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]:

```
#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 Thunder Bay Region only and pasting it ir
df3.insert(0,"Date",df2['Date'],True)
df3.insert(1,"Thunder Bay",df2['Thunder Bay'],True)
```

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

Out[10]:

| | Date | Thunder Bay |
|---|---|---|
| **0** | 1990-01-03 | 56.6 |
| **1** | 1990-01-10 | 56.8 |
| **2** | 1990-01-17 | 56.8 |
| **3** | 1990-01-24 | 56.8 |
| **4** | 1990-01-31 | 56.8 |

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 | Thunder Bay |
|---|---|---|
| **11707** | 2022-01-22 | 148.8 |
| **11708** | 2022-01-23 | 148.8 |
| **11709** | 2022-01-24 | 149.2 |
| **11710** | 2022-01-25 | 149.2 |
| **11711** | 2022-01-26 | 149.2 |
| **11712** | 2022-01-27 | 149.2 |
| **11713** | 2022-01-28 | 149.2 |
| **11714** | 2022-01-29 | 149.2 |

| | Date | Thunder Bay |
|---|---|---|
| **11715** | 2022-01-30 | 149.2 |
| **11716** | 2022-01-31 | 158.4 |

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 | Thunder Bay | Year | Month | Week |
|---|---|---|---|---|---|
| **0** | 1990-01-03 | 56.6 | 1990 | 1 | 1 |
| **1** | 1990-01-04 | 56.6 | 1990 | 1 | 1 |
| **2** | 1990-01-05 | 56.6 | 1990 | 1 | 1 |
| **3** | 1990-01-06 | 56.6 | 1990 | 1 | 1 |
| **4** | 1990-01-07 | 56.6 | 1990 | 1 | 1 |
| **5** | 1990-01-08 | 56.6 | 1990 | 1 | 2 |
| **6** | 1990-01-09 | 56.6 | 1990 | 1 | 2 |
| **7** | 1990-01-10 | 56.8 | 1990 | 1 | 2 |
| **8** | 1990-01-11 | 56.8 | 1990 | 1 | 2 |
| **9** | 1990-01-12 | 56.8 | 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

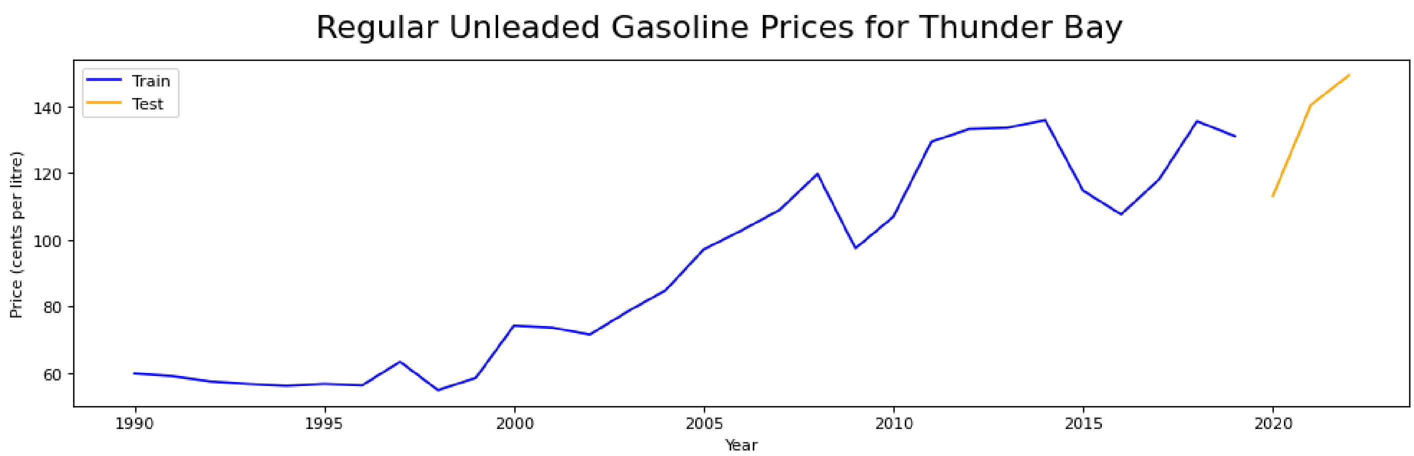
In [17]:

```
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

yearly_train_Price = train.groupby(['Year'])['Thunder Bay'].mean()
yearly_test_Price = test.groupby(['Year'])['Thunder Bay'].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 Thunder Bay', 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,"Thunder Bay Gas Price Train",train['Thunder Bay'],True)

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


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

