International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

A Comparative Study of Classical and Machine Learning Approaches in Time Series Prediction

Harpinder Kaur

Assistant Professor in Mathematics, Guru Gobind Singh Khalsa College, Bhagta Bhai Ka, Bhatinda
Email: *harpinder.brar435[at]gmail.com*

Abstract: ***Time Series Analysis (TSA) is an essential analytical approach which operates across extensive areas. The purpose of this approach is to analyse historical data patterns to predict future values. Time series forecasting uses an analytical method that predicts future outcomes from data points collected over extended time periods. The research investigates various intricate forecasting methods, including Vector Auto Regression (VAR) and ARIMA, among others. Sophisticated time series models enable organizations to make better decisions while streamlining their processes and predicting future trends. The research illustrates recent developments in time series forecasting methods that emphasize real - time analysis and accuracy enhancement through external data integration, while merging traditional techniques with machine learning algorithms.***

Keywords: TSA, ARIMA, VAR, FIR, and SIR

1. Introduction

Time Series Analysis (TSA) is an analytical technique for analyzing data points gathered or documented over time at predetermined intervals. This sort of data frequently displays patterns like trends, Seasonal (SS) consequences, or cyclic conduct, making TSA critical for comprehending previous behaviors and determining potential values in the future [2]. Unlike other types of data analysis, TSA takes into account the sequence and structure of time, allowing for a more in - depth investigation of the time - dependent relationships and variations in the data [3, 4]. The value of TSA rests in its capacity to find significant information from temporal data. Individuals and companies can make informed choices by discovering connections and trends over time [5, 6]. Businesses, for example, employ TSA to forecast sales, regulate inventories, and allocate resources more effectively [7, 9]. Similarly, meteorologists use it to predict weather patterns, while economists use it to analyze market movements and financial cycles. TSA's vast utility makes it valuable in a variety of disciplines [10, 11]. TSA assists in forecasting disease outbreaks in healthcare and forecasting the demand and supply of energy, and it aids in the performance of the systems in real - time applications [12, 13]. With the increase in time - stamped data, TSA plays an even more significant role in making data - driven decisions and forecasting future fluctuations in an ever more intricate world.

2. Significance of Time Series Models

Different significance of TS model is shown in the Fig.1 below.

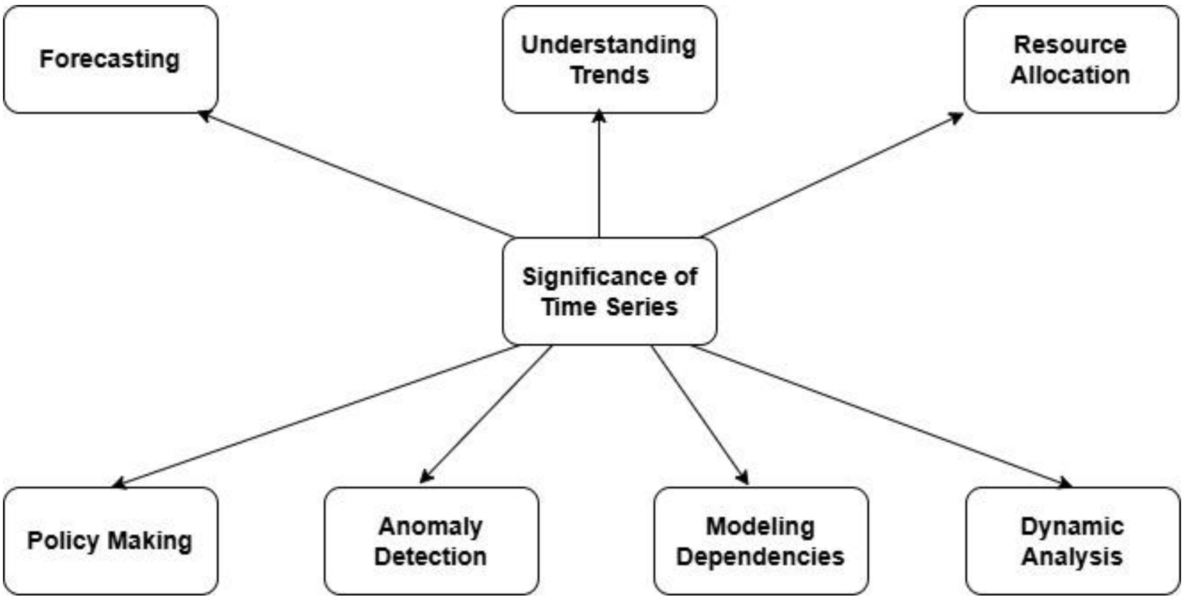

Figure 1: Significance of the TS model

- ***Forecasting:*** TS models are useful to forecast potential outcomes based on historical information, which aids decision - making in a variety of fields such as banking, medicine, and weather forecasting [16].

