In [ ]:
```
# Milestone 4 (Time Series Forecasting)

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Matric ID : WQD170077 (17013672/1)
Github Link :  https://github.com/RinashiniA/WQD7005-Group
```

In [1]:
```
# Importing libraries

import matplotlib
import seaborn as sns
import numpy as np
import scipy as sp
import pandas as pd
from pandas import read_csv
from pandas import datetime
from pandas import DataFrame
import sklearn.linear_model
import sklearn.metrics
import statsmodels.api as sm
import matplotlib.pyplot as plt
import matplotlib.pylab as pylab
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

```
/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:9
: FutureWarning: The pandas.datetime class is deprecated and will
be removed from pandas in a future version. Import from datetime m
odule instead.
  if __name__ == '__main__':
```

In [2]:
```
# Getting the cleaned Crudeoil Price dataset

df = pd.read_csv(r'dataset_cleaned.csv',
                 index_col=['Date'])
print(df)
```

```
            Closing Price   Open  Daily High  Daily Low
Date
29/05/2020          35.49  33.68       35.77      32.36
28/05/2020          33.71  32.10       34.21      31.14
27/05/2020          32.81  34.14       34.32      31.75
26/05/2020          34.35  33.30       34.81      32.48
22/05/2020          33.25  33.95       34.00      30.72
...                   ...    ...         ...        ...
09/02/2006          62.62  62.68       63.73      62.38
08/02/2006          62.55  62.96       63.44      62.29
07/02/2006          63.09  64.82       64.90      62.81
06/02/2006          65.11  66.35       66.50      64.77
03/02/2006          65.37  64.77       65.48      63.93

[3669 rows x 4 columns]
```

In [3]:
```
# Obtaining information about the dataset

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3669 entries, 29/05/2020 to 03/02/2006
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Closing Price  3669 non-null   float64
 1   Open           3669 non-null   float64
 2   Daily High     3669 non-null   float64
 3   Daily Low      3669 non-null   float64
dtypes: float64(4)
memory usage: 143.3+ KB
```

In [4]:
```
#Removing the blank spaces between column names so that they can be called easily

df.columns = df.columns.str.strip().str.replace(" ", "").str.lstrip()
print(df.columns.values)
```

```
['ClosingPrice' 'Open' 'DailyHigh' 'DailyLow']
```

In [5]:
```
# Choosing the closing price column for time series analysis

df1 = df[['ClosingPrice']]
print(df1)
```

```
            ClosingPrice
Date                    
29/05/2020         35.49
28/05/2020         33.71
27/05/2020         32.81
26/05/2020         34.35
22/05/2020         33.25
...                  ...
09/02/2006         62.62
08/02/2006         62.55
07/02/2006         63.09
06/02/2006         65.11
03/02/2006         65.37

[3669 rows x 1 columns]
```

In [6]:
```
# Reindexing the dataset to reverse the order of the data from the latest price at the top of the dataset to the oldest price at the top of the dataset

df2 = df1.iloc[::-1]
print(df2.head(20))
```

```
           ClosingPrice
Date
03/02/2006        65.37
06/02/2006        65.11
07/02/2006        63.09
08/02/2006        62.55
09/02/2006        62.62
10/02/2006        61.84
13/02/2006        61.24
14/02/2006        59.57
15/02/2006        57.65
16/02/2006        58.46
17/02/2006        59.88
20/02/2006        62.77
21/02/2006        62.74
22/02/2006        61.01
23/02/2006        60.54
24/02/2006        62.91
27/02/2006        61.00
28/02/2006        61.41
01/03/2006        61.97
02/03/2006        63.36
```

In [7]:
```
# Plotting the graph of WTI crude oil prices from 03/02/2006 until 29/05/2020

sns.set(rc={'figure.figsize':(22, 7)})
df2.plot()
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x10f9d8450>