```
            Thunder Bay Gas Price Train
Date
2019-12-27                        127.9
2019-12-28                        127.9
2019-12-29                        127.9
2019-12-30                        127.7
2019-12-31                        127.7
            Thunder Bay Gas Price Test
Date
2022-01-27                       149.2
2022-01-28                       149.2
2022-01-29                       149.2
2022-01-30                       149.2
2022-01-31                       158.4
```

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

```
ADF Statistic:  -1.986043079983492
p-value:  0.29272605188212175
Critical Values {'1%': -3.4309490326940666, '5%': -2.8618047392710215, '10%': -2.566910915
5836605}
```

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

In [21]:

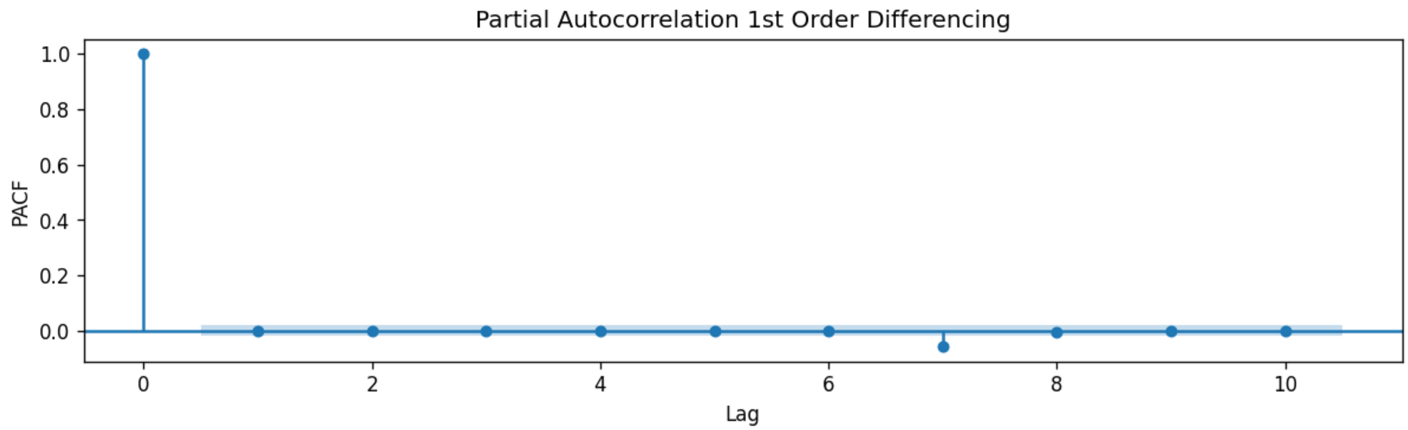
```
train_time_series_stationary1 = train_time_series.diff().dropna()
results1 = adfuller(train_time_series_stationary1['Thunder Bay Gas Price Train'])
print('ADF Statistic: ',results1[0])
print('p-value: ',results1[1])
print('Critical Values', results1[4])
```

