Natural Gas Spot Price Forecasting with Deep Learning

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1 Introduction

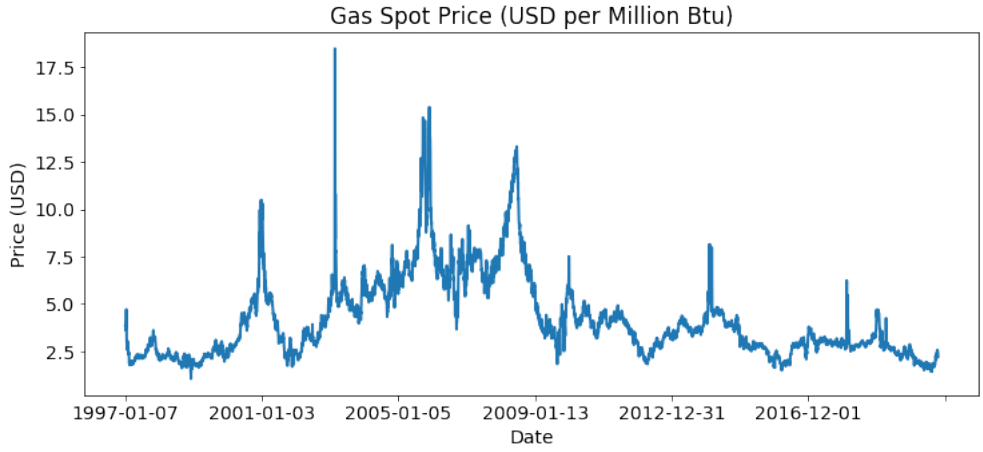
Natural Gas (NG) is a traded commodity with many industrial and commercial applications. The spot price of NG is ultimately controlled by the supply and demand of NG but in addition to other factors such as economics and politics. Our goal is to predict the spot price of NG at the end of the trading day using only historical price data using deep learning. This report looks at a neural network using 2 different lags and then evaluates their performance.

2 Data Description and Analysis

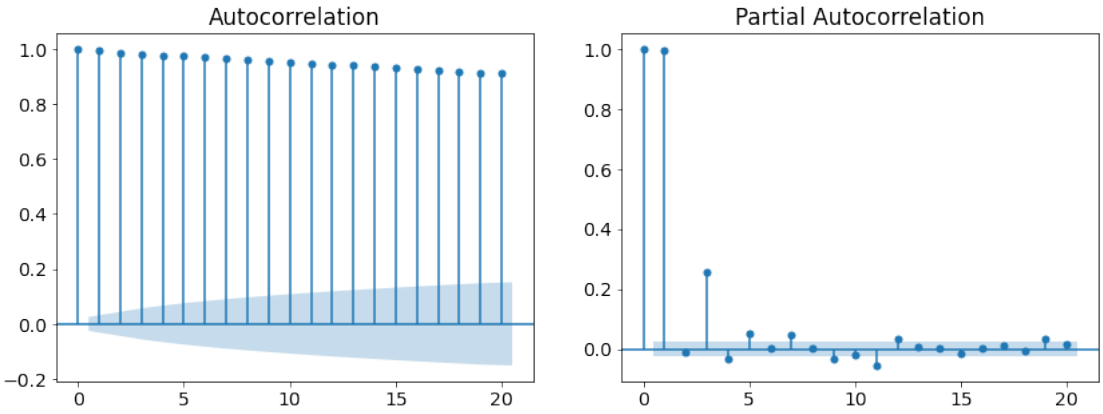
The data is from January 7 th, 1997 to September 1st, 2020 and prices are in USD.

Looking at the plot we can see the time series is not stationary since the mean is not constant and the variance dependence on different lags. Observe, the spot price is gradually decreasing.

Figure 1



The next page shows the auto-correlation function (ACF) and partial auto-correlation function ($PACF$). Both plots confirm the series is not stationary and would be hard to model with typical models such as an ARMA process.



(a) (b)

