

TIME Series Analysis of COVID-19 PCR Testing in USA (2020-2022)

CIND820



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**ABSTRACT**

Covid- 19 had detrimentally affected the lives of millions of Americans from 2020 to 2022 in the U.S. Individuals who experience Covid-19 symptoms, such as fever, cough, soar throat, fatigue, and body aches, are advised by the healthcare provider to undergo PCR (Polymerase Chain Reaction) tests. The PCR test is a nucleic acid amplification test (NAATs) performed in a laboratory. PCR testing is reliable in identifying people who test symptomatic or asymptomatic of Covid-19 (Centers for Disease Control and Prevention, 2022). In effect, the theme discussed is predictive analytics using time series data, and pattern mining, which will examine seasonal changes in PCR testing across the U.S. and forecast trends.

The approach is to compare PCR test results from 2020 to 2022 across the U.S. to identify the new results reported over time. These results will demonstrate the fluctuations and seasonal trends in PCR testing. Hence, the change in PCR testing from 2020 to 2021 will be forecasted. However, the analysis will not be able to account for some individuals who do not have access to PCR testing. To summarize, there will be a focus on trends, variability, and patterns that result in seasonal variance. For example, during the flu season, positive Covid-19 cases were expected to rise because of similar symptoms.

The dataset that will be examined is the [Covid-19 Diagnostic Laboratory Testing (PCR Testing) Time Series](https://healthdata.gov/dataset/COVID-19-Diagnostic-Laboratory-Testing-PCR-Testing/j8mb-icvb) from HealthData.gov. It includes data extracted from viral Covid-19 PCR results across 1000 American laboratories that were electronic, hospital, state, public, and commercial testing locations. The time series data represents diagnostic specimens tested from 2020 to 2022, but it does not represent the current counts for the three most recent days due to a discrepancy in report testing information. In addition, the data may not be inclusive of potential testing sites, such as non-laboratory or test sites. To sum up, it represented the majority of Covid-19 tests carried out in the United States (U.S. Department of Health & Human Services, 2022) and a sample of the population.

The data analysis for the time series dataset will examine the changes in data variables, such as new results reported over time. The dataset is large as there are 152533 rows to display consistency and reliability in producing results using time series techniques, such as autoregressive integrated moving average (ARIMA). Python will be used to analyze how PCR testing has fluctuated over time across the U.S. Furthermore, it will be used to preprocess the data, forecast new results reported, and produce time-series graphs using the sequential data. To sum up, these graphs that are produced will determine patterns in seasonality from 2020 to 2022 in PCR testing.

**RESEARCH QUESTIONS:**

Using Time Series Analysis:

1. To forecast the changes in PCR testing results across the U.S. from 2020 to make predictions in PCR test results for 2021.
2. Reduce overfitting the data and identify an ARIMA model to be used as a benchmark for predicting the accuracy of the time series data.

**DATA VARIABLES AND TYPES**

|  |  |  |
| --- | --- | --- |
| **Name** | **Type** | **Description** |
| state | Text | Patient’s State of residence |
| state\_name | Text | Name of state associated with the test |
| state\_fips | Text | State associated with test (numerical) |
| fema\_region | Text | Regions associated with the test |
| overall\_outcome | Text | Positive, Negative and Inconclusive PCR test outcomes |
| date | Date | Date the test completed, or result reported to the patient.  Neither -the date the specimen was collected and arrived at the testing facility nor the date that the test was ordered |
| new\_results\_reported | Number/Integer | Number of tests completed with the specified outcome in the specified state on the listed date  (large spikes- states submitted several proceeding dates at once with a single date) |
| total\_results\_reported | Number/Integer | The cumulative number of tests completed with the specified outcome in the specified state up the through the listed date |
| geocoded\_state | Point | NAN |
|  | | |
| **Descriptive Statistics** | | |
| 2020-03-01:2020-12-31    2021-01-01: 2021-12-31    2022-01-01: 2022-10-27 | | |

For data analysis on GitHub: click [here](https://github.com/LisaD002/Capstone-Project)