```
ADF Statistic:  -20.119013188892136
p-value:  0.0
Critical Values {'1%': -3.4309490326940666, '5%': -2.8618047392710215, '10%': -2.566910915
5836605}
```

### The Order of Autoregressive Term p; p = 0

In [22]:

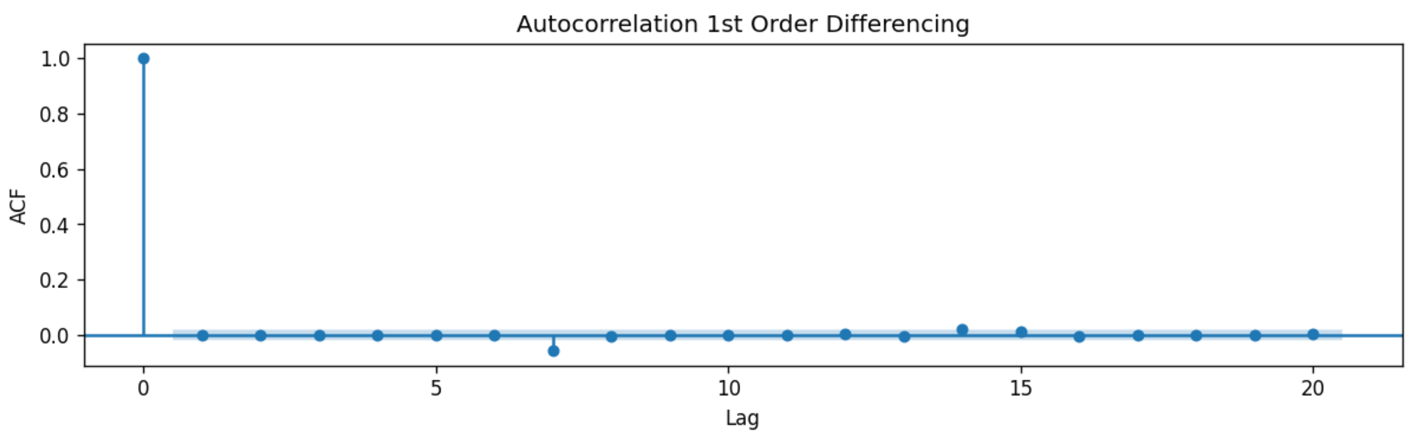
```
plt.rcParams.update({'figure.figsize':(12,3), 'figure.dpi':120})
from statsmodels.graphics.tsaplots import plot_pacf
plot_pacf(train_time_series_stationary1, lags=10,  title="Partial Autocorrelation 1st Orde
plt.xlabel('Lag')
plt.ylabel('PACF')
plt.show()
```




## 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=37619.467, Time=1.58 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=37611.467, Time=0.26 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=37613.467, Time=0.69 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=37613.467, Time=0.90 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=37609.722, Time=0.13 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=37615.467, Time=1.03 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0]
Total fit time: 4.620 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:     Thunder Bay Gas Price Train   No. Observations:        10955
Model:                          ARIMA(0, 1, 0)   Log Likelihood      -18803.861
Date:                         Sun, 06 Mar 2022   AIC                  37609.722
Time:                                 09:50:45   BIC                  37617.023
Sample:                             01-03-1990   HQIC                 37612.182
                                  - 12-31-2019                                
Covariance Type:                           opg                                
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2         1.8137      0.001   1334.193      0.000       1.811       1.816
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):         191691783.11
Prob(Q):                              1.00   Prob(JB):                         0.00
Heteroskedasticity (H):               0.51   Skew:                             4.91
Prob(H) (two-sided):                  0.00   Kurtosis:                       650.99
===================================================================================

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]:

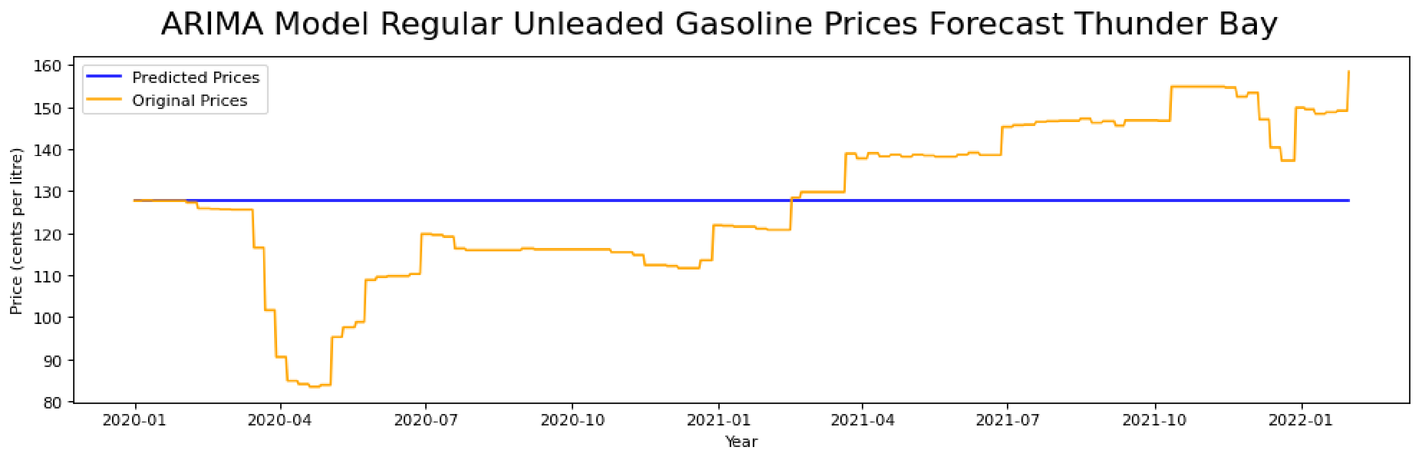
```
ARIMA_Predict_df.tail()
```

Out[27]:

| | predicted_mean |
|---|---|
| **2022-01-27** | 127.7 |
| **2022-01-28** | 127.7 |
| **2022-01-29** | 127.7 |
| **2022-01-30** | 127.7 |
| **2022-01-31** | 127.7 |

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 Thunder Bay', fontsize
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['Thunder Bay Gas Price Test'],ARIMA_Predict)
print('Mean Absolute Error ARIMA = {}'.format(round(maeARIMA, 2)))
```

```
Mean Absolute Error ARIMA = 14.77
```

