In [1]:

```
import numpy as np
import pandas as pd
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import LinearRegression
import os
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
warnings.filterwarnings("ignore")
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_11096\348580981.py:2: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas
(pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interope
rability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

Q.1) Write a modularized python code to predict the number of Lynx (an animal) trapped in a forest. Use time series forecasting and linear regression to predict the future values. Use a 70-30 percent train test split ratio.

In [2]:

```
# split a univariate time series into patterns
def get_Patterns(TSeries, n_inputs,h):
    X,y,z = pd.DataFrame(np.zeros((len(TSeries)-n_inputs-h+1,n_inputs))), pd.DataFrame(
    for i in range(len(TSeries)):
        # find the end of this pattern
        end_ix = i + n_inputs + h - 1
        # check if we are beyond the time series
        if end_ix > len(TSeries)-1:
            break
        # gather input and output parts of the pattern
        for j in range(n_inputs):
            X.loc[i,j]=TSeries.iloc[i+j,0]
        i=i+n_inputs
        #y=y.append(TSeries.iloc[end_ix], ignore_index = True)
        y=pd.concat([y, TSeries.iloc[end_ix]], ignore_index=True)
        sinX=pd.DataFrame(np.sin(X))
        cosX=pd.DataFrame(np.cos(X))
        squareX=pd.DataFrame(np.power(X,2))
        #X1=pd.concat([X,sinX,cosX,squareX], axis=1)
        X1=X
    return pd.DataFrame(X),pd.DataFrame(y)
```

In [3]:

```
def minmaxNorm(originalData, lenTrainValidation):
    max2norm=max(originalData.iloc[0:lenTrainValidation,0])
    min2norm=min(originalData.iloc[0:lenTrainValidation,0])
    lenOriginal=len(originalData)
    normalizedData=np.zeros(lenOriginal)
    normalizedData = []
```

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```
        normalizedData.append((originalData.iloc[i]-min2norm)/(max2norm-min2norm))
    return pd.DataFrame(normalizedData)
```

In [4]:

```
# originalData and forecastedData should be Column Vectored DataFrames
def minmaxDeNorm( originalData, forecastedData, lenTrainValidation):
    # Maximum Value
    max2norm=max(originalData.iloc[0:lenTrainValidation,0])
    # Minimum Value
    min2norm=min(originalData.iloc[0:lenTrainValidation,0])
    lenOriginal=len(originalData)
    denormalizedData=[]
    #De-Normalize using Min-Max Normalization
    for i in range (lenOriginal):
        denormalizedData.append((forecastedData.iloc[i]*(max2norm-min2norm))+min2norm)
    return pd.DataFrame(denormalizedData)
```

In [5]:

```
# Timeseries_Data and forecasted_value should be Column Vectored DataFrames
def findRMSE( Timeseries_Data, forecasted_value,lenTrainValidation):
    l=Timeseries_Data.shape[0]
    lenTest=l-lenTrainValidation
    # RMSE on Train & Validation Set
    trainRMSE=0;
    for i in range (lenTrainValidation):
        trainRMSE=trainRMSE+np.power((forecasted_value.iloc[i,0]-Timeseries_Data.iloc[i
    trainRMSE=np.sqrt(trainRMSE/lenTrainValidation)
    # RMSE on Test Set
    testRMSE=0;
    for i in range (lenTrainValidation,l,1):
        testRMSE=testRMSE+np.power((forecasted_value.iloc[i,0]-Timeseries_Data.iloc[i,0
    testRMSE=np.sqrt(testRMSE/lenTest)
    return trainRMSE, testRMSE
```

In [6]:

```
# Timeseries_Data and forecasted_value should be Column Vectored DataFrames
def findMAE(Timeseries_Data, forecasted_value,lenTrainValidation):
    l=Timeseries_Data.shape[0]
    lenTest=l-lenTrainValidation
    # MAE on Train & Validation Set
    trainMAE=0;
    for i in range (lenTrainValidation):
        trainMAE=trainMAE+np.abs(forecasted_value.iloc[i,0]-Timeseries_Data.iloc[i,0])
    trainMAE=(trainMAE/(lenTrainValidation));
    # MAE on Test Set
    testMAE=0;
    for i in range (lenTrainValidation,l,1):
        testMAE=testMAE+np.abs(forecasted_value.iloc[i,0]-Timeseries_Data.iloc[i,0])
    testMAE=(testMAE/lenTest);
    return trainMAE, testMAE
```

In [7]:

```
def Find_Fitness(x,y,lenValid,lenTest,model):
    NOP=y.shape[0]
    lenTrain=NOP-lenValid-lenTest
    xTrain=x.iloc[0:lenTrain,:]
    xValid=x.iloc[lenTrain:(lenTrain+lenValid),:]
                                    :NOP,:]
    yTrain=y.iloc[0:lenTrain,0]
```

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```
    yValid=y.iloc[lenTrain:(lenTrain+lenValid),0]
    yTest=y.iloc[(lenTrain+lenValid):NOP,0]
    model.fit(xTrain, yTrain)
    yhatNorm=model.predict(x).flatten().reshape(x.shape[0],1)
    return pd.DataFrame(yhatNorm)
```

In [8]:

```
#Read the Time Series Dataset
Timeseries_Data=pd.read_csv('Lynx.csv',header=None)
Timeseries_Data.describe()
```

Out[8]:

	0
count	114.000000
mean	1538.017544
std	1585.843914
min	39.000000
25%	348.250000
50%	771.000000
75%	2566.750000
max	6991.000000

In [9]:

```
plt.title("Autocorrelation Plot")
# Providing x-axis name.
plt.xlabel("Lags")
# Plotting the Autocorrelation plot.
plt.acorr(np.array(Timeseries_Data.iloc[:,0], dtype=float), maxlags = 20)
# Displaying the plot.
print("The Autocorrelation plot for the data is:")
plt.grid(True)
plt.show()
```

```
The Autocorrelation plot for the data is:
```

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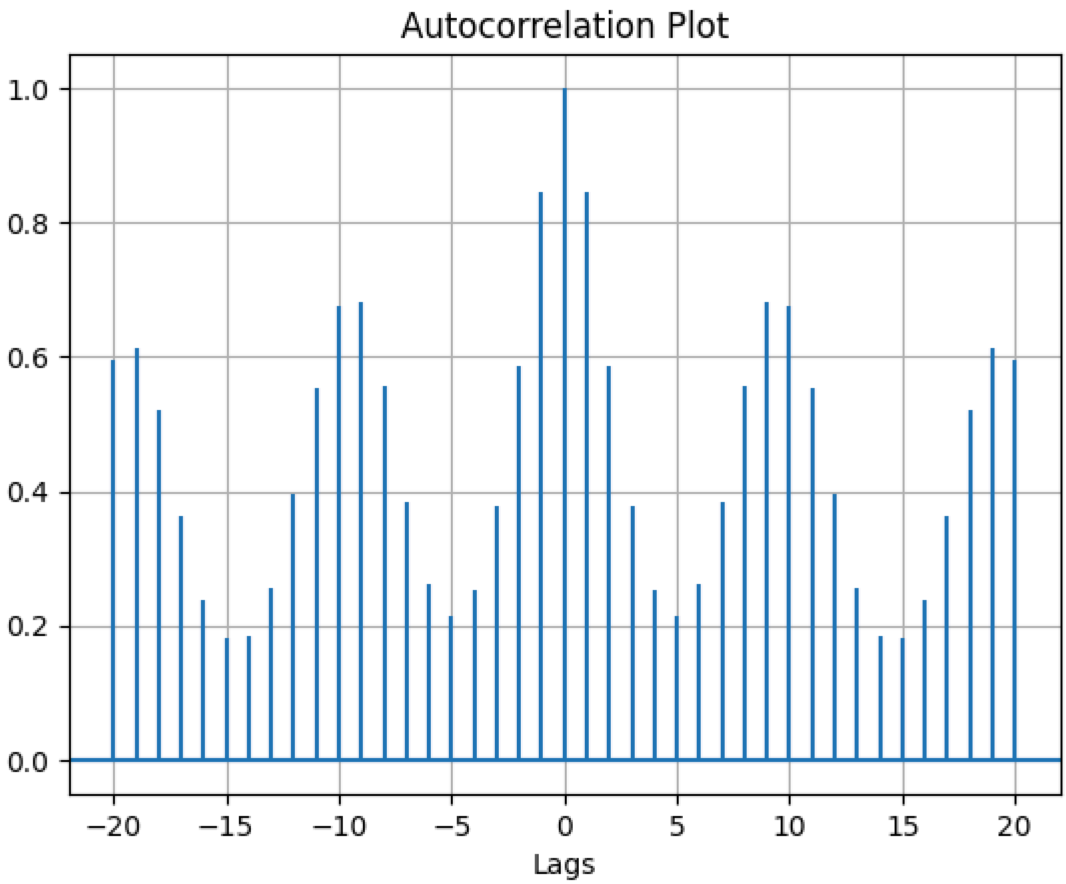

In [10]:

```
#4. Rug plot — sns.rugplot()
sns.rugplot(data=Timeseries_Data, height=.03, color='darkblue')
sns.histplot(data=Timeseries_Data, kde=True)
```

Out[10]:

```
<Axes: ylabel='Count'>
```

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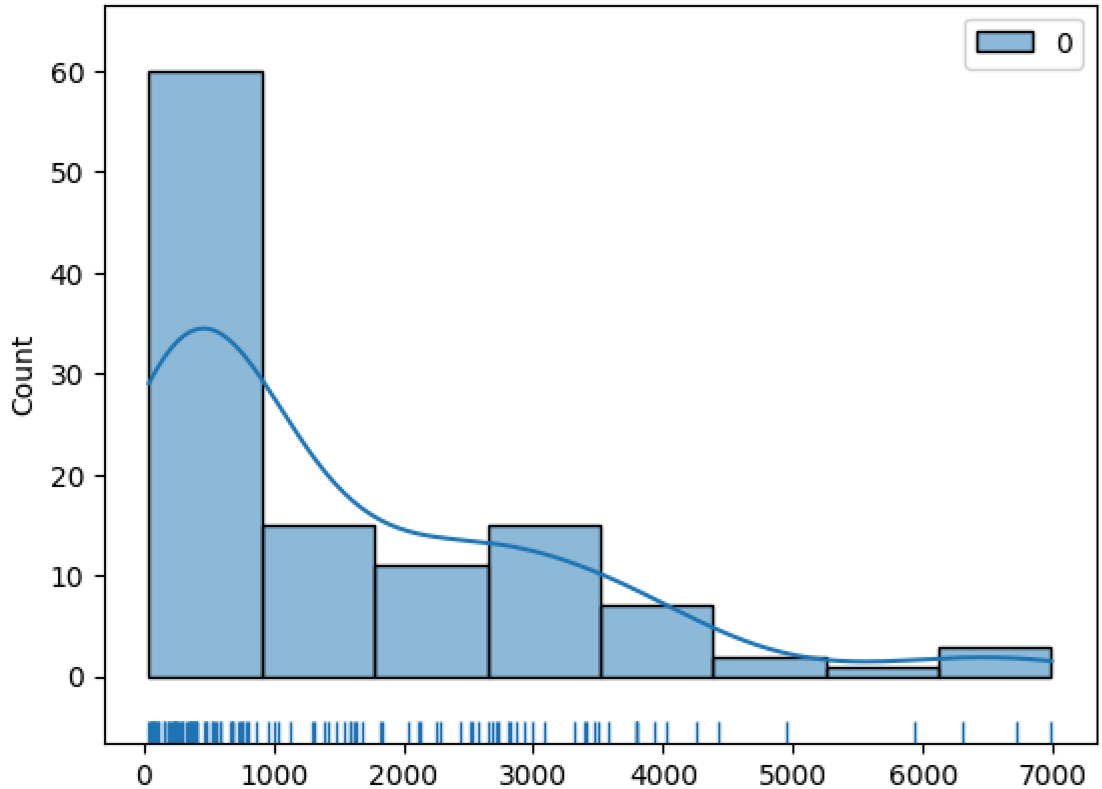

In [11]:

```
LagLength=10
h=1
lt=Timeseries_Data.shape[0]
lenTrain=int(round(lt*0.7))
lenValidation=int(round(lt*0.15))
lenTest=int(lt-lenTrain-lenValidation)
# NORMALIZE THE DATA
normalizedData=minmaxNorm(Timeseries_Data,lenTrain+lenValidation);
# Transform the Time Series into Patterns Using Sliding Window
X, y = get_Patterns(normalizedData, LagLength, h)
model=LinearRegression()
name='LinearRegression'
file1='./'+str(name)+"_Accuracy.xlsx"
file2='./'+str(name)+"_Forecasts.xlsx"
Forecasts=pd.DataFrame()
Accuracy=pd.DataFrame()

ynorm1=Find_Fitness(X,y,lenValidation,lenTest,model)
ynorm=pd.DataFrame(normalizedData.iloc[0:(LagLength+h-1),0])
ynorm=pd.concat([ynorm, ynorm1], ignore_index=True)
yhat=minmaxDeNorm(Timeseries_Data, ynorm, lenTrain+lenValidation)
Accuracy.loc[0,0],Accuracy.loc[0,1]=findRMSE( Timeseries_Data,yhat,lenTrain+lenValidati
Accuracy.loc[0,2],Accuracy.loc[0,3]=findMAE( Timeseries_Data,yhat,lenTrain+lenValidatio
Forecasts=pd.concat([Forecasts, yhat.T], ignore_index=True)
Accuracy.to_excel(file1,sheet_name='Accuracy',index=False)
Forecasts.to_excel(file2,sheet_name='Forecasts',index=False)
print(Accuracy)
```

```
            0           1           2          3
0  804.186429  543.701142  530.371979  440.0537
```

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Q.2) Write a modularized python code to predict the number of Lynx (an animal) trapped in a forest. Use time series forecasting and Multilayer Perceptron (MLP) model to predict the future values. Since MLP is a stochastic model, repeat the simulations for 10 independent times and measure the mean of train and test RMSE and MAE. Use a 70-30 percent train test split ratio.

In [12]:

```
LagLength=10
h=1
lt=Timeseries_Data.shape[0]
lenTrain=int(round(lt*0.7))
lenValidation=int(round(lt*0.15))
lenTest=int(lt-lenTrain-lenValidation)
# NORMALIZE THE DATA
normalizedData=minmaxNorm(Timeseries_Data,lenTrain+lenValidation);
# Transform the Time Series into Patterns Using Sliding Window
X, y = get_Patterns(normalizedData, LagLength, h)

sumAcc=pd.DataFrame()
for i in range(1,10):
    model=MLPRegressor(hidden_layer_sizes=(100,100), activation='relu', solver='adam',
                        learning_rate='constant', learning_rate_init=0.001, shuffle=Tru
                        random_state=None)

    name='MLP'
    file1='./'+str(name)+"_Accuracy.xlsx"
    file2='./'+str(name)+"_Forecasts.xlsx"
    Forecasts=pd.DataFrame()
    Accuracy=pd.DataFrame()

    ynorm1=Find_Fitness(X,y,lenValidation,lenTest,model)
    ynorm=pd.DataFrame(normalizedData.iloc[0:(LagLength+h-1),0])
    ynorm=pd.concat([ynorm, ynorm1], ignore_index=True)

    yhat=minmaxDeNorm(Timeseries_Data, ynorm, lenTrain+lenValidation)
    Accuracy.loc[0,0],Accuracy.loc[0,1]=findRMSE( Timeseries_Data,yhat,lenTrain+lenVali
    Accuracy.loc[0,2],Accuracy.loc[0,3]=findMAE( Timeseries_Data,yhat,lenTrain+lenValid

    sumAcc=pd.concat([sumAcc, Accuracy], ignore_index=True)

Accuracy.loc[0,0]=sumAcc.iloc[:,0].mean()

Accuracy.to_excel(file1,sheet_name='Accuracy',index=False)
Forecasts.to_excel(file2,sheet_name='Forecasts',index=False)
print(Accuracy)
```

```
            0           1           2           3
0  785.399311  384.114148  457.686105  318.196188
```

Q.3) Test whether the Lynx time series has cyclicity or not. If it has cyclicity, what is the cyclicity length? Plot the autocorrelation plot and draw inferences from it. Treat the cyclicity by subtracting cyclic average and model it using Linear Regression and Predict the future values. Use a 70-30 percent train test split ratio.

In [13]:

