INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY: APPLIED BUSINESS AND EDUCATION RESEARCH
2026, Vol. 7, No. 1, 455 – 487
http://dx.doi.org/10.11594/ijmaber.07.01.34

Research Article

Forecasting Unemployment Rates in the Ilocos Region, Philippines, Using Time Series Analysis

Denver Q. Narvasa*

Far Eastern University - Manila

Article history:
Submission 02 December 2025
Revised 30 December 2025
Accepted 23 January 2026

**Corresponding author:*
E-mail:
Narvasaden79@gmail.com

ABSTRACT

Unemployment rates in the Ilocos Region are continuously progressing alongside the data-driven policymaking and strategies for the economy. This study presents a forecasting model that aims to forecast unemployment trends and propose measures to create more job opportunities, enhance workforce skills, and recommend strategies to reduce unemployment in the Ilocos Region. Utilizing time series analysis across the five different models, the ARIMA (1,1,1) model was identified as the most suitable in forecasting unemployment rates over time. Results also indicate that this approach can informed can be made effectively on the unemployment issues. This research helps Filipino economists, encouraging them to come up with new implementing strategies and interventions to enhance economic well-being in the Ilocos Region and the Philippines.

Keywords: *Time Series Analysis, Ilocos Region, Unemployment Rate*

Background

In the Philippines, the unemployment rate in August 2023 was 4.4 percent, down significantly from 5.3 percent in the same month the previous year and 4.8 percent in July 2023. This leads to around 468,000 fewer unemployed individuals. The underemployment rate also decreased from 14.7 percent in August 2022 and 15.9 percent in July 2023 to 11.7 percent in August of this year. This leads to 1.4 million fewer underemployed people, notably those working in the service and industry sectors (Philippine Statistics Authority [PSA], 2024). These developments suggest an economic recovery and, potentially, better job possibilities for Filipinos within the designated time period.

Meanwhile, employment in agriculture and industry reached 203,000. Aside from the decrease in underemployment, several other indications suggest an improvement in employment quality, such as an increase in wage and salary, full-time employment, and a decrease in vulnerable and part-time work. However, more work remained to be done since the number of middle- and high-skilled occupations fell (-354,000), while low-skilled occupations expanded (+551,000) over the previous year (National Economic Development Authority

How to cite:
Narvasa, D. Q. (2026). Forecasting Unemployment Rates in the Ilocos Region, Philippines, Using Time Series Analysis. *International Journal of Multidisciplinary: Applied Business and Education Research*. *7*(1), 455 – 487. doi: 10.11594/ijmaber.07.01.34

[NEDA], 2023). This situation could require investment in education and training programs to provide people with the skills needed for higher-paying and more safe employment opportunities. This could contribute to a more balanced and stable labor market in the Philippines.

The poverty rate dropped from 23.3 percent in 2015 to 18.1 percent in 2021, despite the shocks of the COVID-19 epidemic and other economic factors such as high commodity prices globally and poor financial markets worldwide. The Philippine government is increasing its investments in both human and physical capital in order to improve moderate and future development (World Bank, 2024). The Philippine government can improve on its present work to reduce poverty and support sustainable development.

With significant employment growth over the last decade, the Philippines' unemployment rate has remained high, over double that of neighboring countries. Employment growth was insufficient to eliminate unemployment due to high population growth and increased labor force participation (Brooks, 2002).

The COVID-19 epidemic significantly increased the unemployment rate in the Philippines, resulting in a severe economic collapse and considerable financial suffering. The unemployment rate increased from 5.2% in October 2019 to 22.3% in April 2020, as businesses were forced to cut jobs and reduce back operations due to lockdowns and lower customer demand. This spike in unemployment put a pressure on the country's social safety nets, requiring the government to provide more resources to support the expanding number of unemployed people and their families. The long-term consequences of pandemic-induced employment losses may include skill erosion, diminished job opportunities, and long-term effects on certain industries and labor market systems (International Labor Organization [ILO], 2020).

The unemployment rate is an important economic indicator used to analyze the health of an economy. It fluctuates with the business cycle, rising in recessions and dropping in expansions. Policymakers, investors, and the general public pay close attention to this number. In the Philippines, unemployment and underemployment are the most serious concerns and crucial indications of economic woes. Poverty is mostly driven by the poor's limited earning potential and a lack of consistent and profitable employment possibilities. Behind these are two connected primary causes of in-work poverty: a lack of education among the poor and an absence of acceptable employment possibilities (Narvasa, 2024).

The labor market situations in the Ilocos Region, Philippines, show that the regional economy is on a favorable path, with opportunities for further growth and development. The 5.9% decrease in the unemployment rate, equivalent to 147,000 fewer unemployed people, combined with a high labor force participation rate of 68.5% (higher than the national average), suggests a strong and engaged workforce capable of driving economic activity in agriculture, industry, and the service sector. The broad range of the economic basis provides stability and consistency while also helping to raise the region's overall standard of living. Furthermore, the lower level of COVID-19 restrictions, with the Ilocos Region now on a more relaxed alert level of 1, allows for the development of business skills and a resume of economic activity, strengthening the region's recovery and growth opportunities (Philippine News Agency, 2022).

Methods

The unemployment rate is a widely used economic indicator; however, it can be inconsistent and, at times, misleading. Such limitations may result in misinterpretations of the true level of unemployment within an economy. Moreover, unemployment figures are sensitive to seasonal fluctuations, changes in labor force participation, and differences in definitions and measurement practices across regions and countries. Consequently, the unemployment rate should be interpreted cautiously and analyzed alongside other labor market indicators to obtain a more comprehensive understanding of employment dynamics. Policymakers and analysts must therefore recognize these limitations when evaluating labor market conditions (Pecardo, 2024).

Given the strategic importance of inequality forecasts in policymaking, the analysis proceeds by identifying factors that may contribute to future economic inequality. Previous research indicates that population deceleration and shifts in educational composition significantly influence labor market outcomes, which subsequently affect income distribution among individuals and households (Dabbla-Norris, 2015). These structural variables are thus essential in modeling unemployment dynamics and broader distributional effects.

Time-series modeling enables the identification and prediction of patterns in key variables that are both statistically significant and theoretically relevant in explaining unemployment rates. Such models can also generate general equilibrium–consistent forecasts regarding the future evolution of unemployment.

A stationary time series is characterized by the absence of a deterministic trend, constant variance around a stable mean, and consistent short-term stochastic behavior over time. This implies that the autocorrelation structure remains invariant across periods. A stationary process may be viewed as a combination of signal and noise, where the signal captures mean-reverting behavior, oscillatory movement, rapid sign changes, and potential seasonal components.

The Auto-Regressive Integrated Moving Average (ARIMA) model functions as a statistical "filter" that separates systematic information from random noise prior to extrapolating future values. For stationary series, the ARIMA forecasting equation is linear, with predictors consisting of lagged values of the dependent variable and lagged forecast errors (Boateg, 2018).

ARIMA stands for Auto-Regressive Integrated Moving Average. In this framework, autoregressive (AR) terms represent lagged values of the stationary series, moving average (MA) terms capture lagged forecast errors, and the integrated (I) component refers to the differencing required to achieve stationarity. ARIMA models encompass several special cases, including random-walk, random-trend, pure autoregressive, and exponential smoothing models.

A non-seasonal ARIMA model is denoted as an (p, d, q)process, where:

- $p$is the number of autoregressive terms,
- $d$is the number of non-seasonal differences required to achieve stationarity, and
- $q$is the number of lagged forecast error terms.

The forecasting equation is constructed by defining $y_t$as the d^{th}difference of the original series Y_t, such that:

- If $d = 0$, then $y_t = Y_t$
- If $d = 1$, then $y_t = Y_t - Y_{t-1}$
- If $d = 2$, then

$$y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$$

It is important to note that the second difference $(d = 2)$ does not represent a change from two periods earlier; rather, it is the first difference of the first difference. This operation is the discrete equivalent of a second derivative in continuous time analysis (Nau, 2024).

