In [1]:

```python
import pandas as pd
from openpyxl.workbook import Workbook

#reading excel file
df = pd.read_excel('C:/Users/svasudev/OneDrive - IGMFinancial/Documents/Predictive Analyti
                   engine='openpyxl',sheet_name=0,header=0,index_col=False,keep_default_na=
```

In [2]:

```python
#Top 5 rows of the Excel file
df.head()
```

Out[2]:

	Date	Ottawa	Toronto West/Ouest	Toronto East/Est	Windsor	London	Peterborough	St. Catharine's	Sudbury	Sault Saint Marie	Thunder Bay	N
0	1990-01-03	55.9	49.1	48.7	45.2	50.1	0.0	0.0	56.4	54.8	56.6	
1	1990-01-10	55.9	47.7	46.8	49.7	47.6	0.0	0.0	56.4	54.9	56.8	
2	1990-01-17	55.9	53.2	53.2	49.6	53.7	0.0	0.0	55.8	54.9	56.8	
3	1990-01-24	55.9	53.2	53.5	49.0	52.1	0.0	0.0	55.7	54.9	56.8	
4	1990-01-31	55.9	51.9	52.6	48.6	49.1	0.0	0.0	55.6	54.8	56.8	

In [3]:

```python
#Datatype and Null Information about the columns in the Excel file
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9962 entries, 0 to 9961
Data columns (total 20 columns):
 #   Column                                      Non-Null Count  Dtype
---  ------                                      --------------  -----
 0   Date                                        9962 non-null   datetime64[ns]
 1   Ottawa                                      9962 non-null   float64
 2   Toronto West/Ouest                          9962 non-null   float64
 3   Toronto East/Est                            9962 non-null   float64
 4   Windsor                                     9962 non-null   float64
 5   London                                      9962 non-null   float64
 6   Peterborough                                9962 non-null   float64
 7   St. Catharine's                             9962 non-null   float64
 8   Sudbury                                     9962 non-null   float64
 9   Sault Saint Marie                           9962 non-null   float64
 10  Thunder Bay                                 9962 non-null   float64
 11  North Bay                                   9962 non-null   float64
 12  Timmins                                     9962 non-null   float64
 13  Kenora                                      9962 non-null   float64
 14  Parry Sound                                 9962 non-null   float64
 15  Ontario Average/Moyenne provinciale         9962 non-null   float64
 16  Southern Average/Moyenne du sud de l'Ontario  9962 non-null   float64
 17  Northern Average/Moyenne du nord de l'Ontario 9962 non-null   float64
```

```
 18  Fuel Type                                 9962 non-null   object
 19  Type de carburant                         9962 non-null   object
dtypes: datetime64[ns](1), float64(17), object(2)
memory usage: 1.5+ MB
```

In [4]:
```python
#Creating a new dataframe
df2 = pd.DataFrame()
```

In [5]:
```python
#Choosing rows from the original dataframe with Fuel Type "Diesel" and pasting it into new
df2 = df.loc[df['Fuel Type']=='Diesel']
```

In [6]:
```python
#Datatype and Null Information about the columns in the new dataframe
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1675 entries, 1675 to 3349
Data columns (total 20 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   Date                                      1675 non-null   datetime64[ns]
 1   Ottawa                                    1675 non-null   float64
 2   Toronto West/Ouest                        1675 non-null   float64
 3   Toronto East/Est                          1675 non-null   float64
 4   Windsor                                   1675 non-null   float64
 5   London                                    1675 non-null   float64
 6   Peterborough                              1675 non-null   float64
 7   St. Catharine's                           1675 non-null   float64
 8   Sudbury                                   1675 non-null   float64
 9   Sault Saint Marie                         1675 non-null   float64
 10  Thunder Bay                               1675 non-null   float64
 11  North Bay                                 1675 non-null   float64
 12  Timmins                                   1675 non-null   float64
 13  Kenora                                    1675 non-null   float64
 14  Parry Sound                               1675 non-null   float64
 15  Ontario Average/Moyenne provinciale       1675 non-null   float64
 16  Southern Average/Moyenne du sud de l'Ontario  1675 non-null   float64
 17  Northern Average/Moyenne du nord de l'Ontario 1675 non-null   float64
 18  Fuel Type                                 1675 non-null   object
 19  Type de carburant                         1675 non-null   object
dtypes: datetime64[ns](1), float64(17), object(2)
memory usage: 274.8+ KB
```

