

ANN for Modelling WTI Crude Oil price

Abstract:

The behaviour of oil prices (one of the most important commodities), is complex and difficult to model. The complexity is mainly due to its dependence on many global and national factors i.e. political events, weather conditions, financial speculations, supply, demand, inventories, exchange rates, OPEC oil policy, GDP, financial shocks, price trends, stock market, dollar index, etc.

The magnitude of these linkages is difficult to quantify and the relationship is non linear. The statistical & econometric models do not capture well the oil price behaviour because of its complexity & non linearity.

As a result, new techniques such as artificial neural networks, gradient boosting machine, genetic algorithm and support vector machine have emerged to remedy this inefficiency.

However the network design, feature selection, sample size and division, choice of activation function, choice of loss function optimiser, hyper parameters tuning, etc affects the Machine Learning Algorithm performance.

In this research, we have use artificial neural network and configured the network design to achieve optimal results.

Section 2:

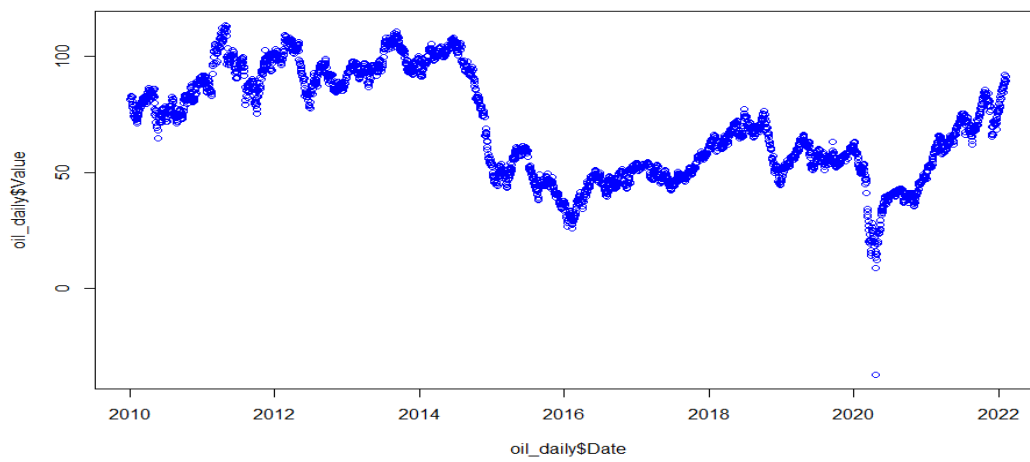
WTI Spot crude prices (2010-2022)

Date	Value (\$/bbl)
2010-01-11	82.54
2010-01-08	82.74
2010-01-07	82.60
2010-01-06	83.12
2010-01-05	81.74
2010-01-04	81.52
⋮	
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2022-02-08	89.32
2022-02-07	91.25
2022-02-04	92.27
2022-02-03	90.17
2022-02-02	88.16
2022-02-01	88.22

