Lab IA - 23MDS010

Load data

In [1]:
```
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:
```
df = pd.read_excel(r"C:\Users\raval\Downloads\TSA_IA2.xlsx")
```

In [3]:
```
df
```

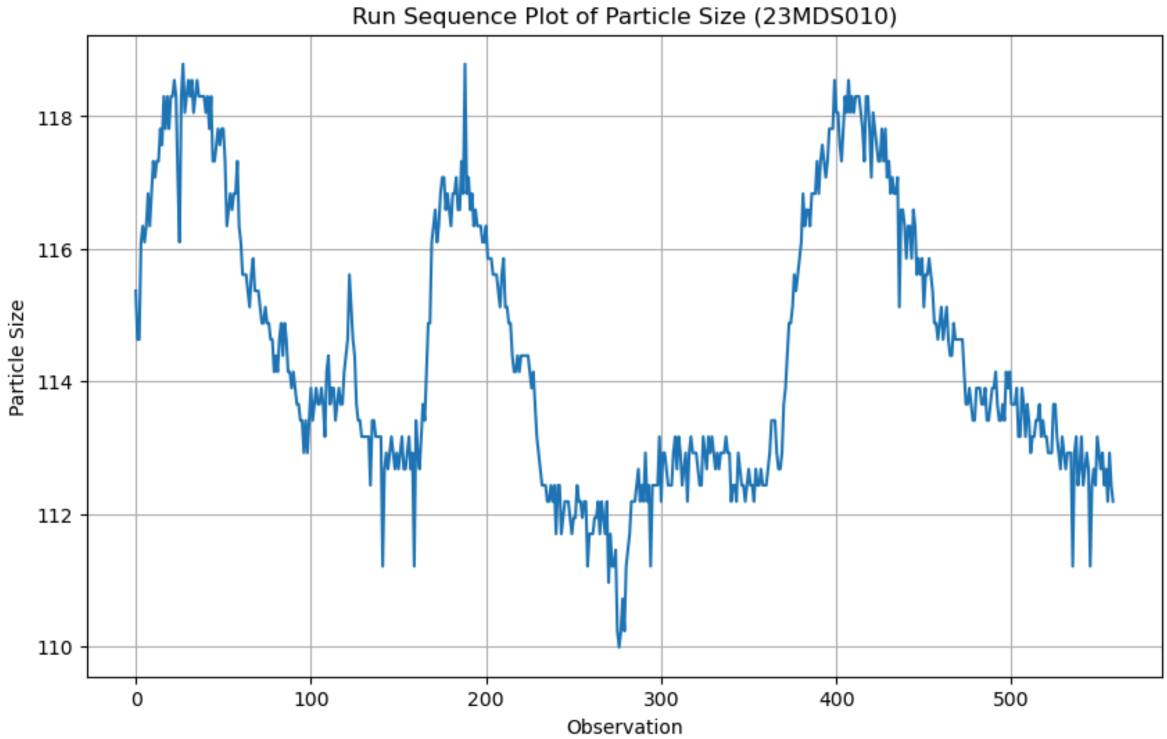
Out[3]:

	data
0	115.36539
1	114.63150
2	114.63150
3	116.09940
4	116.34400
...	...
554	112.67420
555	112.18491
556	112.91890
557	112.42960
558	112.18491

559 rows × 1 columns

Run Sequence Plot

In [4]:
```
plt.figure(figsize=(10, 6))
plt.plot(df.data, linestyle='-')
plt.title('Run Sequence Plot of Particle Size (23MDS010)')
plt.xlabel('Observation')
plt.ylabel('Particle Size')
plt.grid(True)
plt.show()
```



We can make the following conclusions from the run sequence plot:

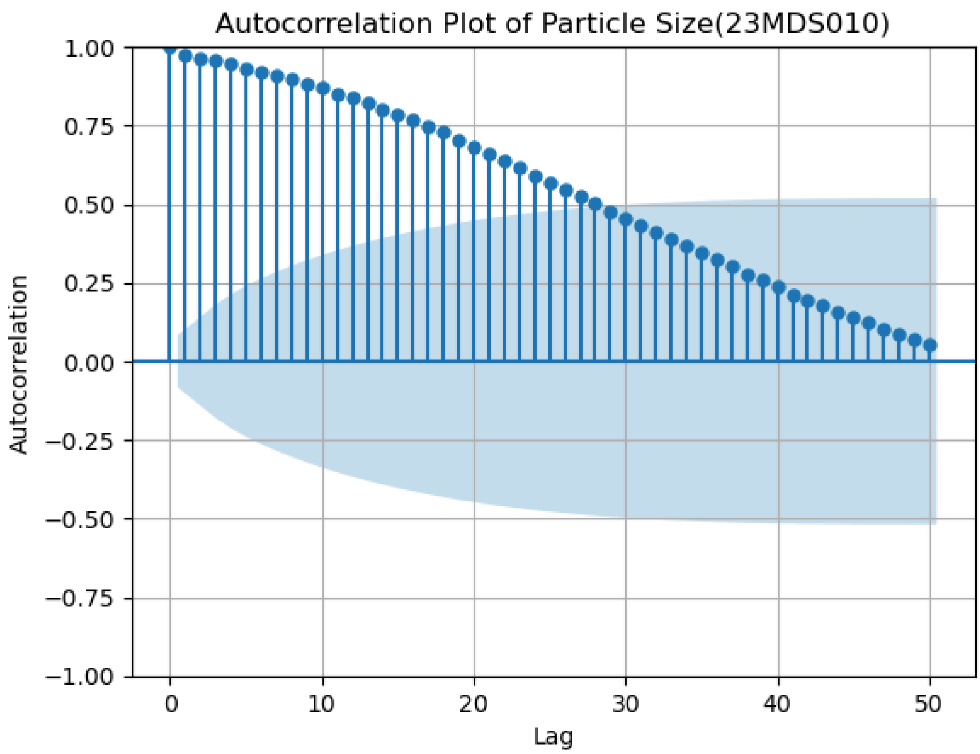
1. The data show strong and positive autocorrelation.
2. There does not seem to be a significant trend or any obvious seasonal pattern in the data.

Autocorrelation Plot

In [5]:
```
from statsmodels.graphics.tsaplots import plot_acf
```

In [6]:
```
plt.figure(figsize=(10, 6))
plot_acf(df.data, lags=50)
plt.title('Autocorrelation Plot of Particle Size(23MDS010)')
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