In [7]:
```python
df2.head()
```

Out[7]:

	Date	Ottawa	Toronto West/Ouest	Toronto East/Est	Windsor	London	Peterborough	St. Catharine's	Sudbury	Sault Saint Marie	Thunder Bay
1675	1990-01-03	49.3	47.6	48.3	46.5	47.2	0.0	0.0	45.4	45.8	46.6
1676	1990-01-10	49.5	47.9	48.6	47.1	47.4	0.0	0.0	45.8	46.1	46.6
1677	1990-01-17	49.5	48.6	48.6	47.3	47.4	0.0	0.0	47.2	46.1	46.6
1678	1990-01-24	50.4	47.9	48.7	47.6	47.7	0.0	0.0	47.2	46.2	47.2

	Date	Ottawa	Toronto West/Ouest	Toronto East/Est	Windsor	London	Peterborough	St. Catharine's	Sudbury	Sault Saint Marie	Thunder Bay
1679	1990-01-31	50.4	47.7	48.7	47.6	47.7	0.0	0.0	47.2	46.5	47.3

In [8]:
```
#Creating a new dataframe
df3 = pd.DataFrame()
```

In [9]:
```
#Analyzing 'Diesel' price for London Region only and pasting it into new dataframe
df3.insert(0,"Date",df2['Date'],True)
df3.insert(1,"London",df2['London'],True)
```

In [10]:
```
df3.head()
```

Out[10]:

	Date	London
1675	1990-01-03	47.2
1676	1990-01-10	47.4
1677	1990-01-17	47.4
1678	1990-01-24	47.7
1679	1990-01-31	47.7

In [11]:
```
#Date column only had weekly values. Sometimes the week started on Wednesday and sometimes
#this inconistency, converting the date column into daily values and assigning the previo
#daily values.
df3.set_index('Date', inplace=True)
df3 = df3.resample('D').ffill().reset_index()
```

In [12]:
```
#Last 10 values from the dataset
df3.tail(10)
```

Out[12]:

	Date	London
11707	2022-01-22	149.7
11708	2022-01-23	149.7
11709	2022-01-24	152.1
11710	2022-01-25	152.1
11711	2022-01-26	152.1
11712	2022-01-27	152.1
11713	2022-01-28	152.1
11714	2022-01-29	152.1
11715	2022-01-30	152.1
11716	2022-01-31	157.1

In [13]:
```
#Checking for null values
df3.isnull().values.any()
```

Out[13]:
```
False
```

In [14]:
```
#Splitting the "Date" column into year, month and week to explore trends
df3['Year']=df3['Date'].dt.year
df3['Month']=df3['Date'].dt.month
df3['Week']=df3['Date'].dt.isocalendar().week
```