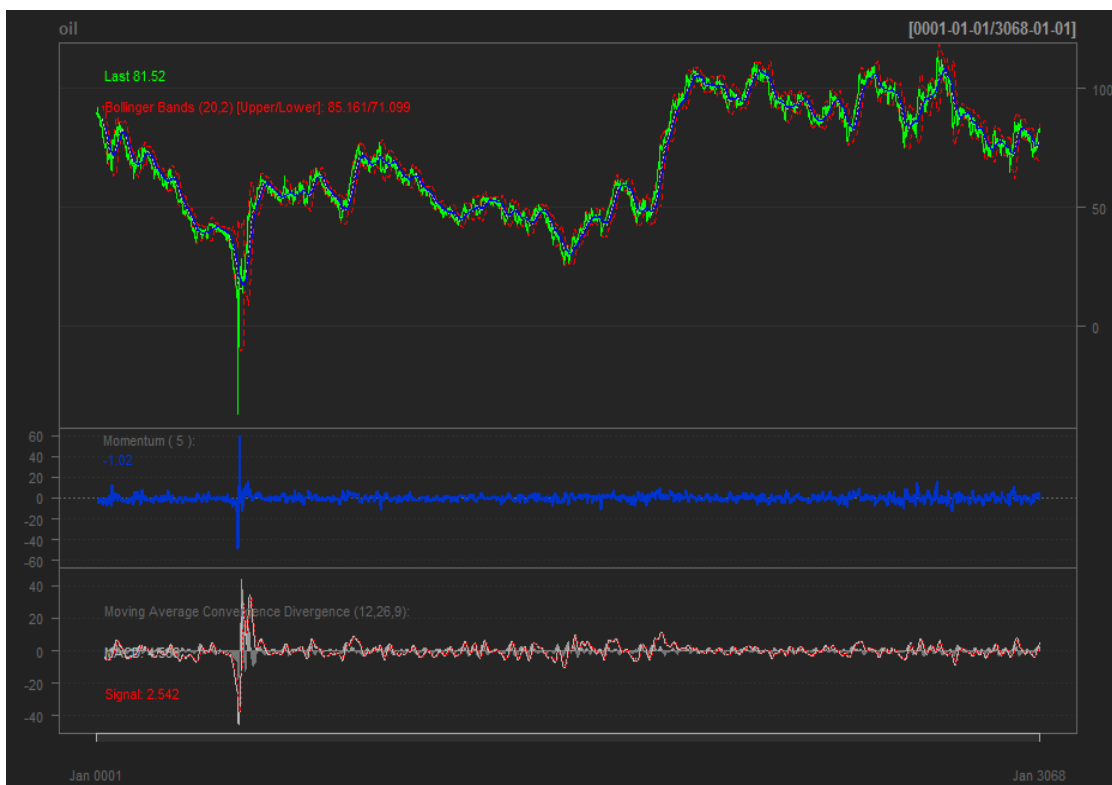
Statistical Summary

Min	Max	Q1	Mean	Median	Q3	std.dev	Coefval	Skew	Kurt
36.98	113.39	50.48	69.36	66.5	90.34	22.33	0.32	0.04	-0.98

Interpretation: Around 50% of time, the price has been in the range of (50-91 \$/bbl). The price distribution is positively skewed with lower fat tails.

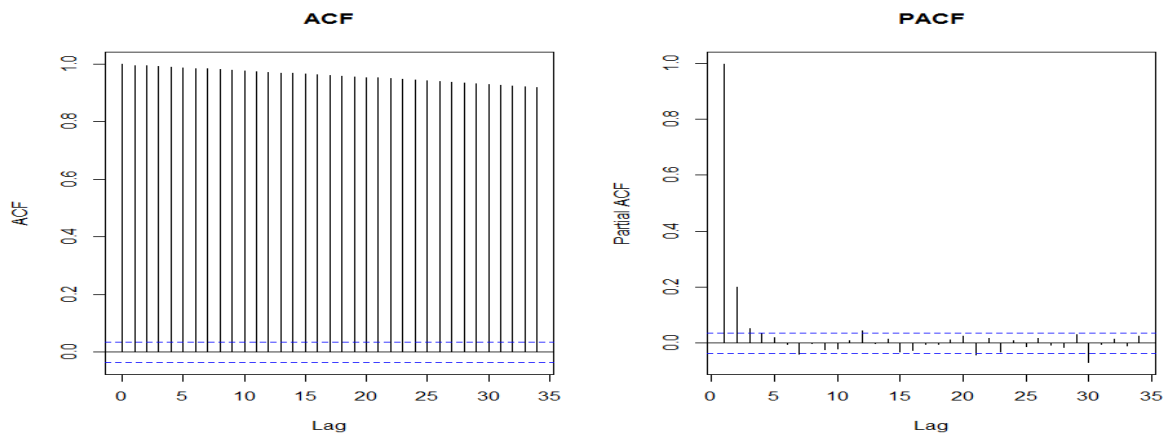


Technical Indicators: BB, SMA, Momentum, Price Signals



Section 3: Statistical testing

To test the trend & seasonality in its data.



existence of monotonic trend
Cox and Stuart Trend test

data: oil
z = 31.187, n = 3068, p-value < 2.2e-16
alternative hypothesis: monotonic trend

stationarity test

head (oil)

Time Series:

Start = 1

End = 6

Frequency = 1

[1] 89.32 91.25 92.27 90.17 88.16 88.22

Augmented Dickey-Fuller Test

data: oil_daily\$Value
Dickey-Fuller = -2.8869, Lag order = 14, p-value = 0.2028
alternative hypothesis: stationary

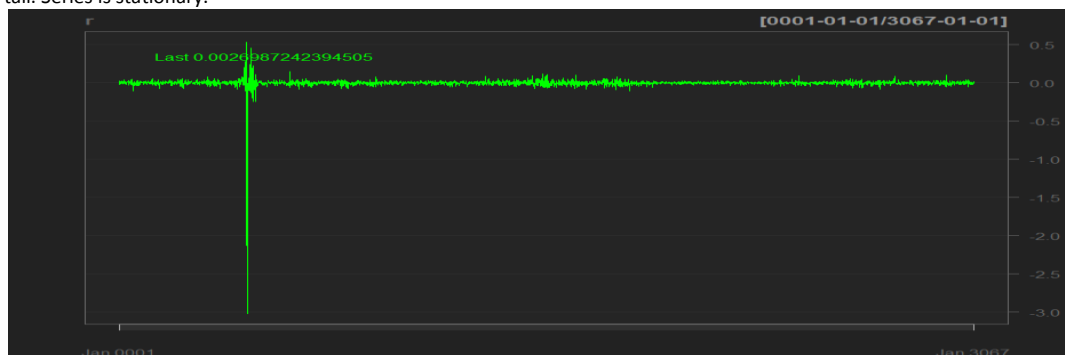
KPSS Test for Level Stationarity

data: oil_daily\$Value
KPSS Level = 14.866, Truncation lag parameter = 9, p-value = 0.01

Oil daily log return(%) statistics:

Min	Max	Q1	Mean	Median	Q3	Std_dev	Coefvar	Skew	Kurt
42.58	28.14	-1.16	-0.03	-0.07	1.1	2.82	-106.44	-1.27	45.06

Interpretation: Daily return averages to zero with negative bias, daily volatility of 2.8% and returns display negative skew and fat upper tail. Series is stationary.



Section 4:

#Fitting Neural Net Model

Series: oil

Model: NNAR(4,2)

Call: nnetar(y = oil)

Average of 20 networks, each of which is

a 4-2-1 network with 13 weights

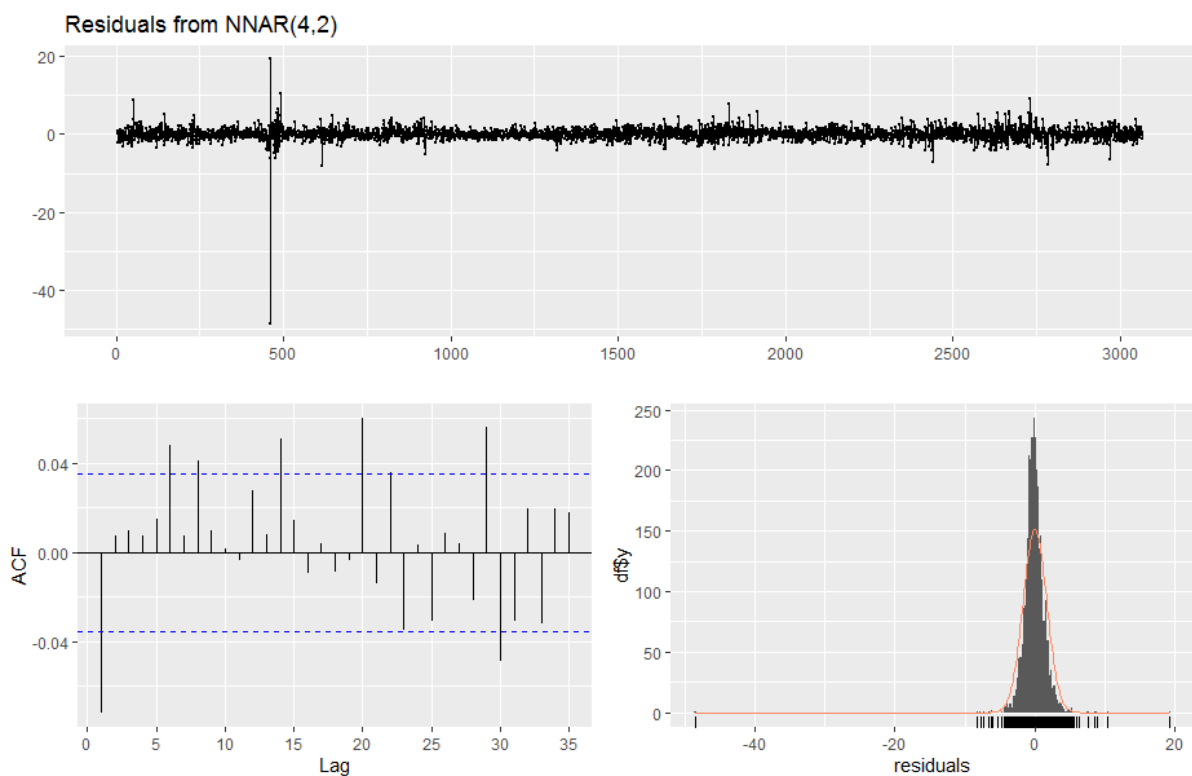
options were - linear output units

sigma² estimated as 2.848

Accuracy(Mod3)

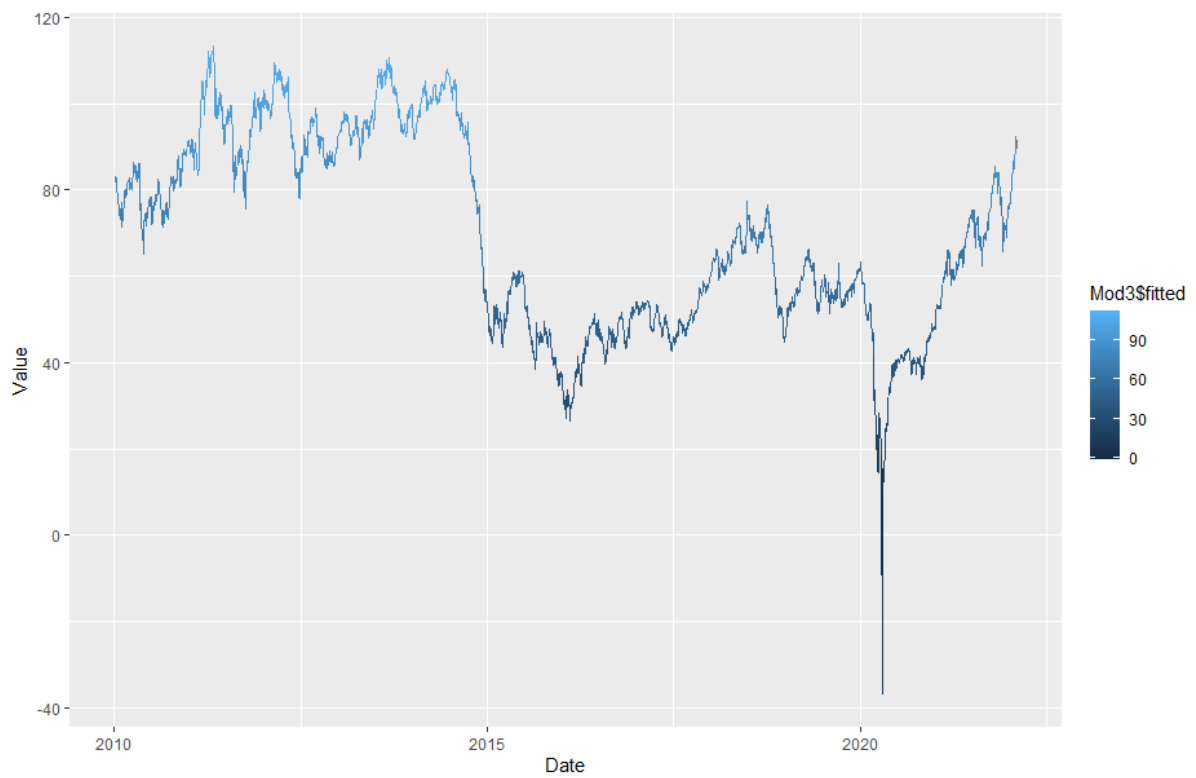
	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.003	1.688	1.04	0.028	1.776	0.996	-0.072

Model diagnostic plots:



Model Forecast(10 days ahead)

Point	Forecast
3069	81.43840
3070	81.39525
3071	81.32636
3072	81.25407
3073	81.17969
3074	81.10457
3075	81.02823
3076	80.95063
3078	80.79158



Conclusion:

The ANN model captures the oil price dynamics well and seems to have better fit than econometric models as exhibited in the above figure.

The Model accuracy supports its robust predictive power.

Accuracy(Mod3)

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.003	1.688	1.04	0.028	1.776	0.996	-0.072

The Research Team,

ALBEDO ENERGY

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