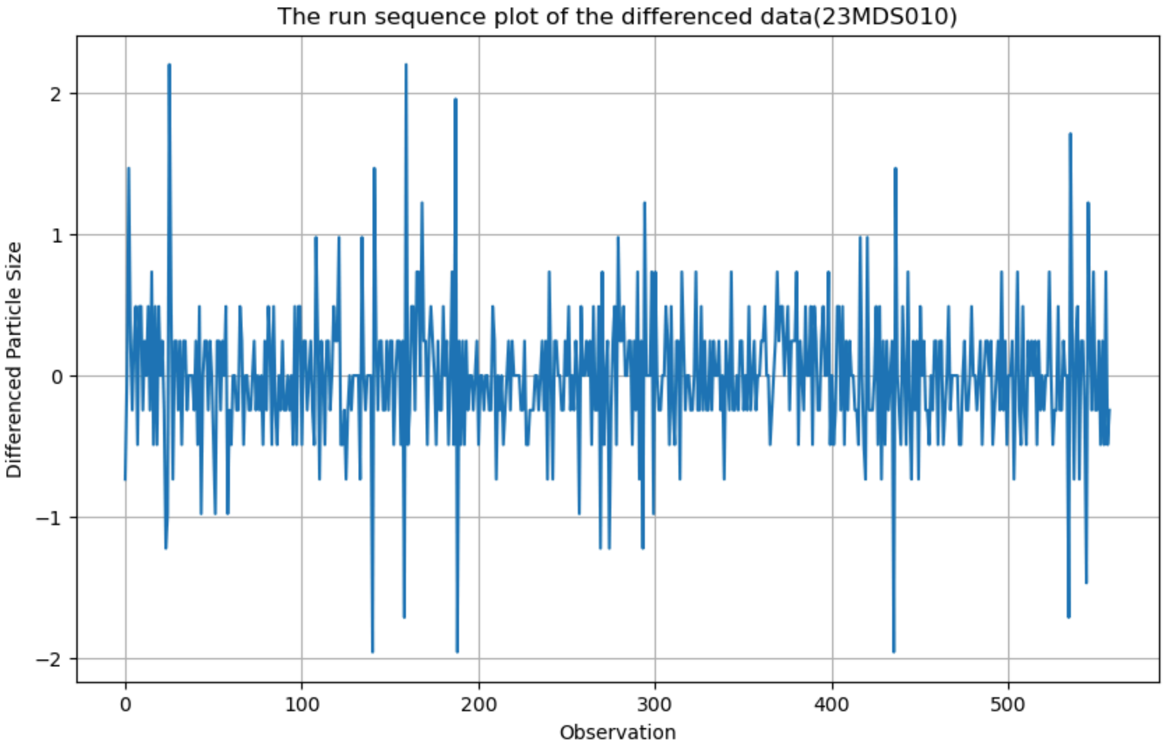
The autocorrelation plot shows that the sample autocorrelations are very strong and positive and decay very slowly. The autocorrelation plot indicates that the process is non-stationary.

The run sequence plot of the differenced data

In [7]:
```
import numpy as np
```

In [8]:
```
differenced_data = np.diff(df.data)
```

In [9]:
```
plt.figure(figsize=(10, 6))
plt.plot(differenced_data, linestyle='-')
plt.title('The run sequence plot of the differenced data(23MDS010)')
plt.xlabel('Observation')
plt.ylabel('Differenced Particle Size')
plt.grid(True)
plt.show()
```

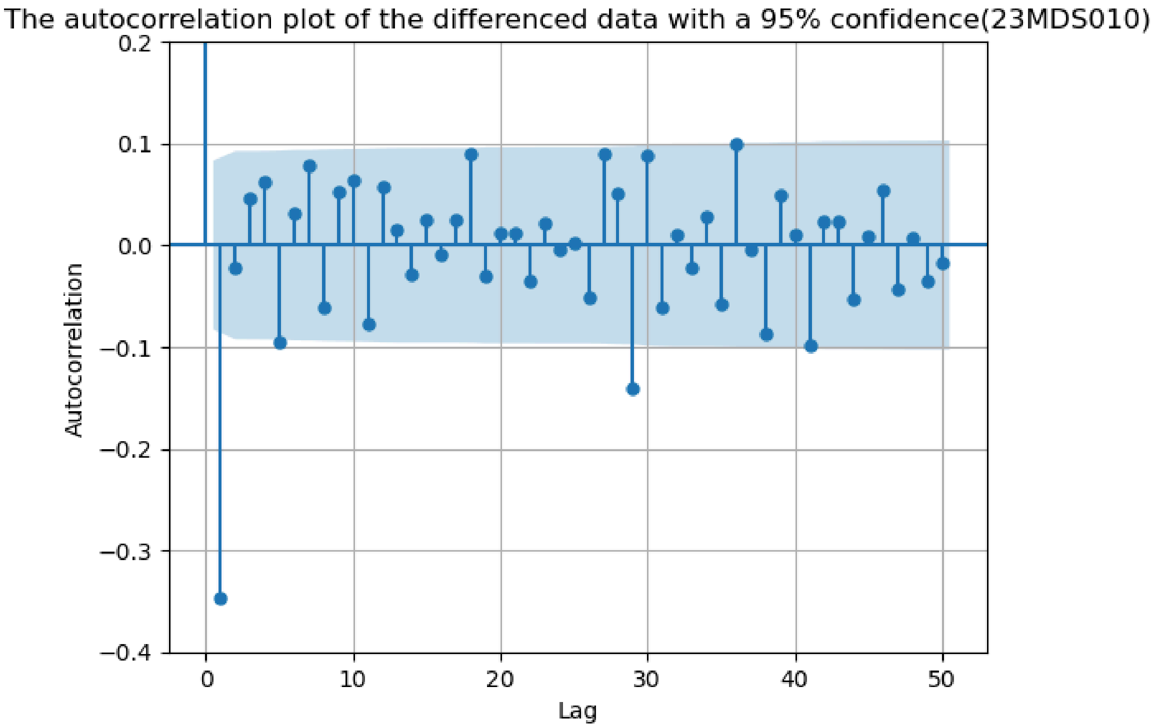


The run sequence plot of the differenced data shows that the mean of the differenced data is around zero, with the differenced data less autocorrelated than the original data.