In [15]:
```
df3.head(10)
```

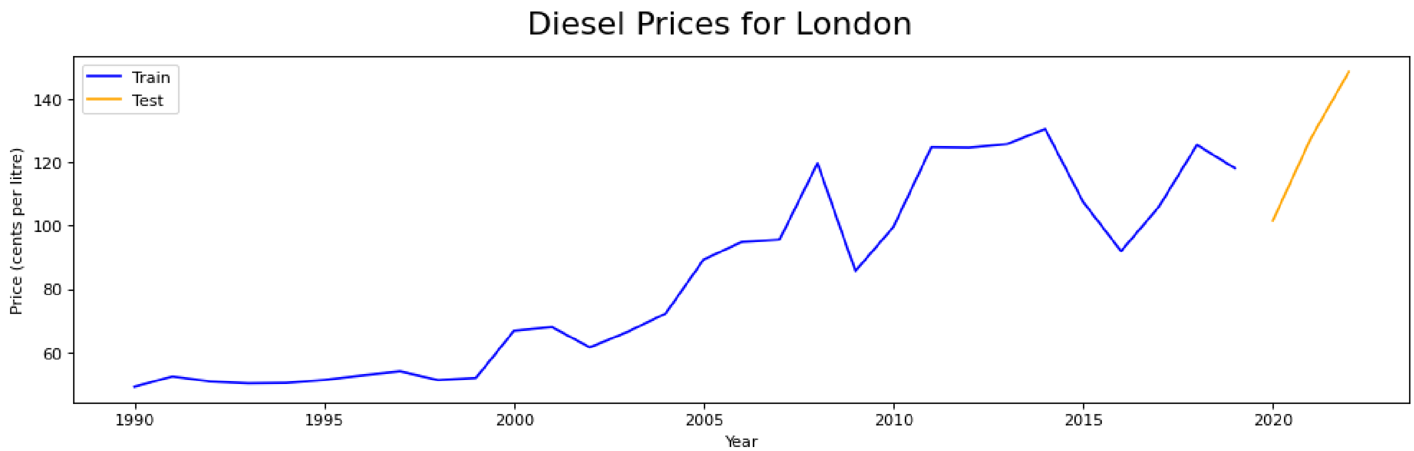
Out[15]:

	Date	London	Year	Month	Week
0	1990-01-03	47.2	1990	1	1
1	1990-01-04	47.2	1990	1	1
2	1990-01-05	47.2	1990	1	1
3	1990-01-06	47.2	1990	1	1
4	1990-01-07	47.2	1990	1	1
5	1990-01-08	47.2	1990	1	2
6	1990-01-09	47.2	1990	1	2
7	1990-01-10	47.4	1990	1	2
8	1990-01-11	47.4	1990	1	2
9	1990-01-12	47.4	1990	1	2

In [16]:
```
#Splitting the dataset in Train and Test
#Train from Year 1990 to Year 2019
#Test from Year 2020

train = df3[(df3['Date'] > '1990-01-01') & (df3['Date'] <= '2019-12-31')]
test = df3[df3['Date'] >= '2020-01-01']
```

Yearly Price Visualization on Train and Test Dataset

In [17]:
```
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

yearly_train_Price = train.groupby(['Year'])['London'].mean()
yearly_test_Price = test.groupby(['Year'])['London'].mean()

figure(figsize=(15, 4), dpi=80)
plt.plot(yearly_train_Price, label='Train',c='blue')
plt.plot(yearly_test_Price, label='Test',c='orange')
plt.legend(loc='best')
plt.suptitle('Diesel Prices for London', fontsize=20)
plt.xlabel('Year')
plt.ylabel('Price (cents per litre)')
plt.show()
```



DataPrep for Time Series

In [18]:
```
train.index = pd.DatetimeIndex(train['Date'])
#Changing the frequency of the index to Daily
train.index = train.asfreq('d').index

test.index = pd.DatetimeIndex(test['Date'])
#Changing the frequency of the index to Daily
test.index = test.asfreq('d').index
```

Train and Time Series Dataset

In [19]:
```
train_time_series = pd.DataFrame()
train_time_series.index = train.index
train_time_series.insert(0,"London Diesel Price Train",train['London'],True)

test_time_series = pd.DataFrame()
test_time_series.index = test.index
test_time_series.insert(0,"London Diesel Price Test",test['London'],True)


print(train_time_series.tail())
print(test_time_series.tail())
```

```
            London Diesel Price Train
Date
2019-12-27                      128.2
2019-12-28                      128.2
2019-12-29                      128.2
2019-12-30                      126.1
2019-12-31                      126.1
            London Diesel Price Test
Date
2022-01-27                     152.1
2022-01-28                     152.1
2022-01-29                     152.1
2022-01-30                     152.1
2022-01-31                     157.1
```

ARIMA Model

To predict time series with ARIMA, we need to set the values of three parameters (p,d,q):

p: The order of the auto-regressive (AR) model (i.e., the number of lag observations)

d: The degree of differencing.

q: The order of the moving average (MA) model.

