In [1]:

```
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]:

```
#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]:

```
#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]:
```
#Creating a new dataframe
df2 = pd.DataFrame()
```

In [5]:
```
#Choosing rows from the original dataframe with Fuel Type "Regular Unleaded gasoline" and
df2 = df.loc[df['Fuel Type']=='Regular Unleaded Gasoline']
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1675 entries, 0 to 1674
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]:
```
df2.head()
```

Out[7]:

	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	

	Date	Ottawa	Toronto West/Ouest	Toronto East/Est	Windsor	London	Peterborough	St. Catharine's	Sudbury	Sault Saint Marie	Thunder Bay	N
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 [8]:

```
#Creating a new dataframe
df3 = pd.DataFrame()
```

In [9]:

```
#Analyzing 'Regular Unleaded Gasoline' price for London Region only and pasting it into ne
df3.insert(0,"Date",df2['Date'],True)
df3.insert(1,"London",df2['London'],True)
```

In [10]:

```
df3.head()
```

Out[10]:

	Date	London
0	1990-01-03	50.1
1	1990-01-10	47.6
2	1990-01-17	53.7
3	1990-01-24	52.1
4	1990-01-31	49.1

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 previou
#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	146.7
11708	2022-01-23	146.7
11709	2022-01-24	147.6
11710	2022-01-25	147.6
11711	2022-01-26	147.6
11712	2022-01-27	147.6
11713	2022-01-28	147.6
11714	2022-01-29	147.6

	Date	London
11715	2022-01-30	147.6
11716	2022-01-31	152.8

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	50.1	1990	1	1
1	1990-01-04	50.1	1990	1	1
2	1990-01-05	50.1	1990	1	1
3	1990-01-06	50.1	1990	1	1
4	1990-01-07	50.1	1990	1	1
5	1990-01-08	50.1	1990	1	2
6	1990-01-09	50.1	1990	1	2
7	1990-01-10	47.6	1990	1	2
8	1990-01-11	47.6	1990	1	2
9	1990-01-12	47.6	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

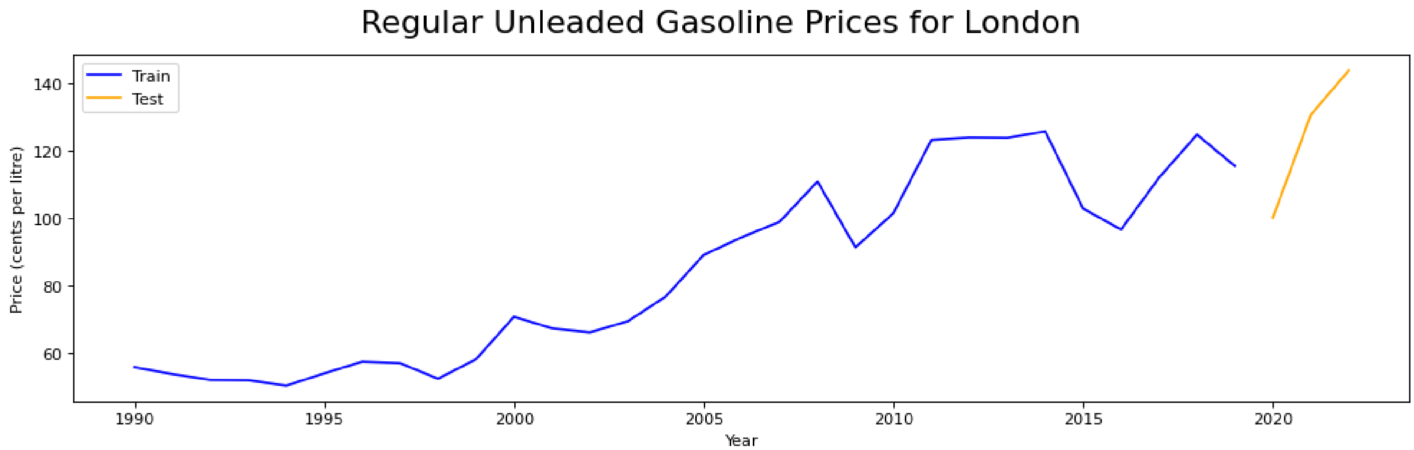
In [17]:

```
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('Regular Unleaded Gasoline 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 Gas Price Train",train['London'],True)

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


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