```
def load_data():
    lynx_data = pd.read_csv('Lynx.csv')
```

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In [14]:

```python
def plot_autocorrelation(time_series, lags=50):
    # Plot autocorrelation to identify cyclicity
    lag_acf = acf(time_series, nlags=lags)
    plt.figure(figsize=(10, 5))
    plt.stem(range(lags + 1), lag_acf)
    plt.axhline(y=0, linestyle='--', color='gray')
    plt.title('Autocorrelation Plot')
    plt.xlabel('Lag')
    plt.ylabel('Autocorrelation')
    plt.show()
    return lag_acf

from scipy.signal import find_peaks
def find_cyclicity_length(acf_values, threshold=0.2):
    # Identify the cyclicity length
    peaks, _ = find_peaks(acf_values, height=threshold)
    if len(peaks) > 0:
        return peaks[0]
    else:
        return None

def subtract_cyclic_average(time_series, cycle_length):
    # Convert the series to a numpy array
    values = time_series.values
    cyclic_averages = []

    # Calculate average for each cycle
    for i in range(cycle_length):
        # Get all elements corresponding to the current cycle position
        values_at_cycle = [values[j] for j in range(i, len(values), cycle_length)]
        cyclic_averages.append(np.mean(values_at_cycle))
    # Apply cyclic average subtraction
    cyclic_adjusted_values = []
    for i in range(len(values)):
        # Determine the appropriate cyclic average to subtract
        cyclic_value = cyclic_averages[i % cycle_length]
        cyclic_adjusted_values.append(values[i] - cyclic_value)

    # Return a new Series with the original index
    return pd.Series(cyclic_adjusted_values, index=time_series.index)

def linear_regression_model(X_train, y_train, X_test):
    # Train a linear regression model
    model = LinearRegression()
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    return predictions

def prepare_features_and_labels(time_series):
    # Prepare the data for regression
    X = np.arange(len(time_series)).reshape(-1, 1)
    y = time_series.values
    return X, y
```

In [15]:

```python
from statsmodels.tsa.stattools import acf
from sklearn.model_selection import train_test_split
ared_error
```

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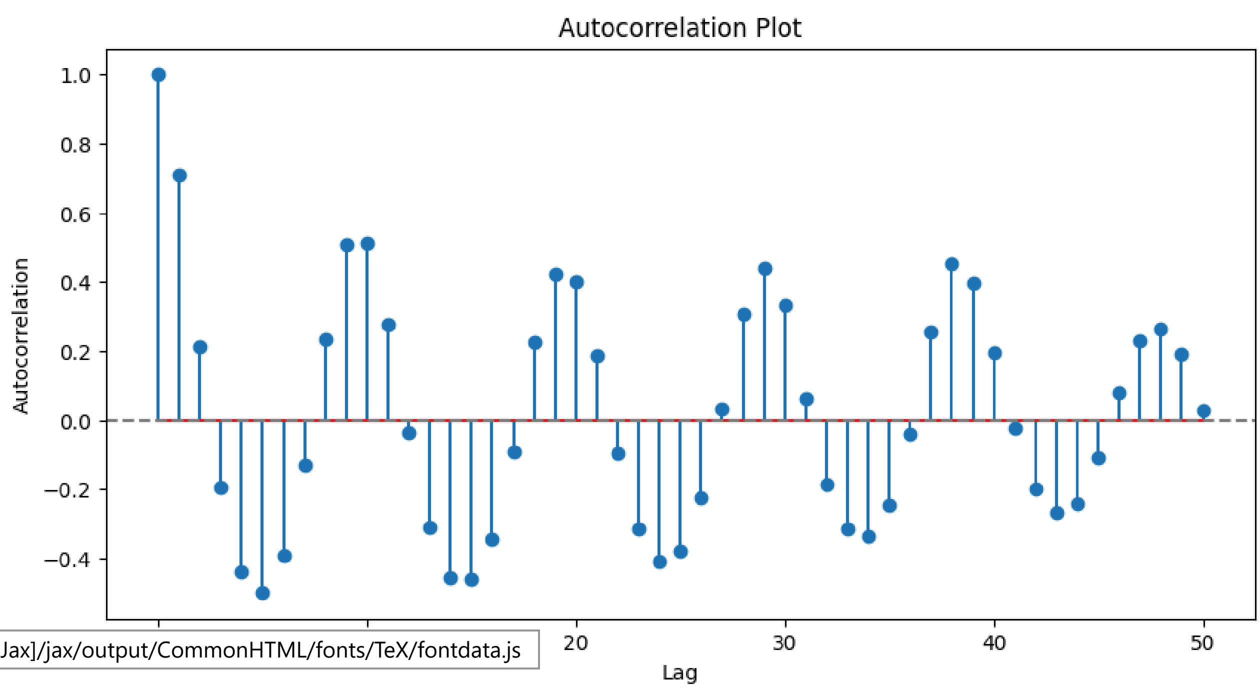
```
lynx_series = load_data()

# Autocorrelation plot
acf_values = plot_autocorrelation(lynx_series)

# Find cyclicity length
cycle_length = find_cyclicity_length(acf_values)
print(f'Cyclicity Length: {cycle_length}')

# Remove cyclicity
if cycle_length:
    detrended_series = subtract_cyclic_average(lynx_series, cycle_length)
else:
    detrended_series = lynx_series

# Prepare features and labels
X, y = prepare_features_and_labels(detrended_series)

# Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=False)