Checking if data is stationary - We can see that it is not based on the P-value - Augmented Dickey Fuller Test

In [20]:
```
from statsmodels.tsa.stattools import adfuller
results = adfuller(train_time_series['London Diesel Price Train'])
print('ADF Statistic: ',results[0])
print('p-value: ',results[1])
print('Critical Values', results[4])
```

```
ADF Statistic:  -1.2018767980435545
p-value:  0.6727878401496852
Critical Values {'1%': -3.4309478825441477, '5%': -2.8618042310196214, '10%': -2.566910645
0424284}
```

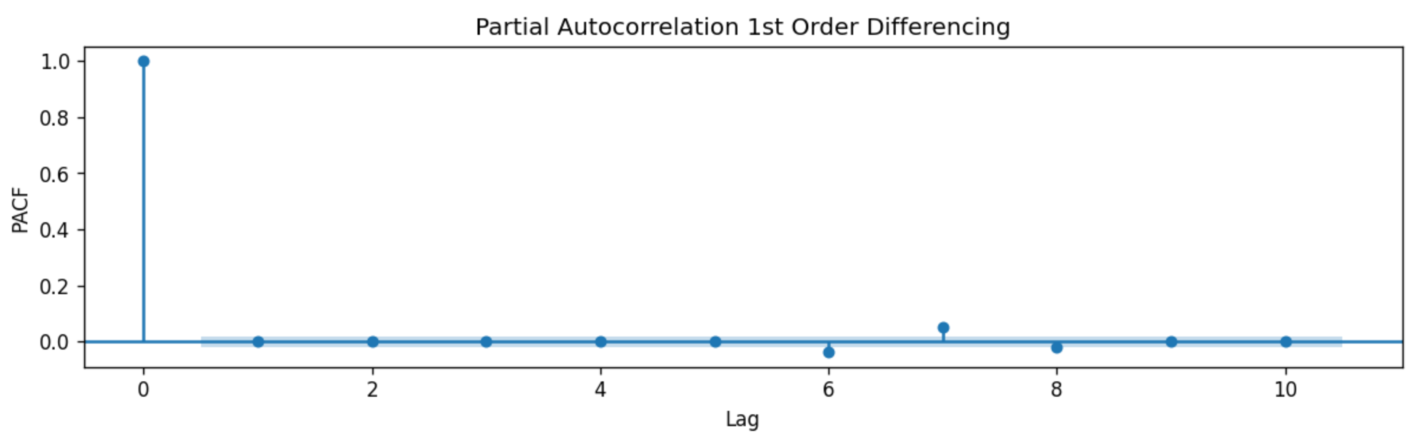
Taking First difference - P value is < 0.05. We can stop at the First Difference; d = 1

In [21]:
```
train_time_series_stationary1 = train_time_series.diff().dropna()
results1 = adfuller(train_time_series_stationary1['London Diesel Price Train'])
print('ADF Statistic: ',results1[0])
print('p-value: ',results1[1])
print('Critical Values', results1[4])
```

```
ADF Statistic:  -24.683177937471015
p-value:  0.0
Critical Values {'1%': -3.4309478825441477, '5%': -2.8618042310196214, '10%': -2.566910645
0424284}
```

The Order of Autoregressive Term p; p = 0

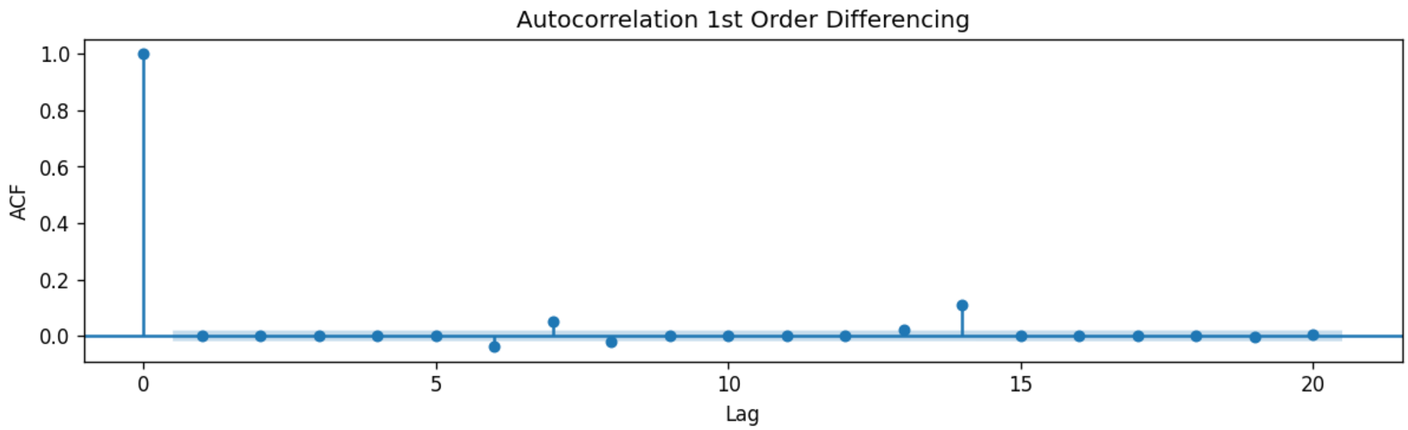
In [22]:
```
plt.rcParams.update({'figure.figsize':(12,3), 'figure.dpi':120})
from statsmodels.graphics.tsaplots import plot_pacf
plot_pacf(train_time_series_stationary1, lags=10,  title="Partial Autocorrelation 1st Orde
plt.xlabel('Lag')
plt.ylabel('PACF')
plt.show()
```



The order of the Moving Average term q; q = 0

In [23]:

```
plt.rcParams.update({'figure.figsize':(12,3), 'figure.dpi':120})
from statsmodels.graphics.tsaplots import plot_acf
plot_acf(train_time_series_stationary1, lags=20,  title="Autocorrelation 1st Order Differe
plt.xlabel('Lag')
plt.ylabel('ACF')
plt.show()
```



Check the above p,d,q parameters with Auto Arima - Best Model ARIMA (0,1,0)

In [24]:

```
import pmdarima as pm
from pmdarima.model_selection import train_test_split
import numpy as np

model1 = pm.auto_arima(train_time_series, trace=True, error_action='ignore', suppress_warn
model1.fit(train_time_series)

forecast1 = model1.predict(n_periods=len(test_time_series))
forecast1 = pd.DataFrame(forecast1,index = test_time_series.index,columns=['Prediction'])
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=22112.404, Time=1.55 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=22104.404, Time=1.19 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=22106.404, Time=0.54 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=22106.404, Time=0.70 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=22103.695, Time=0.15 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=22108.404, Time=1.07 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0]
Total fit time: 5.246 seconds
```

Model Summary

In [25]:

```
import statsmodels.api as sm
model = sm.tsa.arima.ARIMA(train_time_series, order=(0,1,0))
model_result = model.fit()
print(model_result.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:      London Diesel Price Train   No. Observations:        10955
Model:                         ARIMA(0, 1, 0)   Log Likelihood      -11050.847
Date:                        Sat, 05 Mar 2022   AIC                  22103.695
Time:                                14:03:54   BIC                  22110.996
Sample:                            01-03-1990   HQIC                 22106.155
                                 - 12-31-2019
Covariance Type:                          opg
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2         0.4403      0.001    485.300      0.000       0.439       0.442
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):           3222883.91
Prob(Q):                              0.99   Prob(JB):                         0.00
Heteroskedasticity (H):              19.74   Skew:                             2.08
Prob(H) (two-sided):                  0.00   Kurtosis:                        86.93
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Model Prediction

In [26]:

```
import warnings
warnings.filterwarnings('ignore')
ARIMA_Predict = model_result.predict(start='1/1/2020', end='1/31/2022')
ARIMA_Predict_df = pd.DataFrame(ARIMA_Predict)
```

In [27]:

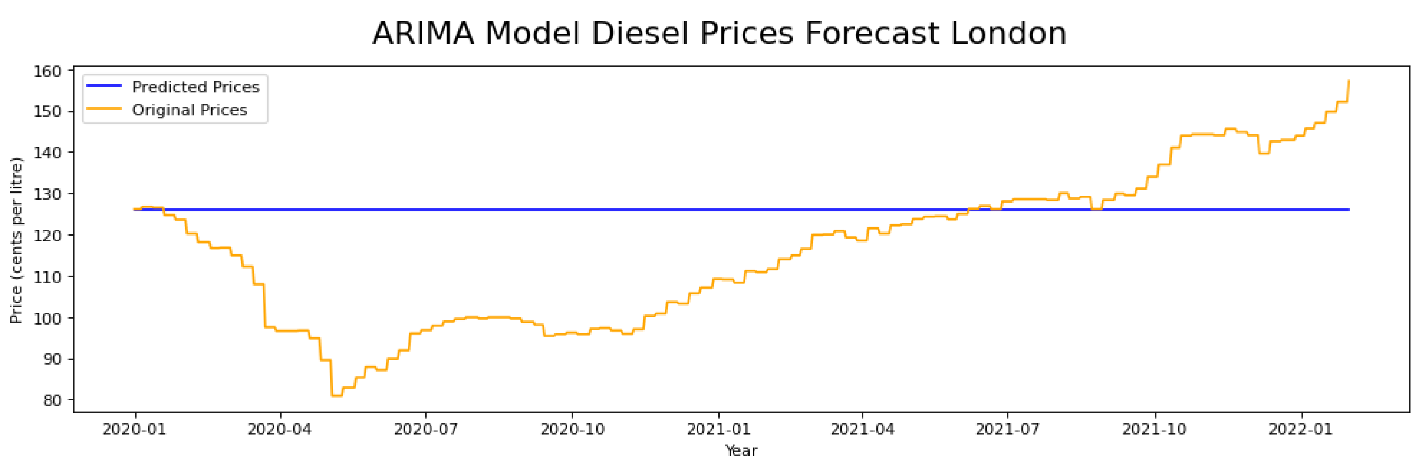
```
ARIMA_Predict_df.tail()
```

Out[27]:

	predicted_mean
2022-01-27	126.1
2022-01-28	126.1
2022-01-29	126.1
2022-01-30	126.1
2022-01-31	126.1

In [28]:

```
figure(figsize=(15, 4), dpi=80)
plt.plot(ARIMA_Predict_df, label='Predicted Prices',c='blue')
plt.plot(test_time_series, label='Original Prices',c='orange')
plt.legend(loc='best')
plt.suptitle('ARIMA Model Diesel Prices Forecast London', fontsize=20)
plt.xlabel('Year')
plt.ylabel('Price (cents per litre)')
plt.show()
```



Evaluation of the Model

Mean Absolute Error (MAE) ARIMA

In [29]:
```
from sklearn.metrics import mean_absolute_error
maeARIMA=mean_absolute_error(test_time_series['London Diesel Price Test'],ARIMA_Predict)
print('Mean Absolute Error ARIMA = {}'.format(round(maeARIMA, 2)))
```

```
Mean Absolute Error ARIMA = 16.71
```

Mean squared error (MSE) ARIMA

In [30]:
```
from sklearn.metrics import mean_squared_error
mseARIMA=mean_squared_error(test_time_series['London Diesel Price Test'],ARIMA_Predict)
print('The Mean Squared Error ARIMA = {}'.format(round(mseARIMA, 2)))
```