The general forecasting equation in terms of y is:

$$\hat{y} = \mu + \emptyset_1 y_{t-1} + \cdots + \emptyset y_{t-p} - \emptyset_1 e_{t-1} - \cdots - \emptyset_q e_{t-q}$$

In ARIMA modeling, the usual guideline is to choose models with at least one of p and q smaller than 1. Attempting to fit a model like ARIMA (2,1,2) is not recommended because it will most likely result in overfitting. Overfitting a model to the data is as harmful as failing to recognize the data's systematic pattern (Tyagi, 2024).

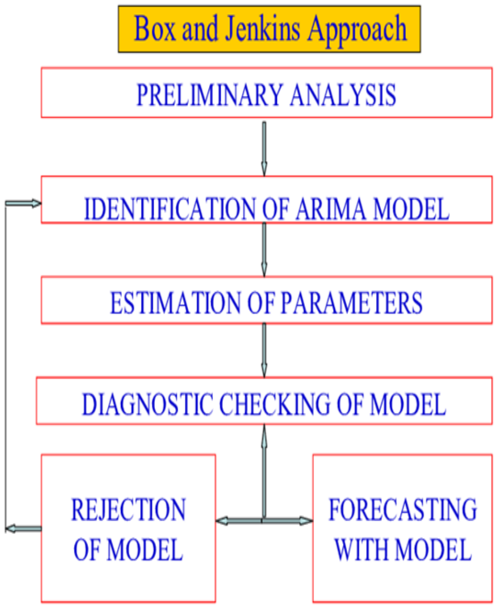


Figure 1. The Univariate Box-Jenkins ARIMA

Methodology

Figure 1 shows the Univariate Box-Jenkins ARIMA process in developing a time series model (Nau, 2024). Univariate Box-Jenkins ARIMA is an iterative approach that consists of the following steps:

1. Model Identification. Use the data and all related information to help select a subclass of model that may best summarize the data.
   1.1 Plot the time series data. Identify any unusual observations.
   1.2 If the data are non-stationary, take first difference of the data until the data are stationary.
2. Model Estimation and Diagnostic Checking. Use the data to train the model's parameters. To quick specify the accurate UBJ ARIMA model being utilized, a standard notation (p,d,q) is used, with the parameters substituted with integer values Brownlee [2023]. The parameter of the ARIMA model are defined as follows:
   - $\boldsymbol{p(AR)}$: The number of lag observations in the model, also known as the lagged order.
   - $\boldsymbol{d(I)}$: The number of times the raw observation is different is also referred to as the degree of difference.
   - $\boldsymbol{q(MA)}$: The size of the moving average window, also known as the moving average order,

To avoid overfitting or under fitting ARIMA models, only use the first three lags in the auto correlation plot (ACF) and partial auto correlation plot (PACF). According to the principle of parsimony, a model's goodness-of-fit is a measure of how well it can explain a given set of observations. In favor of more straightforward models that can apply to new data sets, the researcher forces the principle of parsimony by dropping complex models that are adjusted to fit the observed data (Vandekerckhove, 2015).

When selecting the most suitable model, look for the one with the lowest MAE, AIC, RMSE, MAPE, and the fewest AR and MA coefficients. The Akaike information criterion (AIC) is a mathematical technique for determining how well a model fits the data from which it was derived. In statistics, AIC is used to compare multiple potential models and find which one is the best fit for the data. Mean absolute error (MAE) is a popular metric because, like root mean squared error (RMSE), which is explained in the following subsection, the error value units correspond to the expected goal value units. Unlike RMSE, MAE changes are linear and easy to comprehend. MSE and RMSE punish greater errors more severely by inflating or increasing the mean error value by the square of the error value. In MAE, various errors are not weighted differently, but scores rise linearly as the number of errors increases. The MAE score is calculated as the average of the absolute error numbers. The absolute is a mathematical function that turns a number positive. As a result, while computing the MAE, the difference between an expected value and a forecasted value can be either positive or negative [Bevans 2023]. The mean absolute percentage error (MAPE) is the average of forecast' absolute percentage errors. An error is defined as the difference between the actual or observed value and the projected value. MAPE is calculated by summing percentage mistakes regardless of sign. This measure is simple to understand because it shows the inaccuracy in percentages. Furthermore, because absolute percentage errors are used, the issue of positive and negative errors canceling out is avoided. As a result, MAPE appeals to managers and is a popular forecasting metric. The lower the MAPE, the better the future looks (Swamidass, 2024).

The researcher uses these criteria to evaluate the models' quality as well as their prediction capacity. A model's capacity to estimate future values improves as the error rate decreases, because the difference between actual and expected values is referred to as an error.

Evaluate the fitted model in light of the available data and identify areas for improvement.

Result and Discussion

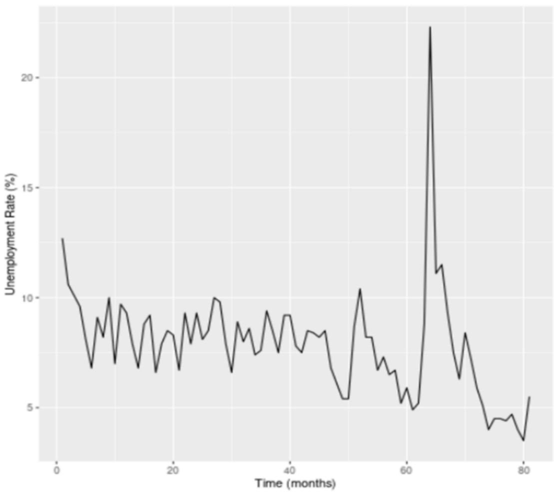
Univariate Box-Jenkins ARIMA Method

Model Identification

In the Univariate Box-Jenkins method, monitoring and evaluating time series data plots, autocorrelation plots, and partial autocorrelation plots assists the researcher in determining whether the series is stable, which is one of the requirements that need to be met, and whether there is a seasonal component.

Quarterly Unemployment Rate Series

The set of data that was observed was the quarterly unemployment series of the unemployment rate, which is the total number of the unemployment rate quarterly in the Ilocos Region, Philippines. For the succeeding methods, the unemployment rate series was used as the input. Figure 2 shows the unemployment rate series from July 2004 to July 2024.



The time series data on the unemployment rate show a fluctuating pattern throughout time, with periods of both high and low unemployment. The data collection period continues for a period of twenty years, from July 2004 to July 2024. The unemployment rate reached 22.3% in April 2020, most likely because of the economic impact of the COVID-19 pandemic. After this spike, unemployment continually dropped, reaching a low of 4% in October 2022. The data indicate that the labor market has been recovering from the pandemic-induced drop, with the unemployment rate stable around 4-5% in recent quarters. The long-term trend points to an annual trend in the unemployment rate, with periods of growth in the economy and a drop reflected in the data.

Figure 3 shows the auto correlation function (ACF) plot of the time series, which was also used to identify the model.

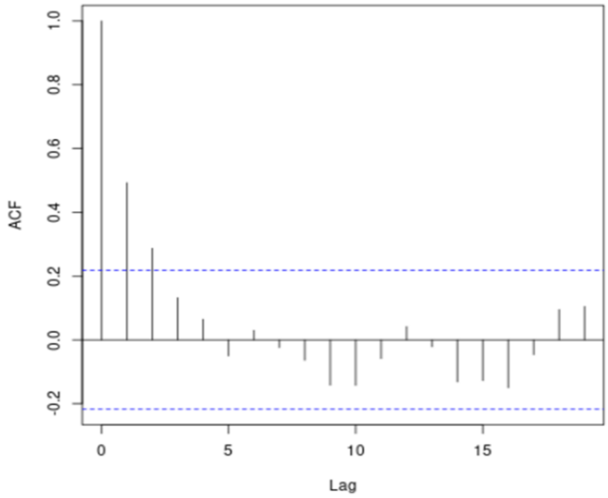


Figure 3 illustrates that the correlation functions are slowly approaching zero, with significant values at lags 0, 1, and 2. According to Sharma [2021], the presence of the lag 0 autocorrelation in the ACF plot serves as a reference point, but the more essential information is obtained by studying the patterns and magnitudes of non-zero lag autocorrelations, such as the lag 1 autocorrelation. Using the UBJ ARIMA model, this method indicates that the researcher believes the most recent past observations (up to 3 lags) are more relevant in forecasting the current values of the time series than longer-term lags.

