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RESEARCH ARTICLE

Milestones and developments in classical statistical time series forecasting: a comprehensive review

Puteri Aiman Syahirah Rosman[1], Nur Haizum Abd Rahman[1,*], Orasa Nunkaw[2] and Aleta C. Fabregas[3]

[1]Centre for Mathematical Sciences, Universiti Malaysia Pahang Al-Sultan Abdullah, Lebuh Persiaran Tun Khalil Yaakob, 26300 Kuantan, Pahang, Malaysia
[2]Department of Mathematics and Statistics, Faculty of Science and Digital Innovation, Thaksin University, Phapayum, Phattalung, 93210, Thailand
[3]Polytechnic University of the Philippines, Sta. Mesa, Manila 1016, Philippines

ABSTRACT - Time series offers a potent framework for forecasting the future based on past data. Time series forecasting, a cornerstone of predictive analytics, is essential to decision-making in many fields, including finance, economics, weather, and healthcare, necessitating various forecasting methodologies. In the 1950s, statistical tools for forecasting began utilising exponential smoothing methods. These approaches were changed depending on the pattern seen in the data sets and the objective of the analysis. Automated functions were used after simple additive and multiplicative effects to assess the complexity of the data for forecasting purposes. This paper thoroughly reviewed the developments and turning points in classical time series forecasting techniques. Time series analysis has long been built on classical forecasting methods, shaping the field's growth. A thorough examination of the literature and historical data has identified noteworthy advancements that have significantly influenced the area. The review emphasises how classical approaches can still be helpful in today's data-driven society and how they can be combined with cutting-edge data science methodologies. This review also provides insightful analyses into the lengthy past and bright future of time series forecasting by charting the development of conventional approaches.

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1. INTRODUCTION

Statistics is the skill of inferring meaning from data. Data is necessary for statistical studies and also largely depends on the selection of the numbers and the interpretation of the results [1]. Statistics can be classified into two main branches: descriptive and inferential. Descriptive statistics refers to the part of statistics that is concerned with the description and data summarisation. Meanwhile, inferential statistics refers to the amount of statistics concerned with predicting and drawing conclusions from the data.

Time series analysis is a branch of statistical analysis that provides the basic approaches and techniques to analyse and infer meaning from time series data. Time series data is a group of observations conducted chronologically across time [2]. Moreover, in order to provide insightful information to guide strategic decision-making, time series forecasting uses statistical methods and models to analyse data. While statistical methods for analysing and forecasting time series data have a long history, forecasting has an even more extended history. Although the two studies' goals may occasionally diverge, forecasting is frequently the aim of a time series study [3]. Note that predicting a future event or events is the process of forecasting. According to Montgomery et al. [4] and Box et al. [5], qualitative and quantitative methods are primarily used in forecasting. Expert judgment is required for qualitative forecasting approaches to produce forecasts. Since qualitative forecasting is based on subjective assessment, it can be influenced by biases and errors performed by human decisions, which can sometimes be less accurate than quantitative methods.

In contrast, quantitative forecasting methodologies extend past and present behaviour into the future, utilising previous information and a forecasting framework. Quantitative forecasting methodologies can be broadly categorised into time-series (mechanistic) approaches and econometric (explanatory) methods. In addition, the forecasts produced by approaches based on statistical notions and principles are sometimes more valuable than those produced by complicated econometric methods for time series forecasting [6].

For several decades, time series forecasting has piqued the interest of numerous academics and is an area of growing interest essential to practically all scientific and engineering fields [7]. In tourism forecasting, Wu et al. [8] presented a novel hybrid technique to tourism forecasting that forecasted daily visitor arrival in the Macau Special Administrative Region (SAR), China, by combining long short-term memory (LSTM) with seasonal autoregressive integrated moving average (SARIMA), where this method outperformed other well-known techniques such as autoregressive integrated moving average (ARIMA), SARIMA and Holt's method. In electric forecasting, Mado et al. [9] forecast the electricity load using data from three years at PT. PLN Gresik Indonesia power plant unit. In finance forecasting, Wawale et al. [10]

***CORRESPONDING AUTHOR | Nur Haizum Abd Rahman** | ✉ haizum@umpsa.edu.my

conducted a study combining two fields, economics and health, to forecast and relate how the foreign exchange rate may affect the stress level of the traders. Perone [11], in healthcare forecasting, used various forecasting methods, including ARIMA, neural network autoregression (NNAR), exponential smoothing (ES) and Trigonometric seasonality, Box-Cox transformation, Autoregressive moving average (ARMA) errors, Trend and Seasonality (TBATS), to forecast the second wave of COVID-19 hospitalisation in Italy. In agriculture forecasting, Yadav et al. [12] used the ARIMA model to forecast the decadal growth of fish production in Assam, India, using the compound growth rate. Also, in automotive forecasting, research was conducted by Sharma and Singhal [13] to predict the demand for engine oil for automotive and industrial lubricant manufacturing companies using neural networks. As a result, they noticed that the primary factors influencing engine oil demand are quality, price, and delivery time. Hence, this justifies the need to use neural networks.

The previous examples suggest that time series forecasting can be further developed into two broad techniques: classical and modern. According to Nor et al. [14], classical methods follow established protocols and exclude using artificial intelligence. Traditional approaches are considered since classical methods significantly contribute to many studies and can be used as benchmark results. Additionally, it is still in the best interests of academics to discover new approaches to enhance the performance of conventional procedures. Examples of well-known classical time series forecasting methods include ES and ARIMA. However, ad hoc data distribution assumptions constrain most of these techniques. Thus, modern forecasting methods that use artificial intelligence have an advantage over traditional methods since they do not rely on such premises. Moreover, these contemporary approaches centre on artificial intelligence, a computer-based system capable of solving problems, storing information, and comprehending human language [14].

Accurate forecasting is essential for, among other things, cost savings and better customer service [15]. Given the various shifting elements in time series data and external circumstances beyond anyone's control, it is challenging to make an accurate prediction. Comprehensive data is necessary to increase the precision of forecasts. Researchers can extrapolate future events using programmable forecasting models trained with relevant data to produce more accurate results. In addition, knowing that no approach or technique works best is critical [16]. Thus, a single model is unable to analyse every dataset or provide an answer to every query. Additionally, forecasting techniques must be customised for each study topic to determine the shifting trend of future data. Makridakis competitions, or M-Competitions initiated by Sypros Makridakis to evaluate the effectiveness of both new and existing forecasting models while also identifying the most successful forecasting techniques for accurate predictions. Note that each of these competitions focuses on different issues. M1-Competition studied the accuracy of other univariate extrapolation (time series) methods and the various factors affecting the forecasting accuracy.

The second M-Competition (M2-Competition) evaluates the post-sample precision of various forecasting techniques by focusing on multivariate time series [17]. The M3-Competition is the authors' ultimate effort to address the accuracy problem with a few time series approaches that involve time series data with different frequencies [15]. The M1 and M2-Competitions' replication and expansion have been its primary goals. More techniques and series are included in the extension. The M4-Competition is then held to continue the previous three competitions involving increasing time series, including machine learning (ML) forecasting methods and evaluating point forecasts and prediction intervals [18]. Using real-life structured sales data, the latest M-Competition, M5, sought to build on the success of the previous four competitions by emphasising retail sales forecasting applications [19]. Up until August 2022, five M-Competitions were held. At the end of 2024, the sixth M-Competition took place to assess the effectiveness of an investment risk model, particularly in its ability to accurately reflect the realised returns of submitted investment portfolios. This evaluation entails comparing the volatility predicted by the model with the actual volatility observed in the portfolios during a designated testing period. The research also explores various optimisation techniques, ranging from traditional methods to dynamic algorithms, for constructing investment portfolios, thereby examining the influence of different strategies on overall investment performance [20].

Until today, classical time series methods are still the main techniques to produce forecasts, even though many modern, including ML methods, have already evolved. Research on traffic volume forecasting by Dissanayake et al. [21] compared three models, including both classical and modern methods, which are vector autoregressive (VAR), autoregressive integrated moving average with exogenous factor (ARIMAX) and LSTM. Their research concluded that the classical multivariate model, VAR, outperforms the advanced neural network method, LSTM. This method selection is based on various factors to ensure higher forecast accuracy. Therefore, this work aims to provide a comprehensive overview of the literature on classical time series forecasting.

2. COMPONENTS IN TIME SERIES

Three components can be identified in an observed time series: trend, seasonal, and cyclical. Trend refers to the long-term movement of the time series over an extended period. It does not have to be linear. The trend can be increasing, decreasing, or even constant. The trend can be called a "changing direction" when it moves from growing to declining. Meanwhile, seasonality is the repeating pattern or fluctuations in the data at a regular interval. Seasonality often corresponds to seasonal factors such as time of the year and day of the week. Cyclic is the third component, which is called a cycle when the data shows both upward and downward trends without a consistent cycle. Usually caused by the state of the economy, these swings last for at least two years [22].