```
The Mean Squared Error ARIMA = 423.88
```

Root mean squared error (RMSE) ARIMA

In [31]:
```
from numpy import sqrt
rmseARIMA = sqrt(mseARIMA)
print('The Root Mean Squared Error ARIMA = {}'.format(round(rmseARIMA, 2)))
```

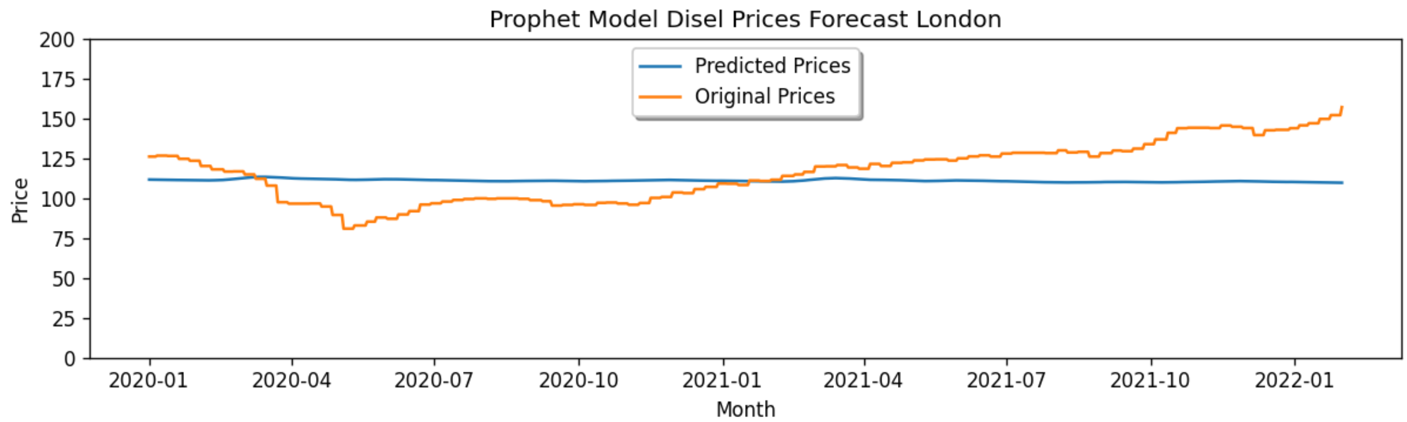
```
The Root Mean Squared Error ARIMA = 20.59
```

Prophet Model

In [32]:
```
from fbprophet import Prophet
d={'ds':train['Date'],'y':train['London']}
df_pred=pd.DataFrame(data=d)
model_prophet = Prophet(daily_seasonality=False)
model_prophet_result = model_prophet.fit(df_pred)
```

In [33]:
```
future = model_prophet.make_future_dataframe(periods=765)
forecast = model_prophet.predict(future)
forecast = forecast[(forecast['ds' ] >= '2020-01-01') & (forecast['ds' ] <= '2022-01-31')]
```

In [34]:
```
fig, ax = plt.subplots()
ax.plot(forecast['ds'], forecast['yhat'], label='Predicted Prices')
ax.plot(test['Date'], test['London'], label='Original Prices')
plt.ylim([0,200])
legend = ax.legend(loc='upper center', shadow=True)
plt.title('Prophet Model Disel Prices Forecast London')
plt.xlabel('Month')
plt.ylabel('Price')
plt.show()
```



Mean Absolute Error (MAE) Prophet

In [35]:
```
maeProphet=mean_absolute_error(test['London'],forecast['yhat'])
print('Mean Absolute Error Prophet = {}'.format(round(maeProphet, 2)))
```

```
Mean Absolute Error Prophet = 16.2
```

Mean squared error (MSE) Prophet

In [36]:
```
mseProphet = mean_squared_error(test['London'],forecast['yhat'])
print('The Mean Squared Error Prophet =  {}'.format(round(mseProphet, 2)))
```

```
The Mean Squared Error Prophet =  359.5
```

Root mean squared error (RMSE) Prophet

In [37]:
```
rmseProphet = sqrt(mseProphet)
print('The Root Mean Squared Error Prophet = {}'.format(round(rmseProphet, 2)))
```

```
The Root Mean Squared Error Prophet = 18.96
```