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Comparative Theoretical Analysis of Time Series Techniques Intended for Forecasting

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Abstract
Time series forecasting plays a crucial role in various domains, enabling organizations and individuals to make informed decisions and predictions based on historical data. This abstract provides an overview of different time series forecasting techniques and their applications. Choosing the most appropriate technique depends on factors such as the presence of trend and seasonality, data stationarity, data dimensionality, interpretability requirements, and the need to quantify uncertainty. Assessing the specific characteristics of the data and evaluating the performance of different techniques are crucial in selecting the most suitable approach for time series forecasting. Time series forecasting techniques continue to evolve, and advancements in machine learning and statistical modeling offer new opportunities for accurate and reliable predictions in diverse domains.

Keywords - ARIMA, Bayesian methods, Neural Networks, Prophet, Spectral Analysis, VAR.

I. INTRODUCTION

Time series forecasting is a statistical technique used to predict future values or patterns in a time series dataset based on past observations. A time series is a sequence of data points collected over successive time intervals, such as hourly, daily, monthly, or yearly. The goal of time series forecasting is to analyze historical data and identify patterns, trends, and dependencies to make accurate predictions about future values [1, 2]. It involves applying various forecasting methods and models to the time series data, considering factors such as seasonality, trend, cyclicality, and any other relevant patterns or factors that influence the data. The choice of the forecasting method depends on the characteristics of the data, the presence of trends or seasonality, the available historical observations, and the specific objectives of the forecasting task. Time series forecasting finds applications in various domains, including economics, finance, sales forecasting, demand planning, weather prediction, stock market analysis, and many other fields where understanding and predicting future trends and patterns are crucial for decision-making and planning [3, 4].

II. PURPOSE OF TIME SERIES ANALYSIS

The purpose of time series forecasting analysis is to predict future values, patterns, and trends in time-dependent data based on historical observations. It serves several important objectives and provides valuable insights for decision-making and planning. Here are some key purposes of time series forecasting analysis:

- Prediction: The primary purpose of time series forecasting is to predict future values of a variable of interest. By analyzing patterns and trends in historical data, forecasting models can provide estimates and projections for future time points [5]. This enables organizations and individuals to anticipate future outcomes and make informed decisions based on the forecasted values.
- Planning and Resource Allocation: Time series forecasting helps in planning and allocating resources effectively. By forecasting future demand, sales, or production levels, organizations can optimize their operations, adjust inventory levels, allocate resources efficiently, and manage supply chains more effectively [6]. This aids in avoiding overstocking or understocking situations, minimizing costs, and improving overall operational efficiency.
- Budgeting and Financial Planning: Time series forecasting assists in budgeting and financial planning processes. It helps organizations project future revenues, expenses, cash flows, and financial performance. By forecasting financial variables such as

sales, revenue, and costs, companies can set realistic targets, allocate budgets, and make financial decisions with greater accuracy and confidence [7].

- Risk Management: Time series forecasting plays a crucial role in risk management. By identifying potential risks and uncertainties, forecasting models enable organizations to assess and manage risks effectively. For example, in finance, forecasting models help in predicting market movements and volatility, assisting investors and financial institutions in making informed decisions to mitigate risks [8].
- Policy Formulation: Time series forecasting provides valuable inputs for policy formulation and planning. Governments and policymakers use forecasting models to predict economic indicators, such as GDP growth, inflation rates, employment levels, and population trends. These forecasts aid in designing appropriate policies, implementing economic interventions, and formulating strategies to address social and economic challenges [9].
- Performance Evaluation: Time series forecasting allows for evaluating the accuracy and performance of existing models and methods. By comparing actual outcomes with forecasted values, organizations can assess the effectiveness of their forecasting models, identify areas of improvement, and refine their forecasting techniques. This iterative process helps in continuous learning and enhancing forecasting capabilities over time [10, 11].