In [8]:
```
# Fitting the dataset into Arima(2,2,10) model.
# This sets the lag value to 2 for autoregression, uses a differenc
e order of 2 to make the time series stationary, and uses a moving
average model of 10.

from statsmodels.tsa.arima_model import ARIMA
model = ARIMA(df2['ClosingPrice'], order=(2,2,10))
model_fit = model.fit(disp=0)
print(model_fit.summary())
# plot residual errors

residuals = DataFrame(model_fit.resid)
print(residuals)
residuals.plot()
plt.show()
residuals.plot(kind='kde')
plt.show()
print(residuals.describe())
```

```
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/base/ts
a_model.py:218: ValueWarning: A date index has been provided, but
it has no associated frequency information and so will be ignored
when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/base/ts
a_model.py:222: ValueWarning: A date index has been provided, but
it is not monotonic and so will be ignored when e.g. forecasting.
  ' forecasting.', ValueWarning)
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it has no associated frequency information and so will be ignored
when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
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it is not monotonic and so will be ignored when e.g. forecasting.
  ' forecasting.', ValueWarning)
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/tsatool
s.py:689: RuntimeWarning: overflow encountered in exp
  newparams = ((1-np.exp(-params))/(1+np.exp(-params))).copy()
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/tsatool
s.py:689: RuntimeWarning: invalid value encountered in true_divide
  newparams = ((1-np.exp(-params))/(1+np.exp(-params))).copy()
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  tmp = ((1-np.exp(-params))/(1+np.exp(-params))).copy()
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  tmp = ((1-np.exp(-params))/(1+np.exp(-params))).copy()
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/base/model.
py:548: HessianInversionWarning: Inverting hessian failed, no bse
or cov_params available
  'available', HessianInversionWarning)
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/arima_m
odel.py:1490: RuntimeWarning: invalid value encountered in sqrt
  return np.sqrt(np.diag(-inv(hess)))
/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/_distn_infr
astructure.py:903: RuntimeWarning: invalid value encountered in gr
eater
  return (a < x) & (x < b)
/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/_distn_infr
astructure.py:903: RuntimeWarning: invalid value encountered in le
ss
  return (a < x) & (x < b)
/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/_distn_infr
astructure.py:1912: RuntimeWarning: invalid value encountered in l
ess_equal
  cond2 = cond0 & (x <= _a)

                             ARIMA Model Results
==================================================================
============
```
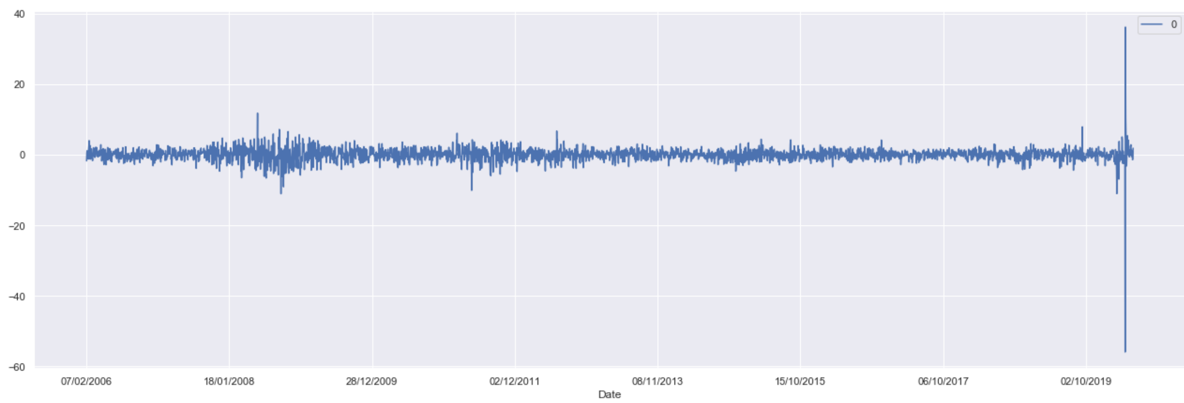
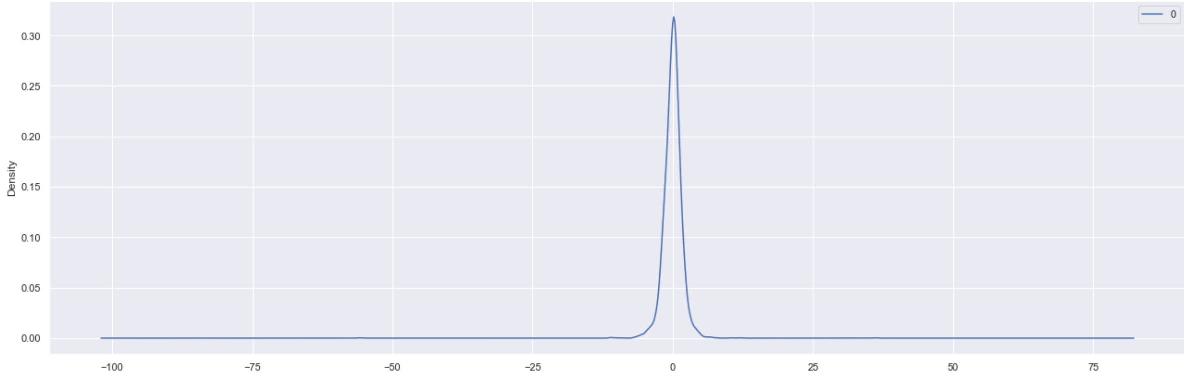

```
Dep. Variable:        D2.ClosingPrice   No. Observations:
3667
Model:                ARIMA(2, 2, 10)   Log Likelihood
-7577.294
Method:                       css-mle   S.D. of innovations