```
            London Gas Price Train
Date
2019-12-27                   118.7
2019-12-28                   118.7
2019-12-29                   118.7
2019-12-30                   119.8
2019-12-31                   119.8
            London Gas Price Test
Date
2022-01-27                  147.6
2022-01-28                  147.6
2022-01-29                  147.6
2022-01-30                  147.6
2022-01-31                  152.8
```

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 Gas Price Train'])
print('ADF Statistic: ',results[0])
print('p-value: ',results[1])
print('Critical Values', results[4])
```

```
ADF Statistic:  -1.851208337743639
p-value:  0.35535055044846636
Critical Values {'1%': -3.4309478825441477, '5%': -2.8618042310196214, '10%': -2.566910645
0424284}
```

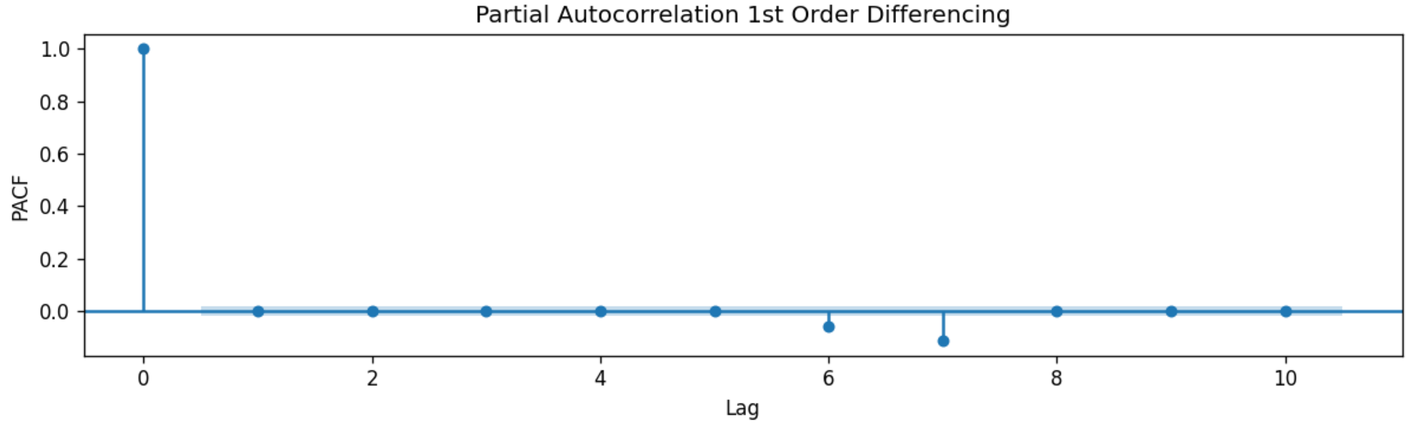
Taking First difference - P value is < 0.05. We can stop at the First Difference; d = 1

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

```
ADF Statistic:  -30.12012802796077
p-value:  0.0
Critical Values {'1%': -3.4309478825441477, '5%': -2.8618042310196214, '10%': -2.566910645
0424284}
```

