walk	Nonlinear Taylor rule-based exchange rate model	FOREX dataset
Taveeapiradeecharoen et al. [8]	Bayesian compressed VAR (BCVAR), Time-varying Bayesian compressed VAR (TVP-BCVAR)	Bayesian AR(4)	time-varying Bayesian compressed VAR (TVP-BCVAR)	EUR-DKK EXCHANGE RATE

- The hybrids incorporating Support Vector Machine (SVM) and Evolutionary Computation (EC) can be employed in the future.
- The soft computing constituencies involving Fuzzy Logic (FL) and Evolutionary Computation (EC) need to be investigated to see their efficiency for time series data.
- The evolutionary computation techniques other than Genetic Algorithms (GA) and Particle Swam Optimization (PSO) such as Differential Evolution (DE) in the financial time series analysis context to form new set of hybrid forecasting models.
- Due to their superior exploring capabilities, Quantum-inspired Evolutionary algorithms demonstrated their worth in classification and prediction. A little or no research on the forecast of financial time series is recorded in this area.
- In this context of forecasting financial time series, Deep learning architectures that displayed enormous potential in Image Processing need to be studied and implemented.
- The application of Hidden Markov Model (HMM) is not found in all of the papers that are reviewed. Therefore, the hybrids involving HMM-based models can be developed for forecasting.
- The Quantile Regression (QR)-based hybrids are another alternate method that needs to focus on time series applications.
- The impact of external variables such as sentiment analysis, factors that affect the price of stock need to be properly incorporated into the time series forecasting models.

References

1. Lee SM, Roberts SJ (2008) Multivariate time series forecasting in incomplete environments. Technical report PARG-08-03. www.robots.ox.ac.uk/~parg/publications.html. University of Oxford
2. Cao L, Mees A, Judd K (1998) Dynamics from multivariate time series. Phys D 121(1–2):75–88
3. Chakraborty K, Mehrotra K, Mohan CK, Ranka S (1992) Forecasting the behavior of multivariate time series using neural networks. Neural Netw 5(6):961–970
4. Chen SM, Tanuwijaya K (2011) Multivariate fuzzy forecasting based on fuzzy time series and automatic clustering techniques. Expert Syst Appl 38(8):10594–10605
5. Han M, Wang Y (2009) Analysis and modeling of multivariate chaotic time series based on neural network. Expert Syst Appl 36(2):1280–1290
6. Yazdanbakhsh O, Dick S (2015) Multi-variate timeseries forecasting using complex fuzzy logic. In: 2015 Annual conference of the North American on Fuzzy information processing society (NAFIPS) held jointly with 2015 5th world conference on soft computing (WConSC). IEEE, pp 1–6
7. Wang R, Morley B, Stamatogiannis MP (2019) Forecasting the exchange rate using nonlinear taylor rule based models. Int J Forecast 35(2):429–442
8. Taveeapiradeecharoen P, Chamnongthai K, Aunsri N (2019) Bayesian compressed vector autoregression for financial time-series analysis and forecasting. IEEE Access 7:16777–16786
9. Veraart AE (2019) Modeling, simulation and inference for multivariate time series of counts using trawl processes. J Multivar Anal 169:110–129

10. Phan TTH, Bigand A, Caillault EP (2018) A new fuzzy logic-based similarity measure applied to large gap imputation for uncorrelated multivariate time series. Appl Comput Intell Soft Comput 2018
11. Che Z, Purushotham S, Cho K, Sontag D, Liu Y (2018) Recurrent neural networks for multivariate time series with missing values. Sci Reports 8(1):6085
12. Sun J, Yang Y, Xiong NN, Dai L, Peng X, Luo J (2017) Complex network construction of multivariate time series using information geometry. IEEE Trans Syst Man Cybern: Syst
13. Zhang L, Aggarwal C, Qi GJ (2017) Stock price prediction via discovering multi frequency trading patterns. In: Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining. ACM, pp 2141–2149
14. Ma R, Boubrahimi SF, Hamdi SM, Angryk RA (2017) Solar are prediction using multivariate time series decision trees. In: 2017 IEEE international conference on big data (Big Data). IEEE, pp 2569–2578
15. Nayak SC (2017) Development and performance evaluation of adaptive hybrid higher order neural networks for exchange rate prediction. Int J Intell Syst Appl 9(8):71
16. Dasgupta S, Osogami T (2017) Nonlinear dynamic boltzmann machines for time-series prediction. In: AAAI, pp. 1833–1839
17. Yazdanbakhsh O, Dick S (2017) Forecasting of multivariate time series via complex fuzzy logic. IEEE Trans Syst Man Cybern: Syst 47(8):2160–2171
18. Kumar S, Gangwar SS (2016) Intuitionistic fuzzy time series: an approach for handling Non-determinism in time series forecasting. IEEE Trans Fuzzy Syst 24(6):1270–1281
19. Rout AK, Dash P (2016) Forecasting foreign exchange rates using hybrid functional link RBF neural network and levenberg-marquardt learning algorithm. Intell Decis Technol 10(3):299–313
20. Opare PE (2015) Time series models for the decrease in under-five mortality rate in ghana case study 1961–2012. Ph.D. thesis
21. Aboagye-Sarfo P, Mai Q, Sanlippo FM, Preen DB, Stewart LM, Fatovich DM (2015) A comparison of multivariate and univariate time series approaches to modeling and forecasting emergency department demand in western australia. J Biomed Inform 57:62–73
22. Ekheden E, Hössjer O (2015) Multivariate time series modeling, estimation and prediction of mortalities. Insur: Math Econ 65:156–171
23. Bagheri A, Peyhani HM, Akbari M (2014) Financial forecasting using ANFIS networks with quantum-behaved particle swarm optimization. Expert Syst Appl 41(14):6235–6250
24. Adhikari R, Agrawal R (2014) A combination of artificial neural network and random walk models for financial time series forecasting. Neural Comput Appl 24(6):1441–1449
25. Khashei M, Bijari M (2012) A new class of hybrid models for time series forecasting. Expert Syst Appl 39(4):4344–4357
26. Akintola K, Alese B, Thompson A (2011) Time series forecasting with neural network: a case study of stock prices of intercontinental bank nigeria. IJRRAS 3:467–472
27. Narayan A, Hipel KW, Ponnambalam K, Paul S (2011) Neuro-fuzzy inference system (ASuP-FuNIS) model for intervention time series prediction of electricity prices. In: 2011 IEEE international conference on systems, man, and cybernetics (SMC). IEEE, pp 2121–2126
28. Rojas I, Valenzuela O, Rojas F, Guillen A, Herrera LJ, Pomares H, Marquez L, Pasadas M (2008) Soft-computing techniques and Arma model for time series prediction. Neurocomputing 71(4–6):519–537
29. Lin WT (1989) Modeling and forecasting hospital patient movements: univariate and multiple time series approaches. Int J Forecast 5(2):195–208
30. Watanabe H, Chakraborty B, Chakraborty G (2007) Softcomputing approach for stock price trend forecasting from multivariate time series. In: Second international conference on Innovative computing, information and control, 2007. ICICIC'07. IEEE, p 40
31. Yang HL, Lin HC (2017) Applying the hybrid model of EMD, PSR, and ELM to exchange rates forecasting. Comput Econ 49(1):99–116