The autocorrelation plot of the differenced data with a 95% confidence

In [10]:
```
plt.figure(figsize=(10, 6))
plot_acf(differenced_data, lags=50)
plt.title('The autocorrelation plot of the differenced data with a 95% confidence(23MDS010)
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.ylim(-0.4, 0.2)  # Set the y-axis limits
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



The autocorrelation plot of the differenced data with a 95% confidence band shows that only the autocorrelation at lag 1 is significant. The autocorrelation plot together with run sequence of the differenced data suggest that the differenced data are stationary. Based on the autocorrelation plot, an MA(1) model is suggested for the differenced data.

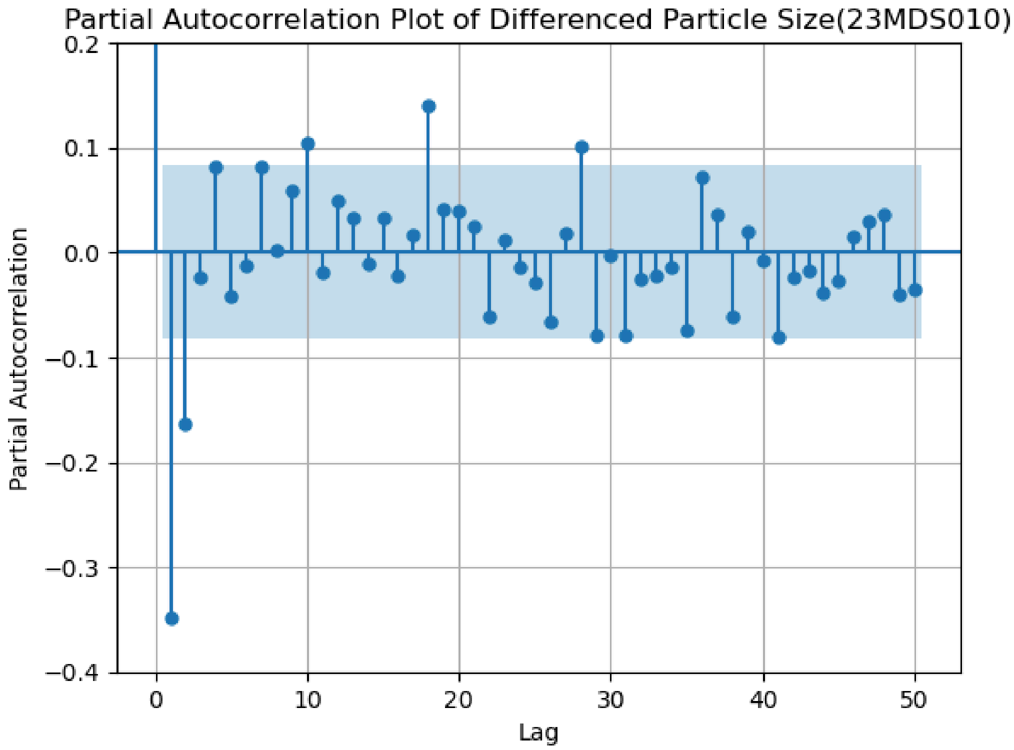
The partial autocorrelation plot of the differenced data with 95% confidence

In [11]:
```
from statsmodels.graphics.tsaplots import plot_pacf
```

In [12]:
```
plt.figure(figsize=(10, 6))
plot_pacf(differenced_data, lags=50)
plt.title('Partial Autocorrelation Plot of Differenced Particle Size(23MDS010)')
plt.xlabel('Lag')
plt.ylabel('Partial Autocorrelation')
plt.grid(True)
plt.ylim(-0.4, 0.2)  # Set the y-axis limits
plt.show()
```

```
C:\Users\raval\AppData\Roaming\Python\Python311\site-packages\statsmodels\graphics\tsaplot
s.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-
1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker ('ywm'). You c
an use this method now by setting method='ywm'.
  warnings.warn(
```

```
<Figure size 1000x600 with 0 Axes>
```



The partial autocorrelation plot of the differenced data with 95% confidence bands shows that only the partial autocorrelations of the first and second lag are significant. This suggests an AR(2) model for the differenced data.

based on above graphs we try ARIMA(2,1,0) and ARIMA(0,1,1)

Auto Regression

In [13]:
```
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import arma_order_select_ic
```

In [29]:
```
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import arma_order_select_ic
import statsmodels.api as sm
import scipy.stats as stats
from statsmodels.tsa.ar_model import AutoReg
from tabulate import tabulate
```

In [31]:
```
df1 = pd.DataFrame({'data': differenced_data})
```

In [32]:
```
model = AutoReg(df1['data'], lags=2).fit()
print(model.summary())
```

```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                   data   No. Observations:                  558
Model:                     AutoReg(2)   Log Likelihood                -334.934
Method:               Conditional MLE   S.D. of innovations              0.442
Date:                Thu, 25 Apr 2024   AIC                            677.868
Time:                        10:43:22   BIC                            695.152
Sample:                             2   HQIC                           684.619
                                  558
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0067      0.019     -0.359      0.719      -0.043       0.030
data.L1       -0.4068      0.042     -9.721      0.000      -0.489      -0.325
data.L2       -0.1647      0.042     -3.941      0.000      -0.247      -0.083
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -1.2348           -2.1321j            2.4639           -0.3335
AR.2           -1.2348           +2.1321j            2.4639            0.3335
-----------------------------------------------------------------------------
```

In [33]:
```
intercept = model.params[0]
ar1 = model.params[1]
ar2 = model.params[2]
se_intercept = model.bse[0]
se_ar1 = model.bse[1]
se_ar2 = model.bse[2]
ci_ar1 = model.conf_int().iloc[1]
ci_ar2 = model.conf_int().iloc[2]
```

In [34]:
```
output_data = [
    ["Intercept", f"{intercept:.4f}", f"{se_intercept:.4f}", ""],
    ["AR1", f"{ar1:.4f}", f"{se_ar1:.4f}", f"({ci_ar1[0]:.4f}, {ci_ar1[1]:.4f})"],
    ["AR2", f"{ar2:.4f}", f"{se_ar2:.4f}", f"({ci_ar2[0]:.4f}, {ci_ar2[1]:.4f})"],
    ["Number of Observations:", len(df1['data']), "", ""],
    ["Degrees of Freedom:", len(df1['data']) - 3, "", ""],
    ["Residual Standard Deviation:", model.scale, "", ""]
]

