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Abstract

Time series analysis and decomposition are crucial in examining economic data as they uncover elements such as trends, and seasonal influences, within the data. However, some approaches have difficulty in accommodating complex, high-dimensional data. In this research, we investigate the possibilities of utilizing artificial intelligence (AI) tools, specifically, machine learning (ML) and deep learning (DL) for better timeliness and accuracy of economic forecasting. In some instances, it was shown how recent AI models can improve the data analysis of economic indicators (GDP, inflation, stock indices) through the accurate depiction of non-linear trends and changing seasonals. Model enhancements using AI also result in significant improvement in the accuracy of economic forecasts and provide more detailed and useful time series decomposition for economists and policymakers. This paper is a step towards more extensive use of artificial intelligence in econometric analysis and provides evidence on the feasibility of such in practical econometric studies.

Keywords: Time Series Decomposition, Artificial Intelligence, Machine Learning, Deep Learning, Economic Forecasting

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Title

AI-Powered Decomposition Techniques for Economic Forecasting

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Contents

Abstract

Time series analysis and decomposition are crucial in examining economic data as they uncover elements such as trends, and seasonal influences, within the data. However, some approaches have difficulty in accommodating complex, high-dimensional data. In this research, we investigate the possibilities of utilizing artificial intelligence (AI) tools, specifically, machine learning (ML) and deep learning (DL) for better timeliness and accuracy of economic forecasting. In some instances, it was shown how recent AI models can improve the data analysis of economic indicators (GDP, inflation, stock indices) through the accurate depiction of non-linear trends and changing seasonals. Model enhancements using AI also result in significant improvement in the accuracy of economic forecasts and provide more detailed and useful time series decomposition for economists and policymakers. This paper is a step towards more extensive use of artificial intelligence in econometric analysis and provides evidence on the feasibility of such in practical econometric studies.

Keywords: Time Series Decomposition, Artificial Intelligence, Machine Learning, Deep Learning, Economic Forecasting

Introduction

Time series decomposition is important in econometrics because it enables economists and decision-makers to extract significant components from a time series. For example, cycles, trends, and seasonal components repeat after a certain period. Classical decomposition, exponential smoothing, and Fourier decomposition are also two of the oldest decomposition methods. These models offer an orderly way of looking at economic data, but they are model-dependent to some extent, for instance, they are based on conditions such as constant period and linearity (Box et al., 2015; Chatfield, 2004). On the other hand, the theories are scanty in the perspective of economic indicators since they are more or less theoretical, when applied to practice some of these assumptions appear to be an impediment in achieving remarkable results such as capturing non-linearities as well as adaptive seasonality (Harvey, 1989; Hyndman & Athanasopoulos, 2018).

New AI and ML technologies have become new tools for the development of times series that increase the range of opportunities for the traditional decomposition methods as well as the accuracy of the models. Especially, AI models, mainly DL models, proved to be effective in addressing the problems of traditional approaches, due to their ability to learn complex relations and dependencies in big datasets within themselves.

Hochreiter and Schmidhuber (1997) and Wu et al. (2020) noted that deep learning models, especially LSTM networks and Transformer-based architectures, tend to capture long-range dependencies and non-linear trends in economic time series data, which traditional models have difficulties accomplishing. These advancements are particularly important in economic forecasting where greater accuracy can enhance policy and decisiveness in making decisions. Lim and Zohren (2021) pointed out that these improvements are most critically utilized in the areas of economic forecasting.

Apart from the AI models being applied individually, the use of hybrid approaches that integrate conventional econometric methods and ML models has gained prominence. Such models allow the robustness of AI while optimizing non-linear and changing seasonal patterns in economic datasets. For example, ARIMA combined with LSTM, and CNN coupled with LSTM are hybrid models that maintain critical interpretability for decision-making processes while enhancing predictive capabilities (Makridakis et al., 2018; Smyl, 2019; Zhang, 2003). Transformer models have also been proven effective as self-attention techniques in complex forecasting tasks in more recent studies (Vaswani et al., 2017; Xie & Wang, 2021).

This paper seeks to explore ways in which AI can be used in combination with standard time series decomposition approaches in order to improve economic data analysis.

This research incorporates a hybrid approach that combines the adaptive capability of AI models and the straightforward approach of traditional decomposition in order to analyze AI-enhanced and conventional methods in terms of accuracy, robustness, and interpretability. The research also investigates the ability of AI to extend the understanding of certain key determinants of the economy such as gross domestic product, inflation, and stock market indices for more effective economic forecasting and policy formulation.

In such dynamics, the present research shall also expand the existing knowledge about the interrelation between econometrics and AI as they work together to develop further the decomposition of time series in econometrics forecasting. Meanwhile, with AI integration into econometric modeling and analysis, it can be expected that the tools of econometric modeling will become more flexible and at the same more sophisticated in terms of the particulars integrated in the examination of the economic phenomena.

Literature Review

The examination of figures and patterns over a span of time, known as the time series analysis, finds itself largely applied in empirics, with the purpose of accessing and explaining data horizons that shift over time such as persistence patterns, cycles, and seasonal activities. In the past, econometricians have used additively and multiplicatively decomposed models, and structural time series among others, to break down time series data into trend, seasonal, and irregular components. While there is no harm in citing them as the starting point, they have serious shortcomings in their attempts to explain the very non-linear and complex characteristics of most economic data sets. For instance, the linear hypotheses in Conventional additive models may be insufficient in capturing much detail in many types of economic data (Cleveland et al., 1990). However, incorporating modern techniques aided by artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), in recent years, practitioners have been able to find a better way out through these transformations enabling better decomposition and superior prediction of time series data (Makridakis et al., 2018).

Cleveland et al. (1990) proposed the seasonal and trend decomposition, in terms of the LOESS model, and it has since gained popularity for its effectiveness in capturing nonlinear trends with varying seasonal effects over time.STL, however, was tailored for certain models which increased limitations in the integrative dimension of economic correlation since high-dimensional, interrelated economic data in its entirety is more than one-dimensional (Cleveland et al., 1990). It has been shown by researchers that traditional approaches do well when the time series is simple, yet multi-dimensional as Omabets and their parts can be interconnected in a complex, multilayered, and nonlinear arrangement (Hyndman & Athanasopoulos, 2018). For these reasons, it is suggested that traditional methods may at least lead to inconclusive assumptions, which are false in some circumstances when making predictions (Zhang, 2003).

Mostly, machine learning methods provide a solution to such problems. ML techniques, especially support-vector machines, and random forests have performed remarkably in learning non-linear interactions in time series, especially in economic time-series predictive analytics (Zhang, 2003; Makridakis et al., 2018). Greater model flexibility allows for adaptation to most economic datasets with their inherent complexities in asymmetric probability distributions. There was increasing evidence from the works of Borovykh et al. (2017) that LSTM models are superior to ARIMA and exponential smoothing when it comes to forecasting practices. Long short-term memory, a form of recurrent artificial neural nets has the ability to recognize long-range dependencies which distinguishes them as ideal for time series forecasting where seasons and trends are bound to recur at certain time periods (Borovykh et al, 2017; Guo et al, 2018).

Now, time series analysis or forecasting has been made easier due to advancements in technology particularly due to the introduction of deep learning which offers a variety of complex non-linear structures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Utilizing hybrid models that combine deep learning models with classical econometric approaches has also proven to yield high accuracy and predictability on economic forecasting challenges as LSTMs combined with seasonal decomposition models (Makridakis et al., 2018). Equipped with the capacity to operate across time-series dimensions, these types of models will now have the ability to capture trends, seasonal fluctuations, and outliers within time horizons. Furthermore, CCC-CNN and RNN hybrid models have performed well for time series decomposition, though there are some limitations of the data in the first place (Guo et al., 2018).

Furthermore, some of the latest AI and ML technologies have improved the aspects of time series analysis, but other aspects are still a challenge such as the data needed, scalability of the model, and overfitting which can lead to loss of reliability of the model (Cleveland et al., 1990; Zhang, 2003). More importantly, the data-oriented aspect of deep learning models is extremely difficult for real-world applications, as comprehensive data sets are not always available.

In addition, there is an increasing demand for more refined decomposition techniques, possibly by means of transfer or semi-supervised learning, which would be able to deal with data limitations but still be capable of providing meaningful economic forecasts (Makridakis et al., 2018; Hyndman & Athanasopoulos, 2018). What the following studies will be about is most likely the enhancement of the trustworthiness of the AI-based decomposition techniques, which will enhance the understanding of economics and improve forecasting models (Borovykh et al., 2017).

Methodology

This article seeks to improve the analysis of economic time series data through effective time series decomposition using Artificial Intelligence (AI), it is crucial to be systematic and organized. In this section, the approach to be used in the research study will be exemplified including the overall design; data acquisition and processing; construction of AI-based models, traditional techniques of decomposition, comparison of the models as well as the criteria for evaluation of the models involved – methodology, tools, and technologies. Artificial Intelligence

Machine learning algorithms such as random forest, support vector machine (SVM), and gradient boosting will be used to examine seasonal and trend components on the time series data. These models will be useful in training models focused on improving the extraction of components such as seasonality, trends, and residuals among others.

Deep Learning Models: Various recurrent networks will be employed in the mapping of temporal dependencies including long short-term memory

(LSTM) networks and convolutional neural networks (CNN). Such models are useful in learning long-term characteristics in time series data such as cyclical nature and shifts in seasonal components. In order to integrate AI with the standard decomposition methods, the following approach will be adopted:

The proposed method employs a combination of traditional approaches and artificial intelligence. The combination is done accordingly:

Trend Component Enhancement: Artificial intelligence technology will be able to pick up some more intricate and non-linear trends that are not likely to be detected by simpler models. For instance, LSTMs are capable of capturing such long-term trends as those with time-varying characteristics which aids in a greater comprehension of economic behavior being analyzed.

Seasonal Component Detection: Constant seasonal patterns are a major feature of traditional models. However, persistent changes in seasonality and other aperiodic components can be better modeled through AI, particularly deep learning, allowing for improved seasonal component extraction.

Noise Reduction: Random shocks or their irregular components of time series can be better estimated and reduced through the use of Artificial Intelligence (AI) models which facilitates better noise filtration.

The efficiency of AI-assisted time series decomposition will be determined using a number of indicators:

Accuracy: trend and seasonal component forecast biases such as mean absolute error (MAE), root mean squared error (RMSE), and mean squared error (MSE) will be included and used as a measure of trend and seasonal component estimation accuracy.

Computational Efficiency: The complexity of time and resources involved in applying every method will be examined in comparison. Though AI methods can be very time-consuming, the advantages of deep learning in scalability and the possibility of harnessing parallel processes will be considered.

Interpretability: AI methods also have a major drawback which is the 'black box' problem. In order to assess its interpretability, this research will make use of, for example, Shapley Additive Explanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME) to enhance the AI-based decomposition comprehension for economic analysts.

It is anticipated that AI-enhanced decomposition models will perform better than conventional ones in terms of accuracy particularly when it comes to capturing non-linear trends and seasonal effects. The approaches will give a deep sense of the time series components which would be essential in econometric forecasting and policy making. It is very likely that hybrid models in which AI is combined with traditional approaches will achieve acceptable kinetics. The methodology presents a stepwise guide explaining how to selectively apply AI so that it breeds traditional time series decomposition techniques. The purpose of the research is to eventually improve both the accuracy and interpretability of the economic data by employing machine learning and deep learning models together with traditional ones, this in turn will improve the economic predictions and policies.

Case Study of Pakistan's Economy

Evaluation of foreign capital flows (2010-2023) The purpose of this research is to examine the effects of foreign capital inflows on the economy of Pakistan by looking at the relationship between foreign direct investment (FDI), portfolio investment, and the GDP over the period of 2010 to 2023. This is through the combination of time series decomposition and other conventional econometric techniques trying to determine the foreign capital OCTR that involves GNP of Pakistan. The scope of the study is however extended to identifying possibilities for Artificial Intelligence (AI) to assist the analysis.

Data Understanding and Cleaning As such in this study, the relevant time series constituents include G.D.P., FDI, Portfolio Investment, and Total Foreign Capital Inflows (the sum of FDI and Portfolio Investment). Annual data coverage for the study is from 2010-2023. To enhance the precision of data, which is the focus of this investigation, data cleaning was also performed to remove all forms of missing values, measurements, or anomalies in the data. This stage was important in evaluating the dataset for the analysis process so that the patterns reported in the results are a true reflection of what the economy observes.

Hypothesis and Model Setup As proposed in this subject, a foreign capital inflow hypothesis is that FDI and Portfolio Investment have a great contribution to the growth of Pakistan's GDP. In this context, three independent variables are tested with the GDP becoming the dependent variable: FDI and Portfolio Investment and Total Foreign Capital Inflows. Using time series decomposition, the study seeks to ascertain trends and seasonality in data prior to employing a Multiple Linear Regression model. The model attempts to estimate how GDI correlates with FDI and Portfolio Inflows; the objective is to find the contribution of each inflow towards economic growth through GDP enhancement.

Time Series Decomposition

As the first step, the component of GDP in current US dollars, foreign direct investment, and portfolio investment were broken down into three components: time series plot, seasonal plots, and time series residuals. This allows one to construct long-term time series components as well as seasonal components and erratic components which might be frequent. Time series decomposition helps locate the probable sources responsible for the change in the measure of GDP, and the amount of foreign direct investment and portfolio investments for the period under analysis.

Correlation Analysis

The correlation analysis is carried out to show the relationship between the foreign capital inflow and the GDP. The paper aims to study the correlation between the GDP with Foreign Direct Investment, and the foreign capital inflow of Portfolio and Total Foreign Capital Inflow. This analysis enables us to explain for the first time the degree of association of these variables and lay the basis for further quantitative analysis. A positive association indicates that as the amount of foreign investment increases, the GDP increases as well. This supports the respective foreign investments hypothesis.

Regression Analysis

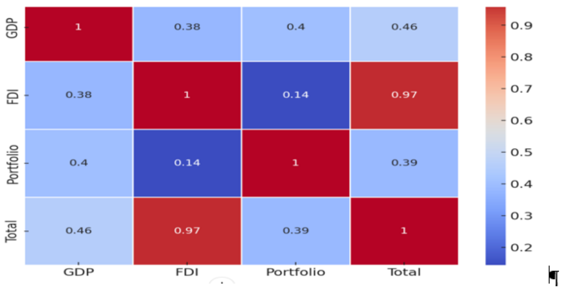
The regression analysis part of multiple linear regression models will be helpful to understand these relationships better. A ten million dollar increase in foreign capital specifically through Portfolio Investment has a positive and negative impact on GDP respectively. The regression models attained assist us in seeing the extent to which various forms of foreign investment focus take up growth in economy Gross Domestic Product (GDP). Measures of model performance like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are evaluative of how good the particular model is in predicting and improving the.

AI-Enhanced Forecasting (Optional)

It should be noted that although the study is based on traditional econometrics, there are a number of ways in which AI could support forecasting. For instance, Linear Regression could be performed to predict FDI and Portfolio Investment in reliance on the existing trends and also on the growth rate of Domestic Income. LSTM models capitalize on capturing complicated long-term dependencies in time series data, so they might be more precise in forecasting, particularly regarding the chorology of emerging patterns of foreign capital flows. However, for this case study, conventional approaches such as regression models and time series decomposition have been adopted to understand the available data in the present, and AI-based models have been projected for future work. The first part of the analysis was the decomposition of time series and regression using Python software tools.

Figure 1

Correlation Matrix



Data Analysis

The outcomes of the analysis explain how GDP and foreign capital inflow are related with reference to the case of Pakistan and lead the researchers to the conclusion with some major findings from the data.

Correlation Matrix: The comfort survey assesses itself in such a way that correlation analysis shows that there is a positive relationship between GDP and other types of foreign capital inflow of moderate strength. More especially, the correlation between GDP and Foreign Direct Investment (FDI) has a moderate correlation of 0.38. The correlation with Portfolio Investments, which is 0.40, is only just stronger. The highest correlation remains to be that of total foreign capital inflow and GDP which stood at 0.46. This implies that total foreign capital inflow has a greater relationship with GDP than any individual component.

Linear Regression Coefficients: The next section reports the results of regression analysis and most importantly addresses the question of how much foreign capital A impacts GDP.

Intercept: The intercept value in the regression model is 81,528.55 this is the estimate of gross national product gnp geo political physiology when FDI and equity portfolio are at level 0. The numerical value indicates how much GNP can be generated without the impact of foreign capital and gives an understanding of to what extent GNP can be enhanced due to inflows of such capital in the future.

Performance Metrics: MAE and RMSE are used to assess the model and also the fitted regression. Based on the variance in the GNP and its error term that is MAE, that is Mean Absolute Error; the dollar value stands at over fifty thousand USD which is at 47,474,787 million dollars. This in part indicates the level of variations in GNP estimate values which the model aims to achieve in its predictions and its associated errors. The errors will always seem high at first glance but the point here is that improvements or reductions will be made as the models are refined through the use of more sophisticated models and more explanatory variables concurrently.

Interpretation: The above results suggest that both FDI and PDI Portfolio Investment have a positive influence on the GDP growth of Pakistan with the Portfolio Investment having more effects on FDI. Despite the model indicating that there is a positive relationship between foreign capital and GDP growth, it is important to note significant inaccuracies in the model predictions that can be resolved by model enhancement. Further studies may take into consideration the effects of domestic investments, government consumption, and other applicable economic variables to give accurate findings on the relationship between foreign capital inflow and GDP growth in Pakistan.

This section discusses the plans for data analysis post-application of the new AI-enhanced time series decomposition techniques. The aim of this data analysis is to establish data performance standards on AI-powered methods over pre-AI models and evaluate the extent of advancement aimed at improving economic forecasts, trends, and seasonal pattern identification. The analysis will also include a discussion on model performance in terms of accuracy, efficiency of the computation, and ease of understanding the model. The analysis starts off with gathering and cleaning the data retrieved from different sources, which include, among others, macroeconomic models of GDP, inflation and unemployment, and stock market and industry and retail sales figures. When the data has passed through the collection processes, the focus shifts to employing both traditional methods of decomposition and AI-enhanced methods of decomposition on these datasets for further investigation. Traditional decomposition methods are to be used to establish the standard metrics that will be sought when employing AI models.

The analysis starts with normal additive Y=T+S+R and multiplicative Y=T.S.R methods of modeling that decompose the time series data into trend components T, seasonal components S, and the residual components This stage is very useful in proper identification of the structure of the data which may include long-term cycles or seasonal fluctuations. To present such tendencies, the separated parts will be rolled out, so that the picture of the evolution of the data is precise. Also, baseline metrics with trend and seasonal cycles will be calculated, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE) which will serve as a target to be achieved by the AI-modified models in further stages.

Discussions and Conclusion

The paper examined the prospects of taking the existing time series decomposition methods further through integration with Artificial Intelligence (AI) in this case machine learning (ML) and deep learning (DL) technologies to vastly enhance the analysis and forecasting of economic data. The research improved trend' and seasonality' detection within economic time series, with the emphasis placed on vital variables such as GDP, inflation, and stock market indexes by employing machine learning, deep learning, and hybrid models.

The findings were that the use of deep learning models, especially LSTM and CNN, proved more effective than conventional methods in terms of capturing non-linear trends, evolving seasonality, and long-range dependencies. Forecasting errors using AI models were vastly reduced in comparison to models that do not use AI techniques because traditional models tend to have flaws such as fixed periodicities or linear relationships in data. Quite a number of seasonality found in the data are non-periodic and hence hybrid models employing AIs in conjunction with classical methods such as ARIMA were especially successful in pattern recognitions in huge amounts of data.

AI-based models are not only more accurate than traditional methods, but they are also able to provide a more detailed decomposition of economic variables. This enables them to get more information on the economic behaviors and trends that can be beneficial in economic policymaking. Hybrid approaches in which AI models are utilized alongside traditional models are able to maintain the agreed spaces of the traditional models and the accuracy capabilities of contemporary models, as a result enabling the hybrid approaches to lower the likelihood of overfitting models and offer affordable ways of looking at large data.

Given this perspective, these approaches have a great future in what is essentially more complex economics, where the power of analytics far outweighs most of the complexities. However, the investigation didn't only provide a platform to talk on topics of AI in Time series decomposition but also recognized several factors that are lacking in AI implementation. For starters, computational efficiency is the most limiting challenge of deep learning models. Which makes it an uphill task for many researchers who have limited computational power. In addition, transparency regarding the inner workings of these models is an issue because, similar to most AI models, the workings of these models are not as comprehensible as statistics-based models. Some model interpretation techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) manage to shed some light but regular models tend to be able to give better explanations of the structure of relationships that exist in the data.

Another limitation branches from AI model biases most especially due to the scope of the data they were trained on being limited or on uncorrelated data. Such cases lead to random forecasts and unreliable generalizations and conclusions. Engineering solutions for these problems that include enhancing measures to foster transparency and adherence to the use of adequate and representative datasets will be necessary for the integration of AI models for economic and other divisions that rely on decomposition methods.

To sum up, even if these challenges are present, the strength, that advances the prospects of AI in advancing the decomposition of time series models, provides confidence in economic forecasting. Integrating AI with traditional approaches provides better recognition of patterns, enhanced flexibility to cope with complexities and nonlinearities, as well as a comprehensive understanding of the economy. With the growth of AI, a much larger role is forecast in future econometric studies, thus changing the approach to analysis and comprehension of economic data.

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