Besides, Figure 4 shows the partial autocorrelation function (PACF) plot. The PACF figure shows that the function continually decreases to zero, with an important lag at was observed at lag 1. The rest of the area falls within the boundary line (broken lines).

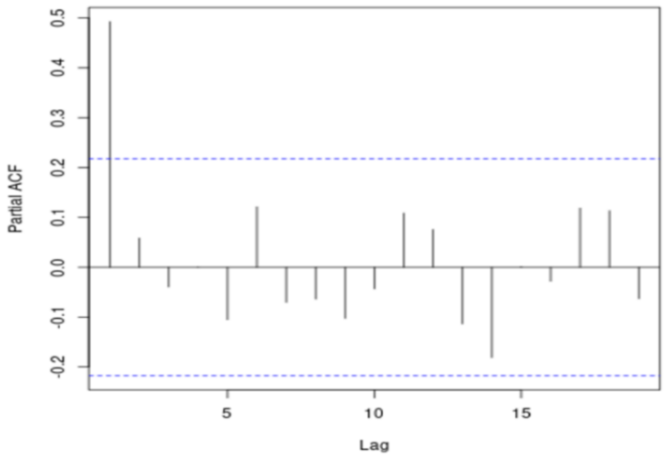


Figure 4. Partial Auto Correlation Plot

As shown in Figures 3 and 4, the time series data supports the ARIMA (1,0,0) and ARIMA (1,0,1) models. The ARIMA (1,0,0) or AR1 model was identified because the PACF diagram revealed a substantial lag at 1. ARIMA (1,0,1) or ARMA (1,1) was also found based on their PACF and ACF plots; there were considerable lags at 1, hence the model was created. Both of these models go through model estimation and evaluation checks, which are discussed in the following sections.

Model Estimation and Diagnostic Checking

The preceding table shows a model's fitting results. The following are the Akaike Information Criterion (AIC), Mean Absolute Error (MAE), Mean Absolute Percentage Errors (MAPE), Root Mean Squared Error (RMSE), estimated coefficients, and standard errors for an ARIMA (1,0,0) model performed using R.

Table 2. Shows the summary of ARIMA (1,0,0) model estimation.

Table 2. Model Estimation for ARIMA (1,0,0) Model

ARIMA (1,0,0)	
Series: tsdata	
Model Summary	
Stable: Yes	
AIC	357.5506
MAE	1.36022
MAPE	17.88475%
RMSE	2.115326
Parameter Estimates	
Term: AR	
Lag 1: 1	
Estimate: 0.5168175	
Standard Error: 0.0975	

Table 2 shows the fitting of an ARIMA (1,0,0) model, an autoregressive model of first order that forecasts unemployment rate changes as an average change plus a fraction of the prior change plus a random error. The table of parameter estimates lists the model's parameters and provides the estimated value as well as the standard error of the estimate.

The table also shows the period of time at which the parameter develops in the model. The autoregressive parameter is known as AR1. This is the coefficient of the lagged value of the change in employment rates, with an estimate of 0.5168175. The AIC for this model is 357.5506, while the MAE is 1.36022.

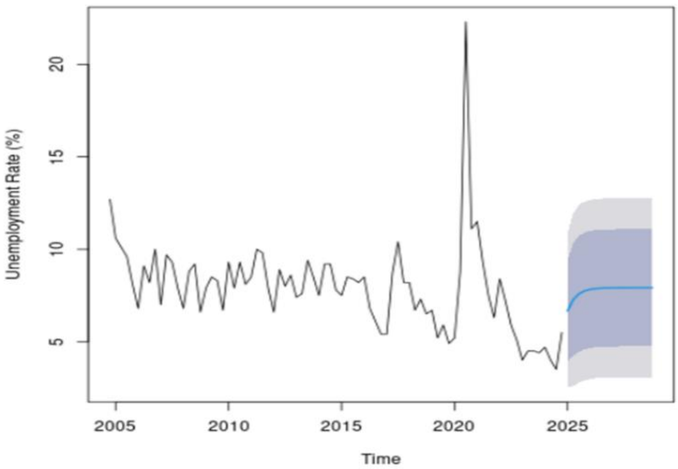


Figure 5. Forecast plot of ARIMA (1,0,0) Model

Figure 4 shows the forecast plot for the ARIMA (1,0,0) model, a first-order autoregressive model. The series is stationary and autocorrelated. Fitting an ARIMA (1,0,0) model resulted in a forecast with a 95% confidence interval (shaded gray zone) over the next few months. Data values are neither increasing nor decreasing over time. The blue line in Figure 6 represents the model's fit. The line fit increased as the model predicted more values. The model failed to capture the appropriate time series data. Because the model assumes no additional seasonal fluctuations, the change in unemployment rates from one quarter to the next is approximately stable in both mean and variance.

Table 3 shows the summary of the model estimation for ARIMA (1,0,1) model

Table 3. Model Estimation for ARIMA (1,0,1) Model

ARIMA (1,0,1)	
Series: tsdata	
Model Summary	
Stable: Yes	
AIC	359.1448
MAE	1.336443
MAPE	17.51123%
RMSE	2.109844
Parameter Estimates	
Term:	
AR(1)	
MA(1)	
Lag 1:	
AR(1): 1	
MA(1): 1	
Estimate:	
AR(1): 0.6155388	
MA(1): -0.1311376	
Standard Error:	
AR(1): 0.1682	
MA(1): 0.2028	
Dickey-Fuller: -3.766, Lag order 4	
p-value: 0.02463	
Alternative hypothesis: stationary	

Table 3 shows the fitting of an ARIMA (1,0,1) model, an autoregressive and a moving average model of order 1. The table also indicates the lag at which the parameter appears in the model. The autoregressive parameter is labeled AR1, this is the coefficient of the lagged value of the change in the unemployment rates and its estimate is 0.6155. The moving average parameter is labeled MA1, and its estimate is -0.1311. The corresponding AIC for this model is 359.1448 and its MAE is 1.336443. Since the p-value is 0.0246 from the ADF test is less than 0.05, this means that the time series is stationary.

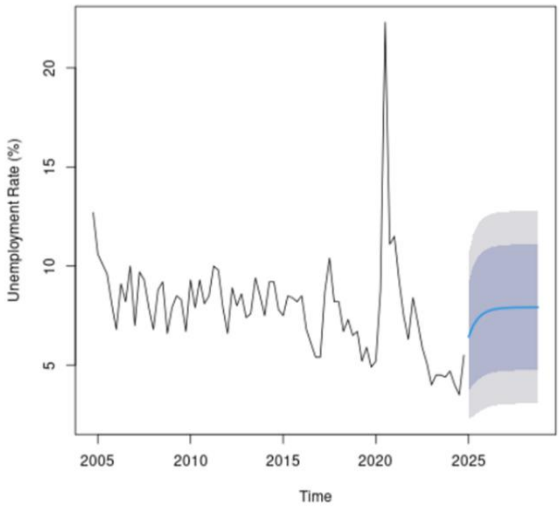


Figure 6. Forecast Plot of ARIMA (1,0,1) Model

Figure 6 shows the forecast plot of the ARIMA (1,0,1) model. There were no regular trends (up or down) across the entire time period. The series appears to steadily move up and down. There were no noticeable outliers.