table_headers = ["Source", "Estimate", "Standard Error", "95% Confidence Interval"]
print(tabulate(output_data, headers=table_headers, tablefmt="pipe"))
```

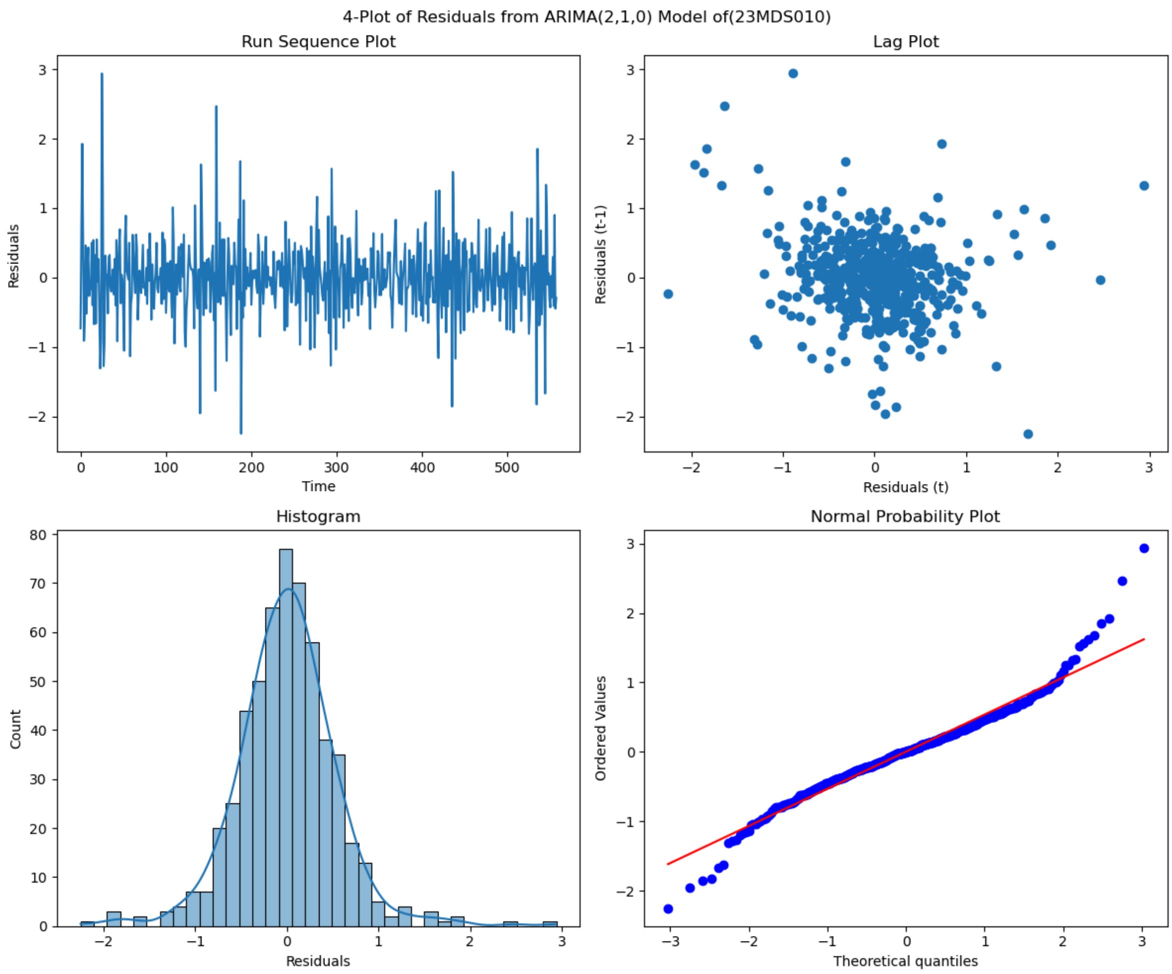
```
| Source                       |   Estimate | Standard Error   | 95% Confidence Interval
|
|:-----------------------------|-----------:|:-----------------|:------------------------
-|
| Intercept                    |  -0.0067   | 0.0187           |
|
| AR1                          |  -0.4068   | 0.0418           | (-0.4888, -0.3248)
|
| AR2                          |  -0.1647   | 0.0418           | (-0.2467, -0.0828)
|
| Number of Observations:      | 558        |                  |
|
| Degrees of Freedom:          | 555        |                  |
|
| Residual Standard Deviation: |   0.195327 |                  |
|
```

In [35]:
```
model = ARIMA(df1['data'], order=(2, 1, 0))
results = model.fit()
residuals = results.resid
```

4-Plot of Residuals from ARIMA(2,1,0) Model

In [37]:
```
import seaborn as sns
```

In [38]:
```
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle('4-Plot of Residuals from ARIMA(2,1,0) Model of(23MDS010)')

axs[0, 0].plot(residuals)
axs[0, 0].set_title('Run Sequence Plot')
axs[0, 0].set_xlabel('Time')
axs[0, 0].set_ylabel('Residuals')

pd.plotting.lag_plot(residuals, lag=1, ax=axs[0, 1])
axs[0, 1].set_title('Lag Plot')
axs[0, 1].set_xlabel('Residuals (t)')
axs[0, 1].set_ylabel('Residuals (t-1)')

sns.histplot(residuals, kde=True, ax=axs[1, 0])
axs[1, 0].set_title('Histogram')
axs[1, 0].set_xlabel('Residuals')

stats.probplot(residuals, dist="norm", plot=axs[1, 1])
axs[1, 1].set_title('Normal Probability Plot')

plt.tight_layout()
plt.show()
```



In [39]:
```
# Writing the AR(2) equation using the extracted variables
equation = f"Y_t = {intercept:.4f} + {ar1:.4f} * Y_{{t-1}} + {ar2:.4f} * Y_{{t-2}} + ε_t"
print(equation)
```