Irregularity and outliers are sometimes included in the components of time series. Irregularities are unanticipated or unusual variations that deviate from the data's regular trend. Measurement errors, unforeseen occurrences, or other noise sources are only a few causes of these oscillations. Abnormalities can significantly impact the accuracy of time series models and forecasts since they conceal the data's underlying trends and seasonality patterns. In contrast, data points that distinguish themselves from the remainder of the series in a time series are known as outliers. These could arise from several things, such as changes to the underlying data-generating processes, exceptional occurrences, or measurement errors. Outliers significantly affect the results of time series analysis and modelling because they can distort the statistical characteristics of the data.

Inaccurate forecasting can occur if these time series components are not considered while performing time series modelling. For example, when the data contains seasonality, the ARIMA method is no longer suitable for forecasting the data. It may work out; however, the result will be inaccurate. Instead, the SARIMA model will perform better and produce higher forecast accuracy. These time series components may be present in time series data. Hence, before proceeding to model the dataset and choosing the best forecasting method, researchers must pay attention to this time series decomposition.

Figure 1 presents a pie chart illustrating the distribution of papers employing various time series models in the International Journal of Forecasting (IJF) from the year 2020 until 2023, including univariate, multivariate, and other related approaches. The results indicate a notable preference for simpler models over more complex alternatives. Among univariate models, ARIMA remains the most widely used and continues to be relevant for contemporary time series forecasting applications. Similarly, the ES model ranks as the second most frequently utilised method after ARIMA. A comparable trend is observed in the use of multivariate models, where the AR model, arguably the simplest form, was the most commonly applied technique in recent years. Of the 37 papers analysed that employed the aforementioned methods in IJF, 11 utilised the AR model, 8 employed ARIMA, 6 applied BVAR, 5 used VAR, 4 used ES and one paper each employed VARMA, GVAR and GSTAR models.

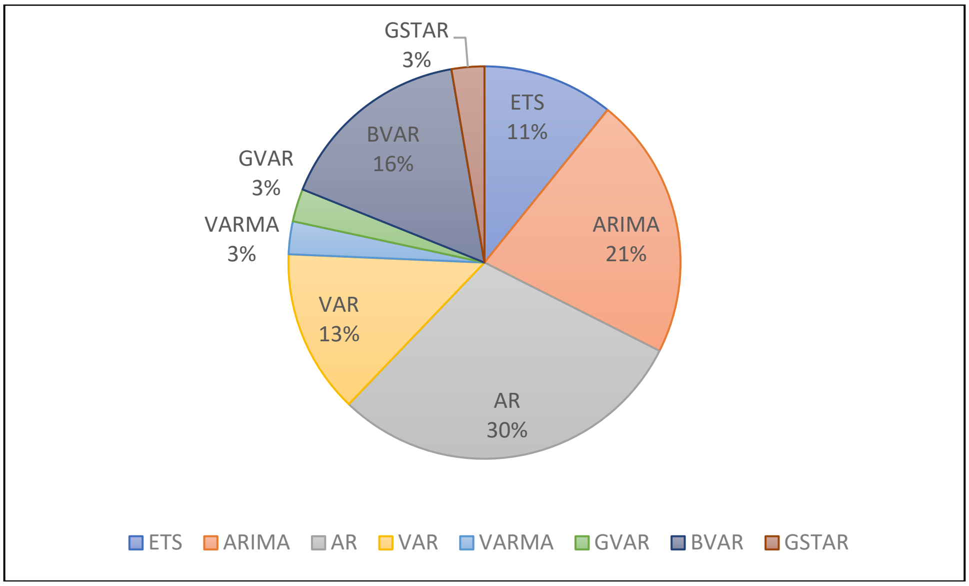

Figure 1. Time series model usage proportions in IJF (2020–2023)

3. UNIVARIATE

3.1 Exponential smoothing

Historically, ES has been used to define a forecasting method based on time series components. The ES is one of the most successful forecasting approaches [23]. This method is widely used in industry and commerce since the method is straightforward to use, and forecasting competitions (M1, M2, and M3-Competitions) have demonstrated that it typically produces predictions for actual data as accurate as alternative methods, even when the method is later more advanced [2]. This method arose when Robert G. Brown, an Operations Research (OR) Analyst for the US Navy in 1944, used a tracking model for fire control information on the location of submarines. He broadened this method from continuous to discrete time series in 1956. One of his first applications was forecasting spare parts demand in the US Navy inventory system. In 1959, Brown presented his work on ES at a conference and then wrote his first book on inventory control. He also developed the ideas in his second book, which emphasises smoothing, forecasting, and prediction of discrete time series.

Brown changed this approach from continuous to discrete time series in the 1950s and added concepts for handling trends and seasonality. According to Gardner [24], Charles C. Holt, in the 1950s, working independently of Brown, developed a method similar to Brown's for ES of additive trends, as well as a completely distinct method for smoothing seasonal data. His work was supported by the Logistics Branch of the Office of Naval Research (ONR). Holt [25] extended simple ES to allow for trend predictions in data. This method is called Holt’s linear trend method or Double ES.

Holt [25] and Winters [26] then extended Holt's approach to account for seasonality. The forecast equation and three smoothing equations that include three main components, level, trend, and seasonal, are part of the Holt-Winters (HW) seasonal technique. HW ES is a famous approach to forecasting seasonal time series. Meanwhile, ES techniques are frequently used in applications, such as inventory control, where many series call for an automated operation due to their robustness and correctness [27].

Hyndman and Athanasopoulos [22] describe two variations of this technique with different seasonal component types. According to research conducted by Bermúdez et al. [28], Wąsik and Chmielowski [29], Siregar et al. [30], Suppalakpanya et al. [31], and Nurhamidah et al. [32], the additive approach is preferred when seasonal fluctuations are nearly consistent across the series. Conversely, the multiplicative method is more effective when the seasonal variations are proportional to the series level [2].

A damped trend can be added as a third option for Holt's linear trend and Holt and Winter's technique. As a result, the growth rate estimates at time t is slowed down in the future period. This entails an additional parameter [2]. Even while HW is still a tried-and-true technique for business forecasting, Goodwin [33] notes that it has lately been expanded to meet three additional concerns. One is the existence of outliers, which, if disregarded, could skew HW estimations. Another is the occurrence of multiple seasonal cycles, like a combination of month-of-year and day-of-week rhythms. Traditional HW methods can only account for a single seasonal trend. Additionally, there is a need for prediction intervals, which are crucial for determining safety stock levels and other factors. Conventional HW intervals are often too narrow, which gives us an illusion of greater accuracy in the predictions.

By proving that simple exponential smoothing (SES) produced the best predictions for a random walk with noise, Muth [34] was the first to propose a statistical basis for SES. SES is the most basic of the ES approaches. This strategy is appropriate for forecasting data that needs a clear trend or seasonal pattern [22]. Muth's work was the first of several statistical models connected to forecasting using ES. Numerous researchers are actively seeking models that deliver precise point forecasts, inspired by the effectiveness demonstrated by ES methods in forecasting and inventory management [35]. Pegels [36] established a straight and helpful framework for categorising trends and seasonal components based on additive (linear) and multiplicative (non-linear) effects, and the categorisation encompassed all nine ES techniques. Two articles released in 1985 boosted ES methods, laying the groundwork for much of the later work in this area [37]. The damped trend was added to Pegal's classification by Gardner [38].

Even though ES techniques have been known since the 1950s, they were recently made known thanks to the work of Ord et al. [39] and Hyndman et al. [40]. They built the modelling framework encompassing stochastic models, likelihood computations, forecast periods, and model selection algorithms. To accommodate a damped additive trend component with either no, an additive, or a seasonal multiplicative element, Hyndman et al. [40] amended Pegal's taxonomy. The new taxonomy provides an effective classification for describing the various approaches, as shown in Table 1. Notably, each technique consists of three forms of seasonality (none, additive, and multiplicative) and one of five types of trend (none, additive, damped additive, multiplicative, and damped multiplicative). There are, thus, 15 distinct approaches, among which the most well-known are SES (no trend, no seasonality), Holt's linear method (additive trend, no seasonality), HW's additive method (additive trend, additive seasonality), and HW's multiplicative method (additive trend, multiplicative seasonality) [37]. To address time series featuring two seasonal patterns, Taylor [27] extended the single seasonal Holt-Winters model by incorporating an additional seasonal component.

