Comparative Analysis of Time Series Models for Forecasting the U.S. Unemployment Rate: A Study of ARIMA, LSTM, and Intervention Approaches

Yunpeng Li[a]

Bachelor of Business Administration (Hons) Programme, Hong Kong Baptist University, Kowloon, Hong Kong, China

Keywords: Time Series Forecasting, Unemployment Rate Prediction, Economic Events, COVID-19 Pandemic, Machine Learning Techniques.

Abstract: The unemployment rate reflects the overall health of the labor market and influences monetary and fiscal strategies. The rapidly changing economic landscape, marked by events like the financial downturn of 2008 and the global health crisis caused by COVID-19, highlights the necessity of stable forecasting models that capture complex dynamics and structural changes. This research centers on comparing various time series models to forecast unemployment rates in the United States (ARIMA, LSTM and intervention approaches). The research collected the US unemployment rate for the 16-24 age group from 1978 to 2023 and applied time series visualization, seasonal decomposition, and intervention analysis to understand trends and event impacts. ARIMA and LSTM are developed and evaluated by evaluation measures like MSE, RMSE, MAE, and MAPE. The study aims to identify which model best captures trends, seasonal patterns, and structural changes in the labor market. Preliminary findings suggest that LSTM models outperform ARIMA in complex scenarios due to their ability to learn long-term dependencies. The results of this research will contribute to improved forecasting methodologies, providing policymakers with more accurate predictions to inform decision-making processes.

1 INTRODUCTION

The unemployment rate has always been a hot topic for economists worldwide. As it affects all countries, forecasting the unemployment rate is critical for policymakers, economists, and businesses (Douglas, S., & Zahed, M.,2024). It provides valuable insights into the overall health of the economy and labor market trends. The United States unemployment rate, in particular, is a key economic indicator that influences monetary policy decisions, fiscal planning, and business strategies. Over the years, various time series models have been developed and applied to predict unemployment rates, each with strengths and limitations.

Recent studies have highlighted the need for a comprehensive comparison of different forecasting models because the performance of these models can vary significantly depending on economic conditions and data characteristics. For instance, Douglas and Zahed demonstrated the limitations of using only ARIMA models for long-term unemployment rate forecasts, emphasizing the need to consider alternative approaches (Douglas & Zahed, 2024). Similarly, Gostkowski and Rokicki compared several predictive methods, including ARIMA and regression models, but they did not include more advanced machine learning techniques such as LSTM (Gostkowski & Rokicki, 2021).

The rapidly evolving economic landscape, particularly considering recent worldwide occurrences, such as the COVID-19 outbreak, has emphasized the significance of reassessing and comparing different forecasting models. Traditional models that performed well in the past may no longer be as effective in capturing the complex dynamics of today's labor market. As Barnichon and Nekarda (2012) noted, models incorporating labor force flow data can significantly outperform traditional forecasting approaches, especially during economic downturns (Barnichon & Nekarda, 2012).

[a] https://orcid.org/0009-0006-2287-6080

Li, Y.
Comparative Analysis of Time Series Models for Forecasting the U.S. Unemployment Rate: A Study of ARIMA, LSTM, and Intervention Approaches.
DOI: 10.5220/0013697600004670

In *Proceedings of the 2nd International Conference on Data Science and Engineering (ICDSE 2025)*, pages 372-378
ISBN: 978-989-758-765-8

Predicting unemployment levels is a critical task for economic policymakers and researchers. However, the data used by a number of studies is already outdated, and they didn't involve the outliers caused by the pandemic. Various methods have been employed by many researchers to predict unemployment rates, including traditional statistical models and advanced machine-learning techniques.

Previous researchers have used various methods to predict unemployment trends in the United States, including traditional ARIMA models, primary economic signals, and automatic time series modeling techniques like Autometrics. Guerard, Thomakos, and Kyriazi built upon earlier work by applying Autometrics to improve models for real GDP and unemployment, accounting for structural breaks and outliers (Guerard, Thomakos & Kyriazi, 2020). Their study emphasized the effectiveness of adaptive learning forecasting and the significance of incorporating leading indicators. However, the effects of the COVID-19 period were not included in their research process, which generated a huge impact on the global unemployment rate.