Overall, the purpose of time series forecasting analysis is to provide reliable and accurate predictions of future values, patterns, and trends. It assists in decision-making, resource allocation, financial planning, risk management, policy formulation, and performance evaluation. By leveraging historical data, forecasting analysis empowers organizations and individuals to make proactive and informed decisions, leading to improved operational efficiency, better financial outcomes, and effective planning for the future.

II. STATE-OF-THE-ART

The purpose of conducting a literature review is to review and combine the arguments and ideas of prevailing knowledge in a specific field without accumulating any new contributions. Being constructed on prevailing knowledge they assist the researcher in even turning the wheels of the topic of research. It is conceivable only with profound knowledge of what is wrong in the existing findings in detail to overpower them. This section illustrates the conducted literature review to gain deep insight into the research area under study.

Matthew Oyeleye et al., 2022 [12] explored numerous noteworthy data-driven models comprising the ARIMA model, linear regression, SVR, and LSTM RNN algorithm for the examination of accelerometer data to make upcoming HR forecasting from healthy people. The consequences of this research disclose that the research data are acceptable and can be discovered using specific data analytic practices to predict future heart rates using ML technique i.e. an accelerometer.

Jongsung Kim et al., 2022 [13] focused on the significance of the proficient water resource supply. Due to the non-linear nature of human activities, predicting the pattern of the data accurately with the ARIMA model was difficult. Therefore, the authors made use of the DL-based LSTM technique to construct a water consumption prediction model for consumers. The ARIMA and LSTM model was developed in the training dataset. The test dataset was used to evaluate the performance of two models. The LSTM model outperformed the ARIMA model in all aspects (correlation coefficient: mean 89% and root mean square error: mean 5.60 m3).

Evangelos D. Spyrou et al., 2022 [14] discussed the concern associated with the quality of the air in the port area of Igoumenitsa in Greece. The research paper elaborates on the work conducted on environmental tracking prominently for coastal areas. The data have been gathered using the wireless environmental sensors system established in the Port of Igoumenitsa, Greece. The ML model has been used to perform a prophecy. The authors used univariate LSTM to predict future values. A comparison between the LSTM and ARIMA model have been conducted and it has been found that the ARIMA model outperforms the LSTM in conducting prediction.

Pushpendra Singh and Anubha Gupta, 2021 [15] stated that the functions models like Gaussian, gamma, and logistics relevant to pandemics are the specific cases of the GSIR model. GSIR solution manages time-varying considerations that develop over time and enclosed expressions are presented for all the system waves. Although the GSIR framework can be used to model any pandemic it is preferred as a data-driven approach for conducting a predictive examination of the COVID-19 pandemic. Using the anticipated model, the study is being made on the COVID-19 data of many countries like the USA, India, Brazil, and many other regions of the world. Furthermore, the GSIR model offers improved outcomes as equated to the SIR model as it is a progressive theory of the SIR model.

G. M. Botelho *et al.*, 2021 [16] elaborated on the ARIMA model for forecasting the unregistered cases related to Hansen's disease during the COVID-19 pandemic in countries like Brazil, Tocantins, and Palmas. The research paper made use of environment-friendly time-series research of infection signals from 2001 to 2020 exhausting the ARIMA model in Palmas. Data was gathered from NIIS and the estimation of the population was made from the Brazilian Institute of Geography and Statistics. The ARIMA model (4, 0, 3) points out the lowest values for the two tested information criteria and the best-fit data as AIC = 431.30 and BIC = 462.28 at a significance level of 0.05.

Christos Katris, 2021 [17] proposed Vector Autoregressive (VAR) models to investigate the consequence of COVID-19 cases on females, Youth, and general unemployment in Greece. The predicting capability of the VAR model is found to be constrained and other univariate applications seem recommendable. Furthermore, a tremor in COVID-19 cases in Greece had the least effect on all types of unemployment. The consequence of COVID-19 cases is anticipated to be concentrated in Greece associated with the EU27 countries. A plan is that the VAR model can be used to discover the influence of disease and should be aided by an ARIMA model for forecasting motives.