Table 1. Taxonomy of the classification of exponential smoothing

Trend Component	N (None)	A (Additive)	M (Multiplicative)
N (None)	N, N	N, A	N, M
A (Additive)	A, N	A, A	A, M
A_d (Additive damped)	A_d, N	A_d, A	A_d, M
M (Multiplicative)	M, N	M, A	M, M
M_d (Multiplicative damped)	M_d, N	M_d, A	M_d, M

Source: Hyndman & Athanasopoulos [22]

Some of these techniques go by different names and are more well-known. For example, cell (A, N) explains Holt's linear approach, cell (A_d, N) discusses the damped trend method, and cell (N, N) describes the SES method. Cell (A, A) provides the Holt-Winters additive approach, and cell (A, M) provides the Holt-Winters multiplicative method. The remaining cells represent analogous but less popular techniques.

When the frequency of seasonal variations escalates, over-parameterisation arises from the necessity of estimating an extensive range of values for the initial seasonal components. Gould et al. [41] divided the main seasonal duration into smaller, more comparable cycles in an effort to lessen the over-parameterisation of this model. Nevertheless, due to its intricacy, this model can only depict double seasonal patterns when one seasonality is numerous. As previously noted, in 2003, Taylor showcased the superiority of prolonged additive seasonal models, capable of managing a third seasonal pattern, over double seasonal ES models. This was demonstrated by analysing six years of electricity demand data from the United Kingdom (UK) and France. However, none of these models proves effective for time series with more than two non-nested seasonal patterns or intricate seasonal features such as non-integer seasonality and calendar effects.

Despite their widespread use, non-linear ES models have certain critical flaws. Most non-linear seasonal ES models are unstable and display infinite forecast variations beyond a particular forecasting horizon, as shown by Akram et al. [42]. Without this issue, sample routes for multiplicative error models will most likely converge to zero [42]. This is true even if the error distribution is not Gaussian. Additionally, analytical findings for the prediction distributions for non-linear ES models are not accessible. These models, however, are unable to handle complicated seasonal time series. An alternative to the current ES models, developed by De Livera et al. [43], works with complex time series, such as those with several seasonal periods, high-frequency seasonality, non-integer seasonality, and dual calendar effects.

If noise dominates the trend and seasonal components of the data, the traditional additive and multiplicative HW approaches may become unreliable [44]. Additionally, multiplicative approaches are impractical for demand time series with zero entries. To cater for this issue, Tratar et al. [45] improved the classical additive HW method by introducing a new smoothing parameter in the level recurrence equation that allowed the smoothing of seasonal factors more or less than the classical method. This new method is called the Extended Holt-Winters method (EHW).

3.2 Autoregressive integrated moving average (ARIMA)

The autoregressive integrated moving average (ARIMA) was a method developed by Box and Jenkins in 1970. It became known as the Box-Jenkins methodology for ARIMA models, where the letter "I" between "AR" and "MA" stood for "Integrated." It indicated the requirement for differential equations to make the series stable. Academicians developed a strong interest in ARIMA models and the Box-Jenkins methodology in the 1970s. This is particularly so because empirical research showed they may sometimes beat the extensive and intricate econometric models that were common at the time [46].

Initially, the Box-Jenkins approach is a logical three-stage iterative cycle known as model identification, parameter estimation, and diagnostic checking [47]. However, Makridakis et al. [48] added two steps to the original Box-Jenkins approach. Box-Jenkins modelling is now a five-step iterative process, as illustrated in Figure 2. The first step is data preparation. This step includes transformations and differentiations. When the variation in a series varies with level, data transformations can assist in stabilising the variance. Differentiation occurs on the data until no glaring patterns remain, such as trends or seasonality. It is frequently simpler to model the different data than the original data. Makridakis and Hibon [46] state that the Box-Jenkins approach proposed the utilisation of both brief and seasonal (extended) differencing to attain stability in the mean, coupled with logarithmic or power transformations to obtain stability in the variance. Additionally, when dealing with seasonal data, the Box-Jenkins approach advises using multiplicative seasonal models and necessary long-term divergence to achieve stationarity in the mean. The problem with this approach is that there is rarely enough information available to make the right level of the seasonal ARMA model with any semblance of confidence. Selecting the ideal seasonal model and long-term (seasonal) differencing requires users to go through a trial-and-error approach. Furthermore, additional data is needed to define the optimal model parameters for seasonality.

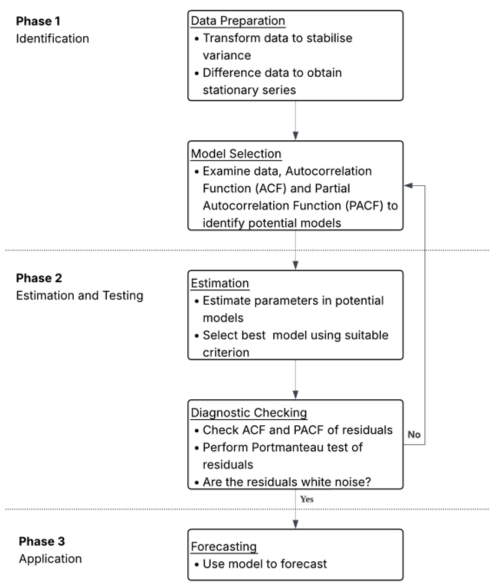

Figure 2. Box-Jenkins Modelling Procedure
Source: Makridakis and Hibon [46]

In model identification, the autocorrelation and partial autocorrelation plots based on the transformed and differenced data are used to identify the potential ARIMA processes involving p, d and q values. Parameter estimation in the third step involves determining the values of the model coefficients that best fit the data. The fourth step, model checking, is putting the model's assumptions to the test to find any places where it falls short. Since it is an iterative process, one can always return to the first step once new information is obtained. The last entire procedure is geared toward making forecasts. Forecasting is typically easy once the model has been chosen, approximated, and checked. This general methodology by Box and Jenkins is the foundation of both univariate and multivariate classical time series forecasting.

Early time series research, mainly done in the 19th century, was generally defined by the idea of a deterministic cosmos. By arguing that any time series can be seen as the realisation of a stochastic process, Yule [49] made a significant contribution to the field by launching the idea of stochasticity in time series. Since then, numerous time series techniques have been created based on this straightforward concept of Wold, combining Autoregressive (AR) and Moving Average (MA) models [37]. The formulation and resolution of Kolmogorov's (1941) linear forecasting issue were made possible by Wold's decomposition theorem. Since then, a significant amount of work dealing with parameter estimates, identification, model checking, and forecasting has been published in the field of time series.

The Box-Jenkins method was published in their book Time Series Analysis: Forecasting and Control. Modern time series analysis and forecasting have greatly benefited from the book's theory and application. Before adding AR and MA components, the methodology emphasised recognising and managing non-stationarity through differencing operations [22]. The usage of ARIMA models and their extensions became more widespread in many scientific fields with the invention of the computer. Although the estimates from the parameter estimation approaches employed in ARMA modelling have quite diverse finite sample features, they share the same normal distribution simultaneously [50]. Apart from ES, ARIMA is the other widely used approach to time series forecasting. This original Box-Jenkins approach caters to univariate time series involving a single time-dependent variable.

In addition to the general ARIMA model, time series with periodic characteristics should be considered. The periodicity of irregular time series is usually due to seasonal changes. To address seasonality, the traditional ARIMA model is extended to a general multiplicative seasonal ARIMA model, commonly known as SARIMA [5]. Box and Jenkins were the first to discover seasonality in the ARIMA model. This enhanced model explicitly supports seasonal components in univariate time series data. In addition to an extra parameter for the seasonality period, the SARIMA model introduces three new hyperparameters to specify the AR, differencing (I), and MA components for the seasonal part of the series. Seasonality can encompass various time frames, such as years, months, days, and hours. Hence, SARIMA models have gained much popularity in forecasting applications [51].

Time series data may exist in double seasonality. Therefore, the SARIMA model is later extended to incorporate the existence of the additional seasonal components. This extension of SARIMA, known as the double seasonal ARIMA model (DSARIMA), is designed to generate a more accurate forecast for data consisting of two seasonal patterns. Taylor [27] was the first to introduce this method. By adding more polynomial functions for the lag operator and more difference operators, the general multiplicative seasonal ARIMA model can be easily expanded to handle three or more seasonality.

An adaptation of ARIMA for many seasonal cycles is the multiple seasonal ARIMA (MSARIMA) model [52]. MSARIMA supports exogenous regressors and words with temporal variability. It computes slowly and is inflexible, though. The state-space ARIMA (SSARIMA) model was presented by Svetunkov and Boylan [53]. It builds ARIMA in a state-space form with several seasonalities. Despite being adaptable and supporting exogenous regressors, SSARIMA is computationally expensive, particularly for high-frequency series [54].