1.909
Date:               Wed, 17 Jun 2020   AIC
15182.588
Time:                        14:21:20   BIC
15269.488
Sample:                             2   HQIC
15213.528

==================================================================
========================
                            coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------
------------------------
const                  -1.975e-05   2.58e-05     -0.766      0.444
-7.03e-05    3.08e-05
ar.L1.D2.ClosingPrice      0.3554        nan        nan        nan
nan         nan
ar.L2.D2.ClosingPrice     -0.5169        nan        nan        nan
nan         nan
ma.L1.D2.ClosingPrice     -1.5615        nan        nan        nan
nan         nan
ma.L2.D2.ClosingPrice      1.1358        nan        nan        nan
nan         nan
ma.L3.D2.ClosingPrice     -0.6832        nan        nan        nan
nan         nan
ma.L4.D2.ClosingPrice      0.1187      0.016      7.309      0.000
0.087       0.151
ma.L5.D2.ClosingPrice     -0.0083      0.038     -0.218      0.827
-0.083       0.066
ma.L6.D2.ClosingPrice      0.0281      0.037      0.761      0.447
-0.044       0.100
ma.L7.D2.ClosingPrice     -0.0413      0.036     -1.142      0.254
-0.112       0.030
ma.L8.D2.ClosingPrice      0.0525      0.035      1.480      0.139
-0.017       0.122
ma.L9.D2.ClosingPrice     -0.0465      0.030     -1.546      0.122
-0.106       0.012
ma.L10.D2.ClosingPrice     0.0060      0.015      0.392      0.695
-0.024       0.036
                                    Roots
==================================================================
============
                  Real          Imaginary           Modulus
Frequency
------------------------------------------------------------------
------------
AR.1            0.3437          -1.3478j            1.3909
```

```
-0.2103
AR.2              0.3437          +1.3478j           1.3909
0.2103
MA.1              1.0003          -0.0000j           1.0003
-0.0000
MA.2             -1.4593          -0.7913j           1.6600
-0.4209
MA.3             -1.4593          +0.7913j           1.6600
0.4209
MA.4             -0.2233          -1.5053j           1.5218
-0.2734
MA.5             -0.2233          +1.5053j           1.5218
0.2734
MA.6              0.4262          -1.2379j           1.3092
-0.1972
MA.7              0.4262          +1.2379j           1.3092
0.1972
MA.8              1.3502          -0.7036j           1.5226
-0.0765
MA.9              1.3502          +0.7036j           1.5226
0.0765
MA.10             6.5971          -0.0000j           6.5971
-0.0000
-------------------------------------------------------------------
------------
                   0
Date
07/02/2006 -1.759980
08/02/2006  0.466959
09/02/2006  1.113142
10/02/2006  0.100956
13/02/2006  0.160620
...              ...
22/05/2020 -0.603176
26/05/2020  0.936357
27/05/2020 -1.436687
28/05/2020  0.561114
29/05/2020  1.839919

[3667 rows x 1 columns]
```






```
                 0
count  3667.000000
mean      0.003777
std       1.909930
min     -55.929231
25%      -0.818301
50%       0.085405
75%       0.855806
max      36.177291
```