Shan Zhong analyzed the U.S. real GDP and unemployment rate data from 1948 to 2023 using linear and nonlinear regression and ARIMA models (Zhong, 2023). The study found that nonlinear regression more accurately represents the relationship between these two factors. ARIMA forecasts showed optimistic future trends with GDP growth and low unemployment but with wide confidence intervals.

Yurtsever proposed a hybrid model combining LSTM and GRU deep learning techniques to forecast unemployment rates in the U.S., U.K., France, and Italy. Generally, the hybrid model outperformed standalone LSTM and GRU models, except in Italy, where GRU performed better. This study highlights the effectiveness of combining different models to enhance forecasting performance (Yurtsever, 2023).

Other researchers have also explored hybrid approaches, such as combining ARIMA with artificial intelligence methods, which have shown promising results in reducing prediction errors (Chakraborty et al., 2021; Ahmad et al., 2021). Additionally, Xiao et al. revisited earlier forecasting methodologies to explore relationships between unemployment rates and leading economic indicators such as data on weekly jobless claims and the U.S. Leading Economic Indicator (LEI), demonstrating that incorporating these variables can enhance predictive accuracy (Xiao et al., 2022). Montgomery et al. further emphasized that forecasting accuracy could be improved by combining multiple time series methods and carefully accounting for structural breaks in historical data (Montgomery et al., 1998). Similarly, Dritsakis and Klazoglou applied the Box-Jenkins methodology extensively to forecast U.S. unemployment rates, highlighting its effectiveness but also acknowledging its limitations when confronted with structural changes or unprecedented economic shocks (Dritsakis & Klazoglou, 2018). These findings collectively reinforce the necessity of exploring diverse forecasting methodologies to better capture complex labor market dynamics.

This study seeks to fill this research gap by comparing three well-known time series forecasting methods to predict unemployment trends in the United States: ARIMA, LSTM neural networks, and intervention approaches. By evaluating these diverse models using the recent data from 1978 to 2023 and considering their performance across different economic conditions, this study seeks to point out which model is best fitted to predict unemployment trends and offer new perspectives on how effectively different forecasting approaches perform in the current financial landscape.

2 DATA AND METHOD

2.1 Data Collection and Description

The dataset used in this analysis contains the unemployment rate for the 16-24 age group from December 1978 to July 2023. The data was cleaned and preprocessed by removing missing values, converting the date column to a date format, and arranging the data in chronological order. The dataset provides a comprehensive view of the trends and patterns in youth unemployment over more than 40 years.

2.2 Methods and Principles

This study employs several methodologies to analyze and predict unemployment rates in the United States. The primary methods are as follows.

2.2.1 Time Series Visualization

Time series visualization is a crucial step in understanding the behavior of the data over time. This involves graphically representing the unemployment rate over time to identify trends, seasonal patterns, and significant events. Visual inspection helps in understanding the overall behavior of the data.

Firstly, this study presents a time series graph depicting unemployment rates among younger age groups. The unemployment rate for the 16-24 age group was plotted over time, as shown in Figure 1, a clear trend and seasonal patterns were displayed. A vertical line was added to mark the start of the pandemic in March 2020, was marked to observe its impact on the trend.

Figure. 1 Youth Unemployment Trends (16-24 years old). (Picture credit: Original)

2.2.2 Seasonal Decomposition

Seasonal decomposition, using techniques such as the STL method, breaks down the time series into its underlying components: trend, seasonal, and residual. This decomposition aids in understanding the underlying structure of the data. In this study, the time series was decomposed into trend, seasonal, and residual components using the STL method, as shown in Figure 2. This provided valuable insights into the underlying structure of the data.