```
Y_t = -0.0067 + -0.4068 * Y_{t-1} + -0.1647 * Y_{t-2} + ε_t
```

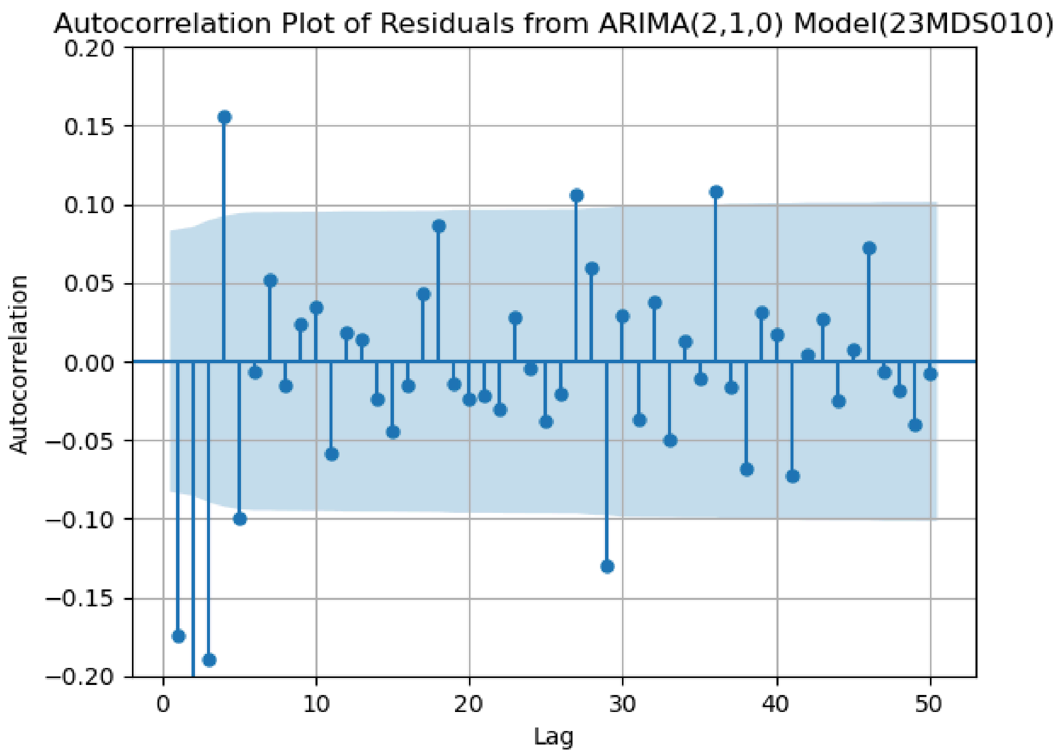
We can make the following conclusions based on the above 4-plot.

1. The run sequence plot shows that the residuals do not violate the assumption of constant location and scale. It also shows that most of the residuals are in the range (-1, 1).
2. The lag plot indicates that the residuals are not autocorrelated at lag 1.
3. The histogram and normal probability plot indicate that the normal distribution provides an adequate fit for this model.

Autocorrelation Plot of Residuals from ARIMA(2,1,0) Model

In [45]:
```
# Plot the autocorrelation of the residuals
plt.figure(figsize=(10, 6))
plot_acf(residuals, lags=50,zero=False)
plt.title('Autocorrelation Plot of Residuals from ARIMA(2,1,0) Model(23MDS010)')
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.ylim(-0.2, 0.2)
plt.grid(True)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```