# Train and predict using linear regression
predictions = linear_regression_model(X_train, y_train, X_test)

# Evaluate the model
rmse = np.sqrt(mean_squared_error(y_test, predictions))
print(f'RMSE: {rmse}')

# Plot the original series, detrended series, and predictions
plt.figure(figsize=(12, 6))
plt.plot(lynx_series.index, lynx_series, label='Original Series')
plt.plot(detrended_series.index, detrended_series, label='Detrended Series')
plt.plot(X_test, predictions, label='Linear Regression Predictions', linestyle='--')
plt.legend()
plt.title('Lynx Time Series and Linear Regression Predictions')
plt.show()
```



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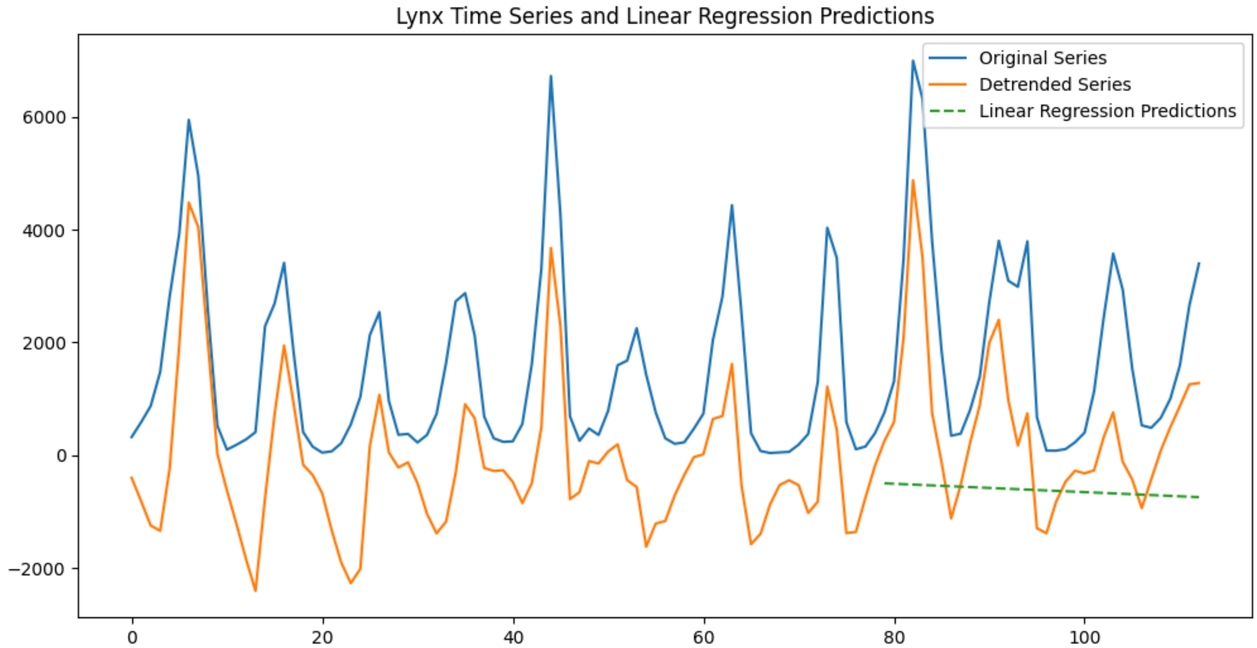
```
Cyclicity Length: 10
RMSE: 1687.6056232323624
```



Q.4) Rewrite the Question-3 using Multilayer Perceptron. Repeat the simulations 10 independent times and measure the mean train and test RMSE and MAE.

In [16]:

```
def mlp_model(X_train, y_train, X_test):
    model = MLPRegressor(hidden_layer_sizes=(100, 100), activation='relu', solver='adam
                         learning_rate='constant', learning_rate_init=0.001, shuffle=Tru
                         random_state=None)
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    return predictions
```

In [17]:

```
from statsmodels.tsa.stattools import acf
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error


lynx_series = load_data()

# Autocorrelation plot
acf_values = plot_autocorrelation(lynx_series)

# Find cyclicity length
cycle_length = find_cyclicity_length(acf_values)
print(f'Cyclicity Length: {cycle_length}')

# Remove cyclicity
if cycle_length:
    detrended_series = subtract_cyclic_average(lynx_series, cycle_length)
else:
    detrended_series = lynx_series