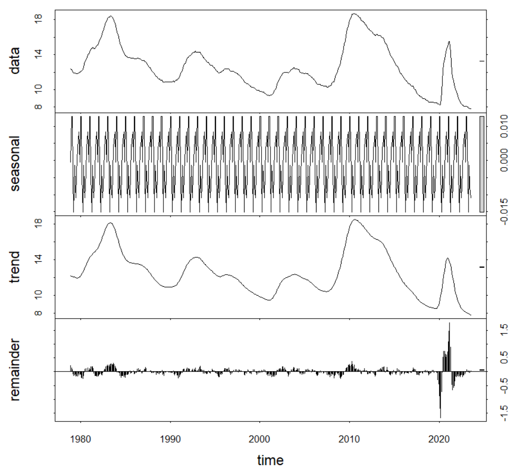

Figure. 2 Seasonal Decomposition by STL model. (Picture credit: Original)

2.2.3 Intervention Analysis

Intervention analysis examines how particular incidents, like the financial crisis in 2008 and the COVID-19 pandemic, influence changes in unemployment rates. Intervention analysis helps in quantifying the effects of these events.

In this paper, a linear regression model was built to analyze the impact of the financial crisis in 2008 and the 2020 pandemic on the unemployment rate. The model included dummy variables for these events and a lagged term of the unemployment rate and also allowed for the quantification of their impacts on the unemployment rate at the same time.

2.2.4 ARIMA Model

The ARIMA approach is widely utilized for forecasting time series data. It integrates autoregressive (AR), differencing (I), and moving average (MA) elements to effectively identify linear dependencies and seasonal variations within the dataset. In this literature, the ARIMA model was applied to forecast the unemployment rate. The data was differenced to achieve stationarity, and the optimal ARIMA model was selected based on the AIC values.

2.2.5 LSTM Model

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that are particularly effective for time series forecasting. They are capable of learning long-term dependencies in the data. This research applied the LSTM approach to predict unemployment rates. The dataset underwent normalization before being divided into training and testing subsets. The training subset was utilized to build the model, while the testing subset was employed to assess its performance.

2.3 Evaluation Metrics

The average squared difference between the expected and actual values is measured by the Mean Squared Error, or MSE. It is a frequently used indicator to assess how well regression models perform.

Root Mean Squared Error (RMSE) is calculated as the square root of Mean Squared Error (MSE) and measures the size of prediction errors, expressed in the original units of the data.

Mean Absolute Error (MAE) calculates the mean of the absolute differences between observed and predicted values, and it is more robust against outliers than MSE.

Mean Absolute Percentage Error (MAPE) calculates the average of absolute differences between actual and predicted values expressed as percentages, offering a relative assessment of forecasting accuracy.

Mean Absolute Scaled Error (MASE) evaluates a model's accuracy by comparing its prediction errors against errors from a simple baseline (naive forecast), resulting in a standardized performance metric.

3 RESULTS AND DISCUSSION

3.1 Intervention Analysis

The intervention analysis model was designed to assess the impact of significant events on the unemployment rate. The results indicate that the 2008 financial crisis had a substantial and statistically significant impact on the unemployment rate, with a coefficient of 0.32035. This suggests that the crisis led to a marked increase in unemployment. Conversely, the 2020 pandemic had a much smaller and statistically insignificant impact, with a coefficient of 0.01223186. This finding may be attributed to government interventions, such as stimulus packages and employment support programs, which mitigated the pandemic's effects on employment.

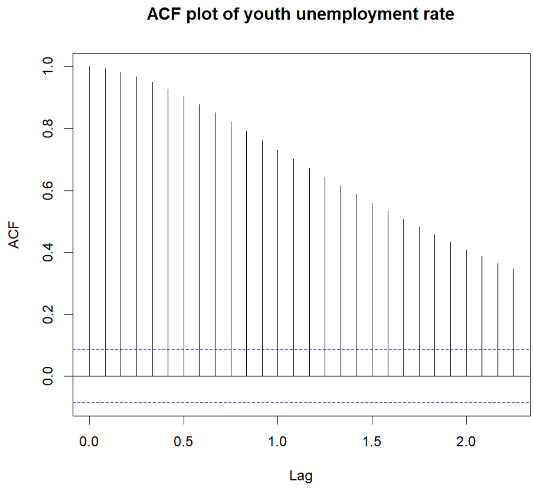

Figure. 3 ACF Plot of Youth Unemployment Rate. (Picture credit: Original)

Figure. 3 presents the ACF plot for the original youth unemployment rate data (ages 16-24). The ACF plot visually represents the correlation between observations at different lag intervals. The horizontal axis represents different lag values, while the vertical axis shows autocorrelation coefficients. The shaded area indicates the confidence interval bounds; correlations extending beyond these bounds are statistically significant. From Figure 3, high initial autocorrelation is observed that there is a very high autocorrelation at lag 0 (as expected, always equal to 1), followed by gradually decreasing autocorrelations at subsequent lags. This indicates strong persistence in the unemployment rate data, meaning past unemployment rates heavily influence current rates. It is also noticeable that notable periodic spikes at regular intervals (approximately every 12 lags) suggest clear seasonal patterns. This aligns with typical labor market dynamics where youth unemployment rates fluctuate seasonally due to school calendars, holidays, and seasonal employment opportunities.

In summary, Figure 3 illustrates that the original unemployment series is non-stationary due to persistent trends and seasonal fluctuations. These characteristics necessitate differencing or other transformations before applying forecasting models such as ARIMA.

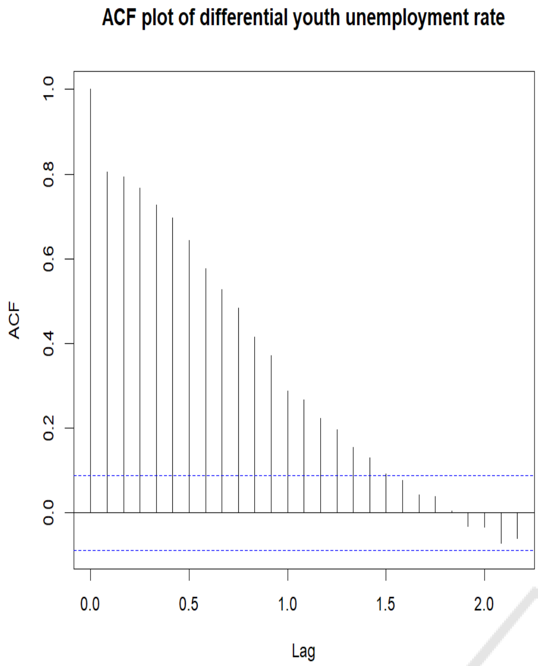

Figure. 4 ACF Plot of Differential Youth Unemployment Rate. (Picture credit: Original)

Figure 4 shows the ACF plot after applying first-order differencing to the youth unemployment rate data. Differencing is a common step in achieving stationarity by removing trends and stabilizing mean values. It is observed that there is a significant reduction in autocorrelation. Compared to Figure 3, the autocorrelation values drop sharply after differencing. This substantial reduction indicates that differencing effectively removed much of the trend component present in the original data. Furthermore, unlike Figure 3, Figure 4 displays a rapid decline of autocorrelation values toward zero after just a few lags. This rapid decay pattern confirms that differencing successfully transformed the series into a stationary one, which is suitable for ARIMA modeling.

In summary, Figure 4 demonstrates that differencing has effectively addressed non-stationarity caused by trends but has not completely eliminated seasonal effects. Therefore, although intervention analysis can now be reliably performed on this stationary series, additional modeling adjustments may still be beneficial for capturing remaining seasonal dynamics accurately. These findings justify using ARIMA models with differencing (as performed in this study).

3.2 ARIMA Model

Figure 5 below in the research paper provides a comparative visualization of Akaike Information Criterion (AIC) values calculated for different ARIMA models tested during the model selection process. The ARIMA model selected based on the lowest AIC value was ARIMA (3,1,2), with an AIC of -1178.4186. This model was chosen because lower AIC values suggest a better trade-off between complexity and explanatory power, which indicates it achieves an optimal balance between capturing sufficient patterns in youth unemployment data and avoiding excessive complexity. Meanwhile, it has the ability to effectively capture the linear relationships and seasonal patterns in the data. However, the model's performance on the test set revealed a relatively high RMSE of 3.51754016, indicating that the predictions were not highly accurate. This suggests that while ARIMA models are useful for understanding linear trends, they may struggle with complex or non-linear dynamics.

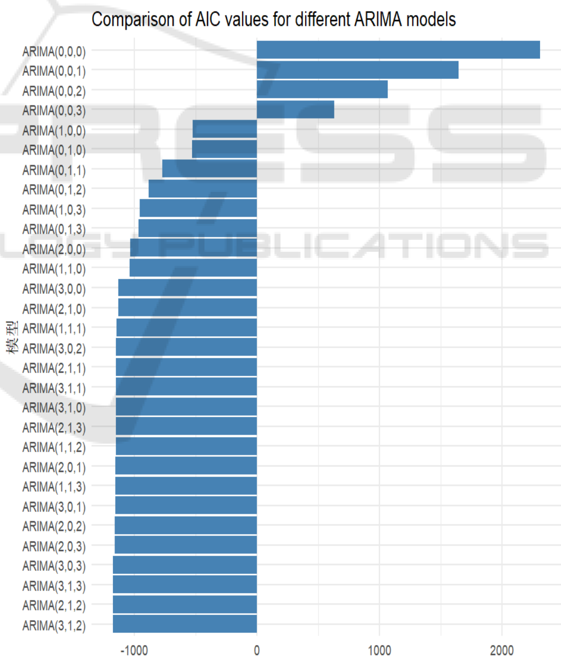

Figure. 5 Comparison of AIC Values for Different ARIMA Models. (Picture credit: Original)

3.3 LSTM Model

The LSTM model's performance was evaluated using RMSE. The RMSE for the LSTM model was 1.030382, which is significantly lower than the ARIMA model's RMSE on the test set. This indicates that the LSTM model yielded more precise predictions. It demonstrated enhanced performance compared to the ARIMA model.

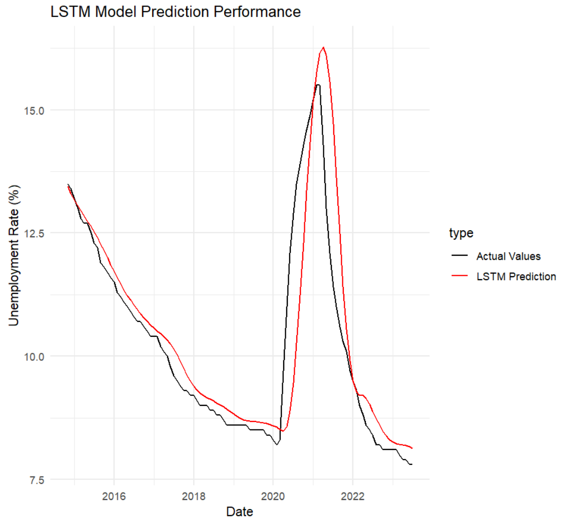

Figure. 6 LSTM Model Prediction Performance. (Picture credit: Original)

However, the LSTM model's predictions, as shown in Figure. 6, exhibit a hysteresis quality, indicating a lagged response to changes in the actual unemployment rate data. This phenomenon can be attributed to the model's design, which prioritizes capturing long-term dependencies over immediate adjustments to new trends. To improve the model's responsiveness in the future, further research could focus on refining the model architecture or optimizing training parameters to better adapt to rapid changes in economic conditions.

3.4 Comparison of Results

3.4.1 Intervention Analysis

The intervention analysis results indicated clear differences in the impacts of major economic events on youth unemployment rates. Specifically, the 2008 Financial Crisis: The unemployment rate increased significantly during the crisis, as indicated by the coefficient of 0.32035. The considerable effect of this event on unemployment rates highlights the necessity of including external shocks in predictive models. In contrast, the 2020 Pandemic, with a coefficient of 0.01223186, indicates a negligible impact on the unemployment rate, which may be due to government interventions or other factors, such as stimulus packages, employment subsidies, and targeted economic support programs implemented during the pandemic period, which effectively cushioning the labor market from severe disruptions. The minimal impact observed may reflect effective policy interventions, highlighting the need for adaptive forecasting approaches that account for such factors.

3.4.2 ARIMA Model

Through model selection based on AIC, the ARIMA (3,1,2) model had the lowest AIC value, indicating it was the best fit among the models tested and was suitable for capturing linear relationships and seasonal patterns present in youth unemployment data. However, for its prediction Error: The RMSE of 3.51754016 on the test set suggests that the model's predictions were not very accurate. The high RMSE suggests limitations in addressing complex scenarios, particularly when nonlinearities and structural breaks exist within the historical data.

3.4.3 LSTM Model

In comparison to ARIMA, the LSTM model achieved a notably lower RMSE of around 1.030382 on test data. The lower RMSE indicates better performance in capturing non-linear dynamics. This improved accuracy highlights LSTM's strength in capturing long-term nonlinear dependencies and complex temporal patterns inherent in youth unemployment rates. Nevertheless, despite its overall better predictive capability, the LSTM model exhibited a delayed response or hysteresis effect when reacting to sudden shifts or structural changes in unemployment trends.

3.5 Discussion

The results of this study highlight the importance of selecting appropriate time series models based on the complexity of the data. While ARIMA models are effective for linear trends, LSTM models offer superior performance in scenarios with non-linear relationships. The intervention analysis underscores the need to incorporate significant events into forecasting models to improve accuracy. These findings have implications for policymakers seeking to improve their ability to foresee and make well-informed choices regarding labor market initiatives.

4 CONCLUSIONS

This literature analyses the youth unemployment rate data using various methods and provides valuable insights into the trends and impacts of significant events on the unemployment rate. The intervention analysis highlighted the significant impact of the 2008 financial crisis, while the 2020 pandemic had a smaller and statistically insignificant impact. The ARIMA model provided a baseline for forecasting, but the LSTM model outperformed it in terms of prediction accuracy, as indicated by the lower RMSE value. The results suggest that deep learning models like LSTM can be more effective for time series forecasting in complex and non-linear scenarios. This study has limitations in involving more related control variables to forecast the unemployment rate in the US because the unemployment rate is affected by factors such as different genders, different races, and the financial crisis period in 2008. If all these highly correlated factors are included in this research, the results should be more precise and accurate. Therefore, the shortcoming of this research is not taking into account all of these correlated control variables. Additionally, as the LSTM exhibits a hysteresis quality, other changes such as adjusting the model architecture and improving data preprocessing are required in future studies. In the future, this study will verify more corresponding factors which perform a big impact on the unemployment rate. Additionally, more forecasting models like linear and non-linear regression models would be applied to get the best-performing model to predict the unemployment rate so that governments and policymakers around the world could look forward to future changes in the unemployment rate and introduce relevant policies in advance to stabilize the economic conditions.

REFERENCES

Barnichon, R., & Nekarda, C. J. (2012). The ins and outs of forecasting unemployment: Using labor force flows to forecast the labor market. Journal of Economic Perspectives, 26(3), 45-66.

Douglas, S., & Zahed, M. (2024). Forecasting U.S. unemployment rates using ARIMA: A time series analysis from 1948 to 2019. SESUG 2024 Proceedings. Retrieved from https://sesug.org/proceedings/sesug_2024_SAAG/PresentationSummaries/Papers/148_Final_PDF.pdf

Dritsakis, N., & Klazoglou, P. (2018). Forecasting unemployment rates in USA using Box-Jenkins methodology. International Journal of Economics and Financial Issues, 8(1), 9.

Gostkowski, M., & Rokicki, T. (2021). Forecasting the unemployment rate: Application of selected prediction methods. European Research Studies Journal, XXIV(3), 985-1000.

Guerard, J., Thomakos, D., & Kyriazi, F. (2019). Automatic time series modeling and forecasting: A replication case study of forecasting real GDP, the unemployment rate, and the impact of leading economic indicators. Cogent Economics & Finance, 7(1), 1-20.

Guerard, J., Thomakos, D., & Kyriazi, F. (2020). Automatic time series modeling and forecasting: A replication case study of forecasting real GDP, the unemployment rate and the impact of leading economic indicators. Cogent Economics & Finance, 8(1), 1759483.

Montgomery, A. L., Zarnowitz, V., Tsay, R., & Tiao, G. C. (1998). Forecasting the U.S. unemployment rate. Journal of the American Statistical Association, 93(442), 478-493.

Xiao, H., Chen, R., & Guerard Jr, J. B. (2022). Forecasting the U.S. unemployment rate: Another look. Wilmott Magazine, November, 20-31.

Yurtsever, M. (2023). Unemployment rate forecasting: LSTM-GRU hybrid approach. Journal for Labour Market Research, 57(1), 1-9.

Zhong, S. (2023). The research and forecasts on real GDP growth and the unemployment rate in the United States. EMFRM, 2023, 159-165.