These univariate forecasting methods have been widely used in various fields since their early development stages. In their study, Promprou et al. [55] forecasted the dengue hemorrhagic fever in Southern Thailand to increase in 2006 by using the ARIMA (1,0,1) model. On the other hand, Gharbi et al. [56] forecast the dengue incidence in Guadeloupe for the year 2007 by implementing the SARIMA model, ARIMA $(0,1,1)(0,1,1)^{52}$, using three different approaches: 1 year-ahead, three months-ahead and one month-ahead, where the three months-ahead approach performed as the best method with an RMSE value of 0.85. Dengue infection cases once again have been forecasted using the SARIMA model, ARIMA $(2,1,3)(1,1,1)^{12}$, in a study by Martinez and Silva [57].

The seasonal ARIMA was further developed by Suhartono and Lee [58]. The authors focused on comparing the performance of three models of SARIMA, which are additive, subset, and multiplicative, where they claimed that the multiplicative model that other researchers frequently use might only sometimes be the best model. This is proven in their study of forecasting tourists' arrivals in Bali, where the multiplicative SARIMA model only works best for predicting in-sample datasets. Whereby, for forecasting out-of-sample datasets, the additive model outperforms the other two models.

A study on the Bovespa stock index by Junior et al. [59] found that the AR(1) model surpasses the other three models, which are single exponential smoothing, double exponential smoothing, and the ARIMA model, for forecasting one month ahead with the mean absolute percentage error (MAPE) value of 0.052%. Meanwhile, Bandyopadhyay [60], in their study on the gold price, compared six ARIMA models with different parameters combination, i.e., ARIMA (1,0,1), ARIMA (1,0,2), ARIMA (1,0,3), ARIMA (1,1,1), ARIMA (1,1,2) and ARIMA (1,1,3), where ARIMA (1,1,1) was chosen as the best model that obtained the lowest value of accuracy forecasting measurement, namely root mean square error (RMSE), MAPE and mean absolute error (MAE). To forecast the students' enrolment in higher education in the United States, Din [61] used ARIMA (1,1,1) model, with other methods that might not perform as well as ARIMA. Moving the average approach would result in large errors; meanwhile, classical regression is not recommended when the assumption of uncorrelated errors is violated.

Next, Kim et al. [62] in their research found that a forecasting margin of error of 5.4% was seen between the actual price of uranium in 2015 and the price forecast for the year 2016 using the ARIMA (2,1,2) model compared to the other nine models that utilised all possible combinations of AR (1, 2), I (1), and MA (1, 2). In both of their research, Darekar and Reddy [63-64] used the ARIMA model to forecast the price of cotton and paddy production. On the other hand, Mado et al. [65] found that the subset DSARIMA model, ([1,2,7,16,18,35,46],1,[1,3,13,21,27,46]) $(1,1,1)^{48}(0,0,1)^{336}$), works the best to forecast the short-term electrical power demand with MAPE of 2.06% that incorporates two different seasonality, which are half-hourly and weekly.

Once again, a study on dengue fever epidemics was done. Somboonsak [51] found that Gaussian SARIMA performed the best in forecasting the dengue fever cases in Northern Thailand, where this model recorded the lowest MAPE, Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values among the other models. On the other hand, Samal et al. [66], in their research on the levels of air pollution in India, they compared the SARIMA, the

Prophet, and the log prophet models. Results found that both the SARIMA and Prophet models produced high forecasting accuracy. However, the prophet model with log transformation has the lowest RMSE and MSE values. Cong et al. [67] studied influenza in Mainland China from 2005 until 2018 using the SARIMA $(1,0,0)(0,1,1)^{12}$ model. This model achieved a shallow relative error, which indicated that this model could forecast future values accurately.

Ismail and El-Metaal [68] forecasted the residential natural gas consumption in Egypt by combining DSARIMA and generalised autoregressive conditional heteroskedasticity (GARCH) models that captured daily and weekly seasonal patterns. Three forecasting horizons were used in this study: one day ahead, one week ahead, and one month ahead. Divisekara et al. [69] incorporated DSARIMA to model and forecast the red lentil prices in Canada. This study used 521 observations spanning eight years, from 2010 to 2019. The findings show that the SARIMA $(2,1,2)$ $(0,1,1)^{52}$ model offers the most outstanding performance in and out of the sample. Another study was done in India using the ARIMA model. Yadav et al. [70], in their research on growth trends and forecasting of fish production, they found that ARIMA(1,1,0) is the best fit, which recorded a low standard error of forecast.

In another study on natural gas production in the United States, Manigandan et al. [71] compared the performance of two forecasting models, SARIMA and SARIMAX (SARIMA with exogenous variable). The SARIMAX model outperformed the SARIMA model in both in-sample and out-of-sample data, as indicated by lower MAPE and RMSE values. Ray et al. [72] analysed the future patterns of monthly average rainfall and temperature in South Asian countries, including Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka, using the SARIMA model. Different SARIMA models work best depending on the country's dataset. According to the AIC, BIC, RMSE and MAE values, SARIMA $(1,0,0)(1,1,0)^{12}$ model works the best for Bangladesh rainfall, SARIMA $(1,0,0)(2,1,0)^{12}$ for Bhutan, SARIMA $(0,0,0)(2,1,0)^{12}$ for India and Nepal, SARIMA $(2,0,0)(2,0,0)^{12}$ for Pakistan and SARIMA $(1,0,0)(2,10,0)^{12}$ for Sri Lanka. A study on the currency exchange rates by Wawale et al. [10] found that the ARIMA method is an accurate model for forecasting this data type. On the other hand, research by Deretić et al. [73] on the traffic accidents in the city of Belgrade found that the SARIMA model with monthly seasonality, SARIMA (0,1,2)(1,1,0)12, can produce the highest forecasting accuracy with an MAPE of 5.22% specifically for short forecasting horizons.

In a comparison of a few methods, including ARIMA, ES, neural network autoregression (NNAR), TBATS, and a hybrid model to forecast the second wave of COVID-19 hospitalisations in Italy, Perone [74] through his study concluded that NNAR and ARIMA methods performed the best to forecast the number of patients with mild symptoms and admitted to Intensive Care Unit (ICU). On the other hand, Mado [75], in one of his research projects on electricity load demand, found that the subset DSARIMA model works the best for this dataset. The DSARIMA model, ([1, 2, 7, 11, 16, 18, 35, 46], 1, [1, 3, 13, 21, 27, 46] $(1, 1,1)^{48}(0, 0, 1)^{336}$, recorded the MAPE of 2.06% when compared to the actual data. As a continuity of his past study, Mado et al. [75], in their research, improved the AR and MA parameters, which before this had the tendency not to meet the normality condition and were expected to have outliers. This new subset DSARIMA model, with the addition of two new MA parameters ([1, 2, 5, 6, 7, 11, 16, 18, 35, 46], 1, [1, 3, 13, 21, 27, 46] $(1, 1,1)^{48}(0, 0, 1)^{336}$, has produced a lower MAPE value, which is 1.56%. In another case of comparing two methods, which are SARIMA and NNAR, Orang et al. [76] found that the SARIMA $(1,0,2)(2, 1, 0)^{52}$ model performed better than the NNAR $(7, 1, 1)^{52}$ model for both RMSE and MAE predictive accuracy measurements. This research for the past 15 years has shown that the classical forecasting method is still relevant and in particular, studies outperformed the modern one.

4. MULTIVARIATE

The prominent classical univariate AR and MA models can also be developed to cater to multiple time-dependent variables simultaneously. Multivariate time series forecasting techniques imply interdependencies between variables by nature. In other words, each variable depends on both other variables and its past values in addition to both [77]. The multivariate generalisation of the univariate ARIMA model is called the vector ARIMA (VARIMA) model. Jenkins and Quenouille [78] appear to have first developed the population properties of vector ARMA (VARMA) processes.

The more general class of VARMA models includes vector autoregressions (VARs), a specific case. A VAR model approximates the simplified version of a broad range of dynamic econometric models that are relatively unconstrained [37]. Variety research builds the VAR models. Using a monthly industrial production series, Funke [79] compared the prediction capacities of five distinct VAR formulations. Dhrymes and Thomakos [80] explored problems with structural VAR identification. Hafer and Sheehan demonstrated that model structure changes impact VAR projections [81]. Furthermore, VAR can illustrate their interactions and incorporate more valuation information to increase forecast accuracy by displaying a lead-lag relationship between variables. However, VAR cannot demonstrate the long-term link between the explanatory variables. Therefore, due to this flaw, VAR cannot accurately predict prices over longer time horizons [82]. This is supported by Khan et al. [83], who conducted research that forecasts daily COVID-19 cases, deaths, and recovery cases only up to 10 days ahead using the VAR model. Katris [84], through her study, also claimed that VAR was found to be limited, and another univariate approach, referred to as ARIMA specifically, performed better. In cases involving COVID-19 cases and death, the VAR framework has shown good performance in modelling these datasets. In their study, Rajab et al. [85] proved that the VAR model outperformed the ARIMA model for forecasting COVID-19 cases.

However, the VAR model encountered several problems. First, a modest number of variables is optimal for a conventional VAR model to function well. VAR models typically experience overfitting with too many unnecessary free parameters. Second, because VAR models often only incorporate a small number of variables, they are often not very good at forecasting or doing structural analyses for bias resulting from omitted variables. Lastly, if the lag length grows to an excessive length, the VAR method loses its degree of freedom. As a result, even while within-sample fitting is good, these models may produce subpar out-of-sample forecasts. To express their conviction that a lot of economic parameters act like a random walk, unlike what is usually done, which is to constrain some of the parameters, Litterman [86] placed an initial distribution on all of them. This method is then called Bayesian VAR (BVAR).

BVAR models have primarily been used for economic applications such as macroeconomic forecasting [87], market share forecasting [88], and labour market forecasting [89]. In the health field, Lopreite and Zhu [90] studied the shifting connections between China's health spending, economic growth, life expectancy, and ageing index by using the BVAR model, which works better than the standard VAR model. Kopytin et al. [91] studied the effects of global oil prices, interest rate policies, and exchange rates on consumer inflation and economic growth in three post-Soviet oil exporting nations, Russia, Kazakhstan, and Azerbaijan, using the BVAR model. Oil prices were found to be the main factor contributing to the inflation in all three countries.

Another multivariate method is global vector autoregressive (GVAR). The models which do not treat countries as isolated from the rest of the world. The single-country models in the GVAR framework are stacked to depict the global economy thoroughly [79]. Han and Ng [92] discovered that GVAR models outperformed stand-alone VAR specifications for one-step forecasts of short-term interest rates and actual equity prices in five Asian economies. Additionally, across forecast horizons longer than four quarters, Greenwood-Nimmo et al. [93] verified the superiority of GVAR specifications over univariate benchmark models. In the tourism field, few recent studies used the GVAR model. Cao et al. [94] model the interdependence of tourism demand using GVAR and demonstrate how the model can overcome endogeneity and over-parameterisation problems. Gunter (2018) [95] analyses conditional projections of tourism exports and export prices using the GVAR framework. Later, Gunter and Zekan [96] in their study analysed the joint micro (forecasts for the single airport) and macro (interdependence and joint dependence) perspectives using the GVAR framework. Li and Shi [97] proposed a GVAR model that could produce consistent mortality projections between any two ages in any population and provide acceptable mortality forecasts in various scenarios. Salisu et al. [98], through their research, used a large-scale GVAR model on 26 advanced and emerging stock markets to investigate how shocks related to oil price uncertainty spread to actual equity prices. Cuaresma et al. [99] developed a new method for dealing with international macroeconomics and financial variables incorporating the Bayesian technique. This method is called B-GVAR. Assaf et al. [100] incorporated the B-GVAR model in their study of international tourist flow in nine Southeast Asian countries. They compared the forecasting performance of the classic VAR, BVAR, GVAR, B-GVAR, and ARMA methods and found that B-GVAR performed better than the other methods in all forecasting horizons and for all nine countries.

The notion of cointegration, first introduced by Engle and Granger [101], has prompted a number of intriguing queries about the predictive power of error correction models (ECMs) compared to unconstrained VARs and BVARs. Empirical evidence presented by Shoesmith [102], Shoesmith [102], and Tegene and Kuchler [103] suggest that ECMs perform better than VARs in levels, especially over extended predicting periods. In the Kuo [82] study, longer forecasting horizons result in fewer forecasting errors and significantly higher performance for the vector error correction model (VECM) than VAR, indicating that VECM's potential to boost VAR prediction accuracy grows stronger with time. This is contradictory with Ampountolas [104]. In his research using the hotels' occupancy time series, he found that the classical VAR model outperformed BVAR and VECM in both shorter and longer horizons.

Another model to handle multivariate data involving the space-time model, such as Space-Time Autoregressive (STAR) and Space-Time Autoregressive Moving Average (STARMA), was introduced in 1975 by Cliff and Ord [105]. The researchers introduced these two models with fewer parameters than the VARMA models. Since all sites have the same time series and space-time parameter values, the STAR model only applies to homogeneous locations [105,106]. Pfeifer and Deutsch [106] explained how Box and Jenkins' three-stage iterative model creation process was expanded to include the STARMA models' space-time, time series model class. Several approaches have been created to suit various inferential requirements and data kinds. Pfeifer and Deutsch [106-107] first outlined some works' STAR integrated moving average (STARMA) methodology. Since then, various spatial time series data have been integrated into the STARMA model.

Borovkova et al. [108] developed a more flexible multivariate time series model, namely the GSTAR model. This model is the natural generalisation of STAR models that allows the AR parameters to vary depending on the location, making it usable for sample locations with varied characteristics [109]. Mukhaiyar et al. [110] proposed a novel method for modelling space-time using the inverse of the autocovariance matrix (IAcM). They selected a suitable model for the space-time data series by assessing the IAcM behaviours that support the GSTAR process stationarity. According to research by Zewdie et al. [111], the models STAR (1,1) and GSTAR (1,1) are discovered to be two possibilities, and the best-fitted model is GSTAR (1,1), with a strong forecasting capability and the smallest RMSE for forecasting the space-time variation of temperature in Northern Ethiopia.

The generalised space-time autoregressive moving average (GSTARMA) model is developed from the GSTAR model by re-modelling the GSTAR error model and including the MA [112]. According to their study, the GSTARMA model can rectify prediction errors from the GSTAR model on carbon dioxide data.

5. OTHER METHODS

Forecasting methods can be extremely simple and surprisingly effective. For example, the naïve method forecasts the most recent observation. For a large number of economic and financial time series, this technique performs exceptionally well. These are also called random walk forecasts since a naive forecast is the best option when data behave randomly

[22]. Even though this method is simple, researchers still use the naïve method as a benchmark method and sometimes outperform other famous complex methods. Nikolopoulos et al. [113] conducted a study wherein eleven methods were compared, such as diffusion models (Repeat Purchase Diffusion Model (RPDM) and Bass model), ARIMA, ES (Simple and Holt), naïve, and regression methods. The study concluded that ARIMA, being a highly adaptive method, yielded the most accurate, least biased, and least volatile one-year estimates. However, the naïve method outperformed the other ten methods for longer horizons. Jan et al. [114] used Naïve and AR methods as benchmark models to be compared with the new proposed model, namely functional autoregressive (FAR). Additionally utilised in projecting electricity prices, the FAR extends the AR technique to infinite-dimensional space.

Box and Jenkins [47] developed a new method called Box-Cox transformation, ARMA errors, trend and seasonal components (BATS) that was part of the broader Box-Jenkins methodology. Box-Cox transformation is included to deal with non-constant variance and the ARMA errors component to simulate autocorrelation. According to De Livera et al. [43], BATS is the extended model of the general ES. The fundamental model for the well-known HW additive single seasonal technique is BATS (1, 1, 0, 0, m_1). BATS (1, 1, 0, 0, m_1, m_2) yields the double seasonal HW additive seasonal model that Taylor [52] describes, and BATS (1, 1, 1, 0, m_1, m_2) yields the Taylor [52,115] model with the residual AR (1) adjustment. In Taylor [115], the HW additive triple seasonal model with AR (1) adjustment is provided by the formula BATS (1, 1, 1, 0, m_1, m_2, m_3). An improved version of BATS called TBATS allows for many seasonal erroneous cycles. BATS and TBATS are the two innovative state-space modelling frameworks that can handle intricate seasonal time series fluctuations. BATS and TBATS are only different in the way they model seasonal effects. BATS uses a more conventional methodology and can only simulate integer period lengths. In TBATS, Fourier terms are combined with a Box-Cox transformation, an exponentially smoothing state space model, and both. It enables terms to change over time and generate precise forecasts. However, TBATS possesses some limitations, including inflexibility, potential for slowness, and inability to account for variables [54]. According to Naim et al. [116], TBATS, which used fewer parameters, performed better than BATS in forecasting daily natural gas consumption in India, where the research demonstrated that the data contained various weekly, monthly, and annual seasonality.

Another method is the seasonal trend decomposition (STL) method, first introduced by Cleveland et al. [117]. STL is another classical time series forecasting method that deals with non-linearity. The STL utilised seasonal decomposition and local regression (Loess) strength to capture short-term and long-term fluctuations in time series data. Various studies involving various fields used STL as the primary method of research. Theodosiou [118] proposed a new method based on the disaggregation of time series components using the STL decomposition process, extending the disaggregated sub-series by linear combinations and then reaggregating the extrapolations to get estimates for the global series. Li et al. [119] later proposed a novel combined model for predicting dam displacement time series using the STL method, extra-trees model, and LSTM model. Yin et al. [120] proved that a combination of STL and the neural network method LSTM, STL-LSTM, produces the highest accuracy in predicting vegetable prices. However, Ouyang et al. [121] compared the application of STL to seven different forecasting methods, including classical and modern time series methods (classical, ML, and neural network methods). They concluded that STL decomposition only benefits forecasting using statistical methods. A study on converting stock time series into a directed and weighted symbolic network using STL was also done by Tian et al. [122]. The STL method's biggest drawback is that it derives a flux by correlating outliers in the random component. It is essentially speculative since the outliers only illustrate how well STL can model the data [123].

6. CONCLUSION AND A LOOK INTO THE FUTURE

In the 1950s, basic tools and techniques were employed to examine the data for statistical analysis. Modern technology has revolutionised statistical analysis approaches to better meet the needs of analysing numerous data sets. Algorithms, simulations, and many factors depending on various data sets significantly increased the complexity of approaches and tools. Similarly, as time passed and new data sets and analysis requirements changed, so did the statistical tools used for forecasting. However, as mentioned before, even the simplest classical models, such as ARIMA, ES, and VAR, are still relevant today. Also noteworthy is that the statistical forecasting model has yet to prove superior to other approaches in this review.

Not to mention, a few other elements influence a technique's forecasting precision. For example, the same method with different forecasting horizons may produce different results. Certain methods work well with shorter forecasting periods, while some work better with longer forecasting horizons. Therefore, it is necessary to analyse the forecasting data using various methods to determine the exact or near accuracy, depending on the kinds of data sets and attributes that need to be assessed. There are a number of actual applications included throughout the paper that clearly demonstrate that classical time series methods are still relevant despite the emergence of many modern methods.

Undeniably, classical time series forecasting techniques, which rely on probability and statistics, have produced excellent outcomes in a variety of industries and fields, including economics and meteorology. Compared to when it first emerged, the field of time series forecasting has seen a significant transformation. It has matured with the development of more advanced statistical models, better processing capacity, and more developed forecasting methods. However, there is still much work to be done as several issues still need to be solved and new problems developed. As the big data era develops, large, non-linear time series data that follow numerous distribution patterns are continuously generated, which increases the difficulty of time series forecasting techniques.

Furthermore, an issue arises as to forecasting the analysis of future data, researchers typically build predictive models using historical data. Nevertheless, in real-world uses, it is discovered that the prediction model's performance and accuracy steadily deteriorate with time. The primary cause is the gap between historical and current data. In other words, the research on the revised model of time series forecasting based on online incremental data has become an urgent problem to be solved.

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DECLARATION OF ORIGINALITY

The authors declare no conflict of interest to report regarding this study.

REFERENCES

[1] Frost J. Introduction to statistics: An intuitive guide for analyzing data and unlocking discoveries. State College (PA): Statistics by Jim Publishing; 2020.
[2] Chatfield C, Koehler A, Ord K, Snyder R. A new look at models for exponential smoothing. Journal of the Royal Statistical Society: Series D (The Statistician). 2001;50(2):147–159.
[3] Tsay RS. Time series and forecasting: Brief history and future research. Journal of the American Statistical Association. 2000;95(450):638–43.
[4] Montgomery DC, Jennings CL, Kulahci M. Introduction to time series analysis and forecasting. Hoboken (NJ): Wiley; 2008.
[5] Box GEP, Jenkins GM, Reinsel GC, Ljung GM. Time series analysis: forecasting and control. 5th ed. Hoboken (NJ): Wiley; 2016.
[6] Granger CWJ, Newbold P. Forecasting economic time series. 2nd ed. Orlando (FL): Academic Press; 1986.
[7] Faloutsos C, Gasthaus J, Januschowski T, Wang Y. Classical and contemporary approaches to big time series forecasting. In Proceedings of the 2019 international conference on management of data 2019 (pp. 2042-2047).
[8] Hu YC, Wu G, Jiang P. Tourism demand forecasting using nonadditive forecast combinations. Journal of Hospitality & Tourism Research. 2021;47(5):775–799.
[9] Mado I, Soeprijanto A, Suhartono S. Applying of double seasonal ARIMA model for electrical power demand forecasting at PT. PLN Gresik Indonesia. International Journal of Electrical and Computer Engineering. 2018;8(6):4892–4901.
[10] Wawale S, Bisht A, Vyas DS, Narawish C, Ray S. An overview: Modeling and forecasting of time series data using different techniques in reference to human stress. Neuroscience Informatics. 2022;2(3):100052.
[11] Perone G. Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy. The European Journal of Health Economics. 2022;23:917–940.
[12] Yadav AK, Das K, Das P, Raman R, Kumar J, Das B. Growth trends and forecasting of fish production in Assam, India using ARIMA model. Journal of Applied and Natural Science. 2020;12(3):415–421.
[13] Sharma R, Sharma R. Demand forecasting of engine oil for automotive and industrial lubricant manufacturing company using neural network. Materials Today: Proceedings. 2019;18:2308–2314.
[14] Nor ME, Safuan HM, Md Shab NF, Asrul M, Abdullah A, Nurul Mohamad NAI, Lee MH. Neural network versus classical time series forecasting models. In: AIP Conference Proceedings 2017;1842:030027.
[15] Makridakis S. The M3-Competition: results, conclusions and implications. International Journal of Forecasting. 2000;16(4):451–476.
[16] Makridakis S, Andersen A, Carbone R, Fildes R, Hibon M, Lewandowski R, Newton J, Parzen E, Winkler R. The accuracy of extrapolation (time series) methods: Results of a forecasting competition. Journal of Forecasting. 1982;1(2):111–153.