- ***Understanding Trends:*** These models aid in the identification of fundamental shifts and seasonal patterns, yielding useful insights into long - term data behavior [17].
- ***Resource Allocation:*** Estimating demand or load with TS models allows organizations to achieve optimal resource allocation and inventory management [18].
- ***Policy Making:*** TS analysis helps to formulate policies in fields such as economics and public health by simulating future situations and evaluating interventions.
- ***Anomaly detection:*** TS models are critical for detecting unforeseen modifications or abnormalities, such as corruption in financial transactions or malfunctions in equipment during predictive maintenance [19].
- ***Modeling Dependencies:*** TS models like ARIMA and SARIMA, encapsulate interconnections between past and future outcomes and use this relationship to make reliable projections [20].

3. Time Series Prediction Models

Additive and Multiplicative ARIMA Model: Several types of TS data are encountered in the real world. The types of TS data are classified as additive and multiplicative [21]. The three main components to capture for the additive and multiplicative TS model are Trend, Seasonality, and Irregularity mentioned as under.
An additive TS is a combination (addition) of trend, seasonality, and irregularity.
Value = Base level + Trend + Seasonality + Error
Multiplicative TS is a multiplication of trend, seasonality, and irregularity.
*Value = Base level * Trend * Seasonality * Error*

Numerous TS composed intermittently (e. g., quarterly or monthly) display a seasonal trend, signifying there is an association between observations made during the same period in continuous years. In addition to this seasonal relationship, there can also be a relationship between observations made during successive periods [22]. The multiplicative ARIMA model is an extension of the ARIMA model that reports seasonality and potential seasonal unit roots.

Vector Auto - Regressive (VAR) Model: The Vector Auto - Regressive (VAR) model is a workhouse of multivariate TS that communicates existing observations of a variable with previous observations of itself and past observations of other variables in the system [23]. A VAR model is composed of multiple equations signifying the association among multiple variables. VAR models fluctuate from univariate autoregressive models because they permit responses to occur between the variables in the model. For example, one could use a VAR model to demonstrate how real GDP is a function of policy rate and how policy rate is, in turn, a function of real GDP.

VAR modeling is a multi - step process and a comprehensive VAR exploration comprises of facts shown in Fig.2 and discussed below.

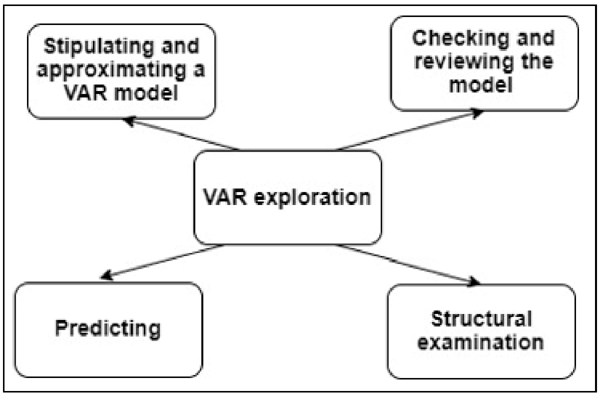

Figure 2: VAR exploration

1) Stipulating and approximating a VAR model
2) Using implications to check and review the model (as required)
3) Predicting
4) Structural examination

VAR models are conventionally extensively used in finance and econometrics because they propose an agenda for achieving vital modeling objectives, comprising Data description, Forecasting, Structural inference, and Policy Analysis. However, more recently VAR models have been attaining desirability in supplementary fields like epidemiology, medicine, and biology. The VAR model offers a methodical but flexible methodology for apprehending multifaceted real - world behavior. VAR possesses enhanced predicting performance and the ability to seize the tangled dynamics of TS data.

Finite Impulse Response (FIR): FIR is a filter whose impulse response (or response to any finite length input) is of *finite* duration because it settles to zero in finite time. Earlier in traditional methods, in all the instances of a particular condition, a single best - fitting parameter is expected [22]. FIR enables inspection of the average time course of the activity after the onset of the condition.

In FIR one stipulates the length of the time window and how many time points one wants to evaluate. One estimates the activity at each time point instead of the single estimate of the average amplitude of the response [23, 24]. For instance, if one desires to approximate the movement for a condition across a ten - second window every two seconds, this would create five beta estimates [25]. One could then equate the movement for the condition at definite time points, instead of the complete amplitude of the condition.

An FIR filter has a few valuable properties shown in Fig.3 and stated as under.