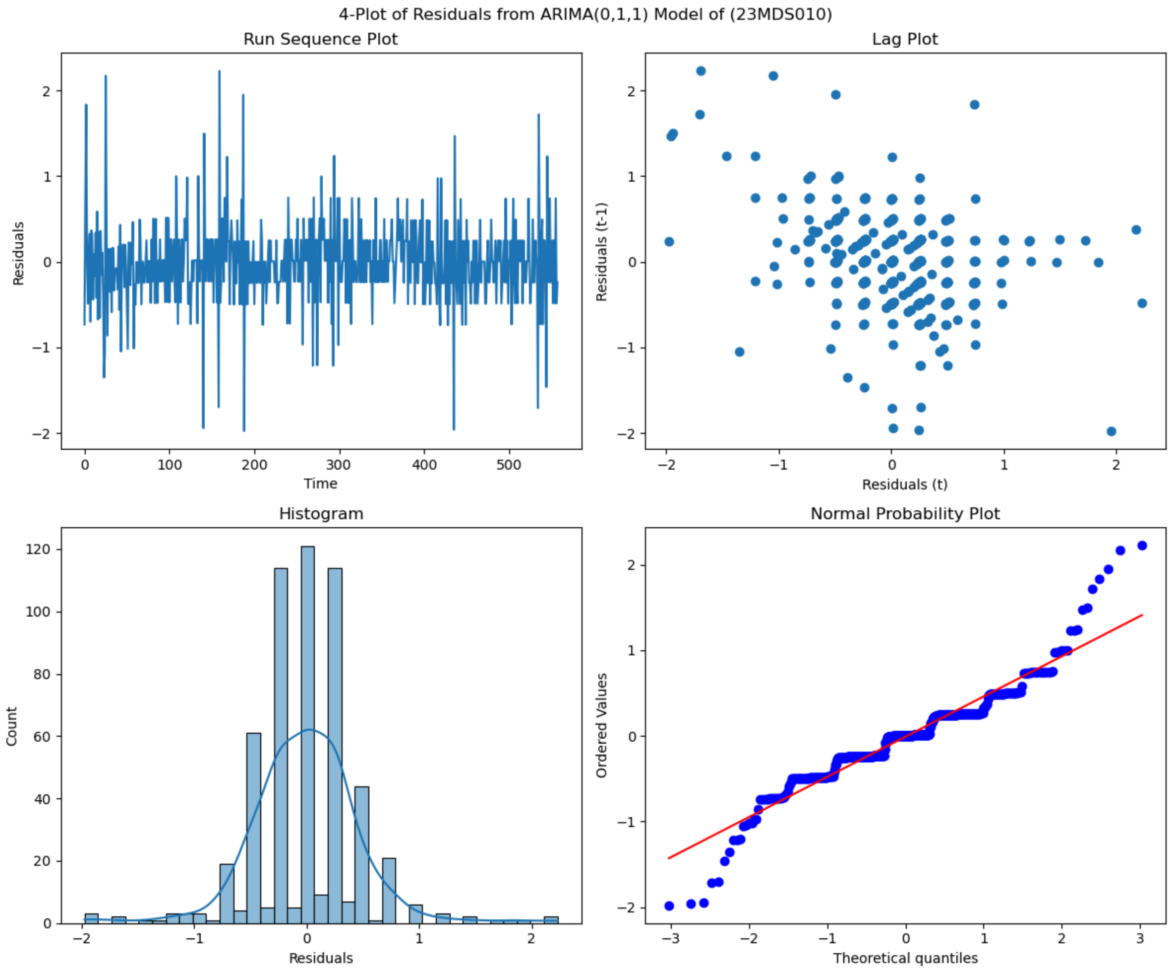


The autocorrelation plot shows that for the first 25 lags, all sample autocorrelations except those at lags 1,2,3,4 and 28 fall inside the 95 % confidence bounds indicating the residuals appear to be random.

4-Plot of Residuals from ARIMA(0,1,1) Model

In [41]:
```
model_011 = ARIMA(df1['data'], order=(0, 1, 1))
results_011 = model_011.fit()
residuals_011 = results_011.resid

fig, axs = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle('4-Plot of Residuals from ARIMA(0,1,1) Model of (23MDS010)')

axs[0, 0].plot(residuals_011)
axs[0, 0].set_title('Run Sequence Plot')
axs[0, 0].set_xlabel('Time')
axs[0, 0].set_ylabel('Residuals')

pd.plotting.lag_plot(residuals_011, lag=1, ax=axs[0, 1])
axs[0, 1].set_title('Lag Plot')
axs[0, 1].set_xlabel('Residuals (t)')
axs[0, 1].set_ylabel('Residuals (t-1)')

sns.histplot(residuals_011, kde=True, ax=axs[1, 0])
axs[1, 0].set_title('Histogram')
axs[1, 0].set_xlabel('Residuals')

stats.probplot(residuals_011, dist="norm", plot=axs[1, 1])
axs[1, 1].set_title('Normal Probability Plot')

plt.tight_layout()
plt.show()
```

```
C:\Users\raval\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\statespace\s
arimax.py:978: UserWarning: Non-invertible starting MA parameters found. Using zeros as st
arting parameters.
  warn('Non-invertible starting MA parameters found.'
```



We can make the following conclusions based on the above 4-plot.

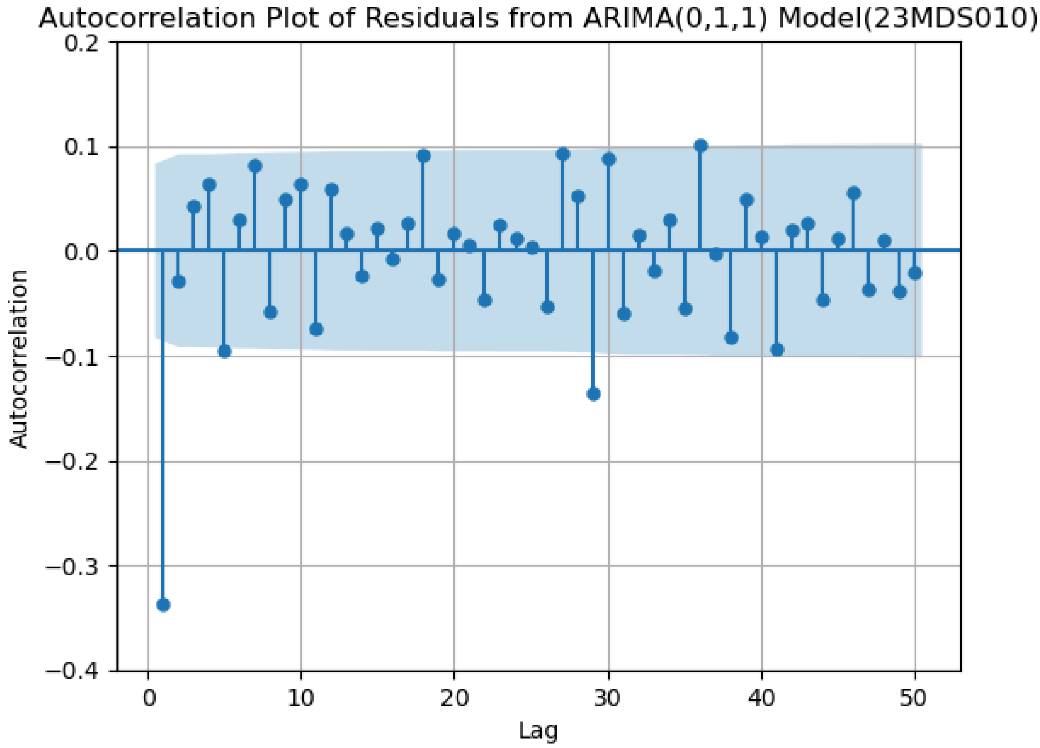
1. The run sequence plot shows that the residuals do not violate the assumption of constant location and scale. It also shows that most of the residuals are in the range (-1, 1).

2. The lag plot indicates that the residuals are not autocorrelated at lag 1.
3. The histogram and normal probability plot indicate that the normal distribution provides an adequate fit for this model.