**METHODOLOGY**

Use COVID-19 PCR test results from 2020 to 2022 across USA

Preprocess the data

Index – “date

Variable – new\_results\_reported

Examine the data using EDA and describe() method

Fitting the model

* Make predictions on future values

Split the data into training and test sets – 80% train and 20% test

Develop ARIMA models

* Proceed auto regressing models until benchmark model is found

*Count of Values for new\_results\_reported*

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | 2020-03-01: 2020-12:31 | 2021-01-01: 2021-12-31 | 2022-01-01:2022-10-27 |
| new\_results\_reported  (Int64) | 48402 | 60694 | 47873 |

**)**

**Technique:** ARIMA model using Time Series (non-linear stationary data)

**Exploratory Data Analysis in Time-Series Forecasting**

1. new\_results\_reported

Chart

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* Strong seasonality
* Trend – cyclical
* Highest peak – 2021-09 to 2022-09
* Lowest peak– 2020-05
* Trend: positive linear – 2020-05 to 2022-09
* Stationary data

**Goal:** To use a machine learning time series forecasting technique, such as ARIMA to apply to predict PCR testing from 2020 to 2022 and identify a benchmark model with lowest autocorrelation and the highest log-likelihood

**Data Literature Review**

1. [“Healthcare use and RT-PCR testing during the first wave of the COVID-19 pandemic in Japan](https://onlinelibrary.wiley.com/doi/10.1002/jgf2.512)” (Masaru Kurihara MD, 2021)

In 2020, Japan conducted RT-PCR test policy which adhered to a guideline for public hospital visits or clinic visits using a 4-day rule for mild symptoms among low-risk patients.

**Methodology**:

* online survey (September 2020) - sample of adults across Japan
* To understand guidelines and experiences with the healthcare system if they had cold-like symptoms

**Results:** Outcome of 2137 surveyed people:

* 1698 (79.5%) understood the guidelines
  + 422 people misunderstood the guidelines
  + 144 people developed cold-like symptoms
    - 25/144 (17%) visited healthcare providers
    - 15/25 (60%) did not receive testing due to physicians’ decisions

**Conclusion:** Testing capacity should increase for effective care of COVID-19 patients in Japan

1. “[COVID -19 Infection in Pediatric Solid Organ Transplant Patients](https://onlinelibrary-wiley-com.ezproxy.lib.ryerson.ca/doi/full/10.1111/petr.14156)” (Neha Bansal, 2021)

**Introduction:**

* Comparison with the mortality rates of Adult Solid Organ Transplant (SOT) recipients with COVID-19 between the general population
* Data – cross-sectional ( pediatric SOT recipients)

**Methodology:**

* To investigate COVID-19 infection and outcomes in pediatric SOT (heart, liver, and kidney) recipients
* Determine demographic/ clinical characteristics of COVID-19 testing (PCR or AB test) results using medical records
* Comparison between patients who were positive or negative for COVID-19
* P-value <0.5 – significant results

**Results:**

* 108 SOT recipients - the median age of 13.1 and 4.2 years (transplant) tested for COVID-19 via PCR or AB test
* Positive PCR outcome – 10 patients (9.3%)
* Positive for COVID-19 Ab - 12 patients (11.1%)
* Positive in the cohort of transplant recipients:

9/50 (18%) heart

6/68 (8.8%) kidney

7/50 (14%) liver

**Conclusion**:

* COVID 19 infection was asymptomatic or mild
* data used by clinicians to counsel patients

1. “[Our Anesthesia Experiences in COVID-19 Positive Patients Delivering by Cesarean Section: A Retrospective Single-Center Cohort Study](https://obgyn-onlinelibrary-wiley-com.ezproxy.lib.ryerson.ca/doi/full/10.1111/jog.14852)” (Derya Karasu, Our anesthesia experiences in COVID-19 positive patients delivering by cesarean section: A retrospective single-center cohort study, 2021)

**Introduction:** To evaluate anesthesia practices in pregnant women with COVID-19 who undertake cesarean section

**Methodology:**

* 61 patients ( cesarean section) - positive PCR testing for COVID-19

**Results:**

Outcome of 61 patients:

* general anesthesia – 3 patients (4.9%)
* Spinal anesthesia – 58 patients (95.1%)
* Hypotension – 25.9% in the spinal anesthesia group
* 41 patients (67.2%) were asymptomatic
* Pneumonia in symptomatic patients - 45% (9/20)
* Pneumonia in SARS-CoV-2 PCR (+) patients – 14% (9/61)
* intensive care - 3 (4.9%) COVID-19 patients
* Overall mortality rate -1.6% (1/61) COVID-19 patients with cesarean section
* Pneumonia - 11.1% (1/9) of patients

**Conclusion:**

* COVID-19 is a related factor of the mortality in pregnant women with cesarean section
* Spinal anesthesia was administered effectively in COVID-19 patients and also, in patients with pneumonia

1. “[How Should Our Testing Behaviour Change with Time in Children in Current COVID-19 Pandemic](https://onlinelibrary-wiley-com.ezproxy.lib.ryerson.ca/doi/full/10.1111/eci.13351)” (Yin Zhang, 2020)

**Introduction:** To determine key points and provide suggestions on screening pediatric COVID-19 patients better

**Methods:**

* Pediatric patients- SARS-Cov-2 RT-PCR testing at Children’s Hospital of Chonqing Medical University (Jan 2020 – Feb 2020)
* comparison with pediatric confirmed COVID-19 cases

**Results:**

Outcome of 46 suspected cases:

* SARS-CoV-RT-PCR testing - all negative
* Epidemic history - lower in (P<.001)
* Literature review - 29 studies from 488 paediatric COVID-19 cases
* 88.6% with epidemiological history – cough and fever common
* Older patients – fever, respiratory symptoms, lethargy, and headache or dizziness were lower

**Conclusion:**

* Children with cough or fever needed extra care
* Need more studies to identify pediatric COVID-19

1. “[Optimisation of COVID-19 Diagnostic Pathways in Acute Hospital Admissions to prevent Nosocomial Transmission](https://onlinelibrary-wiley-com.ezproxy.lib.ryerson.ca/doi/full/10.1111/crj.13530)” (Robert Livingstone, 2022)

**Introduction:**

* Screening strategies - sensitive and rapid to prevent nosocomial transmission for COVID-19
* monitor patient flow

**Methods:**

* COVID-19-positive and suspected cases screened by RT (reverse transcription) PCR testing (04/04/2020 to 06/28/2020)
* RT- PCR positivity (7 days) – assessed sensitivity and net benefit
* 3 admission criteria (screening strategies): single admission, composite, and CSR
* RT-PCR – repeat in 48 hours

**Results:**

* RT-PCR single-test sensitivity – 91.5%
* RT-PCR/CXR composite testing - 97.7%
* Repeated RT-PCR – 95.1%
* Net-benefit:
  + 0.83 for a single RT-PCR
  + 0.89 for RT-PCR/CXR
  + 0.87 for repeated RT-PCR ( threshold: p = 0.2%)

1. “[Evaluation of Sample Pooling for Diagnosis of COVID-19 by Real-time PCR: A Resource-Saving Combat Strategy](https://onlinelibrary-wiley-com.ezproxy.lib.ryerson.ca/doi/full/10.1002/jmv.26475)” (Jaya Garg, 2020)

**Introduction:**

* 80% Covid-19 cases – mild
* 20% Covid-19 cases - severe
* Evaluating pooled strategy base on accuracy of testing, usage of consumables, and identifying borderline positive cases

**Methods:**

* RT-PCR COVID-19 testing (04/2020- 06/2020) 🡪 laboratory in Lucknow
* Samples – pools of 5 or 10 (RT-PCR)
* Negative pool – negative
* Positive pools of 5 – 10 🡪 deconvoluted and tested individually

**Results:**

Tested:

* 4620 samples - pools of 10
* 14940 samples - 2990 pools of 5
* Positive – 10 samples pool
  + 13% positive in first step
* 61 pools deconvoluted strategy
  + 72 samples positive
* 76% to 93% reduction in testing
* Group sizes: 5-10 in population

**Conclusions:**

* Pooled-sample PCR strategy – saved substantial resources than individual testing
* Facilitate mass screening in the early onset of COVID-19 outbreaks
* Increased pandemic surveillance

**Results**

**Part 1) Examined White Noise**

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**White Noise Plot in Time Series**

**Chart

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* Constant mean
* Constant variance
* No pattern in data
* No autocorrelation - no clear relationship between past and present values
* Cannot predict the future

**Comparison of White Noise to New Results Reported Plot**

Chart

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**AD-Fuller Test**

|  |  |  |
| --- | --- | --- |
|  | PCR test | White Noise |
| T-test | -7.408732170618658 | -175.90984783413657 |
| P-value | 7.228139124737943e-11 | 0.0 |
| Number of lags | 72 | 3 |
| Number of Observations | 125502 | 125571 |
| Significance level at 1% | -3.4304021062115018 | -3.430402077579078 |
| Significance level at 5% | -2.861563030180707 | -2.861563017525707 |
| Significance level at 10% | -2.566782258150325 | -2.566782251414497 |
| Maximized information criterion | 2417073.7975664325) | 2863771.8795680264 |

**QQ Plot**

Chart, line chart

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QQ plot takes all the values a variable can take and arranges them in ascending order

* y axis- New Results Reported
* x axis- theoretical quantile
  + how many standard deviations away from the mean these values are
* red diagonal line- what the data points should follow if they are normally distributed
* not normally distributed - more values on the 500,000 mark
* split data into a training and a test set to use machine learning to forecast the future
* trend – upward sloping
* QQ plot line is stationary until 2 quantiles and moves upward when approaching 4 quantiles

**ACF and PACF Analysis**

1. Auto Correlation Function (ACF) for new results reported

Chart

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**Description**

TS = time series

AC= autocorrelation

ACF= autocorrelation function

Corr= correlation

* ACF: correlation between a time series and itself
* bottom = lags; left = values of AC coefficient
* Corr = values between 1 and -1
* thin line - represents the AC from the TS and a lagged copy of itself – no present
* 1st line - ac one time period ago - t-1 etc.
* the greater the distance in time, the more unlikely it is that this AC persists
* AC coefficient in higher lags is sufficiently greater to be significantly different from 0
* AC barely diminishes as the lags decrease

**Results**

* High Lags: t-3 , t-21, and t-38
* Lags are Uniform
* Many points on the origin
* No Autocorrelation between time series and itself as thin blue line is not present

**2.** Partial Auto Correlation Function (PACF) for new results reported

Chart

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**Results**

* Highest lag – t-3
* Lots of fluctuations
* Stationary at 28 to 35
* PACF decreases as the number of lags increases

1. ACF for White Noise

Chart, scatter chart

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* Did not compute – numerical error due to small decimal numbers resulting in 0
* No pattern

1. PACF for White Noise

**Chart, scatter chart

Description automatically generated**

* Did not compute – numerical error due to small decimal numbers resulting in 0
* No pattern

**ARIMA Approach**

* Identify an ARIMA model to use as a benchmark for forecasting the change in New Results Reported in PCR testing using daily stationary data across the US

**How?**

* Splitting the data with an 80% split for trained data and a 20% split for tested data
* Trained different ARIMA models with lags of 40 in order to find a good benchmark to compare with the actual values for PCR testing

Part A: ARIMA(1,1,1)

Table

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**Analysis**

* Both coefficients for AR and MA are negative
* Standard errors for both AR and MA are low
* AR has a greater standard error with a difference of 0.02
* P-value is 0 for both AR and MA
* AIC and BIC are similar

1. ACF of Residuals for ARIMA(1,1,1)

Chart

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**Results**

* residuals follow the same pattern as ACF
* no significant time period to use

1. ACF of Residuals for ARIMA(1,1,2)

Chart

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1. ACF of Residuals for ARIMA(6,1,3)

Chart, scatter chart

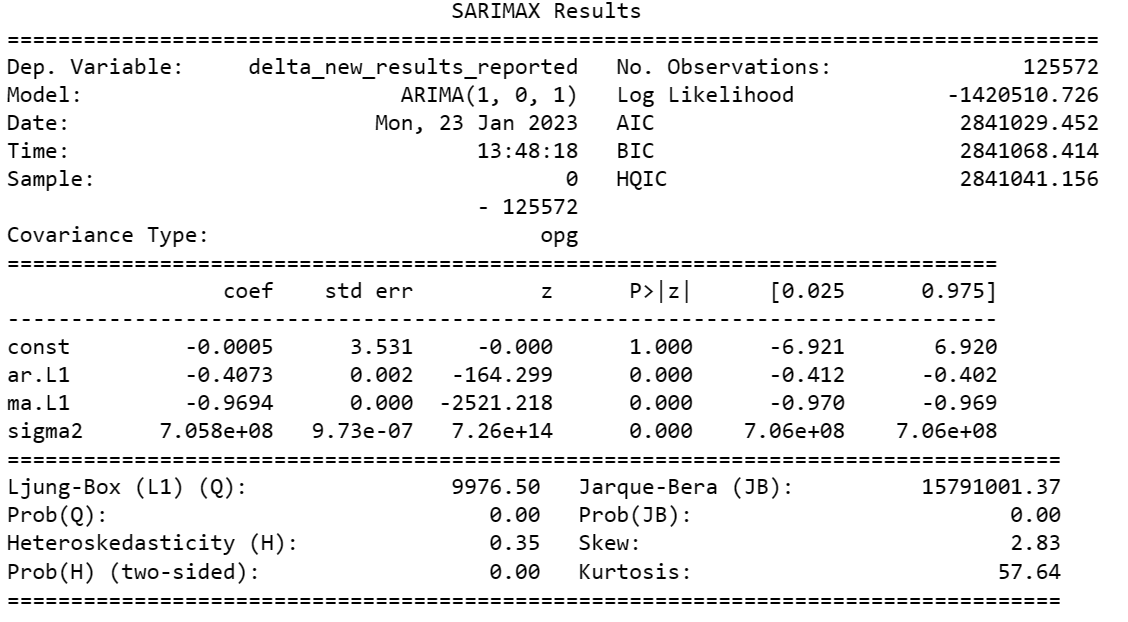
Description automatically generated

**Analysis**

* t-21 is significant for both ACF residual plots
* captured effects incorporated into the 6th lag without including it in model
* the further back in time we go, the less relevant the values become
* include up to 40 lags into the model - presence of white noise residuals
* the model parameters will become too dependent on the data set - leading to overfitting (removing predictive power)
* best estimator for PCR tests - ARIMA(6,1, 3)

**Delta of New Results Reported**

* ARIMA(P,1,Q) for new results reported
* fit ARMA(1,1) to the delta of new results reported
* ARIMA(1,0,1) is equivalent to an ARMA(1,1)



**AD-Fuller Test**

|  |  |
| --- | --- |
|  | New Results Reported |
| T-test | -47.07809765885331 |
| P-value | 0.0 |
| Number of lags | 71 |
| Number of Observations | 125500 |
| Significance level at 1% | -3.4304021070418966 |
| Significance level at 5% | -2.861563030547726 |
| Significance level at 10% | -2.566782258345677 |
| Maximized information criterion | 2417071.9290318624 |

**Analysis**

* Test statistic is 14x greater in absolute value and the critical 1% value
* p-value is 0.0 - confirmation of stationarity
* no need for additional layers of integration
* fitting ARIMA models with d> 1 is not recommended since the series is already stationary
* ARIMA models estimate stationary data

**Part 1. Higher- Lag ARIMA Model**

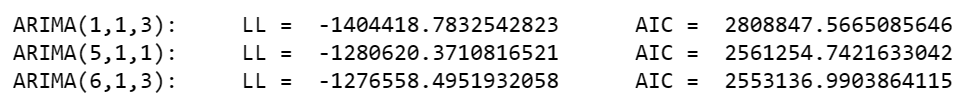
**Text

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**Analysis**

* Highest log-likelihood and the lowest AIC is model 2 – ARIMA(1,1,2)

**Part 2. Higher- Lag ARIMA Model**

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**Analysis**

* Highest log-likelihood and the lowest AIC is model 2 – ARIMA(6, 1, 3)
* The ARIMA(1,1,3) and ARIMA (5,1,1) are nested in the ARIMA (6,1,3)
* ARIMA(1,1,3) - 4 degrees of freedom
* ARIMA(6,1,3) - 9 degrees of freedom

**Simple Forecasting**

* Time series: expect patterns to persist as we progress through time
  + 1. find the pattern - selecting the correct model
  + 2. predict the future

**A picture containing table

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* start\_date = 2020-03-01
* end\_date = 2021-01-01

**Chart, line chart

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* Upward sloping trend
* Ending of Dec 2020 to Jan 2022- new results reported in PCR testing had surged to 6720
* Over the course of the interval actual PCR test results moved cyclically and fluctuated up and down compared to the stationary predicted values

**Graphical user interface, chart

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* Constant line at the 0 - model makes no predictions since it assumes all future returns will be 0, or extremely close to it
* coefficients for the past values and values themselves must have low absolute values
* actual values are many times higher than predictions – e.g. Dec 2020 new results reported were 120,000

**Evaluation of Machine Learning Algorithm**

Built a statistically significant time series model with ARIMA to forecast the prediction of PCR testing of new results reported in 2020 to 2022 using sequential data from COVID-19 in U.S.

Used a Benchmark model to compare it to the other ARIMA models in order to obtain accurate prediction of PCR testing

**Features of Benchmark Model:**

* Estimator – ARIMA(6, 1, 3)
* Lag = 40

**Analysis Limitations**

**ARIMA models**

* more computationally expensive than regular ARIMA models as there are more layers and more background work the program has to create before fitting the data
* transform the data several times
* differentiate the values from zero - harder as values become smaller and the presence of information loss
* the margin of something being significant and insignificant becomes really narrow
* models failing to converge after many iterations
* the more layers we add, the harder it is to interpret the results
* integrating stationary data makes it more difficult for the model to estimate the coefficients
* generate every layer of integration one by one and fit the data using ARIMA models
* **Data Attrition** - lose observations because of the conversion of new results reported and lose more data points for each layer of integration computed by delta
* the more unnecessary layers we add, the more our model suffers

**Downfalls of Forecasting**

* model-specific
* data-dependent
* models we examined in forecasting were non-integrated
* picking an incorrect type of model (integrated vs non-integrated) depending on the data
* ARIMA - integrated models
* lack of visualization
* we can't accurately plot the integrated predictions against actual new results reported
* lack of meaningful statistical measures

**Study Implications**

This study can change how new results are forecasted when long-term illnesses, such as COVID-19 affect the health of many individuals across the U.S. With the best estimator ARIMA(6,1,3), there is a log-likelihood of -1276558.50 and an AIC of 2553136.99.

**Ethical Considerations**

It is important that participation in research is voluntary and participants can withdraw any time from the study. Participants must provide informed consent after obtaining knowledge about the implications of participating in the study. Participants also have the right to withdraw from the study. Privacy act and anonymity must be adhered to in the study by the researcher for individuals and organizations participating in it. Lastly, there should be an acknowledgment of all works that us used by different authors in any part of the academic paper and this should be done via APA sourcing (Bryman, 2007).

**Project Continuity**

ARIMA is an auto-regressive moving average technique in time series, which is used for forecasting data by predicting future points in the series based on data from the past. ARIMA models can be improved to forecast accurate results by comparing parameters such as p-value and t-statistic and identifying the ACF of the residuals. Also, it accounts for white noise in the data as there is moving average part (Abugaber, n.d.). Due to the lack of independent variables, there is not much interpretation of the significance of the time series data; therefore, the project should not be continued for further studies.

*Assumption of ARIMA:* residuals are uncorrelated and normally distributed.

*Benefits of ARIMA* (Bora, 2021)*:*

* Pattern recognition
* Uses prior data of time series to forecast
* Performs well on short-term forecast
* Models of stationary data

*Cons* (Bora, 2021)*:*

* Unable to perform for seasonal time series
* Less explainable
* Expensive to compute
* Cannot perform well on long-term forecasts

**Critical Insights – Shortcomings and Improvement**

* The data set was stationary and not highly cyclical
* ACF of residuals for ARIMA(1,1,1) were uniform
* The further back in time we go, the less relevant the values become
* The model parameters will become too dependent on the data set which will lead to overfitting 🡪 lack of predictive power
* Best model was ARIMA(6,1,3) with a higher log-likelihood and a lower AIC
* Included up to 40 lags and there were white noise residuals
* Improved the accuracy of the ARIMA models by computing higher lags and increasing the moving average
* As we computed the change in residuals, the adfuller test increased the test-statistic by 14 times
* Limited number of meaningful independent variables
  + Time Series Data with only new results reported for PCR testing
* Predictions were not as accurate in the graph as there were much lower than the actual values when plotting in the ‘Predictions vs. Actual” graph

**Conclusion**

ARIMA model identified the time period that was best suited to forecast the predictions for new results reported as the data set had a lot of white noise. The best ARIMA model used as a benchmark for predictions was ARIMA(6, 1, 3) with a higher log-likelihood of -1,276,558.50 and lower AIC of 2,553,136.99 and it identified the time period t-21 as the lag with the highest autocorrelation.

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