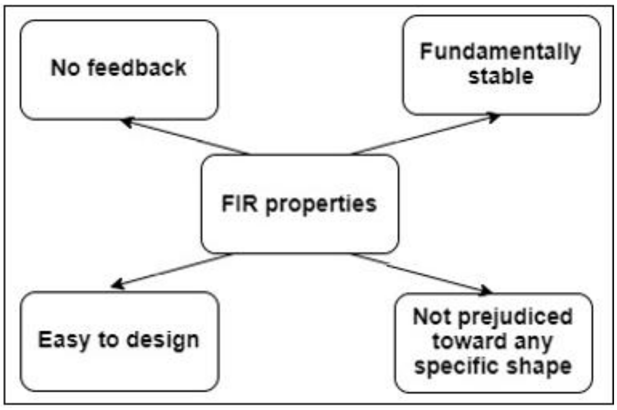

Figure 3: FIR properties

- Need no feedback. The rounding errors are not compounded by summed iterations. Each calculation witnesses the same relative error which helps in making implementation simple [26].
- FIR filter is fundamentally stable. The output is a totality of a fixed number of fixed multiples of the input values.
- FIR filter is easy to design to be a linear phase by creating the coefficient sequence symmetric [26].
- FIR analysis is not prejudiced toward any specific shape. The shape is unrestricted which means that the discrete - time points can in theory be of any value.

FIR requires higher computation power in a general - purpose processor as compared to an Infinite Impulse Response (IIR) filter with alike perceptiveness or choosiness, particularly when low frequency (relative to the sample rate) deadlines are required [27].

Susceptible, Infectious, and/or Recovered (SIR) Model: SIR models are used to forecast diverse situations associated with epidemiologic issues and conceivable results to evaluate epidemic spread. The reproduction number (R_0) is used to approximate the volume of viral transmission from one person to another. The effective reproduction number (R_e or R_t) denotes the number of infected people in a specific time interval based on the R0. The susceptible fraction (F_{so}) takes into account the percentage of infected people that might exist in an epidemic. These indices show how a population and a virus are related to making predictions and considering the consequences at a given moment.

4. Conclusion

Our research has highlighted the fundamental components and inherent complexity of these models. We have systematically covered these aspects to provide a comprehensive understanding of how different models work. The use and accuracy of time series forecasting are continually improving due to the introduction of new technology and approaches. To sum up, time series modelling remains an essential tool in the analytical toolbox, offering invaluable insights and forecasts in a variety of fields. Through ongoing developments, time series (TS) models will persist to be crucial for strategic planning and decision - making processes, advancing efficiency and progress across a range of industries.

References

[1] K. K. R. Samal, K. S. Babu, S. K. Das, and A. Acharaya, “Time series based air pollution forecasting using SARIMA and prophet model, ” *ACM Int. Conf. Proceeding Ser.,* pp.80–85, 2019, doi: 10.1145/3355402.3355417.

[2] Y. Hua, Z. Zhao, R. Li, X. Chen, Z. Liu, and H. Zhang, “Deep Learning with Long Short - Term Memory for Time Series Prediction, ” *IEEE Commun. Mag.,* vol.57, no.6, pp.114–119, 2019, doi: 10.1109/MCOM.2019.1800155.

[3] S. Siami - Namini, N. Tavakoli, and A. S. Namin, “A Comparative Analysis of Forecasting Financial Time Series Using ARIMA, LSTM, and BiLSTM, ” no. April 2020, 2019, doi: 10.48550/arXiv.1911.09512.

[4] S. Elsworth and S. Güttel, “Time Series Forecasting Using LSTM Networks: A Symbolic Approach, ” pp.1–12, 2020, [Online]. Available: http: //arxiv. org/abs/2003.05672

[5] Chatterjee, H. Bhowmick, and J. Sen, “Stock Price Prediction Using Time Series, Econometric, Machine Learning, and Deep Learning Models, ” 2021 *IEEE Mysore Sub Sect. Int. Conf. MysuruCon 2021*, pp.289–296, 2021, doi: 10.1109/MysuruCon52639.2021.9641610.

[6] Y. Kong *et al.,* “Unlocking the Power of LSTM for Long Term Time Series Forecasting, ” 2024, [Online]. Available: http: //arxiv. org/abs/2408.10006

[7] B. Li and Y. Qian, “Weather Prediction Using CNN - LSTM for Time Series Analysis : A Case Study on Delhi Temperature Data”.

[8] F. Dama and C. Sinoquet, “Time Series Analysis and Modeling to Forecast: a Survey, ” pp.1–76, 2021, [Online]. Available: http: //arxiv. org/abs/2104.00164

[9] L. Wulandari, Y. Farida, A. Fanani, and M. Syai’in, “Optimization of Autoregressive Integrated Moving Average (ARIMA) for Forecasting Indonesia Sharia Stock of Index (ISSI) using Kalman Filter, ” pp.295–303, 2020, doi: 10.5220/0008906902950303.