Autocorrelation Plot of Residuals from ARIMA(0,1,1) Model

In [43]:
```
# Plot the autocorrelation of the residuals
plt.figure(figsize=(10, 6))
plot_acf(residuals_011, lags=50,zero=False)
plt.title('Autocorrelation Plot of Residuals from ARIMA(0,1,1) Model(23MDS010)')
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.ylim(-0.4, 0.2)
plt.grid(True)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



Similar to the result for the ARIMA(2,1,0) model, it shows that for the first 50 lags, all sample autocorrelations expect those at lags 1 and 29 fall outside the 95% confidence bounds indicating the residuals appear to be random.

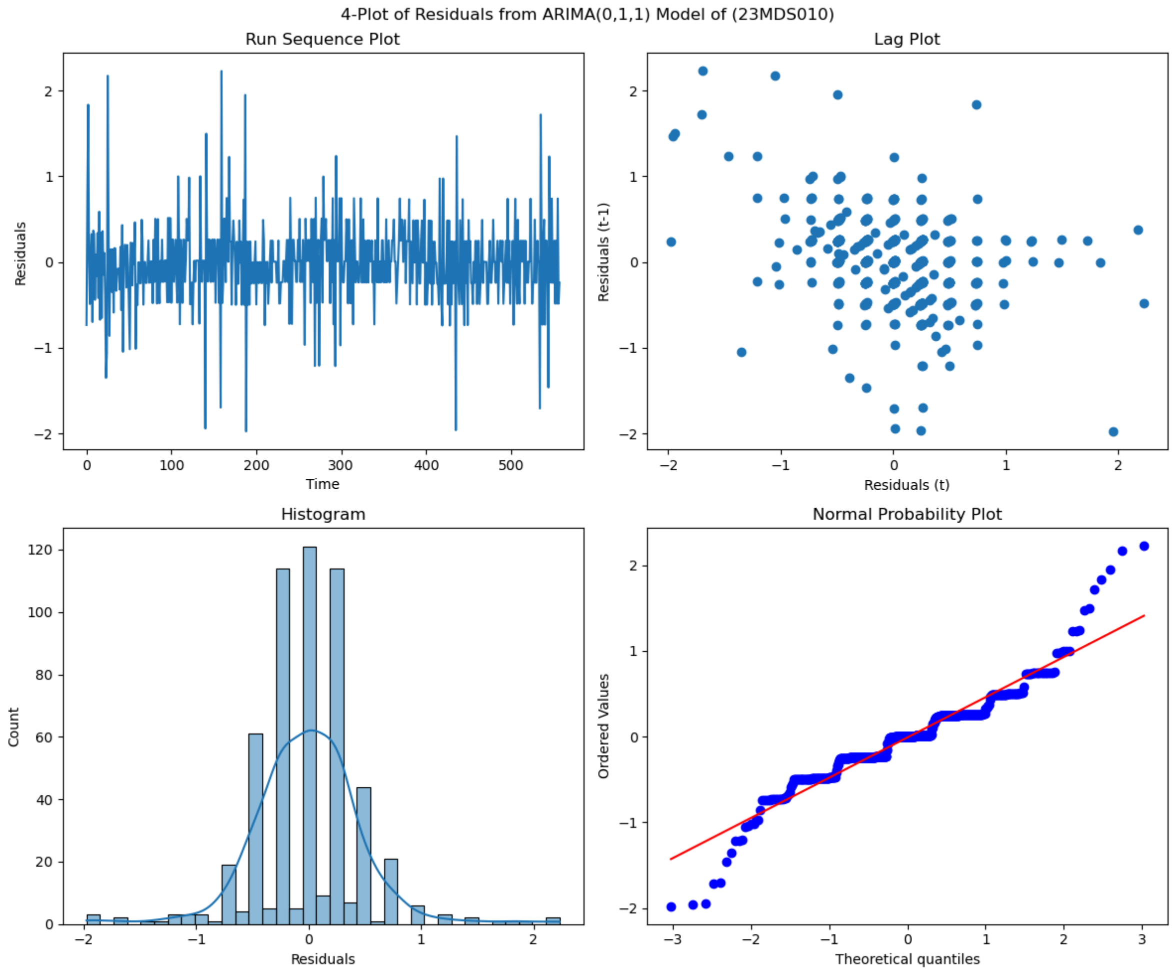
Moving average

In [49]:
```
model = AutoReg(df1, lags=1).fit()
print(model.summary())
intercept = model.params[0]
ma1 = model.params[1]
se_intercept = model.bse[0]
se_ma1 = model.bse[1]
ci_ma1 = model.conf_int().iloc[1]
output_data = [
    ["Intercept", f"{intercept:.4f}", f"{se_intercept:.4f}", ""],
    ["MA1", f"{ma1:.4f}", f"{se_ma1:.4f}", f"({ci_ma1[0]:.4f}, {ci_ma1[1]:.4f})"],
    ["Number of Observations:", len(df1['data']), "", ""],
    ["Degrees of Freedom:", len(df1['data']) - 2, "", ""],
    ["Residual Standard Deviation:", model.scale, "", ""]
]

table_headers = ["Source", "Estimate", "Standard Error", "95% Confidence Interval"]
print(tabulate(output_data, headers=table_headers, tablefmt="pipe"))
```