Fitting an ARIMA (1,0,1) model provided a forecast with a 95% confidence interval (shaded gray zone) for the coming months. The blue line in Figure 7 shows the model's initial output. The line fit approaches a straight line as the model forecasts more values. Because the model assumes no further seasonal changes, the change in unemployment rates from one quarter to the next is rather consistent in both mean and variance.

An *ndiff* function in R determines the number of differencing operations required to make the time series data stable. With this function, the time series data becomes stationary. To achieve stationarity with this function, the time series data needs to go through first differencing.

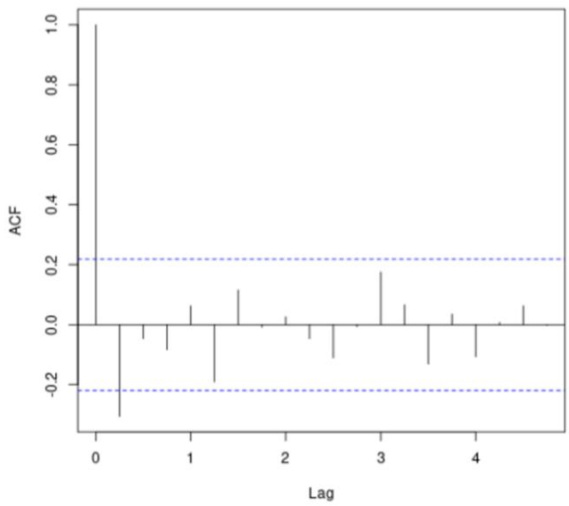


Figure 7 shows the time series data plot after the 1st differencing

Figure 7 shows that the time series data appears to be stationary, with almost all points concentrated along the middle line. Figures 8 and 9 show the ACF and PACF plots on the differenced data.

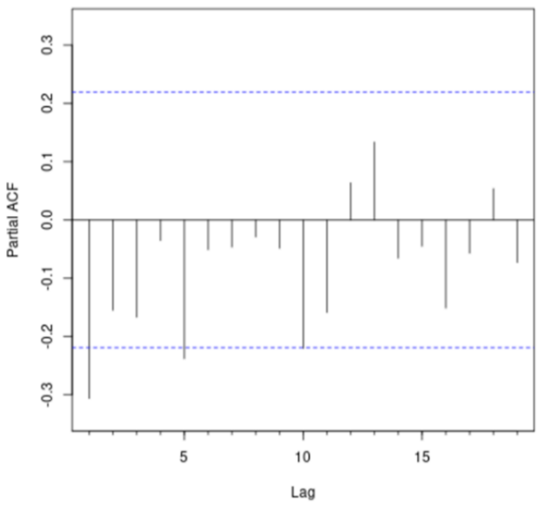


Figure 8. The ACF Plot of the Differenced Unemployment Data

Figure 8 shows that the autocorrelation function is slowly getting closer to zero, with considerable lags at lag 0 and in other lags. Using the UBJ ARIMA model, the researcher only analyzed immediate delays, which might range from 0 to 2. Assuming the process is a moving average process, the autocorrelation plot of the time series data with differencing is created with a 95% confidence band. The autocorrelation graphic indicates that autocorrelations gradually decrease to zero after a few lags.

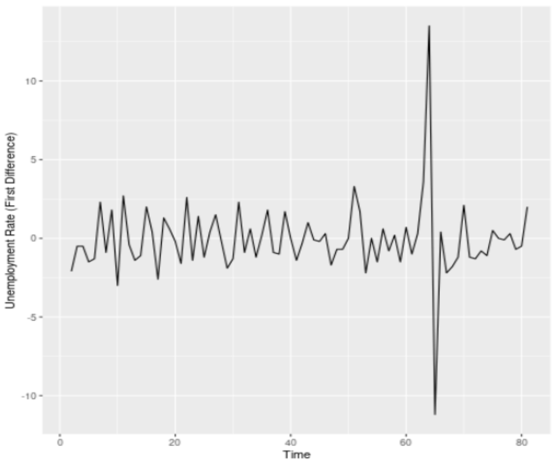


Figure 9. Partial Auto Correlation Plot of the Unemployment Data with Differencing

Figure 9 shows a partial auto correlation plot of the time series data. The partial auto correlation graphic reveals substantial spikes at lags 1 and 5. The researcher used the UBJ ARIMA model and only analyzed the 1st significant lags.

Using the data from the ACF and PACF plots, the following models were considered: ARIMA (1,1,0), ARIMA (1,1,1), and ARIMA (2,1,1). The following parts cover the estimates and diagnostic testing of the previously mentioned models.

Model Estimation for ARIMA (1,1,0), ARIMA (1,1,1), and ARIMA (2,1,1)

Table 4 Model Estimation for ARIMA (1,1,0) Model

ARIMA (1,1,0)	
Series: tsdata	
Model Summary	
Stable: Yes	
AIC	364.3069
MAE	1.382182
MAPE	16.35593 %
RMSE	2.284516
Parameter Estimates	
Term: AR1	
Lag 1: 1	
Estimate: -0.3059722	
Standard Error: 0.1066	

Table 4 shows the fitting of an ARIMA (1,1,0) model, which is a first-order autoregressive model. The table also shows the latency at which the parameter emerges in the model. The autoregressive parameter is referred to as AR1. This is the coefficient of the lagged value of the change in employment rates, estimated at 0.3059722. The AIC for this model is 364.3069, and the MAE is 1.382182

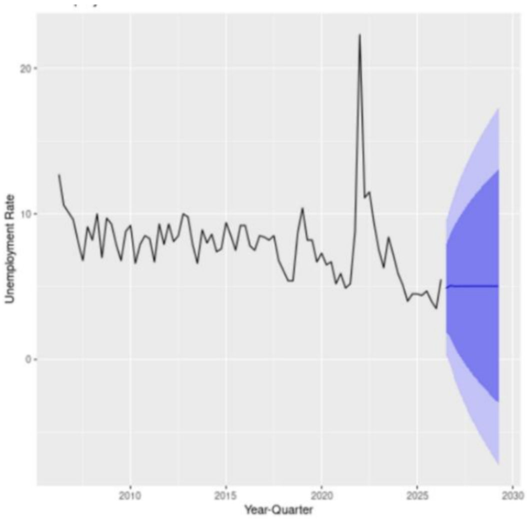


Figure 10. Forecast Plot of ARIMA (1,1,0) Model

Figure 10 shows the forecast plot for the ARIMA (1,1,0) model. An ARIMA (1,1,0) model was used to forecast the coming months. The blue line in Figure 8 represents the model's fit. As the model forecasts more values, the fit becomes more like a straight line. Because the model assumes no additional seasonal fluctuations, the change in unemployment rates from one four-month period to the next is approximately stable in mean and variance.

The ACF and PACF plots guided the researcher in fitting the values of the ARIMA (1,1,1) model. Table 5 shows the model fitting results. From R, the Akaike Information Criterion (AIC), Mean Absolute Error (MAE), estimated coefficients, and standard errors for an ARIMA (1,1,1) model are as follows:

Table 5 Model Estimation for ARIMA (1,1,1) Model

ARIMA (1,1,1)	
Series: tsdata	
Model Summary	
Stable: Yes	
AIC	356.03
MAE	1.372259
MAPE	18.30392 %
RMSE	2.12672
Parameter Estimates	
Term:	
AR(1)	
MA(1)	
Lag 1:	
AR(1): 1	
MA(1): 1	
Estimate:	
AR(1): 0.4799278	
MA(1): -0.9437569	
Standard Error:	
AR(1): 0.1161	
MA(1): 0.0528	

Table 5 shows the fitting of an ARIMA (1,1,1) model, which is an autoregressive integrated moving average model with order 1. The table also shows the time interval at which the parameter emerges in the model. The autoregressive parameter is labeled AR (1); it represents the coefficient of the lagged value of the change in unemployment rates, with an estimate of 0.4799. The moving average parameter is denoted as MA (1), and its estimate is -0.9438. The AIC for this model is 356.03, and the MAE is 1.372259.

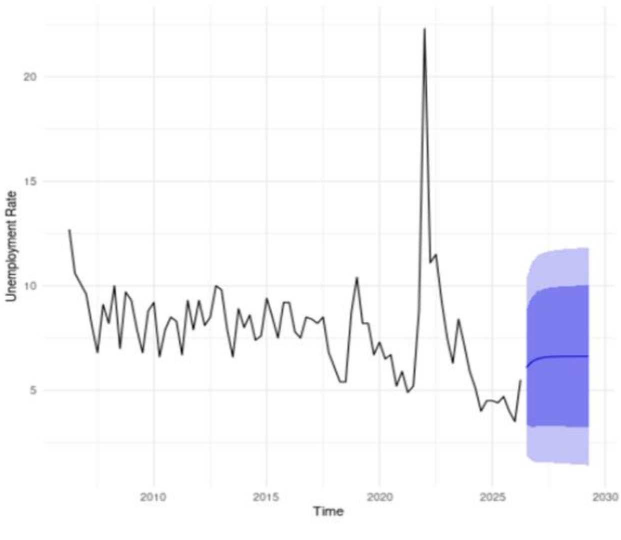


Figure 11. Forecast Plot of ARIMA (1,1,1) Model

Figure 11 shows the forecast plot for the ARIMA (1,1,1) model. Forecasts for the coming months were derived using an ARIMA (1,1,1) model. The frequencies following the vertically shaded zone represent the forecast using the ARIMA (1,1,1) model. Figure 12 depicts the fit provided by the model. As the model forecasts more values, the line fit becomes more similar to a straight line. Because the model assumes no additional seasonal oscillations, the shift in unemployment rates from the fourth month to the next is approximately stable in mean and variance.

Table 6 shows the model fitting findings. The Akaike Information Criterion (AIC), Mean Absolute Error (MAE), estimated coefficient, and standard errors for an ARIMA (2,1,1) model are calculated in R as follows:

Table 6. Model Estimation for ARIMA (2,1,1) Model

ARIMA (2,1,1)	
Series: tsdata	
Model Summary	
Stable: Yes	
AIC	357.68
MAE	1.35351
MAPE	18.0183 %
RMSE	2.122396
Parameter Estimates	
Term:	
AR(1)	
MA(1)	
Lag 1:	
AR(1): 1	
AR(2): 2	
MA(1): 1	
Estimate:	
AR(1): 0.4570	
AR(2): 0.0693	
MA(1): -0.9504	
Standard Error:	
AR(1): 0.1202	
AR(2): 0.1176	
MA(1): 0.0493	

Table 6 shows the fitting of an ARIMA (2,1,1) model, which is an autoregressive integrated moving average model of order 2. The table also shows the period of time at which the parameter develops in the model. The autoregressive parameter, AR (1), is the coefficient of the lagged value of the change in unemployment rates, with an estimate of 0.4570. The autoregressive parameter is written as AR2. This is the coefficient of the lagged value of the change in unemployment rates, with an estimate of 0.0693. The moving average parameter, chosen as MA1, has an estimate of -0.9504. The AIC for this model is 357.68, and the MAE is 1.35351.

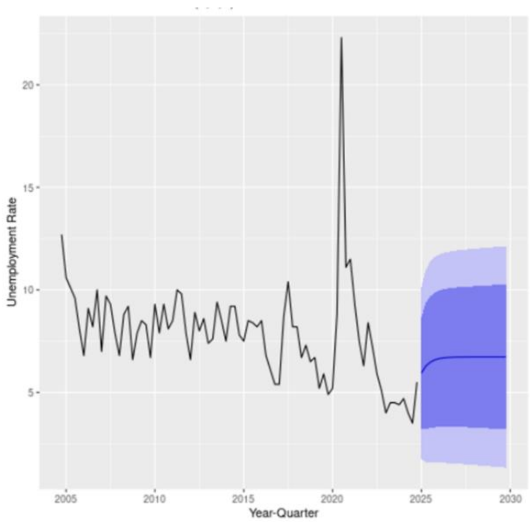


Figure 12. Forecast Plot of ARIMA (2,1,1) Model

Figure 12 shows the forecast plot for the ARIMA (2,1,1) model. An ARIMA (2,1,1) model was used to forecast the next few months. The frequencies following the vertically shaded zone represent the forecast using the ARIMA (2,1,1) model. The blue line in Figure 13 represents the model's fit. The line approaches a straight line as the model expects more values. Because the model assumes no additional seasonal fluctuations, the change in unemployment rates from one four-month period to the next is approximately stable in mean and variance.

Table 7 provides a summary of the model estimates from the five selected models.

Table 7. Summary of the Model Estimates of the Five Selected Models

Model	AIC	MAE	MAPE	RMSE	No. of AR and MA coefficients
1. ARIMA (1,0,0)	357.5506	1.360220	17.88475%	2.115326	1
2. ARIMA (1,0,1)	359.1448	1.336443	17.51123%	2.109844	2
3. ARIMA (1,1,0)	364.3039	1.382182	16.35593%	2.284516	1
4. ARIMA (1,1,1)	356.0300	1.372259	18.30392%	2.126720	2
5. ARIMA (2,1,1)	357.6800	1.353510	18.01830%	2.122396	3

Table 7 summarizes the model estimates for five different ARIMA (Autoregressive Integrated Moving Average) models. The ARIMA (1,1,1) model has the lowest AIC (Akaike Information Criterion) value of 356.03, resulting in the best-fitting of the five. However, the ARIMA (1,0,1) model has the lowest MAE (Mean Absolute Error) of 1.336443 and the ARIMA (1,0,1) model has the lowest RMSE (Root Mean Square Error) of 2.109844, indicating that it is the most accurate. The ARIMA (1,1,0) model has the smallest MAPE (Mean Absolute Percentage Error) of 16.36%, making it the most reliable in terms of percentage error. In terms of complexity, the ARIMA (1,0,0) and ARIMA (1,1,0) models have the fewest number of AR (Autoregressive) and MA (Moving Average) coefficients at a single one, while the ARIMA (2,1,1) model has the most coefficients (3). The ARIMA (1,1,1) model stands out with the lowest AIC value of 356.03, indicating it offers the best fit among the models evaluated, despite not being the top in every single metric. Therefore, ARIMA (1,1,1) was the most appropriate model to represent the time series for the unemployment rates in the Ilocos Region. The data variable was fitted with the ARIMA (1,1,1) in order to predict the number of quarterly unemployment rates in the future.

As a way to predict the quarterly unemployment rates in October 2023, January 2024, April 2024, July 2024, October 2024, January 2025, April 2025, and July 2025 the researcher chose ARIMA (1,1,1) from the UBJ ARIMA Models. Table 7 displays the ARIMA (1,1,1) forecast values as well as the actual values using Mat Lab for the months of October 2023 through July in 2025. At the time of authoring this paper, the actual values were not yet available.

Table 8. Forecast Values and Actual Values

Month and Year	Forecast Values	Actual Values	$Percentage\ Error = \left\lvert \frac{FV - AV}{AV} \right\rvert$
January 2024	5.2	4	30%
April 2024	5.1	3.5	45.71%
July 2024	5	5.5	9.09%
October 2024	4.9	TBD	-----
January 2025	4.8	TBD	-----
April 2025	4.7	TBD	-----
July 2025	4.6	TBD	-----

The table 8 analyzes predicted and actual unemployment rates for the quarters of January 2024 to July 2025, using the ARIMA (1,1,1) model. In January 2024, the forecast anticipated a rate of 5.2%, but the actual rate was 4%, resulting in a percentage error of 30%. Similarly, predictions for April 2024 were 5.1%, compared to an actual rate of 3.5%, with a percentage error of 45.71%. For July 2024, the predicted value was 5%, and the actual rate was 5.5%, resulting in a percentage error of 9.09%. Certain discrepancies reflect the model's varying ability to predict unemployment patterns over certain time periods. However, from January 2024 to July 2025, the actual values are displayed as "TBD," suggesting that the % errors cannot yet be determined. This emphasizes the ARIMA model's predictive aspect, which seeks to predict future economic situations based on historical data patterns, while the accuracy of it can only be completely evaluated after all actual values are available.

The researcher shows the full algebraic equation of the model ARIMA (1, 1, 1). The ARIMA (1,1,1) model expression is:

$$y_t - y_{t-1} = \phi_1(y_{t-1} - y_{t-2}) + \varepsilon_t - \theta_1\varepsilon_{t-1}$$

$Where$: $\boldsymbol{y_t}$ $=$ $the\ time\ series\ variable\ we\ are\ trying\ to\ model\ or\ predict\ at\ time\ t.$

$\boldsymbol{y_{t-1}} = the\ value\ of\ a\ time\ series\ at\ time\ t-1.$

$\boldsymbol{y_{t-2}} = the\ value\ of\ a\ time\ series\ at\ time\ t-2.$

$\boldsymbol{\phi_1} = the\ autoregressive\ (AR) coefficient\ for\ lag\ 1.$

$\boldsymbol{\theta_1} = the\ moving\ average\ (MA) coefficient\ for\ lag\ 1.$

$\boldsymbol{\varepsilon_t} = the\ error\ term\ (white\ noise) at\ time\ t.$

$\boldsymbol{\varepsilon_{t-1}} = the\ error\ term\ (white\ noise) at\ time\ t-1.$

Hence, the algebraic equation representation of the model ARIMA (1,1,1) is:

$$y_t = y_{t-1} + 0.4799(y_{t-1} - y_{t-2}) + \varepsilon_t - 0.9438\varepsilon_{t-1}$$

Conclusion

The following conclusions were drawn from the results of the study:

1. Over the 20-year period from July 2004 to July 2024, the unemployment rate in the Philippines' Ilocos Region was highly varia-

ble and unpredictable. The rate has fluctuated significantly, from 4.0% to 22.3%, showing how economic downturns and changes affect the job market.

2. The economic consequences of the COVID-19 pandemic directly contributed to a significant increase in the number of unemployed, which reached 22.3% in April 2020.The drop in the rate, and also the current stability of 4-5%, this shows an unpredictable however consistent come back in the labor market.
3. The ARIMA (1,1,1) model was chosen as the best fit for forecasting the quarterly unemployment rate in the Ilocos Region. This model was chosen based on several model estimates and the parsimony principle, demonstrating its ability to represent the underlying patterns in the time series data.
4. The study reveals that the ARIMA (1,1,1) is suitable to model the unemployment rate predictions from October 2023 to July 2024. This shows the significant variations in predicting accuracy for the unemployment rates. The percentage errors of the model have a big difference in January and April in the year 2024 it shows the model's ability to capture the economic condition with the complexities during those months. It also shows the limitations of using historical data-driven models. These discrepancies may fail for driving unemployment rates or unforeseen economic shocks. Some improvements were somewhat reduced in July 2024, this means that there was improvement. However, it also demonstrates the model's ability to predict the actual rates. Therefore, ARIMA models are utilized for economic forecasting; the performance is dependent on ongoing validation and adjustment to enhance the reliability and accuracy of the model to better change the economic systems in the Ilocos Region.

Acknowledgement

The author extends his gratitude to the Philippines Statistics Authority Regional Statistical Services Office Region I for their assistance in providing the data for this study. My sincerest gratitude to the Far Eastern University-Manila for providing funding support for this research study. Our Lord God Almighty, who gave us the strength and perseverance to finish the study.

References

Bevans, R. (2023) Akai Information Criterion/When and How to Use It. https://www.scribbr.com/statistics/akaike-information-criterion/

Brooks, R. (2002) Why is unemployment high in the Philippines? International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2016/12/30/Why-is-Unemployment-High-in-the-Philippines-15591

Boateg, N. (2018) Building Arima Models for Forecasting, Time Series Analysis Methods. https://rpubs.com/mr148/303786.

Dabbla-Norris E. (2015) Poverty rates by Regions Causes and Consequences of Income Inequality: A Global Perspective. https://www.imf.org/external/pubs/ft/sdn/2015/, (2015), pp. 15-16

International Labor Organization (2020) Initial labor markets impacts of COVID-19, https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/

Dabbla-Norris E. (2015) Poverty rates by Regions Causes and Consequences of Income Inequality: A Global Perspective. https://www.imf.org/external/pubs/ft/sdn/2015/, (2015), pp. 15-16

National Economic Development Authority (2023). Neda Reiterates Gov't Focus on High-Quality Job Creation as Unemployment Rate Further Declines. https://neda.gov.ph/neda-reiterates-govt-focus-on-high-quality-job-creation-as-unemployment-rate

Nau, C. (2024) ARIMA models for time series. https://people.duke.edu/~rnau/411arim.htm. Accessed 18 April 2024.

Nau, R. (2020) Statistical Forecasting: Identify the numbers of AR or MA terms in an ARIMA model. https://people.duke.edu/~rnau//411arim3.htm.

Narvasa, D. (2024) An Application of the First – Order Linear Ordinary Differential Equation to Regression Modeling of Unemployment Rates, Journal of Interdisciplinary Perspectives. https://www.jippublication.com/an-application-of-the-first-order-linear-ordinary-differential-equation-to-regression-modeling-of-unemployment-rates

Pecardo, E. (2024) Employment vs Unemployment How The Unemployment Rate Affect Everybody? https://www.investopedia.com/articles/economics/10/unemployment-rate-get-real

Philippine News Agency (2022) Employment rate up 94% in Ilocos. https://www.pna.gov.ph/articles/1178217

Philippine Statistics Authority (2024) Labor force survey. https://psa.gov.ph/statistics/

Sharma, V. (2021) Application of geographic information system and remote sensing in heavy metal assessment. Science Direct. https://www.sciencedirect.com/topics/earth-and-planetary-sciences/autocorrelation

Swamidass, P. (2024) Mean Absolute Percentage Error (MAPE) https://link.springer.com/referenceworkentry/10.1007/1-4020-0612-8_580%2

Tyagi, S. (2024) "Introduction to time series forecasting" https://towardsdatascience.com/introduction-to-time-series

Vandekerckhove, J (2015) Model comparison and the principle of parsimony. https://psycnet.apa.org/record/2015-10090-014

World Bank in the Philippines (2024) Overview domestic growth is strong in the Philippines, while global challenges are affecting prospects https://www.worldbank.org/

R compiler codes and MatLab code
Quarterly Unemployment Rate Series

```
# Load the data into a data frame
data <- data.frame(
  Reference.Period = c(1:81),
  Time = c(1:81),
  Unemployment.Rate = c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)
)
# Plot the unemployment rate over time
library(ggplot2)
ggplot(data, aes(x = Time, y = Unemployment.Rate)) +
  geom_line() +
  labs(x = "Time (months)", y = "Unemployment Rate (%)")
```

ACF

```
# Load the data
unemployment_rate <- c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)

# Generate the autocorrelation plot
acf(unemployment_rate, main = "Autocorrelation Plot of Unemployment Rate")
```

PACF

```
# Load the data
unemployment_rate <- c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)

# Compute the Partial Autocorrelation Function (PACF)
pacf(unemployment_rate)
```

Model Estimation and Diagnostic Checking

Model Estimation for ARIMA (1,0,0) with summary table

```
# Load necessary libraries
library(forecast)
library(tseries)

# Convert the data into a time series object
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 10),
frequency = 4)

# Fit the ARIMA(1,0,0) model
model <- arima(unemployment_rate, order = c(1, 0, 0))

# Obtain the summary of the model
summary(model)

# Calculate the performance metrics
residuals <- model$residuals
mae <- mean(abs(residuals))
mape <- mean(abs(residuals / unemployment_rate)) * 100
rmse <- sqrt(mean(residuals^2))

# Print the results
cat("AIC:", model$aic, "\n")
cat("MAE:", mae, "\n")
cat("MAPE:", mape, "%\n")
cat("RMSE:", rmse, "\n")
cat("\nParameter Estimates:\n")
cat("Term\tLag\tEstimate\tStd. Error\n")
cat("ar1\t1\t", model$coef[1], "\t", model$se[1], "\n")
cat("intercept\t-\t", model$coef[2], "\t", model$se[2], "\n")
```

Unemployment rate Forecast – ARIMA (1,0,0) Model

```
# Load the necessary libraries
library(forecast)
library(ggplot2)

# Convert the data to a time series object
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 4), fre-
quency = 4)

# Fit the ARIMA(1,0,0) model
arima_model <- arima(unemployment_rate, order = c(1, 0, 0))

# Generate the forecast
forecast_result <- forecast(arima_model, h = 16)

# Plot the forecast with 95% confidence intervals
plot(forecast_result, main = "Unemployment Rate Forecast",
    xlab = "Time", ylab = "Unemployment Rate (%)")
```

Model Estimation for ARIMA (1,0,1) with summary table

```
# Load necessary libraries
library(forecast)
library(tseries)

# Correct and properly formatted unemployment data
unemployment_data <- c(
  10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6,
  7.9, 8.5, 8.3, 6.7, 9.3, 3.9, 9.3, 8.1, 8.5, 10, 9.8, 7.3, 6.6, 3.9, 8, 7, 8, 7.4, 7.5, 9.9, 8.4, 8.5, 7.5, 3.2, 9.2,
9.2, 7.8, 7.5
)

# Convert the data into a time series object
unemployment_ts <- ts(unemployment_data, start = c(2004, 10), frequency = 4)

# Perform the Augmented Dickey-Fuller (ADF) test
adf_result <- adf.test(unemployment_ts)

# Print the ADF test results
print(adf_result)

# Fit the ARIMA(1,0,1) model
model <- arima(unemployment_ts, order = c(1, 0, 1))

# Obtain the summary of the model
summary(model)

# Calculate evaluation metrics
mae <- mean(abs(fitted(model) - unemployment_ts))
rmse <- sqrt(mean((fitted(model) - unemployment_ts)^2))
mape <- mean(abs((fitted(model) - unemployment_ts)/unemployment_ts) * 100)

# Print the results
cat("AIC:", model$aic, "\n")
cat("MAE:", mae, "\n")
cat("MAPE:", mape, "%\n")
cat("RMSE:", rmse, "\n")
cat("Parameter Estimates:\n")
cat("Term | Lag | Estimate | Std. Error\n")
cat("ar1 | 1 |", model$coef[1], "|", model$se[1], "\n")
cat("ma1 | 1 |", model$coef[2], "|", model$se[2], "\n")
cat("intercept | 0 |", model$coef[3], "|", model$se[3], "\n")
```

Unemployment rate Forecast – ARIMA (1,0,1) Model

```
# Load the required library
library(forecast)

# Convert the data to a time series
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 4), fre-
quency = 4)

# Fit the ARIMA(1,0,1) model
arima_model <- arima(unemployment_rate, order = c(1, 0, 1))

# Generate the forecast
forecast_periods <- 16 # Forecast for the next 4 years (16 quarters)
forecast_results <- forecast(arima_model, h = forecast_periods)

# Plot the forecast with 95% confidence interval
plot(forecast_results, main = "Unemployment Rate Forecast",
    xlab = "Time", ylab = "Unemployment Rate (%)")
```

Time series data plot after 1st differencing.

```
# Load the data
unemployment_data <- data.frame(
  Reference_Period = c("Jul-04", "Oct-04", "Jan-05", "Apr-05", "Jul-05", "Oct-05", "Jan-06", "Apr-
06", "Jul-06", "Oct-06", "Jan-07", "Apr-07", "Jul-07", "Oct-07", "Jan-08", "Apr-08", "Jul-08", "Oct-
08", "Jan-09", "Apr-09", "Jul-09", "Oct-09", "Jan-10", "Apr-10", "Jul-10", "Oct-10", "Jan-11", "Apr-
11", "Jul-11", "Oct-11", "Jan-12", "Apr-12", "Jul-12", "Oct-12", "Jan-13", "Apr-13", "Jul-13", "Oct-
13", "Jan-14", "Apr-14", "Jul-14", "Oct-14", "Jan-15", "Apr-15", "Jul-15", "Oct-15", "Jan-16", "Apr-
16", "Jul-16", "Oct-16", "Jan-17", "Apr-17", "Jul-17", "Oct-17", "Jan-18", "Apr-18", "Jul-18", "Oct-
18", "Jan-19", "Apr-19", "Jul-19", "Oct-19", "Jan-20", "Apr-20", "Jul-20", "Oct-20", "Jan-21", "Apr-
21", "Jul-21", "Oct-21", "Jan-22", "Apr-22", "Jul-22", "Oct-22", "Jan-23", "Apr-23", "Jul-23", "Oct-
23", "Jan-24", "Apr-24", "Jul-24"),
  Unemployment_Rate = c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6,
7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8,
7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3,
11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)
)

# Calculate the first difference
unemployment_data$Unemployment_Rate_Diff <- c(NA, diff(unemployment_data$Unemploy-
ment_Rate))

# Create the time series plot
library(ggplot2)
ggplot(unemployment_data, aes(x = 1:nrow(unemployment_data), y = Unemploy-
ment_Rate_Diff)) +
  geom_line() +
  labs(x = "Time", y = "Unemployment Rate (First Difference)")
```

The ACF Plot of the Differenced Unemployment Data

```
# Load the necessary libraries
library(ggplot2)
library(ggfortify)

# Convert the data into a time series object
unemployment_data <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 4), fre-
quency = 4)

# Calculate the differenced time series
diff_unemployment <- diff(unemployment_data)

# Create the ACF plot
autoplot(acf(diff_unemployment), main = "Autocorrelation Function (ACF) Plot of Differenced
Unemployment Data")
```

Partial Auto Correlation Plot of the Unemployment Data with Differencing

```
# Load the necessary libraries
library(tseries)
library(forecast)

# Unemployment time series data
unemployment_data <- c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6,
7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8,
7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3,
11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)

# Check the stationarity of the series
adf.test(unemployment_data)

# Take the first difference to make the series stationary
diff_unemployment_data <- diff(unemployment_data)

# Create the PACF plot
par(mfrow = c(1, 1))
Acf(diff_unemployment_data, type = "partial", main = "Partial Autocorrelation Function (PACF)")
```

```
Augmented Dickey-Fuller Test

data:  unemployment_data
Dickey-Fuller = -3.766, Lag order = 4, p-value = 0.02463
alternative hypothesis: stationary
```

Model Estimation for ARIMA (1,1,0) with summary table

```
# Load the necessary libraries
library(forecast)

# Convert the data to a time series object
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 4), fre-
quency = 4)

# Fit the ARIMA(1,1,0) model
model_arima_110 <- arima(unemployment_rate, order = c(1, 1, 0))

# Obtain the summary of the model
summary(model_arima_110)

# Calculate the performance metrics
residuals <- model_arima_110$residuals
mae <- mean(abs(residuals))
mape <- mean(abs(residuals / unemployment_rate)) * 100
rmse <- sqrt(mean(residuals^2))

# Print the results
cat("AIC:", model_arima_110$aic, "\n")
cat("MAE:", mae, "\n")
cat("MAPE:", mape, "%\n")
cat("RMSE:", rmse, "\n")

cat("\nParameter Estimates:\n")
cat("Term\tLag\tEstimate\tStd. Error\n")
cat("ar1\t1\t", model_arima_110$coef[1], "\t", model_arima_110$se[1], "\n")
cat("intercept\t-\t", model_arima_110$coef[2], "\t", model_arima_110$se[2], "\n")
```

Unemployment rate Forecast – ARIMA (1,1,0) Model

```
# Load required libraries
library(forecast)
library(ggplot2)

# Convert the unemployment rate data to a time series
unemployment_rates <- c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6,
7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8,
7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3,
11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)
unemployment_ts <- ts(unemployment_rates, start = c(2004, 10), frequency = 4)

# Fit the ARIMA(1,1,0) model
arima_model <- arima(unemployment_ts, order = c(1, 1, 0))

# Generate the forecast plot
forecast_plot <- autoplot(forecast(arima_model, h = 12)) +
  labs(x = "Year-Quarter", y = "Unemployment Rate", title = "Unemployment Rate Forecast")
print(forecast_plot)
```

Model Estimation for ARIMA (1,1,1) Model

```
library(forecast)

# Convert the data to a time series object
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 4), fre-
quency = 4)

# Fit the ARIMA(1,1,1) model
model_arima_111 <- arima(unemployment_rate, order = c(1, 1, 1))

# Obtain the summary of the model
summary(model_arima_111)

# Calculate additional metrics
fitted <- fitted(model_arima_111)
residuals <- residuals(model_arima_111)
rmse <- sqrt(mean(residuals^2))
mape <- mean(abs(residuals / unemployment_rate)) * 100
mae <- mean(abs(residuals))

cat("RMSE:", rmse, "\n")
cat("MAPE:", mape, "%\n")
cat("MAE:", mae, "\n")

# Estimated parameters
cat("Estimated parameters:\n")
print(model_arima_111$coef)

# Standard errors of the estimated parameters
cat("Standard errors of the estimated parameters:\n")
print(sqrt(diag(model_arima_111$var.coef)))

# Lag of the model
cat("Lag of the model:", model_arima_111$order, "\n")
```

Forecast of ARIMA (1,1,1) Model

```
# Load the necessary libraries
library(forecast)
library(ggplot2)

# Create the time series data
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 10),
frequency = 4)

# Fit the ARIMA(1,1,1) model
arima_model <- arima(unemployment_rate, order = c(1, 1, 1))

# Generate the forecast
forecast_arima <- forecast(arima_model, h = 12) # Forecast 12 periods ahead

# Plot the forecast
autoplot(forecast_arima) +
  labs(title = "Forecast Plot of ARIMA(1,1,1) Model",
       x = "Time",
       y = "Unemployment Rate") +
  theme_minimal()
```

Model Estimation for ARIMA (2,1,1) with summary table

```
library(forecast)

# Convert the data to a time series object
unemployment_rate <- ts(c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2,
6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2,
7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8,
22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5), start = c(2004, 4), fre-
quency = 4)

# Fit the ARIMA(2,1,1) model
model_arima_211 <- arima(unemployment_rate, order = c(2, 1, 1))

# Obtain the summary of the model
summary(model_arima_211)

# Calculate additional metrics
fitted <- fitted(model_arima_211)
residuals <- residuals(model_arima_211)
rmse <- sqrt(mean(residuals^2))
mape <- mean(abs(residuals / unemployment_rate)) * 100
mae <- mean(abs(residuals))

cat("RMSE:", rmse, "\n")
cat("MAPE:", mape, "%\n")
cat("MAE:", mae, "\n")
```

Forecast Plot of ARIMA (2,1,1) Model

```
library(forecast)
library(ggplot2)

# Create the unemployment rate time series
unemployment_rate <- c(12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6,
7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8,
7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3,
11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5)

unemployment_ts <- ts(unemployment_rate, start = c(2004, 4), frequency = 4)

# Fit the ARIMA(2,1,1) model
arima_model <- arima(unemployment_ts, order = c(2, 1, 1))

# Generate the forecast
forecast_arima <- forecast(arima_model, h = 20)

# Plot the forecast
autoplot(forecast_arima) +
 labs(title = "Forecast Plot of ARIMA(2,1,1) Model",
    x = "Year-Quarter",
    y = "Unemployment Rate")
```

Mat lab codes for Forecast Values with 95% Confidence Interval

```
% Load the time series data
y = [12.7, 10.6, 10.1, 9.6, 8.1, 6.8, 9.1, 8.2, 10, 7, 9.7, 9.3, 7.9, 6.8, 8.8, 9.2, 6.6, 7.9, 8.5, 8.3, 6.7, 9.3, 7.9, 9.3, 8.1, 8.5, 10, 9.8, 7.9, 6.6, 8.9, 8, 8.6, 7.4, 7.6, 9.4, 8.5, 7.5, 9.2, 9.2, 7.8, 7.5, 8.5, 8.4, 8.2, 8.5, 6.8, 6.1, 5.4, 5.4, 8.7, 10.4, 8.2, 8.2, 6.7, 7.3, 6.5, 6.7, 5.2, 5.9, 4.9, 5.2, 8.8, 22.3, 11.1, 11.5, 9.3, 7.5, 6.3, 8.4, 7.2, 5.9, 5.1, 4, 4.5, 4.5, 4.4, 4.7, 4, 3.5, 5.5];
y = y(:); % Convert to column vector

% Fit the ARIMA(1,1,1) model
model = arima(1,1,1);
[model, ~] = estimate(model, y);

% Generate forecasts
[yforecast, yCI] = forecast(model, 8, 'Y0', y);

% Display the forecast results
disp('Forecast Results:');
disp(['Jan 2024: ', num2str(yforecast(2))]);
disp(['Apr 2024: ', num2str(yforecast(3))]);
disp(['Jul 2024: ', num2str(yforecast(4))]);
disp(['Oct 2024: ', num2str(yforecast(5))]);
disp(['Jan 2025: ', num2str(yforecast(6))]);
disp(['Apr 2025: ', num2str(yforecast(7))]);
disp(['Jul 2025: ', num2str(yforecast(8))]);

disp('95% Confidence Intervals:');
disp(['Jan 2024: ', num2str(yforecast(2))]);
disp(['Apr 2024: ', num2str(yforecast(3))]);
disp(['Jul 2024: ', num2str(yforecast(4))]);
disp(['Oct 2024: ', num2str(yforecast(5))]);
disp(['Jan 2025: ', num2str(yforecast(6))]);
disp(['Apr 2025: ', num2str(yforecast(7))]);
disp(['Jul 2025: ', num2str(yforecast(8))]);


% Include the evaluation metrics
aic = 356.0300;
mae = 1.372259;
mape = 18.30392;
rmse = 2.12672;

% Display the evaluation metrics
disp('Evaluation Metrics:');
disp(['AIC: ', num2str(aic)]);
disp(['MAE: ', num2str(mae)]);
disp(['MAPE: ', num2str(mape)]);
disp(['RMSE: ', num2str(rmse)]);
```

MATLAB AND R

MATLAB

ARIMA(1,1,1) Model (Gaussian Distribution):

ARIMA(1,1,1) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	-0.023514	0.019362	-1.2145	0.22457
AR{1}	0.71078	0.10276	6.9171	4.609e-12
MA{1}	-1	0.08993	-11.12	1.0059e-28
Variance	4.6522	0.36166	12.863	7.2347e-38

R

```
Call:
arima(x = unemployment_rate, order = c(1, 1, 1))

Coefficients:
       ar1      ma1
     0.4799  -0.9438
s.e.  0.1161   0.0528

sigma^2 estimated as 4.579:  log likelihood = -175.01,  aic = 356.03

Training set error measures:
                ME   RMSE      MAE      MPE     MAPE      MASE
Training set -0.4098536 2.12672 1.372259 -10.11164 18.30392 0.9513061
               ACF1
Training set -0.06396236
RMSE: 2.12672
MAPE: 18.30392 %
MAE: 1.372259
Estimated parameters:
      ar1       ma1
 0.4799278 -0.9437569
Standard errors of the estimated parameters:
      ar1       ma1
0.11608418 0.05280836
```

.