[17] Makridakis S, Chatfield C, Hibon M, Lawrence M, Mills T, Ord K, Simmons LF. The M2-competition: A real-time judgmentally based forecasting study. International Journal of Forecasting. 1993;9(1):5–22.
[18] Makridakis S, Spiliotis E, Assimakopoulos V. The M4 Competition: Results, findings, conclusion and way forward. International Journal of Forecasting. 2018;34(4):802–808.
[19] Makridakis S, Spiliotis E, Assimakopoulos V. The M5 competition: Background, organization, and implementation. International Journal of Forecasting. 2021;38(4):1325–1336.
[20] Makridakis S, Spiliotis E, Hollyman R, Petropoulos F, Swanson N, Gaba A. The M6 forecasting competition: Bridging the gap between forecasting and investment decisions. International Journal of Forecasting. Forthcoming 2024. Corrected proof.
[21] Dissanayake B, Hemachandra O, Lakshitha N, Haputhanthri D, Wijayasiri A. A comparison of ARIMAX, VAR, and LSTM on multivariate short-term traffic volume forecasting. In: Proceedings of the 28th Conference of the Open Innovations Association FRUCT; 2021 Jan 27–29; Moscow, Russia. Moscow: FRUCT Oy; 2021. pp. 564–570.
[22] Hyndman RJ, Athanasopoulos G. Forecasting: Principles and practice. OTexts; 2021.
[23] Hyndman RJ, Koehler AB, Ord KJ, Snyder RD. Forecasting with exponential smoothing: The State Space Approach. Springer; 2008.
[24] Gardner Jr E. Exponential smoothing: The state of the art—Part II. International Journal of Forecasting. 2006;22(4):637–666
[25] Holt CC. Forecasting seasonals and trends by exponentially weighted moving averages. International journal of forecasting. 2004;20(1):5-10.
[26] Winters PR. Forecasting sales by exponentially weighted moving averages. Management Science Journal of the Institute of Management Science: Application and Theory Series. 1960;6(3):324–342.
[27] Taylor JW. Short-term electricity demand forecasting using double seasonal exponential smoothing. Journal of the Operational Research Society. 2003;54(8):799–805.
[28] Bermúdez J, Segura-Heras JV, Vercher E. Holt-Winters forecasting: An alternative formulation applied to UK air passenger data. Journal of Applied Statistics. 2007;34(9):1075–1090.
[29] Wąsik E, Chmielowski K. The use of Holt–Winters method for forecasting the amount of sewage inflowing into the wastewater treatment plant in Nowy Sącz. Environmental Protection and Natural Resources. 2016;27(2):7–12.
[30] Siregar B, Butar-Butar IA, Rahmat RF, Andayani U, Fahmi F. Comparison of exponential smoothing methods in forecasting palm oil real production. Journal of Physics: Conference Series. 2017;801:012004.
[31] Suppalakpanya K, Booranawong A, Booranawong T, Nikhom R. An evaluation of Holt-Winters methods with different initial trend values for forecasting crude palm oil production and prices in Thailand. Suranaree Journal of Science and Technology. 2019;26(1):13–22.
[32] Nurhamidah, Wan N, Faisol A. Forecasting seasonal time series data using the Holt-Winters exponential smoothing method of additive models. Jurnal Matematika Integratif. 2020;16(2):151–157.
[33] Goodwin P. The Holt-Winters approach to exponential smoothing: 50 years old and going strong. Foresight: The International Journal of Applied Forecasting. 2010:19;30–33.
[34] Muth JF. Optimal properties of exponentially weighted forecasts. Journal of the American Statistical Association. 1960;55(290):299–306.
[35] Gould PG, Koehler AB, Ord JK, Snyder RD, Hyndman RJ, Vahid-Araghi F. Forecasting time series with multiple seasonal patterns. European Journal of Operational Research. 2008;191(1):207–222.
[36] McCormick GP. Communications to the editor—Exponential forecasting: Some new variations. Management Science. 1969;15(5):311–315.
[37] De Gooijer JG, Hyndman RJ. 25 years of time series forecasting. International Journal of Forecasting. 2006;22(3):443–473.
[38] Gardner ES. Exponential smoothing: The state of the art. Journal of Forecasting. 1985;4(1):1–28.
[39] Ord K, Koehler A, Snyder R. Estimation and prediction for a class of dynamic nonlinear statistical models. Journal of the American Statistical Association. 1997;92(440):1621–1629.
[40] Hyndman R, Koehler A, Snyder R, Grose S. A state space framework for automatic forecasting using exponential smoothing methods. International Journal of Forecasting. 2002;18(3):439–454.
[41] Gould PG, Koehler AB, Ord JK, Snyder RD, Hyndman RJ, Vahid-Araghi F. Forecasting time series with multiple seasonal patterns. European Journal of Operational Research. 2008;191(1):207–222.
[42] Akram M, Hyndman RJ, Ord JK. Exponential smoothing and non-negative data. Australian & New Zealand Journal of Statistics. 2009;51(4):415–432.
[43] De Livera AM, Hyndman RJ, Snyder RD. Forecasting time series with complex seasonal patterns using exponential smoothing. Journal of the American Statistical Association. 2011;106:1513–1527.
[44] Ferbar Tratar L. Forecasting method for noisy demand. International Journal of Production Economics. 2015;161:64–73.
[45] Ferbar Tratar L, Mojškerc B, Toman A. Demand forecasting with four-parameter exponential smoothing. International Journal of Production Economics. 2016;181:162–173.
[46] Makridakis S, Hibon M. ARMA models and the Box-Jenkins methodology. Journal of Forecasting. 1997;16(3):147–163.
[47] Box GEP, Jenkins GM. Time series analysis: Forecasting and control. San Francisco: Holden-Day; 1976.

[48] Makridakis S, Winkler RL. Averages of forecasts: Some empirical results. Management Science. 1983;29(9):987–996.
[49] Yule GU. On a method of investigating periodicities in disturbed series, with special reference to Wolfer's sunspot numbers. In: The Foundations of Econometric Analysis [Internet]. Cambridge: Cambridge University Press; 2012. pp. 267–273.
[50] Majid R, Mir S. Advances in statistical forecasting methods: An overview. *Economic Affairs* 2018;63(4):815–831.
[51] Somboonsak P. Forecasting dengue fever epidemics using ARIMA model. In: Proceedings of the 2019 2nd Artificial Intelligence and Cloud Computing Conference, New York, NY, USA: Association for Computing Machinery; 2020. p. 144–150.
[52] Taylor JW. Exponential smoothing with a damped multiplicative trend. International Journal of Forecasting 2003;19(4):715–725.
[53] Svetunkov I, Boylan J. State-space ARIMA for supply-chain forecasting. International Journal of Production Research 2019;58(1):1–10.
[54] Petropoulos F, Apiletti D, Assimakopoulos V, Babai MZ, Barrow DK, Ben Taieb S, et al. Forecasting: theory and practice. International Journal of Forecasting 2022;38(3):705–871.
[55] Promprou S, Jaroensutasinee M, Jaroensutasinee K. Forecasting Dengue Haemorrhagic Fever cases in Southern Thailand using ARIMA Models. Dengue Bulletin. 2006;30:99–106.
[56] Gharbi M, Quenel P, Gustave J, Cassadou S, Ruche GL, Girdary L, et al. Time series analysis of dengue incidence in Guadeloupe, French West Indies: forecasting models using climate variables as predictors. BMC Infectious Diseases. 2011;11:166.
[57] Martinez EZ, da Silva EAS. Predicting the number of cases of dengue infection in Ribeirão Preto, São Paulo State, Brazil, using a SARIMA model. Cadernos de Saúde Pública. 2011;27(9):1809–1819.
[58] Suhartono. Time series forecasting by using seasonal autoregressive integrated moving average: Subset, multiplicative or additive model. Journal of Mathematics and Statistics. 2011;7(1):20–27.
[59] Junior PR, Salomon FLR, de Oliveira Pamplona E. ARIMA: An applied time series forecasting model for the Bovespa stock index. Applied Mathematics. 2014;5(21):3383–3391.
[60] Bandyopadhyay G. Gold price forecasting using ARIMA model. Journal of Advanced Management Science. 2016;4(2):117–121.
[61] Din MA. ARIMA by Box-Jenkins methodology for estimation and forecasting models in higher education. Athens: ATINER's Conference Paper Series; 2016. No. EMS2015-1846.
[62] Kim S, Ko W, Nam H, Kim C, Chung Y, Bang S. Statistical model for forecasting uranium prices to estimate the nuclear fuel cycle cost. Nuclear Engineering and Technology. 2017;49(5):1063–1070.
[63] Darekar A, Reddy AA. Cotton price forecasting in major producing states. Economic Affairs. 2017;62(3):373–378.
[64] [64] Darekar A, Reddy AA. Forecasting of common paddy prices in India. SSRN Electronic Journal. 2017;10(1):71–75.
[65] Mado I, Soeprijanto A, Suhartono S. Applying of double seasonal ARIMA model for electrical power demand forecasting at PT. PLN Gresik Indonesia. International Journal of Electrical and Computer Engineering. 2018;8(6):4892–4901.
[66] Samal KKR, Babu KS, Das SK, Acharya A. Time series-based air pollution forecasting using SARIMA and Prophet model. In: Proceedings of the 2019 International Conference on Information Technology and Computer Communications; 2019 Sep 20–22; Singapore, Singapore. New York (NY): Association for Computing Machinery; 2019. pp. 80–85.
[67] Cong J, Ren M, Xie S, Wang P. Predicting seasonal influenza based on SARIMA model, in mainland China from 2005 to 2018. International Journal of Environmental Research and Public Health. 2019;16(23):4760.
[68] Ismail MA, El-Metaal EMA. Forecasting residential natural gas consumption in Egypt. Journal of Humanities and Applied Social Sciences. 2020;2(4):297–308.
[69] Divisekara RW, Jayasinghe GJMSR, Kumari KWSN. Forecasting the red lentils commodity market price using SARIMA models. SN Business & Economics. 2021;1(20):1–20.
[70] Yadav A, Jha C, Sharan A. Optimizing LSTM for time series prediction in Indian stock market. Procedia Computer Science. 2020;167:2091–2100.
[71] Manigandan P, Alam MDS, Alharthi M, Khan U, Alagirisamy K, Pachiyappan D, Rehman A. Forecasting natural gas production and consumption in United States—evidence from SARIMA and SARIMAX models. Energies. 2021;14(19):6021.
[72] Ray S, Das SS, Mishra P, Khatib AMG Al. Time series SARIMA modelling and forecasting of monthly rainfall and temperature in the South Asian countries. Earth Systems and Environment. 2021;5:531–546.
[73] Deretić N, Stanimirović D, Awadh MA, Vujanović N, Djukić A. SARIMA modelling approach for forecasting of traffic accidents. Sustainability. 2022;14(8):4403.
[74] Perone G. Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy. The European Journal of Health Economics. 2022;23:917–940.
[75] Mado I, Rajagukguk A, Triwiyatno A, Fadllullah A. Short-term electricity load forecasting model based DSARIMA. International Journal of Electrical, Energy and Power System Engineering. 2022;5(1):6–11.