The distribution of the residual errors is displayed. The results show that there is limited bias in the prediction (approximately zero mean value in the residuals).

In [9]:
```
from statsmodels.tsa.arima_model import ARIMA

model = ARIMA(df2['ClosingPrice'], order=(2, 2, 10))
results_ARIMA = model.fit(disp=-1)
```

```
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/base/ts
a_model.py:218: ValueWarning: A date index has been provided, but
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  tmp = ((1-np.exp(-params))/(1+np.exp(-params))).copy()
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  tmp = ((1-np.exp(-params))/(1+np.exp(-params))).copy()
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py:548: HessianInversionWarning: Inverting hessian failed, no bse
or cov_params available
  'available', HessianInversionWarning)
```

In [10]:

```
arima_pred = results_ARIMA.predict(df2['ClosingPrice'].index[3000],
df2['ClosingPrice'].index[-1], typ="levels")
```

In [11]:
```
plt.plot(df2['ClosingPrice'], label='Original')
plt.plot(arima_pred, label='Prediction')
plt.legend(loc=2)
plt.title('RMSE: %.4f'% np.sqrt(sum((arima_pred-df2.ClosingPrice[30
00:])**2)/len(df2.ClosingPrice[3000:])))
```

Out[11]:
```
Text(0.5, 1.0, 'RMSE: 2.9446')
```

In [13]:
```
# Accuracy metrics for overall ARIMA Time Series Forecasting Model

## Mean Absolute Percentage Error (MAPE)
## Mean Error (ME)
## Mean Absolute Error (MAE)
## Mean Percentage Error (MPE)
## Root Mean Squared Error (RMSE)
## Correlation between the Actual and the Forecast (corr)
## Min-Max Error (minmax)

def forecast_accuracy(forecast, actual):
    mape = np.mean(np.abs(forecast - actual)/np.abs(actual))  # MAP
E
    me = np.mean(forecast - actual)             # ME
    mae = np.mean(np.abs(forecast - actual))    # MAE
    mpe = np.mean((forecast - actual)/actual)   # MPE
    rmse = np.mean((forecast - actual)**2)**.5  # RMSE
    corr = np.corrcoef(forecast, actual)[0,1]   # corr
    mins = np.amin(np.hstack([forecast[:,None],
                              actual[:,None]]), axis=1)
    maxs = np.amax(np.hstack([forecast[:,None],
                              actual[:,None]]), axis=1)
    minmax = 1 - np.mean(mins/maxs)             # minmax
    return({'mape':mape, 'me':me, 'mae': mae,
            'mpe': mpe, 'rmse':rmse,
            'corr':corr, 'minmax':minmax})

forecast_accuracy(arima_pred, df2.ClosingPrice[3000:])
```

Out[13]:
```
{'mape': 0.028931008740698802,
 'me': -0.014264406061127088,
 'mae': 1.0955971718904844,
 'mpe': -0.009067680055309172,
 'rmse': 2.9446097770535267,
 'corr': 0.9719284741359818,
 'minmax': 0.030594148811295296}
```

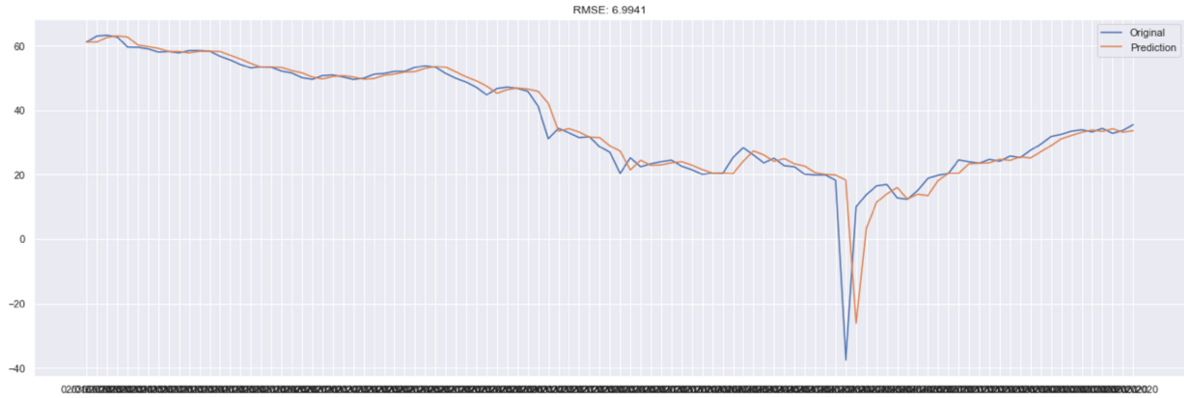
A Mean Absolute Percentage Error (MAPE) of 0.0289 means that this ARIMA time series forecasting model has an accuracy of approximately 97.11% in predicting the next 669 observations.

Recent Predictions (for the year of 2020)

In [14]:
```
arima_pred_2020 = results_ARIMA.predict(df2['ClosingPrice'].index[3
566], df2['ClosingPrice'].index[-1], typ="levels")
```

In [15]:
```
plt.plot(df2.ClosingPrice[3566:], label='Original')
plt.plot(arima_pred_2020, label='Prediction')
plt.legend(loc=1)
plt.title('RMSE: %.4f'% np.sqrt(sum((arima_pred_2020-df2.ClosingPri
ce[3566:])**2)/len(df2.ClosingPrice[3566:])))
```

Out[15]:
```
Text(0.5, 1.0, 'RMSE: 6.9941')
```



In [16]:
```
# Accuracy metrics for ARIMA time series forecasting model for the
year 2020

forecast_accuracy(arima_pred_2020, df2.ClosingPrice[3566:])
```

Out[16]:
```
{'mape': 0.10944525963154746,
 'me': 0.25144724237308513,
 'mae': 2.4706601146387994,
 'mpe': -0.05418044422655465,
 'rmse': 6.994126472937059,
 'corr': 0.9147084710463056,
 'minmax': 0.12134490016500876}
```

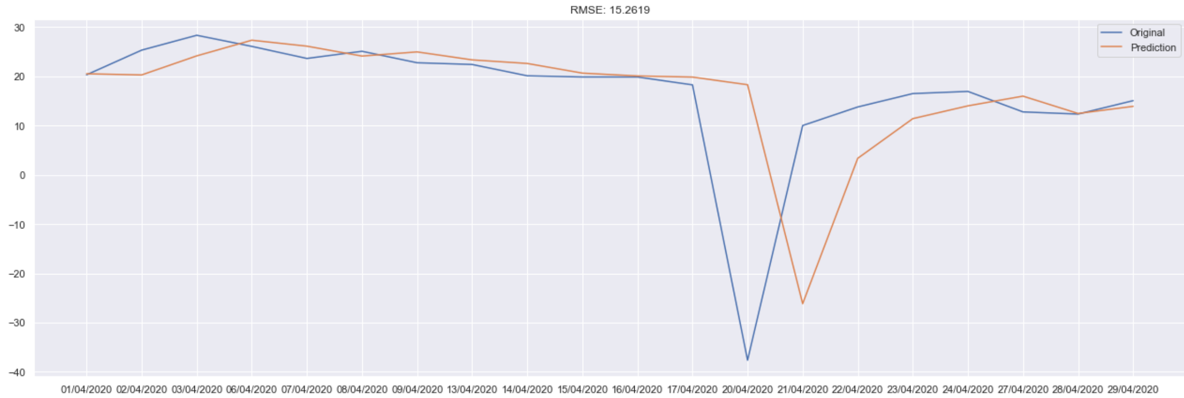
The Mean Absolute Percentage Error (MAPE) of 0.1094 means that this ARIMA time series forecasting model for the year 2020 has an accuracy of approximately 89.06% in predicting the next 103 observations.

Recent Predictions (for the month of April 2020)

In [17]:
```
arima_pred_April = results_ARIMA.predict(df2['ClosingPrice'].index[
3628], df2['ClosingPrice'].index[-22], typ="levels")
```

In [18]:
```
plt.plot(df2.ClosingPrice[3628:3648], label='Original')
plt.plot(arima_pred_April, label='Prediction')
plt.legend(loc=1)
plt.title('RMSE: %.4f'% np.sqrt(sum((arima_pred_April-df2.ClosingPr
ice[3628:3648])**2)/len(df2.ClosingPrice[3628:3648])))
```

Out[18]:
```
Text(0.5, 1.0, 'RMSE: 15.2619')
```



In [19]:
```
# Accuracy metrics for ARIMA time series forecasting model for the
month of April 2020

forecast_accuracy(arima_pred_April, df2.ClosingPrice[3628:3648])
```

Out[19]:
```
{'mape': 0.38122129642575187,
 'me': 0.2728831943590796,
 'mae': 6.870153135750627,
 'mpe': -0.29882022348400883,
 'rmse': 15.26191415735579,
 'corr': 0.24932432294534335,
 'minmax': 0.45496525712496005}
```

The Mean Absolute Percentage Error (MAPE) of 0.3812 means that this ARIMA time series forecasting model for the month of April 2020 has an accuracy of approximately 61.88% in predicting 21 observations between the end of Mac 2020 and beginning of May 2020.