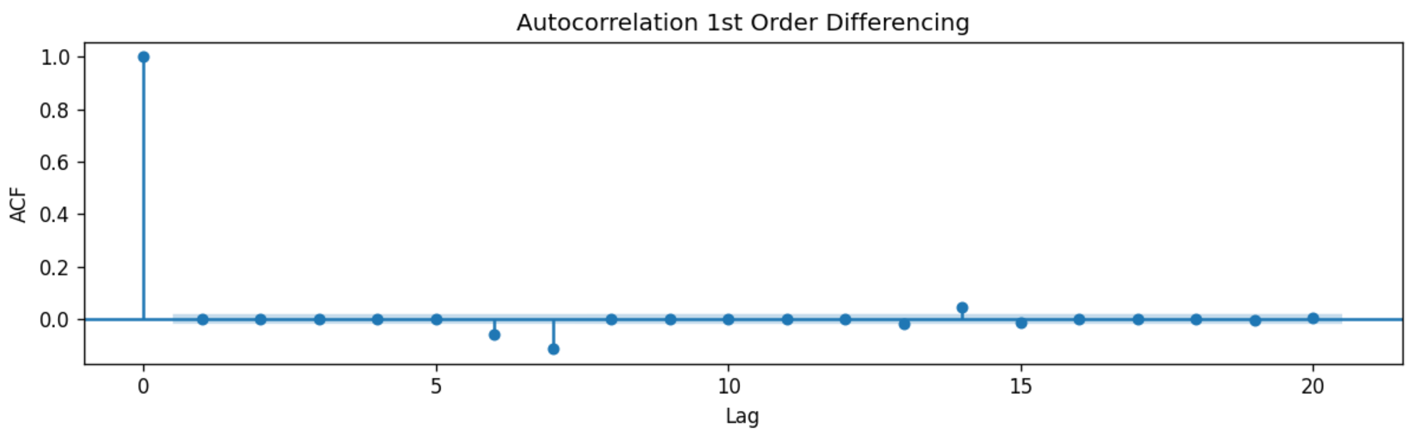
The Order of Autoregressive Term p; p = 0

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=35166.713, Time=1.57 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=35158.714, Time=0.21 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=35160.714, Time=0.65 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=35160.714, Time=0.70 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=35157.019, Time=0.14 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=35162.714, Time=1.04 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0]
Total fit time: 4.342 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 Gas Price Train   No. Observations:              10955
Model:                      ARIMA(0, 1, 0)   Log Likelihood            -17577.510
Date:                     Sat, 05 Mar 2022   AIC                        35157.019
Time:                             13:51:06   BIC                        35164.321
Sample:                         01-03-1990   HQIC                       35159.480
                              - 12-31-2019
Covariance Type:                       opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2         1.4499      0.003    526.840      0.000       1.445       1.455
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):           4509085.96
Prob(Q):                              1.00   Prob(JB):                         0.00
Heteroskedasticity (H):               1.78   Skew:                             1.79
Prob(H) (two-sided):                  0.00   Kurtosis:                       102.33
===================================================================================

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

Model Prediction

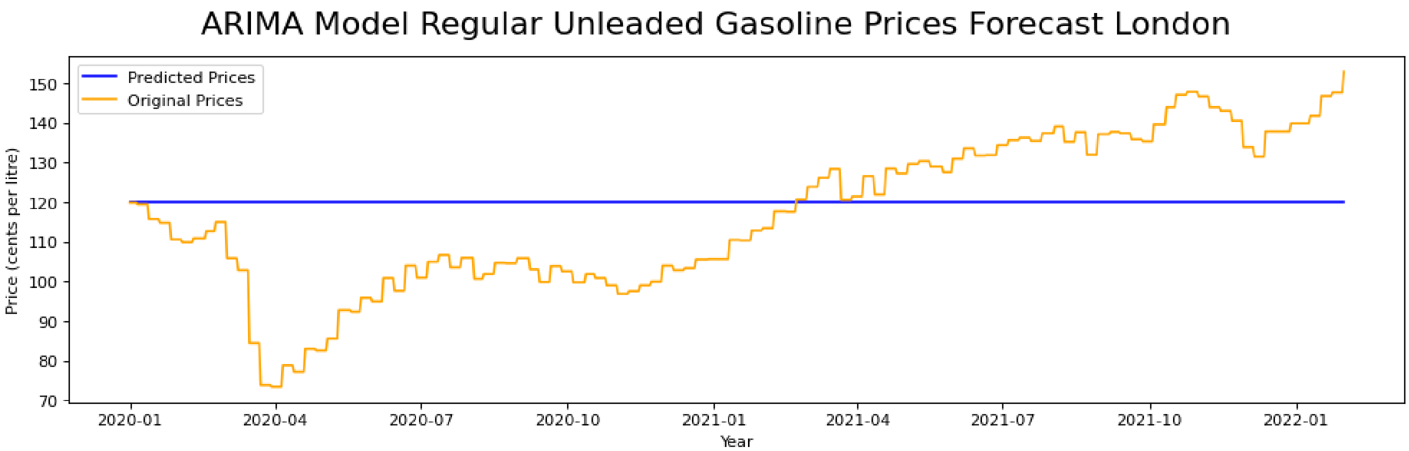
In [26]:
```
import warnings
warnings.filterwarnings('ignore')
ARIMA_Predict = model_result.predict(start='1/1/2020', end='1/31/2022')
ARIMA_Predict_df = pd.DataFrame(ARIMA_Predict)
```

In [27]:
```
ARIMA_Predict_df.tail()
```

Out[27]:

	predicted_mean
2022-01-27	119.8
2022-01-28	119.8
2022-01-29	119.8
2022-01-30	119.8
2022-01-31	119.8

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 Regular Unleaded Gasoline 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 Gas 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 Gas Price Test'],ARIMA_Predict)
print('The Mean Squared Error ARIMA = {}'.format(round(mseARIMA, 2)))
```

```
The Mean Squared Error ARIMA = 368.56
```

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)))
```

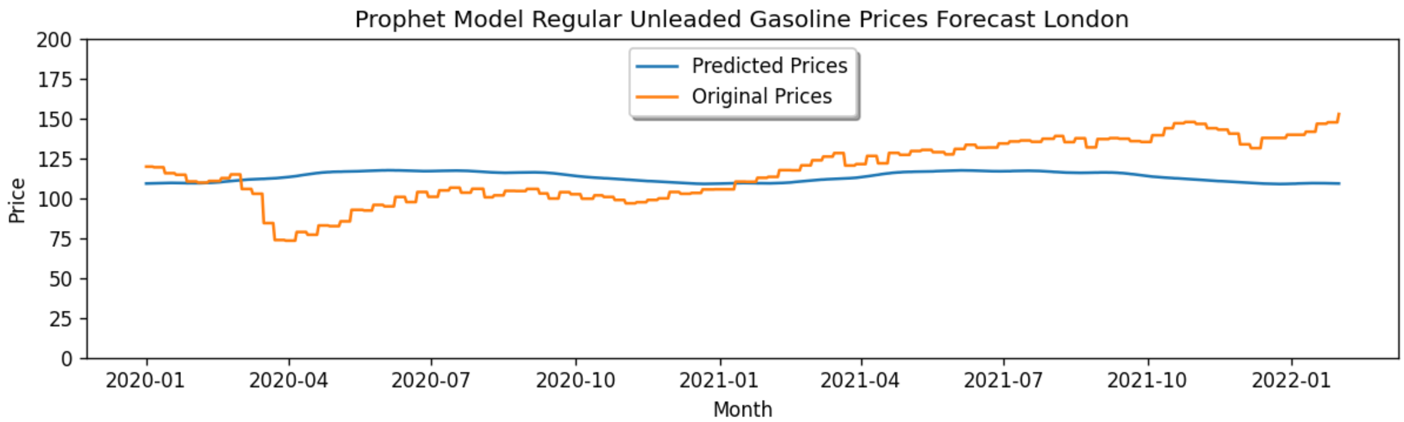
```
The Root Mean Squared Error ARIMA = 19.2
```

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 Regular Unleaded Gasoline 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 = 16.89
```

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 = 391.51
```

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 = 19.79
```