## Mean squared error (MSE) ARIMA

In [30]:

```
from sklearn.metrics import mean_squared_error
mseARIMA=mean_squared_error(test_time_series['Thunder Bay Gas Price Test'],ARIMA_Predict)
print('The Mean Squared Error ARIMA = {}'.format(round(mseARIMA, 2)))
```

```
The Mean Squared Error ARIMA = 312.81
```

## 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 = 17.69
```

## Prophet Model

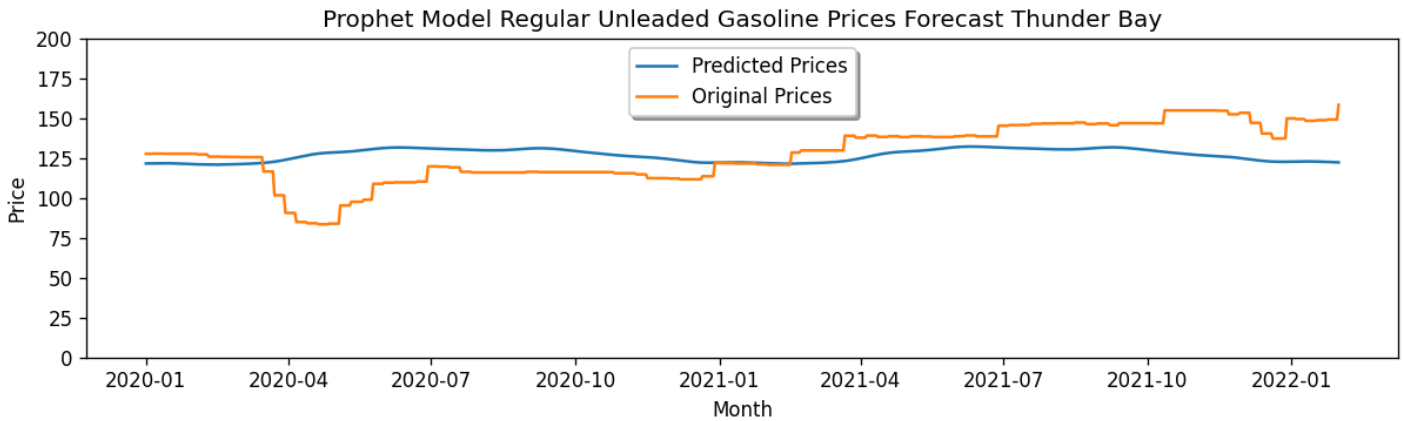
In [32]:

```
from fbprophet import Prophet
d={'ds':train['Date'],'y':train['Thunder Bay']}
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['Thunder Bay'], label='Original Prices')
plt.ylim([0,200])
legend = ax.legend(loc='upper center', shadow=True)
plt.title('Prophet Model Regular Unleaded Gasoline Prices Forecast Thunder Bay')
plt.xlabel('Month')
plt.ylabel('Price')
plt.show()
```




## Mean Absolute Error (MAE) Prophet

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

```
Mean Absolute Error Prophet = 15.05
```

## Mean squared error (MSE) Prophet

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

```
The Mean Squared Error Prophet = 322.31
```

## 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 = 17.95
```