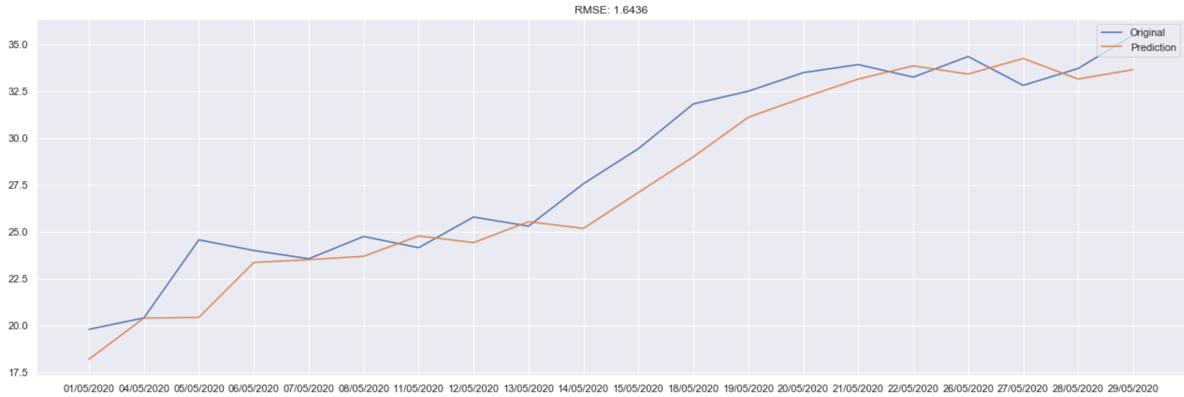
In this model predicted for the month of April 2020, we can observe a lower accuracy in forecasting with 61.88% as compared to the accuracy level of the overall prediction model with 97.11% due to the sudden sharp collapse in oil demand in mid-April 2020 leaving the global market oversupplied with more than enough crude oil. The lack of oil demand is due to most countries experiencing lockdowns to overcome the Covid-19 outbreak. This then caused the price of the WTI crude oil to drop to levels of negative as shown in the plot as above.

Recent Predictions (for the month of May 2020)

In [20]:
```
arima_pred_May = results_ARIMA.predict(df2['ClosingPrice'].index[36
49], df2['ClosingPrice'].index[-1], typ="levels")
```

In [21]:
```
plt.plot(df2.ClosingPrice[3649:], label='Original')
plt.plot(arima_pred_May, label='Prediction')
plt.legend(loc=1)
plt.title('RMSE: %.4f'% np.sqrt(sum((arima_pred_May-df2.ClosingPric
e[3649:])**2)/len(df2.ClosingPrice[3649:])))
```

Out[21]:
```
Text(0.5, 1.0, 'RMSE: 1.6436')
```



In [22]:
```
# Accuracy metrics for ARIMA time series forecasting model for the
month of May 2020

forecast_accuracy(arima_pred_May, df2.ClosingPrice[3649:])
```

Out[22]:
```
{'mape': 0.046392416443926 71,
 'me': -1.0170999384358732,
 'mae': 1.3078302727395044,
 'mpe': -0.036651376155181 09,
 'rmse': 1.6436342660705818,
 'corr': 0.9674922560498354,
 'minmax': 0.046247022714284824}
```

The Mean Absolute Percentage Error (MAPE) of 0.0464 means that this ARIMA time series forecasting model for the month of May 2020 has an accuracy of approximately 95.36% in predicting the final 21 observations in the month of May 2020.

While in the month of May 2020, we can observe a more stable increase in the price of WTI crude oil per barrel as countries are moving from tighter lockdowns to looser lockdowns due to most countries having reduced rise in the number of daily Covid-19 cases. Hence, the prediction of WTI crude oil price for the month of May 2020 is more stable with 95.36% accuracy as there isn't sudden external parameters affecting the price of WTI crude oil.