Ewa Chodakowska et al., 2021 [18] elaborated on the glitch of inadequate knowledge of the influence of noise on the ARIMA model identification. The research work anticipates a simulation-based solution to the investigation of the tolerance to the noise of the ARIMA model in predicting the electrical load. The ARIMA model has been acquired from the real load data of the Polish Power System. The model has been re-identified and the parameters were assessed to compute the new forecasts. The prediction was made that the response of the ARIMA model to the random disturbances of the modeled time series was comparatively feeble. The obtained results emphasize the critical role played by the data preprocessing stage in data mining and learning. The contribution to making precise decisions in an uncertain environment has been enhanced.

III. COMPARING DIFFERENT FORECASTING TECHNIQUES

This section elaborates on the difference between different forecasting techniques based on seasonal handling, model components, seasonal periodicity, parameter estimation, and forecasting performance.

ARIMA V/S SARIMA

ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) are both popular time series forecasting models that capture the dependencies, trends, and seasonality in the data. Here's a comparison between ARIMA and SARIMA:

Seasonality Handling:

- ARIMA: ARIMA models are suitable for capturing the dependencies and trends in non-seasonal time series data. They do not explicitly handle seasonality in the data [19].
- SARIMA: SARIMA models are specifically designed to handle time series data with seasonal patterns. They incorporate additional seasonal components to capture and model the seasonality in the data.

Model Components:

- ARIMA: ARIMA models consist of three components: autoregressive (AR), differencing (I), and moving average (MA). The AR component captures the relationship between an observation and a lagged value of the series, the MA component models the dependency on the residual errors, and the I component represents the differencing required to make the series stationary.
- SARIMA: SARIMA models extend the ARIMA framework by incorporating additional seasonal components. They include seasonal AR, differencing, and MA components along with the regular non-seasonal ARIMA components. The seasonal components capture the relationship between an observation and a lagged value at the same point in the seasonal cycle [20].

Seasonal Periodicity:

- ARIMA: ARIMA models do not explicitly handle seasonal periodicity in the data. They are suitable for non-seasonal time series forecasting.
- SARIMA: SARIMA models explicitly account for the seasonal periodicity in the data. They are designed to capture and model seasonality by including seasonal components in addition to non-seasonal components.

Parameter Estimation:

- ARIMA: In ARIMA models, the parameters (order of AR, I, and MA components) are estimated based on the autocorrelation and partial autocorrelation functions of the time series data. The model is selected based on information criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion).
- SARIMA: SARIMA models involve estimating additional parameters related to the seasonal components. The selection of the SARIMA model is typically performed using a combination of AIC or BIC criteria, along with an analysis of seasonal patterns in the data [21].

Forecasting Performance:

- ARIMA: ARIMA models are effective for forecasting non-seasonal time series data with dependencies and trends. They can capture patterns and relationships in the data but may not be able to capture seasonal variations.
- SARIMA: SARIMA models are specifically designed for forecasting seasonal time series data. They can effectively capture both the non-seasonal patterns and the seasonal variations in the data, making them suitable for forecasting tasks with strong seasonal components [22].

The choice between ARIMA and SARIMA depends on the presence or absence of seasonality in the data. If the data exhibits clear seasonal patterns, SARIMA models are more appropriate as they explicitly incorporate seasonal components. For non-seasonal data, ARIMA models can provide accurate forecasts by capturing the dependencies and trends.

VAR V/S/ Neural Networks

VAR (Vector Autoregression) and Neural Networks are both widely used techniques for time series forecasting, but they have different approaches and characteristics. Here's a comparison between VAR and Neural Networks:

Model Structure:

- VAR: VAR models are based on linear relationships between multiple variables in a time series. They assume that each variable is influenced by its own lagged values as well as the lagged values of other variables in the system. VAR models capture the dynamic relationships and dependencies among the variables in a multivariate time series.
- Neural Networks: Neural Networks, especially architectures like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, are based on non-linear relationships. They can capture complex patterns and dependencies in the data by processing sequential information and learning from the historical time series data [23].

Handling Non-linearity:

- VAR: VAR models assume linearity in the relationships between variables. While they can capture linear dependencies, they may struggle to model and capture non-linear relationships present in the data.
- Neural Networks: Neural Networks are well-suited for capturing non-linear relationships in time series data. They can learn complex patterns, interactions, and dependencies among variables, allowing for more accurate forecasting when the underlying dynamics are non-linear.

Adaptability:

- VAR: VAR models assume that the relationships among variables are stationary over time. They may not adapt well to changes in the data or shifts in the underlying dynamics.
- Neural Networks: Neural Networks are more adaptable and can handle changing dynamics in the time series. They can capture evolving patterns and adjust their parameters to adapt to changing relationships in the data.

Handling High-Dimensional Data:

- VAR: VAR models can handle multivariate time series data with multiple variables, making them suitable for forecasting in high-dimensional settings.
- Neural Networks: Neural Networks can handle high-dimensional time series data as well. They can effectively process and extract relevant features from multidimensional data using architectures like Multilayer Perceptrons (MLPs) or Convolutional Neural Networks (CNNs) [24].

Interpretability:

- VAR: VAR models provide interpretable coefficients that represent the relationships between variables. The coefficients can offer insights into the direction and strength of the relationships.
- Neural Networks: Neural Networks are often considered "black-box" models because they lack explicit interpretability. While they can provide accurate predictions, understanding the underlying relationships in the data can be challenging.

Training and Parameter Estimation:

- VAR: VAR models typically involve estimating the parameters through methods like Ordinary Least Squares (OLS) or Maximum Likelihood Estimation (MLE). The model selection and order determination can be based on statistical criteria and analysis of the data.
- Neural Networks: Neural Networks require training through an iterative process of forward and backward propagation. The model architecture, hyperparameters, and training algorithms need to be chosen carefully. Training may involve techniques such as gradient descent or stochastic gradient descent [25].

The choice between VAR and Neural Networks depends on the characteristics of the data, the complexity of relationships, and the forecasting goals. VAR models are suitable when linear relationships among variables are assumed, and interpretability is important. Neural Networks excel in capturing non-linear relationships, handling high-dimensional data, and adapting to changing dynamics, but they may lack interpretability. It's advisable to evaluate the data, consider the specific requirements, and compare the performance of both approaches to determine the most suitable technique for a given time series forecasting task.

Moving Averages V/S Exponential Soothing Methods

Moving Averages and Exponential Smoothing are two commonly used techniques for time series forecasting. Here's a comparison between Moving Averages and Exponential Smoothing methods:

Calculation Approach:

- Moving Averages: Moving Averages calculate the average of a fixed-size window of past observations to generate forecasts. The window size can be chosen based on the desired level of smoothing and the characteristics of the data.
- Exponential Smoothing: Exponential Smoothing methods assign exponentially decreasing weights to past observations, with more recent observations receiving higher weights. The weights are determined by a smoothing parameter, and the forecast is generated as a weighted sum of past observations.

Flexibility:

- Moving Averages: Moving Averages provide a simple approach to smoothing the data. They can effectively remove short-term fluctuations and highlight long-term trends. Different types of moving averages, such as Simple Moving Average (SMA) and Weighted Moving Average (WMA), offer flexibility in adjusting the weights assigned to past observations.
- Exponential Smoothing: Exponential Smoothing methods offer greater flexibility in capturing different types of patterns and trends in the data. They can handle various levels of smoothing, including simple exponential smoothing (SES) for no trend or seasonality, Holt's Linear Exponential Smoothing for trended data, and Holt-Winters' Exponential Smoothing for data with both trend and seasonality [26].

Handling Trend and Seasonality:

- Moving Averages: Moving Averages can help smooth out the effects of random fluctuations and highlight long-term trends in the data. However, they may not explicitly handle seasonality or capture complex patterns related to trend and seasonality.

- Exponential Smoothing: Exponential Smoothing methods, especially Holt-Winters' Exponential Smoothing, are designed to handle both trend and seasonality in the data. They incorporate additional components, such as trend and seasonality factors, to capture and forecast these patterns effectively [27].

Weighting of Observations:

- Moving Averages: Moving Averages assign equal weights to all observations within the window, resulting in a uniform smoothing effect. This can lead to slower adaptation to changes in the data.
- Exponential Smoothing: Exponential Smoothing assigns higher weights to more recent observations, allowing for quicker adaptation to changes in the data. The weighting scheme ensures that recent observations have a larger impact on the forecast.

Forecasting Performance:

- Moving Averages: Moving Averages are relatively simple and robust methods. They can provide reasonable forecasts for stable and slowly changing time series data. However, they may struggle to capture and adapt to sudden changes or complex patterns in the data [28].
- Exponential Smoothing: Exponential Smoothing methods can capture and forecast a wider range of patterns and trends. They are particularly useful when the data exhibits trends or seasonality. Exponential Smoothing methods generally perform well for forecasting in various settings, but the specific variant used should align with the characteristics of the data.

The choice between Moving Averages and Exponential Smoothing methods depends on the characteristics of the data, the presence of trend and seasonality, and the desired level of smoothing. Moving Averages offer simplicity and straightforwardness, while Exponential Smoothing methods provide greater flexibility and better handling of trend and seasonality. It's advisable to analyze the data, consider the underlying patterns, and evaluate the performance of both methods to determine the most suitable technique for a particular time series forecasting task.

Prophet V/S State Space Models

Prophet and State Space models are both widely used techniques for time series forecasting, but they have different approaches and characteristics. Here's a comparison between Prophet and State Space models:

Modeling Approach:

- Prophet: Prophet is a forecasting model developed by Facebook's Core Data Science team. It is designed to handle time series data with strong seasonality, multiple trends, and holiday effects. Prophet utilizes an additive modeling approach, decomposing the time series into trend, seasonality, and holiday components.
- State Space Models: State Space models are a flexible framework for modeling time series data. They consist of two components: the observation equation and the state equation. The observation equation describes the relationship between observed data and latent states, while the state equation represents the evolution of the latent states over time.

Seasonality Handling:

- Prophet: Prophet has built-in capabilities to handle various types of seasonality, including daily, weekly, and yearly patterns. It incorporates the Fourier series to capture the seasonality components and provides flexibility in modeling seasonality with different frequencies.
- State Space Models: State Space models can handle complex time series dynamics, including trend, seasonality, and other forms of dependencies. They can capture nonlinear relationships, time-varying parameters, and state dependencies [29].

Trend Modeling:

- Prophet: Prophet incorporates a piecewise linear trend model by fitting a set of linear regression models to the historical data. It captures changes in the trend over time and allows for the identification of change points.
- State Space Models: Estimating the parameters of a State Space model typically involves using techniques like Maximum Likelihood Estimation (MLE) or Bayesian Inference. These methods provide efficient parameter estimation and uncertainty quantification.

Automatic Feature Selection:

- Prophet: Prophet performs automatic feature selection, identifying relevant features from the data. It can handle missing values and outliers, making it robust to data quality issues [30].
- State Space Models: State Space models offer flexibility in model specification and customization. They can incorporate various components and structures, such as ARIMA, trend models, and seasonal effects. State Space models can be tailored to the specific characteristics and dynamics of the time series data.

Interpretability:

- Prophet: Prophet provides interpretable results, allowing users to understand the contributions of trend, seasonality, and holiday effects to the forecast. It also offers the ability to analyze the forecast components individually.
- State Space Models: State Space models are powerful for forecasting, especially in complex scenarios where multiple dependencies and nonlinearities exist. They can capture and model intricate patterns and dynamics, making them suitable for a wide range of time series forecasting tasks.

The choice between Prophet and State Space models depends on the specific requirements of the forecasting task. Prophet is particularly well-suited for handling time series data with strong seasonality, multiple trends, and holiday effects, while State Space models offer greater flexibility and can handle complex dynamics and dependencies. It's recommended to analyze the data, consider the underlying patterns, and evaluate the performance of both techniques to determine the most suitable approach for a given time series forecasting problem.

Spectral Analysis V/S Bayesian Methods

Spectral Analysis and Bayesian Methods are two different approaches used in time series forecasting. Here's a comparison between Spectral Analysis and Bayesian Methods:

Spectral Analysis:

Frequency Domain Analysis:

- Spectral Analysis: Spectral Analysis focuses on analyzing the frequency components of a time series. It involves decomposing the time series data into its constituent frequencies using techniques such as Fourier Transform or Wavelet Transform. Spectral Analysis helps identify dominant frequencies, periodic patterns, and the presence of seasonality in the data.
- Bayesian Methods: Bayesian Methods approach time series forecasting from a probabilistic perspective. They involve specifying a prior distribution and updating it with observed data to obtain a posterior distribution. Bayesian Methods allow for incorporating prior knowledge, expert opinions, and uncertainty quantification in the forecasting process [31].

Identifying Periodic Components:

- Spectral Analysis: Spectral Analysis is useful for identifying and characterizing periodic components in the time series data, such as daily, weekly, or yearly cycles. It provides insights into the strength and nature of different frequency components, allowing for the detection of patterns and periodic behavior.
- Bayesian Methods: Bayesian Methods use Bayesian inference to estimate the model parameters. This involves updating the prior distribution using Bayes' theorem and obtaining the posterior distribution of the parameters. Markov Chain Monte Carlo (MCMC) methods or variation inference techniques are commonly used for parameter estimation.

Power Spectrum Estimation:

- Spectral Analysis: Spectral Analysis allows for the estimation of the power spectrum, which indicates the distribution of energy across different frequencies. It helps identify important frequencies or spectral peaks in the data, aiding in the understanding of dominant periodicities.
- Bayesian Methods: Bayesian Methods offer flexibility in model specification, allowing for the incorporation of different model structures, prior distributions, and assumptions. They provide a framework for model comparison, model selection, and model averaging based on probabilistic measures such as Bayes factors or posterior model probabilities.

Stationarity Assumption:

- Spectral Analysis: Spectral Analysis assumes stationarity in the time series data, meaning that the statistical properties of the data do not change over time. If the time series exhibits non-stationarity, pre-processing steps such as detrending or differencing may be required before applying spectral analysis techniques.
- Bayesian Methods: Bayesian Methods naturally provide a way to quantify uncertainty in the forecasting process. They generate posterior predictive distributions, which capture the uncertainty associated with the forecasts. This information can be valuable for decision-making and risk management [32].

The choice between Spectral Analysis and Bayesian Methods depends on the nature of the time series data and the goals of the analysis. Spectral Analysis is particularly suitable for identifying periodic components and understanding the frequency structure of the data. Bayesian Methods, on the other hand, provide a probabilistic framework for modeling, parameter estimation, and uncertainty quantification. They are well-suited for incorporating prior knowledge, handling complex models, and providing a comprehensive probabilistic analysis. The choice depends on the specific requirements of the forecasting task and the nature of the data being analyzed.

IV. CONCLUSION

In conclusion, time series forecasting techniques offer a range of approaches to analyze and predict future values of a time-dependent variable. Each technique has its strengths and weaknesses, and the choice of the most suitable technique depends on the specific characteristics of the data and the objectives of the analysis. The research paper elaborated on the difference between the popular time series forecasting techniques on aspects like seasonal handling, model components, seasonal periodicity, parameter estimation, and forecasting performance.

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