plt.figure(figsize=(12, 6))
                                      ies, label='Original Series')
plt.plot(detrended_series.index, detrended_series, label='Detrended Series')
```

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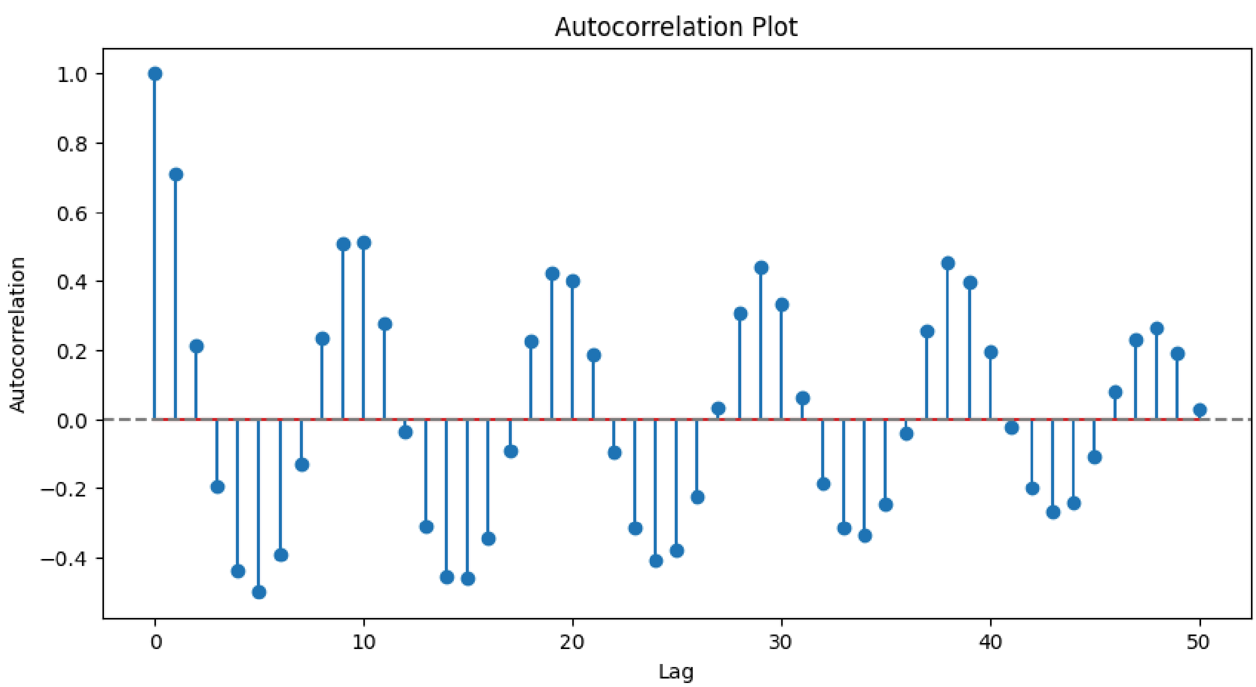
```python
total_rmse = 0

for count in range(10):
    X, y = prepare_features_and_labels(detrended_series)

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=Fa

    predictions = mlp_model(X_train, y_train, X_test)

    rmse = np.sqrt(mean_squared_error(y_test, predictions))
    print(f'RMSE {count+1}: {rmse}')
    total_rmse += rmse

    plt.plot(X_test, predictions, label=f'MLP Predictions {count}', linestyle='--')

print(f'Average RMSE: {total_rmse / 10}')
plt.legend()
plt.title('Lynx Time Series and Linear Regression Predictions')
plt.show()
```




```
Cyclicity Length: 10
RMSE 1: 1645.6294515187574
RMSE 2: 1646.069617930085
RMSE 3: 1645.236140603216
RMSE 4: 1646.7871528046858
RMSE 5: 1645.8480258578313
RMSE 6: 1658.9289293211439
RMSE 7: 1646.0094701479238
RMSE 8: 1658.5377842076691
RMSE 9: 1658.370714553287
RMSE 10: 1645.270989241245
Average RMSE: 1649.6688276185844
```

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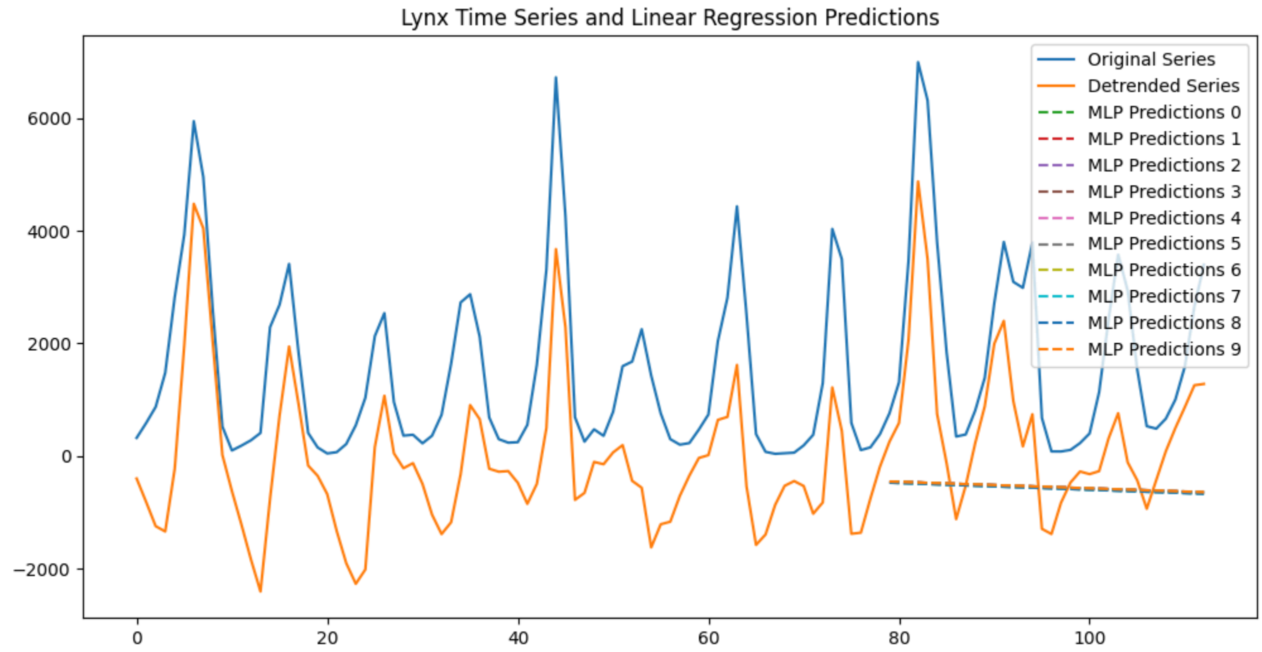

Q.5) Treat the cyclicity by differencing and predict it using Linear Regression. Use a 70-30 percent train test split ratio.

In [18]:

```
def difference_series(time_series):
    differenced_series = time_series.diff().dropna()
    return differenced_series

def prepare_lagged_features(time_series, lag=1):
    X = pd.concat([time_series.shift(i) for i in range(1, lag + 1)], axis=1).dropna()
    y = time_series[lag:]
    return X.values, y.values

def linear_regression_model(X_train, y_train, X_test):
    model = LinearRegression()
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    return predictions

def invert_differencing(original_series, differenced_predictions):
    last_value = original_series.iloc[-len(differenced_predictions) - 1]

    # Initialize list with the last known value
    inverted_predictions = [last_value]

    # Add cumulative sum of differences to the last known value
    for diff in differenced_predictions:
        inverted_predictions.append(inverted_predictions[-1] + diff)

    # Skip the first value which is just the last known value
    return pd.Series(inverted_predictions[1:], index=original_series.index[-len(differe



lynx_series = load_data()

differenced_series = difference_series(lynx_series)
```

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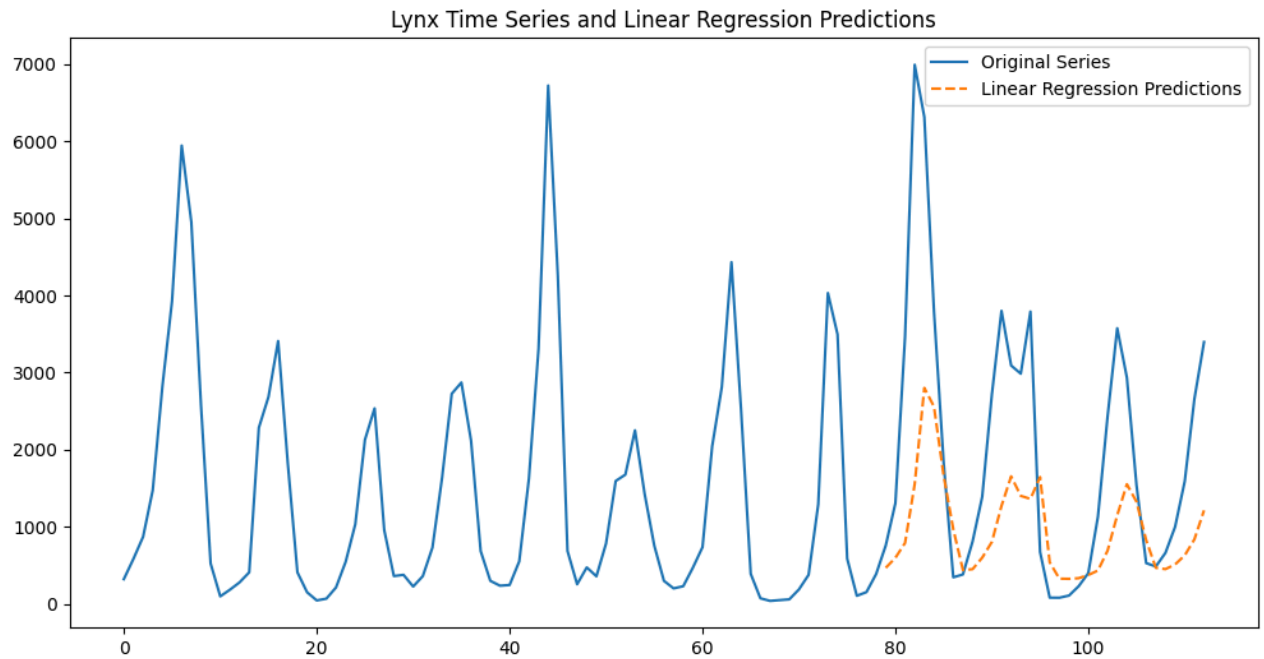
```
X, y = prepare_lagged_features(differenced_series)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=False)

differenced_predictions = linear_regression_model(X_train, y_train, X_test)

# Invert the differencing to get predictions on the original scale
predictions = invert_differencing(lynx_series, differenced_predictions)

rmse = np.sqrt(mean_squared_error(lynx_series[-len(predictions):], predictions))
print(f'RMSE: {rmse}')

plt.figure(figsize=(12, 6))
plt.plot(lynx_series.index, lynx_series, label='Original Series')
plt.plot(lynx_series.index[-len(predictions):], predictions, label='Linear Regression P
plt.legend()
plt.title('Lynx Time Series and Linear Regression Predictions')
plt.show()
```

RMSE: 1670.3683210506654



Q.6) Rewrite the Question-5 using Multilayer Perceptron. Repeat the simulations 10 independent times and measure the mean train and test RMSE and MAE.

In [20]:

```
def mlp_model(X_train, y_train, X_test):
    # Train a MLP model
    model = MLPRegressor(hidden_layer_sizes=(100, 100), activation='relu', solver='adam
                         learning_rate='constant', learning_rate_init=0.0001, shuffle=Tr
                         random_state=None)
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    return predictions
```

In [28]:

```
def difference_series(time_series):
    # differencing by cyclic period
                                     .diff(periods=9).dropna()
```

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```python
def prepare_lagged_features(time_series, lag=9):
    # Create lagged features for regression
    lagged_data = pd.concat([time_series.shift(i) for i in range(1, lag + 1)], axis=1)
    lagged_data.columns = [f'lag_{i}' for i in range(1, lag + 1)]

    # Drop rows with NaN values that result from shifting
    lagged_data.dropna(inplace=True)

    # Define target values (shifted by lag)
    y = time_series.iloc[lag:]

    # Ensure y is aligned with the lagged_data by trimming the start
    y = y.iloc[:len(lagged_data)]

    return lagged_data.values, y.values

def invert_differencing(original_series, differenced_predictions):
    cycle_length = 9
    inverted_predictions = []

    # Start inversion process
    for i, diff in enumerate(differenced_predictions):
        # Find the correct point in the original series to add the difference
        reference_point = original_series.iloc[-len(differenced_predictions) - cycle_le
        inverted_value = reference_point + diff
        inverted_predictions.append(inverted_value)

    # Convert to pandas Series with correct index
    return pd.Series(inverted_predictions, index=original_series.index[-len(differenced_



# Load data
lynx_series = load_data()

# Differencing the time series
differenced_series = difference_series(lynx_series)

# Prepare lagged features
X, y = prepare_lagged_features(differenced_series)


total_rmse = 0
# Split the data into train and test sets
plt.figure(figsize=(12, 6))
plt.plot(lynx_series.index, lynx_series, label='Original Series')
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=False)
for count in range(1, 11):

    # Train and predict using linear regression
    differenced_predictions = mlp_model(X_train, y_train, X_test)

    # Invert the differencing to get predictions on the original scale
    predictions = invert_differencing(lynx_series, differenced_predictions)

    # Evaluate the model
    rmse = np.sqrt(mean_squared_error(lynx_series[-len(predictions):], predictions))
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    total_rmse += rmse
```

```
    # Plot the original series and predictions

    plt.plot(lynx_series.index[-len(predictions):], predictions, label=f'MLP Prediction

print(f'Average RMSE: {total_rmse / 10}')

plt.legend()
plt.title('Lynx Time Series and Linear Regression Predictions')
plt.show()
```

```
RMSE 1: 1117.1128880266683
RMSE 2: 1127.6443870664998
RMSE 3: 1078.8541225286308
RMSE 4: 1109.3944718283774
RMSE 5: 1042.5127855002092
RMSE 6: 1073.353685209629
RMSE 7: 1154.4284451474248
RMSE 8: 1093.8610491255738
RMSE 9: 1062.169646506976
RMSE 10: 1114.2258982384403
Average RMSE: 1097.355737917843
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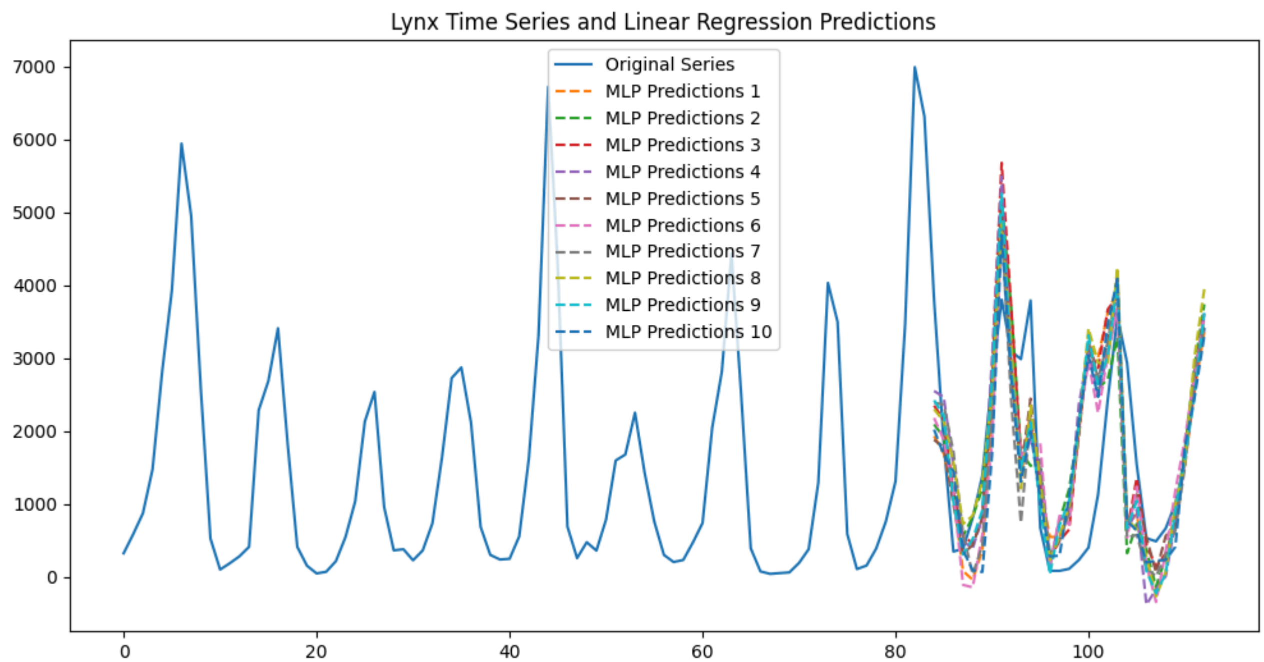

Q.7) Which model is more appropriate for predicting the Lynx time series. Whether treatment of cyclic component improve the performance or not? If yes which cyclic component treatment method is more appropriate.

The models having cyclic treatment generally performs better as they handle the data's structure more effectively. So, if we remove the cyclicity, it will lead to a better generalization.

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