```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                   data   No. Observations:                  558
Model:                     AutoReg(1)   Log Likelihood                -342.864
Method:               Conditional MLE   S.D. of innovations              0.448
Date:                Thu, 25 Apr 2024   AIC                            691.728
Time:                        11:04:54   BIC                            704.695
Sample:                             1   HQIC                           696.792
                                  558
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0062      0.019     -0.328      0.743      -0.043       0.031
data.L1       -0.3477      0.040     -8.771      0.000      -0.425      -0.270
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -2.8760           +0.0000j            2.8760            0.5000
-----------------------------------------------------------------------------
| Source                       |   Estimate | Standard Error   | 95% Confidence Interval
|
|:-----------------------------|-----------:|:-----------------|:------------------------
-|
| Intercept                    |  -0.0062   | 0.0190           |
|
| MA1                          |  -0.3477   | 0.0396           | (-0.4254, -0.2700)
|
| Number of Observations:      | 558        |                  |
|
| Degrees of Freedom:          | 556        |                  |
|
| Residual Standard Deviation: |   0.200535 |                  |
|
```

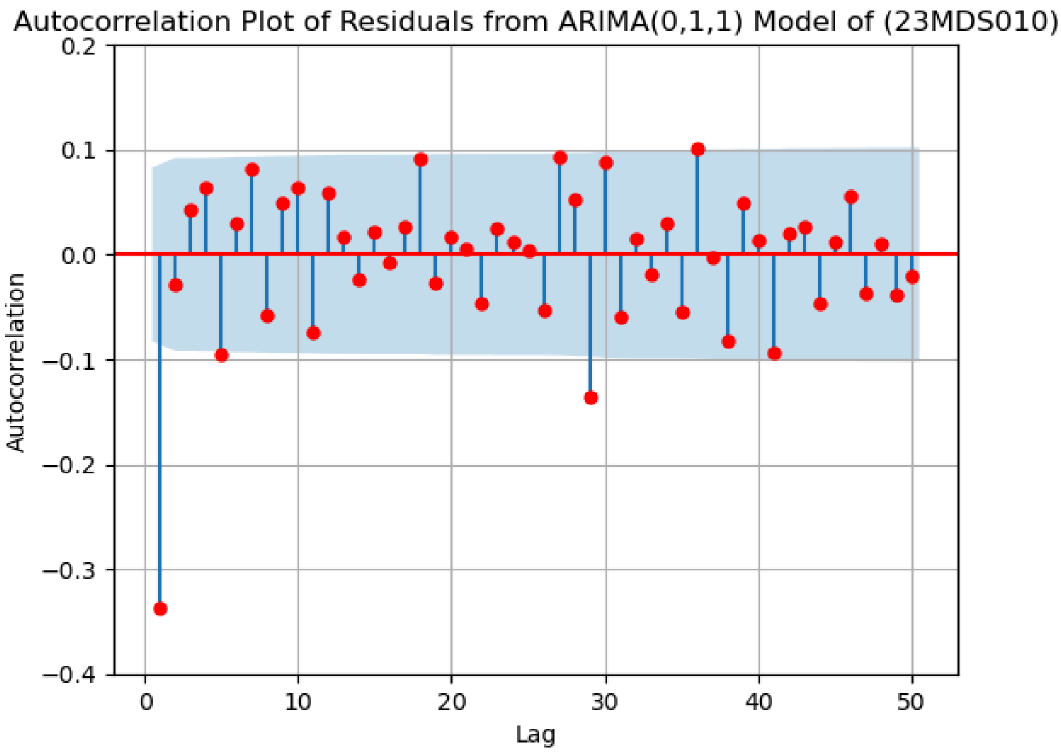
In [51]:
```
model = ARIMA(df1['data'], order=(0, 1, 1))
results = model.fit()
residuals = results.resid
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle('4-Plot of Residuals from ARIMA(0,1,1) Model of (23MDS010)')

axs[0, 0].plot(residuals)
axs[0, 0].set_title('Run Sequence Plot')
axs[0, 0].set_xlabel('Time')
axs[0, 0].set_ylabel('Residuals')

pd.plotting.lag_plot(residuals, lag=1, ax=axs[0, 1])
axs[0, 1].set_title('Lag Plot')
axs[0, 1].set_xlabel('Residuals (t)')
axs[0, 1].set_ylabel('Residuals (t-1)')

sns.histplot(residuals, kde=True, ax=axs[1, 0])
axs[1, 0].set_title('Histogram')
axs[1, 0].set_xlabel('Residuals')

stats.probplot(residuals, dist="norm", plot=axs[1, 1])
axs[1, 1].set_title('Normal Probability Plot')

plt.tight_layout()
plt.show()
```

```
C:\Users\raval\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\statespace\s
arimax.py:978: UserWarning: Non-invertible starting MA parameters found. Using zeros as st
arting parameters.
  warn('Non-invertible starting MA parameters found.'
```



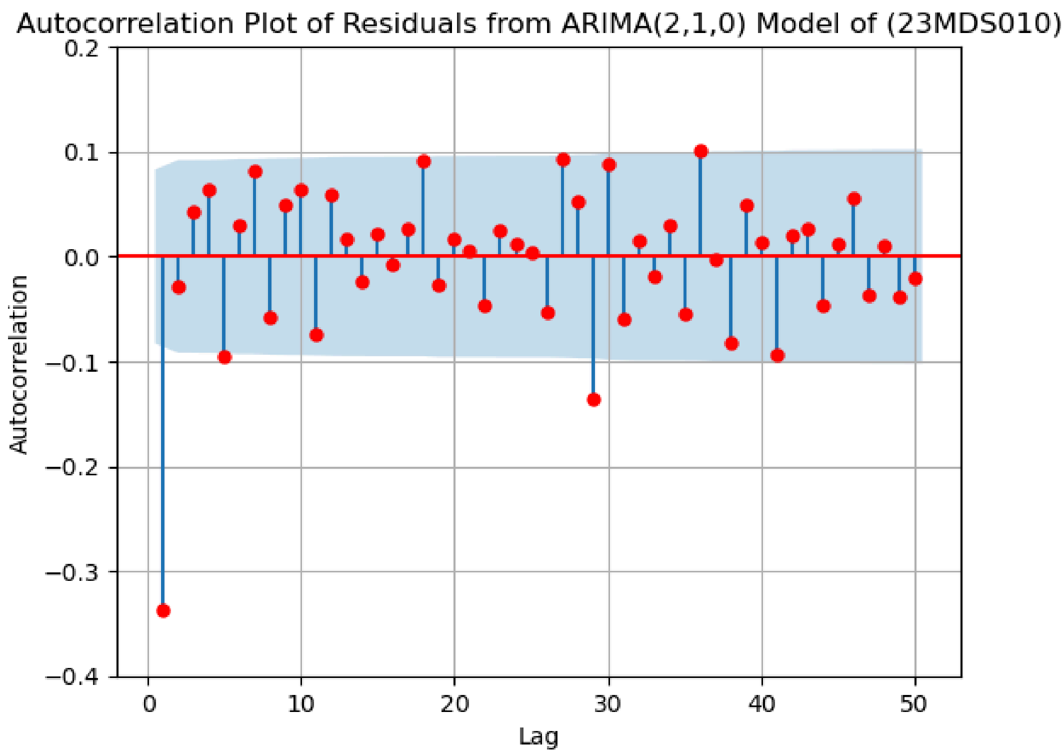
In [52]:
```
plt.figure(figsize=(10, 6))
plot_acf(residuals, lags=50,color="red", zero=False)
plt.title('Autocorrelation Plot of Residuals from ARIMA(0,1,1) Model of (23MDS010)')
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.ylim(-0.4, 0.2)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



In [53]:
```
plt.figure(figsize=(10, 6))
plot_acf(residuals, lags=50,color="red", zero=False)
plt.title('Autocorrelation Plot of Residuals from ARIMA(2,1,0) Model of (23MDS010)')
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.ylim(-0.4, 0.2)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



ARIMA (2,1,0) perfomes batter than ARIMA(0,1,1)

In [ ]: