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Article *in* INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS · April 2024

DOI: 10.1729/Journal.38816

IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

A Review of Time Series Forecasting Methods

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Abstract : There appears to be an increased interest in time series methods within the field of forecasting research methods. The exponential increase in the amount of time series data generated can be attributed to the adoption of technology and enhanced resources for data recording and storage. The data generated across every domain serves as the foundation for research on various time series methods. These data is dynamic, complex, and chaotic; thus, building forecasting models is challenging. In this paper, we study the existing econometric models for time series and machine learning models and classify them based on their characteristics. In addition, we conducted a comparative analysis to identify the characteristics of these models.

Index Terms - Time Series, Hybrid Models, Machine Learning Models, Classical Linear Models, Nonlinear Models

1. Introduction

A time series is a collection of observations made sequentially over time. The main aim of time series analysis is to make forecasts based on historical data comprising one or more time series [1]. Time series models provide forecasts, and this forecasted value can be compared against the observed value, which helps in decision-making. Time series data are generated rapidly in various domains such as medicine and healthcare, manufacturing, logistics, social science, finance, and marketing [2].

The study of time series forecasting has gained significant momentum as it finds applications across all domains. Time series analysis enables one to understand patterns in historical data and make long-term and short-term forecasts. It helps decision-makers make predictions, anticipate future trends, mitigate risks, and make informed and unbiased decisions [2].

Traditional time series forecasting techniques based on statistical probabilistic models have demonstrated remarkable efficiency; however, the rapid increase in data and the advent of big data have created a new landscape. These high-volume and high-velocity data are non-linear and have diverse patterns. Machine learning and artificial intelligence methods are leveraged to study these complex patterns and build a forecasting model. This shift has yielded significant results in terms of predictive accuracy and capability.

In this study, we perform a comparative analysis of various existing time series forecasting methods. The rest of the paper is organised as follows: section 2 discusses the challenges in time series forecasting, and section 3 discusses the existing time series forecasting methods (Traditional statistics methods, Machine learning methods and Hybrid models). Finally, Section 4 summarises the paper.

2. First-order Challenges in Time Series Methods

In today's data-driven world, time series forecasting methods have demonstrated remarkable results, but there are still a few problems. In this section, we discuss some of these issues. The major issues are data quality and the time required to update the model for live data.

2.1 Data Quality

The quality of the data plays a crucial role in the process of data analysis. The accuracy of the data analysis and model is significantly influenced by the quality of the data [3]. In practice, time series data are generated from multiple sources, such as field data collection, sensors, IT systems, economic indicators, network data, smart instruments, and servers. Due to diverse factors and objective conditions, these data inherit irregularities such as noise and missing values. Therefore, such irregularities must be dealt with using data processing methods before building a time series model.

The time series models were built using historical data. In this world of big data, data is generated continuously, and hence, the source of data is updated from time to time. Because the historical data is updated regularly, the long-term forecast model build does not give accurate results. To fix this, one needs to update the model and build a rolling window to obtain accurate forecasts. The main reason for this is that the model does not learn the features of the new data as it comes in, which in turn affects the predictions. Thus, it is crucial to continuously improve the forecasting model, which is quite a challenge.

2.2 Real-time Analysis

Real-time data analysis has become imperative in today's digital world. The ability to analyse the data as it is generated enables us to provide immediate insights and make timely decisions. Traditional time series models cannot keep pace with the influx of high volumes of data generated in real-time. This real-time series requires complex computational algorithms and must be integrated into the existing system, which is a resource-intensive and expensive process. In summary, although real-time analysis of time series has posed challenges in terms of data quality and scalability, it also offers data-driven insights.

3. Time Series Methods

In this section, we will discuss the existing time series methods. We classify these methods as traditional statistical models, machine learning models and hybrid models.

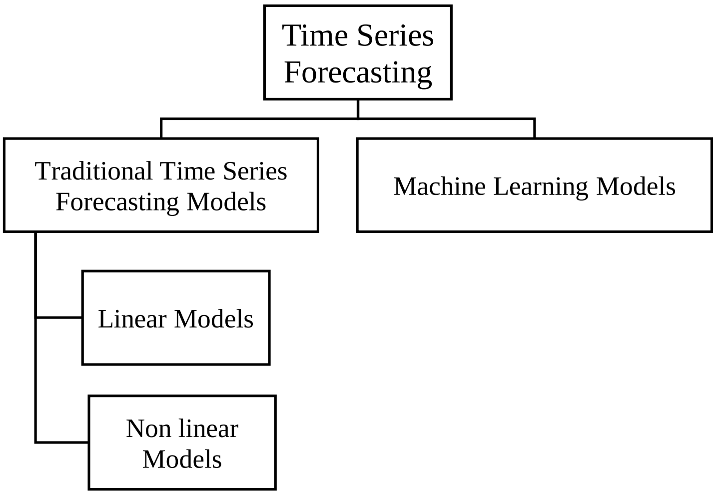

Figure 1: Types of Time Series Methods

4. Traditional Time Series Forecasting Models

Traditional time series forecasting methods are based on mathematical and statistical models. These models can be further classified into two categories: linear and non-linear models. The linear model includes the autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), and autoregressive integrated moving average model (ARIMA). It also includes exponential smoothing techniques such as simple exponential smoothing (SES), double exponential smoothing (DES), and triple exponential smoothing (TES).

The non-linear model mainly includes autoregressive conditional heteroscedasticity models (ARCH) and generalized autoregressive conditional heteroscedasticity models (GARCH). Table 1 discusses the comparative analysis of the characteristics of traditional time series models.

4.1 Linear Models

Slutsky, Walker, Yaglom, and Yule first developed the concept of autoregressive (AR) and moving average (MA) models [4]. In his work on forecasting stationary time series, Yule pioneered the incorporation of randomness into the analysis of such series [5]. He viewed each time series as an exemplification of a stochastic process and developed the concept of an autoregressive (AR) model within this framework. Wold proposed the famous decomposition theorem, which serves as a foundation for time series analysis methods [6]. The groundwork for time series forecasting was established early on. By 1970, the seminal work of Box and Jenkins introduced the ARMA model, which comprises three fundamental models: the AR model, the MA model, and the ARMA model itself. This model has been extensively applied in the analysis of stationary time series data [7].

The ARMA model stands as a prevalent approach for forecasting stationary time series data. It conceptualizes time series as a stochastic process, in which interdependence among the stochastic variables mirrors the temporal continuity of the original data. Consider the variables x_1 , x_2 , … x_m , that can be predicted as:

$$Y_t = \beta_0 + \sum_{i=1}^{m} \beta_1 x_{t-i} + E_t \qquad (1)$$

Here, Y represents the observed value of the prediction target and E signifies the error term. Being the subject of prediction, Y_t is influenced by its fluctuations, which are encapsulated by the following formula:

$$Y_t = \beta_0 + \sum_{i=1}^{m} \beta_1 Y_{t-i} + E_t \qquad (2)$$

The error term exhibits interdependencies across different time periods and is mathematically expressed as:

$$Z_t = \alpha_0 \epsilon_t + \alpha_1 \epsilon_{t-1} + \alpha_2 \epsilon_{t-2} + \cdots + \alpha_q \epsilon_{t-q} \qquad (3)$$

Consequently, the expression for the ARMA model can be given as:

$$Y_t = \beta_0 + \sum_{i=1}^{m} \beta_i Y_{t-i} + \sum_{j=1}^{n} \alpha_j Z_{t-j} \qquad (4)$$

When a time series y_t adheres to the aforementioned formula, it conforms to ARMA(p,q) process.

ARMA models are used to effectively model and analyse time series data and are applied across various fields such as signal processing and forecasting [8]. Chu, F. L. et al. forecasted tourism demand using ARMA-based methods, as detailed in a paper published in Tourism Management, demonstrating the effectiveness of ARMA models in predicting tourism trends and informing decision-making in the tourism industry [9]. Pappas, S. S., et al. used an ARMA model to forecast the electricity demand load for the Hellenic power system, showcasing the model's efficacy in predicting energy consumption patterns and aiding in effective grid management. This paper discusses the accuracy and reliability of the ARMA model in capturing the temporal dynamics of electricity demand, thereby facilitating efficient resource allocation and infrastructure planning within the Hellenic power system [10].

The ARMA forecasting time series model has achieved significant success in predicting stationary time series data. However, in real-world time series data, there is almost no purely stationary data. Therefore, the application of this model is limited by the characteristics of the data, and its versatility is poor. The non-stationary time series can be converted to a stationary time series by taking the difference. ARIMA(p,d,q) is a well-known non-stationary time series model. The ARIMA model comprises autoregressive (AR) components denoted by *p*, differencing is denoted by *d*, and moving average (MA) is denoted by *q*.

Historical data decomposes through an AR process that preserves past occurrences, an integrated (I) process that stationarise data and an MA process that captures errors. The *p* in the AR component represents a linear relationship that dependent variables share with their lagged values. The resultant model with the combination of AR (p) and MA (q) is expressed as follows:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \varepsilon_t y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (5)$$

Where ε_t is white noise$\sim N(\mu, \sigma^2)$, $\{\emptyset = 1,2, \dots p\}$ and $\{\theta = 1,2, \dots p\}$ are the coefficients of AR(p) and MA(q) components respectively.

To determine p and q values in the ARIMA model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) are used. In addition to that, AIC and BIC values are used for reference [11]. Mondal et al. (2014) conducted a study to evaluate the effectiveness of time series modelling, specifically ARIMA, in forecasting stock prices. They aimed to provide insights into the applicability and accuracy of ARIMA models in predicting stock market trends. The findings contribute to the ongoing discourse on the utility of statistical methods in financial forecasting, offering valuable implications for investors and analysts seeking reliable predictive tools in stock market analysis [12].

Exponential smoothing (ETS) methods are used to analyse stationary and non-stationary time series. It is widely used in various business sectors. Gardner Jr. (1985) discusses various aspects of exponential smoothing techniques [13]. This study covers the theoretical foundations of exponential smoothing, different types of exponential smoothing models (simple exponential smoothing, double exponential smoothing and triple exponential smoothing method), parameter estimation methods, forecasting accuracy measures, and empirical studies showcasing the effectiveness of exponential smoothing in forecasting tasks. In addition, this paper also highlights advancements in exponential smoothing methodologies and discusses practical applications in forecasting time series data across different domains such as business, economics, and finance.

The general forms of these exponential smoothing models provide a systematic framework for modeling time series data, it can be expressed as:

Single exponential smoothing:

$$L_t = \alpha \cdot Y_t + (1-\alpha) \cdot L_{t-1} \quad (6)$$

Double exponential smoothing:

$$L_t = \alpha \cdot Y_t + (1-\alpha) \cdot (L_{t-1} + T_{t-1}) \text{ and } T_t = \beta \cdot (L_t - L_{t-1}) + (1-\beta) \cdot T_{t-1} \quad (7)$$

Triple exponential smoothing:

$$L_t = \alpha \cdot \left(\frac{Y_t}{C_{t-m}}\right) + (1-\alpha) \cdot (L_{t-1} + T_{t-1}) \quad (8)$$

$$T_t = \beta \cdot (L_t - L_{t-1}) + (1-\beta) \cdot T_{t-1} \text{ and } C_t = \gamma \cdot \left(\frac{Y_t}{L_t}\right) + (1-\gamma) \cdot C_{t-m} \quad (9)$$

Here, L_t represents the level component at time t, Y_t denotes the observed value at time t, T_t is the trend component at time t and C_t represents the seasonal component at time t. The parameters α, β and γ control the smoothing of the level, trend, and seasonal components respectively. Additionally, *m* denotes the seasonal period.

Chukwulozie et al. (2017) performed an analysis of cigarette production using the double exponential smoothing model. In their study, they explored the application of this forecasting technique to predict trends and patterns in cigarette production data. This approach involves capturing both the level and trend components of the time series data to provide accurate forecasts, which can be valuable for decision-making processes in the tobacco industry. In Table 1, a comparative analysis of linear models is summarised.

Model	Characteristics
AR (p)	• It captures the relationship between a variable and its lagged values. • Suitable for data with an underlying trend but no seasonality. It uses past observations to predict future values.

MA (q)	• It focuses on the relationship between a variable and its past prediction errors (residuals). • Ideal for data with no trend but possibly some seasonality. It accounts for short-term fluctuations.
ARMA (p,q)	• It combines both AR and MA components. • Appropriate for data with both trend and short-term fluctuations. It balances the effects of past values and predictions.
ARIMA (p,d,q)	• It extends ARMA by incorporating differencing (integration) to achieve stationarity. • It is suitable for non-stationary data with trends and/or seasonality. ARIMA models handle both short-term and long-term dependencies.
SES	• It is suitable for data without trend or seasonality; and uses a single smoothing factor. • It is most suitable for stationary time series data with no clear trend or seasonal pattern.
DES	• It accounts for trends in data; and it uses two smoothing factors (level and trend). • Ideal for data with a trend but without seasonality.
TES	• It incorporates seasonality in addition to level and trend; and it uses three smoothing factors. • Appropriate for data with trends and seasonality.

Table 1: A Comparative Analysis of Linear Models

4.2 Non-linear models

Linear forecasting models offer ease of understanding and simplicity in implementation; however, their effectiveness diminishes with nonlinear time series data due to inherent linear assumptions. Thus, to address this limitation, non-linear time series forecasting models are proposed. Among the classical nonlinear models, the Autoregressive Conditional Heteroscedasticity Model (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity models (GARCH) have contributed valuable insights in this field.

Nonlinear models are flexible and allow us to capture intricate relationships in data that linear models often miss. ARCH models focus on modelling the conditional variance of a time series, allowing for varying volatility over time. They are particularly useful for financial data where volatility clusters are, whereas GARCH models extend ARCH by incorporating lagged conditional variances. They capture both short-term and long-term volatility patterns, making them valuable for risk management and financial forecasting. These ARCH models were introduced by Engle in 1982 and allow the variance of the current error term to be a function of the sizes of previous periods' errors [14]. The GARCH model was developed by Bollerslev in 1986 and is an extension of the ARCH model by including past conditional variances in addition to past squared errors [15].

ARCH model captures the essence of volatility clustering by allowing the conditional variance to be a function of past squared errors. The ARCH (q) model can be represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 \quad (10)$$

Where σ_t^2 is the conditional variance, ϵ_t is the error term and $\alpha_0, \alpha_1, \ldots, \alpha_q$ are the parameters to be estimated.

The GARCH model extends the ARCH model by including lagged conditional variances in the equation, thus providing a more comprehensive representation of volatility. The GARCH (p, q) model is formulated as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 \quad (11)$$

where β_j represents the coefficients for the lagged conditional variances. This model is particularly adept at capturing the persistence of shocks to volatility over time.

Chand et al. (2012) studies the modelling and volatility analysis of share prices by employing ARCH and GARCH models. Their study demonstrates that the utilization of ARCH and GARCH models leads to enhanced results in predicting and analysing share price volatility. By incorporating these advanced econometric techniques, they provide valuable insights into understanding the dynamics of share price movements, thereby contributing to more accurate risk management and investment decision-making processes [16].

5. Machine Learning Models

Traditional time series forecasting models excel in identifying and leveraging linear patterns within small datasets. However, their effectiveness diminishes when faced with complex, large-scale, nonlinear datasets. This has shifted the focus of researchers toward machine learning and deep learning approaches for time series prediction. Artificial neural networks like multi-layer perceptrons (MLPs) and radial basis function (RBF) networks are some of the machine learning models that offer adaptive and self-organizing learning mechanisms, making them adept at handling nonlinear time series forecasting tasks across various domains [17]. Additionally, techniques such as Gaussian process regression, support vector machines and LSTM networks have been employed, showcasing promising forecasting abilities in nonlinear time series analysis [17].

5.1 Artificial Neural Network

Artificial neural networks (ANN) are a data-driven predictive models inspired by the human brain. It has remarkable capabilities like self-organisation, self-learning and robust nonlinear approximation. These are the non-linear structures part of the models that can effectively capture the nonlinearity of the data and effectively capture intricate patterns within time series data. [18]. ANN is a general, flexible, nonlinear tool used for approximating any arbitrary function. ANN architecture includes neurons like our brain's architecture. Figure 2 shows the basic structure of ANN architecture.

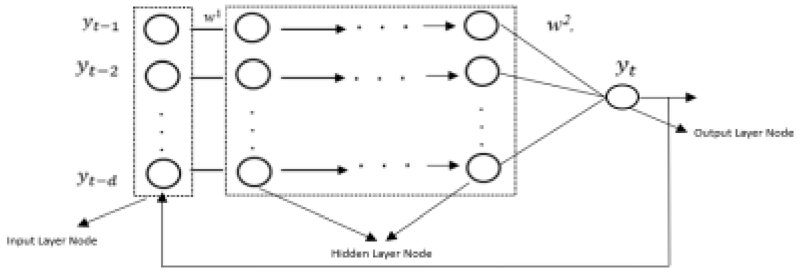

Figure 2: ANN Architecture

For time series forecasting, it is advisable to use a dynamic neural network (DNN), where the network depends upon the current and past values. DNN network structures can be written as:

$$y_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \dots, y_{t-d}) + \varepsilon_t \quad (12)$$

Where y_t is the original series, ε_t is the error term, $f(\cdot)$ is a nonlinear function, and $y_{t-1}, y_{t-2}, y_{t-3}, \dots, y_{t-d}$ are the feedback lags.

At present, neural networks are widely used in time series forecasting and demonstrate promising potential in time series forecasting, offering competitive performance compared to traditional forecasting methods [20].

The study by Borghi et al. (2021) yielded promising results, showcasing the MLP ANN model's superior performance in accurately forecasting COVID-19 transmission rates compared with traditional methods. Their primary objective was to develop a reliable forecasting tool to assist policymakers and healthcare authorities in making informed decisions during the pandemic [21].

5.2 Support Vector Machines

The support vector machine (SVM) was proposed by vapnik [22]. It has significant benefits in managing limited datasets and tackling complex, nonlinear challenges. It provides robust solutions [23]. Unlike other neural networks, SVM minimizes the upper bound of the generalisation error rather than the empirical error, based on the structured risk minimization principle. In addition, a collection of high-dimensional linear functions is applied by the SVMs model to create a regression function. The SVM regression function is expressed as follows:

$$y = w\emptyset(x) + b; \quad (13)$$

Where $\emptyset(x)$ is the high dimensional feature space which is non-linear mapped from the input space x. The coefficients w and b are estimated by minimising:

$$R_{SVM_s} = C\frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(d_i y_i) + \frac{1}{2}\|w\|^2 \quad (14)$$

$$L_\varepsilon(d_i y_i) = \begin{cases} |d-y| - \varepsilon, |d-y| \geq \varepsilon \\ \quad otherwise \end{cases} \quad (15)$$

Where, C and ε are prescribed parameters, E is the tube size of SVM, d_i is the actual closing price in i^{th} period

$C\frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(d_i y_i)$ is the empirical risk measured by ε intensive loss function

$\frac{1}{2}\|w\|^2$ is regularised term

C is the regularisation constant that evaluates the trade-off between the empirical risk and the flatness of the model

ς and ς^* are the slack variables representing the distance from actual values to the corresponding boundary values of ε tube.

The above equation 14 can be transformed to the following constrained formation:

Minimise:

$$R(w, \varsigma, \varsigma^*) = \frac{1}{2}ww^T + C^*\left(\sum_{i=1}^{N}(\varsigma_i + \varsigma_i^*)\right) \quad (16)$$

Subject to:

$$w\phi(x_i) + b_i - d_i \leq \varepsilon + \varsigma_i^* \quad (17)$$

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \varsigma_i \quad (18)$$

$$\varsigma_i, \varsigma_i^* \geq 0, \qquad i = 1,2, \dots, N$$

Equation 16 can be solved by Langragian multiplier and maximising dual function of equation 16.

A kernel function $K(x_i, x_j)$is a function that measures the similarity between two vectors x_i and x_j in a high-dimensional space $\phi(x_i)$ and $\phi(x_j)$.It does this by computing the dot product of $\phi(x_i)$ and $\phi(x_j)$, i.e., $K(x_i, x_j)$= $\phi(x_i) \cdot \phi(x_j)$. Different kernel functions can produce different inner products, which can be used to build machines with various kinds of non-linear decision boundaries in the input space. The best model is the one that minimises the error estimate among the different kernel functions.

SVMs are known for their capability to model nonlinear relationships using kernel functions, allowing them to capture complex patterns and dependencies present in time series data more accurately than linear methods [24]. Puspita (2019) applied Support Vector Machines (SVMs) for electricity consumption forecasting, leveraging their capacity to capture complex, nonlinear patterns in time series data. The dataset comprised historical electricity consumption records, incorporating variables such as time of day, day of the week, and potential weather conditions. SVMs are employed to develop accurate predictive models, aiming to forecast future consumption trends. Additionally, kernel principal component analysis (kPCA) was employed to preprocess the data, extracting pertinent features and enhancing forecasting precision [25]. Table 2 shows the Comparative Analysis of time series forecasting models.

Models	Characteristics
ANN	• Ability to capture nonlinear relationships. • Robustness to noisy data. • Requires significant computational resources.
SVM	• Effective in handling nonlinear relationships. • Suitable for small to medium-sized datasets. • Versatile with various kernel functions. • Generalization capability.
GARCH	• Specialized in modelling volatility clustering. • Captures time-varying volatility. • Incorporates past variance to predict future volatility. • Commonly used in financial markets.
ARCH	• Models conditional heteroscedasticity. • Captures volatility clustering. • Suitable for modelling time-varying variance. • Utilizes lagged squared residuals for forecasting.

Table 2: Comparative Analysis of Machine Learning Models for Time series

6. Hybrid Forecasting Models

In the realm of time series forecasting, traditional statistical and machine learning methods offer distinct advantages. However, real-world time series data exhibit specific characteristics such as determining linearity versus non-linearity which is challenging, and assessing model validity remains elusive. Purely linear or nonlinear time series are rare; hence, most data combine both linear and nonlinear elements, and no single model universally fits all scenarios and capturing diverse time series patterns simultaneously is difficult.

To address this issue a hybrid approach merging traditional and machine learning techniques has emerged as a development trend. The hybrid algorithm, which integrates ARIMA or exponential smoothing models and machine learning techniques, has found successful applications across various domains, yielding favorable outcomes.

Cadenas and Rivera (2010) studied wind speed forecasting in three distinct regions of Mexico. They built a hybrid model that combined the strengths of both time series models (ARIMA) and artificial neural networks (ANN). The results demonstrate the superiority of this hybrid approach, emphasizing the significance of incorporating additional meteorological variables for accurate wind speed forecasts. Their study underscores the effectiveness of the hybrid ARIMA–ANN model for wind speed prediction, especially when considering additional variables beyond historical wind speed data [26].

Complex time series data pose challenges for single statistical or machine learning models, leading to poor performance and weak generalization. Hybrid models, which combine different methodologies, offer superior accuracy and generalization, making them a preferred choice when uncertainty exists about the most suitable forecasting approach [27].

7. Conclusion

In this age of big data, time series forecasting has emerged as a focal point of research. The proliferation of time series data across all domains has laid a robust foundation for investigating novel methods in time series analysis. As this field continues to evolve, researchers are struggling to fine-tune the distribution patterns inherent in large-scale time series datasets. To enhance forecasting accuracy and performance, a growing number of experts are turning to hybrid models that capture these complexities.

This paper commences by elucidating the fundamental concept of time series. It then delves into the pressing issues currently faced in the study of time series forecasting. We then categorize the various time series forecasting techniques, providing a comprehensive overview. We hope that this comprehensive survey will serve as a valuable reference for other researchers navigating the dynamic landscape of time series forecasting.

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