[76] Orang A, Berke O, Poljak Z, Greer AL, Rees EE, Ng V. Forecasting seasonal influenza activity in Canada—Comparing seasonal Auto-Regressive Integrated Moving Average and artificial neural network approaches for public health preparedness. Zoonoses Public Health. 2024;71(3):304–313.
[77] Wu DCW, Ji L, He K, Tso KFG. Forecasting tourist daily arrivals with a hybrid SARIMA–LSTM approach. Journal of Hospitality and Tourism Research. 2021;45(1):52–67.
[78] Jenkins GM, Quenouille MH. Analysis of multiple time-series. Biometrika. 1959;46(1-2):267.
[79] Funke M. Assessing the forecasting accuracy of monthly vector autoregressive models: The case of five OECD countries. International Journal of Forecasting. 1990;6(3):363–378.
[80] Dhrymes PJ, Thomakos DD. Structural VAR, MARMA and open economy models. International Journal of Forecasting. 1998;14(2):187–198.
[81] Hafer RW, Sheehan RG. The sensitivity of VAR forecasts to alternative lag structures. International Journal of Forecasting. 1989;5(3):399–408.
[82] Kuo CY. Does the vector error correction model perform better than others in forecasting stock price? An application of residual income valuation theory. Economic Modelling. 2016;52:772–789.
[83] Khan F, Saeed A, Ali S. Modelling and forecasting of new cases, deaths and recover cases of COVID-19 by using Vector Autoregressive model in Pakistan. Chaos, Solitons & Fractals. 2020;140:110189.
[84] Katris C. Unemployment and COVID-19 Impact in Greece: A vector autoregression (VAR) data analysis. Engineering Proceedings. 2021;5(1):41.
[85] Rajab K, Kamalov F, Cherukuri AK. Forecasting COVID-19: Vector autoregression-based model. Arabian Journal for Science and Engineering. 2022;47:6851–6860.
[86] Litterman RB. Forecasting with Bayesian vector autoregressions—five years of experience. Journal of Business & Economic Statistics. 1986;4(1):25–38.
[87] Artis MJ, Zhang W. BVAR forecasts for the G-7. International Journal of Forecasting. 1990;6(3):349–362.
[88] Ramos FFR. Forecasts of market shares from VAR and BVAR models: A comparison of their accuracy. International Journal of Forecasting. 2003;19(1):95–110.
[89] LeSage JP, Magura M. Using interindustry input-output relations as a Bayesian prior in employment forecasting models. International Journal of Forecasting. 1991;7(2):231–238.
[90] Lopreite M, Zhu Z. The effects of ageing population on health expenditure and economic growth in China: A Bayesian-VAR approach. Social Science & Medicine. 2020;265:113513.
[91] Kopytin IA, Pilnik NP, Stankevich IP. Modelling five variables BVAR for economic policies and growth in Azerbaijan, Kazakhstan and Russia: 2005–2020. International Journal of Energy Economics and Policy. 2021;11(5):510–518.
[92] Han F, Ng TH. ASEAN-5 macroeconomic forecasting using a GVAR model. Asian Development Bank Working Paper. 2011.
[93] Greenwood-Nimmo M, Nguyen VH, Shin Y. Probabilistic forecasting of output growth, inflation, and the balance of trade in a GVAR framework. Journal of Applied Econometrics. 2012;27(4):554–573.
[94] Cao Z, Li G, Song H. Modelling the interdependence of tourism demand: The global vector autoregressive approach. Annals of Tourism Research. 2017;67:1–13.
[95] Gunter U. Conditional forecasts of tourism exports and tourism export prices of the EU-15 within a global vector autoregression framework. Journal of Tourism Futures. 2018;4(2):121–38.
[96] Gunter U, Zekan B. Forecasting air passenger numbers with a GVAR model. Annals of Tourism Research. 2021;89:103252.
[97] Li H, Shi Y. Forecasting mortality with international linkages: A global vector-autoregression approach. Insurance: Mathematics and Economics. 2021;100:59–75.
[98] Salisu AA, Gupta R, Demirer R. Oil price uncertainty shocks and global equity markets: Evidence from a GVAR model. Journal of Risk and Financial Management. 2022;15(8):355.
[99] Cuaresma JC, Feldkircher M, Huber F. Forecasting with global vector autoregressive models: A Bayesian approach. Journal of Applied Econometrics. 2016;31(7):1371–1391.
[100] Assaf AG, Li G, Song H, Tsionas MG. Modeling and forecasting regional tourism demand using the Bayesian global vector autoregressive (BGVAR) model. Journal of Travel Research. 2018;58(3):383–397.
[101] Engle RF, Granger CWJ. Co-integration and error correction: Representation, estimation, and testing. Applied Econometrics. 2015;39(3):106–35.
[102] Shoesmith GL. Multiple cointegrating vectors, error correction, and forecasting with Litterman's model. International Journal of Forecasting. 1995;11(4):557–567.
[103] Tegene A, Kuchler F. Evaluating forecasting models of farmland prices. International Journal of Forecasting. 1994;10(1):65–80.
[104] Ampountolas A. Forecasting hotel demand uncertainty using time series Bayesian VAR models. Tourism Economics. 2019;25(5):734–756.
[105] Cliff AD, Ord JK. Space-Time Modelling with an Application to Regional Forecasting. Transactions of the Institute of British Geographers. 1975;64:119–128.
[106] Pfeifer PE, Deutsch SJ. A three-stage iterative procedure for space-time modeling. Technometrics. 1980;22(1):35–47.

[107] Pfeifer PE, Deutsch SJ. Identification and interpretation of first order space-time ARMA models. Technometrics. 1980;22(3):397–408.
[108] Borovkova S, Lopuhaä H, Ruchjana B. Consistency and asymptotic normality of least squares estimators in generalized STAR models. Statistical Neerlandica. 2008;62(4):482–508.
[109] Ruchjana B, Borovkova S, Lopuhaä H. Least squares estimation of generalized space-time autoregressive (GSTAR) model and its properties. AIP Conference Proceedings. 2012;1450:61–64.
[110] Mukhaiyar U, Pasaribu US. A new procedure for generalized STAR modeling using IAcM approach. Journal of Mathematical and Fundamental Sciences. 2013;44(2):1721–1792.
[111] Zewdie M, Wubit G, Ayele A. G-STAR Model for Forecasting Space-Time Variation of Temperature in Northern Ethiopia. Turkish Journal of Forecasting. 2018;2(1):9–19.
[112] Akbar MS, Setiawan, Suhartono, Ruchjana BN, Prastyo DD, Muhaimin A, et al. A Generalized Space-Time Autoregressive Moving Average (GSTARMA) Model for Forecasting Air Pollutant in Surabaya. Journal of Physics: Conference Series. 2020;1490(1):012022.
[113] Nikolopoulos K, Buxton S, Khammash M, Stern P. Forecasting branded and generic pharmaceuticals. International Journal of Forecasting. 2016;32(2):344–357.
[114] Jan F, Shah I, Ali S. Short-Term electricity prices forecasting using functional time series analysis. Energies. 2022;15(9):3423.
[115] Taylor, James W. Triple seasonal methods for short-term electricity demand forecasting. European Journal of Operational Research, 2010;204(1):139–152.
[116] Naim I, Mahara T, Idrisi AR. Effective short-term forecasting for daily time series with complex seasonal patterns. Procedia Computer Science. 2018;132:1832–1841.
[117] Cleveland RB, Cleveland WS, McRae JE, Terpenning I. STL: A seasonal-trend decomposition procedure based on loess. Journal of Official Statistics. 1990;6(1):3–73.
[118] Theodosiou M. Forecasting monthly and quarterly time series using STL decomposition. International Journal of Forecasting. 2011;27(4):1178–1195.
[119] Li Y, Bao T, Gong J, Shu X, Zhang K. The prediction of dam displacement time series using STL, Extra-Trees, and stacked LSTM neural network. IEEE Access. 2020;8:94440–94452.
[120] Yin H, Jin D, Gu YH, Park CJ, Han SK, Yoo SJ. STL-ATTLSTM: Vegetable price forecasting using STL and attention mechanism-based LSTM. Agriculture. 2020;10(12):612.
[121] Ouyang Z, Ravier P, Jabloun M. STL decomposition of time series can benefit forecasting done by statistical methods but not by machine learning ones. Engineering Proceedings. 2021;5(1):42.
[122] Tian F, Wang D, Wu Q, Wei D. An empirical study on network conversion of stock time series based on STL method. Chaos. 2022;32(10):103111.
[123] Scotch CG, Murgulet D, Constantz J. Time-series temperature analyses indicate conduction and diffusion are dominant heat-transfer processes in fine sediment, low-flow streams. Science of the Total Environment. 2021;768:144367.