[10] Y. Dong, S. Li, and X. Gong, “Time Series Analysis: An application of ARIMA model in stock price forecasting, ” vol.29, no. Iemss, pp.703–710, 2017, doi: 10.2991/iemss - 17.2017.140.

[11] M. Elsaraiti and A. Merabet, “A comparative analysis of the Arima and Lstm predictive models and their effectiveness for predicting wind speed, ” *Energies*, vol.14, no.20, 2021, doi: 10.3390/en14206782.

[12] S. H. Shin *et al.,* “Prediction of Carbon Dioxide Concentrations in Strawberry Greenhouse by Using Time Series Models, ” *Agric.,* vol.14, no.11, pp.1–23, 2024, doi: 10.3390/agriculture14111895.

[13] G. Van Houdt, C. Mosquera, and G. Nápoles, “A review on the long short - term memory model, ” *Artif. Intell. Rev.,* vol.53, no.8, pp.5929–5955, 2020, doi: 10.1007/s10462 - 020 - 09838 - 1.

[14] H. Al - Chalabi, Y. K. Al - Douri, and J. Lundberg, “Time Series Forecasting using ARIMA Model A Case Study of Mining Face Drilling Rig, ” no. c, pp.4–6, 2018.

[15] S. Mehtab and J. Sen, “Analysis and Forecasting of Financial Time Series Using CNN and LSTM - Based Deep Learning Models, ” *Lect. Notes Networks Syst.,*

vol.302, no. December, pp.405–423, 2022, doi: 10.1007/978 - 981 - 16 - 4807 - 6_39.

[16] E. Production, "Models in Time Series Forecasting: A Case Study of Wind Farm Energy Production," 2024.

[17] Khalil, M. J. Awan, A. Yasin, T. Kousar, A. Rahman, and M. S. Youssef, "Hybrid Time Series Model for Advanced Predictive Analysis in COVID - 19 Vaccination," Electron., vol.13, no.13, 2024, doi: 10.3390/electronics13132468.

[18] Liu, S. C. H. Hoi, P. Zhao, and J. Sun, "Online learning of ARIMA for time series prediction," Proc. Thirtieth AAAI Conf. Artif. Intell., pp.1867–1873, 2016, [Online]. Available: https: //ink. library. smu. edu. sg/sis_research/3411

[19] E. Chodakowska, "ARIMA Models in Electrical Load Forecasting and There," 2021.

[20] H. Abbasimehr and R. Paki, "Improving time series forecasting using LSTM and attention models," *J. Ambient Intell. Humaniz. Comput.,* vol.13, no.1, pp.673–691, 2022, doi: 10.1007/s12652 - 020 - 02761 - x.

[21] L. - H. Le, "Time series analysis and applications in data analysis, forecasting and prediction," *HPU2 J. Sci. Nat. Sci. Technol.,* vol.3, no.1, pp.20–29, 2024, doi: 10.56764/hpu2. jos.2024.3.1.20 - 29.

[22] S. H. Chai, J. S. Lim, H. Yoon, and B. Wang, "A Novel Methodology for Forecasting Business Cycles Using ARIMA and Neural Network with Weighted Fuzzy Membership Functions, " *Axioms*, vol.13, no.1, p.56, 2024, doi: 10.3390/axioms13010056.

[23] Y. Yuan and A. G. Wylie, "Comparing Machine Learning and Time Series Approaches in Predictive Modeling of Urban Fire Incidents: A Case Study of," 2024.

[24] J. D. Borrero, J. Mariscal, and A. Vargas - Sánchez, "A New Predictive Algorithm for Time Series Forecasting Based on Machine Learning Techniques: Evidence for Decision Making in Agriculture and Tourism Sectors, " *Stats*, vol.5, no.4, pp.1145–1158, 2022, doi: 10.3390/stats5040068.

[25] A. Alqatawna, B. Abu - Salih, N. Obeid, and M. Almiani, "Incorporating Time - Series Forecasting Techniques to Predict Logistics Companies' Staffing Needs and Order Volume, " *Computation*, vol.11, no.7, 2023, doi: 10.3390/computation11070141.

[26] T. Case, S. Korea, M. H. Alsharif, and M. K. Younes, "SS symmetry Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation," pp.1–17, 2019, doi: 10.3390/sym11020240.

[27] R. Adhikari and R.. Agrawal, "An Introductory Study on Time Series Modeling and Forecasting Ratnadip Adhikari R. K. Agrawal," *arXiv Prepr. arXiv1302.6613*, vol.1302.6613, pp.1–68, 2013.