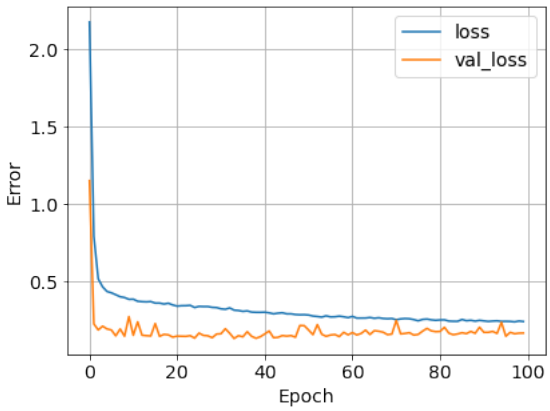
Figure 2

3 Feedforward Neural Network with 5 Lags

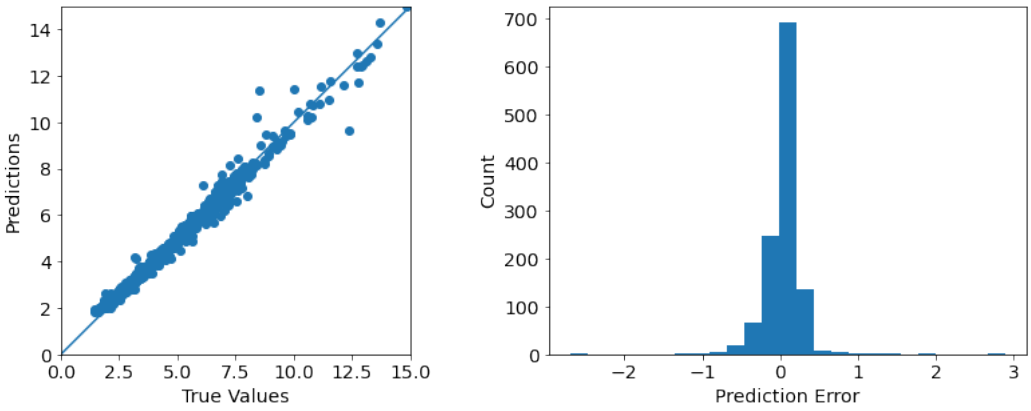
Recall the $PACF$ plot above, we will use a lag of 5 since it indicates that all higher-order autocorrelations are effectively explained by the lag-5 autocorrelation.

We format the data to be such that the predictors are $x_{i1}, x_{21}, \ldots, x_{i5}$ with response y_i where $1 \leq i \leq n$. The training data set will have 80% of the data and the remaining 20% will be the test data set. Moreover, the model will also have a validation set of 20% and a dropout rate of 20%, to help the model not over fit. After normalizing the training set, we fit the model. The loss function used is the Mean Squared Error (MSE). The figure below shows the loss function as the model is training. We see that the loss function decreases for the training set and the validation set.

Figure 3



The next set of plots shows the model is predicting well. Figure (a) shows the predicted values versus the true values. Observe, most of the points lie on or close to $y = x$ showing the model is predicting well. In addition, Figure (b) shows that most of the prediction error lies in bin with 0. Thus, the prediction errors are very small.

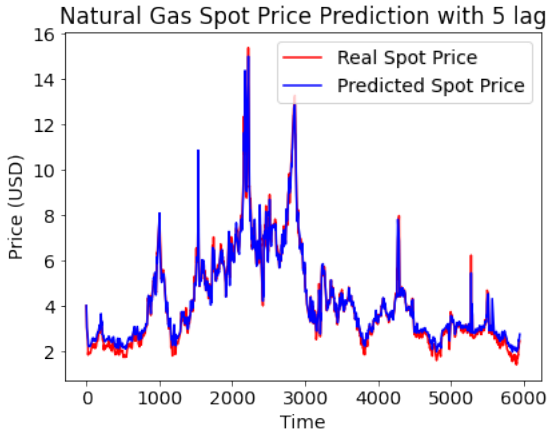


(a) (b)

Figure 4

Another way of showing the model's prediction capabilities is overlying the true values with the predicted values.

Figure 5



Taking a look at the MSE for the training set and the test set.

Train MSE	Test MSE
0.165	0.157

We can see the model is not overfitting or underfitting since there is not a big difference between the 2 metrics.

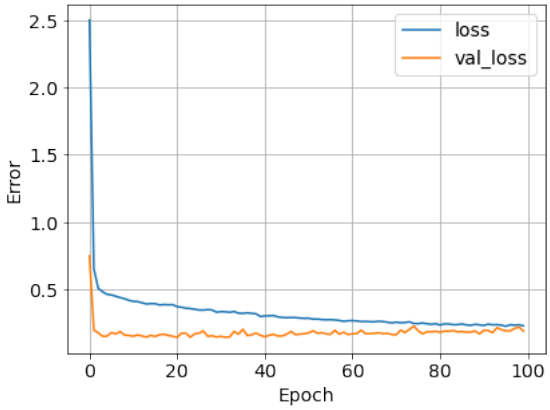
To illustrate a prediction take for example the 5 lag spot prices $[2.39, 2.57, 2.54, 2.52, 2.52]$. The real value is 2.46 and the model predicted 2.64.

We see that the neural network does a reasonable job predicting the spot prices however we need the past 5 spot prices to make a prediction.

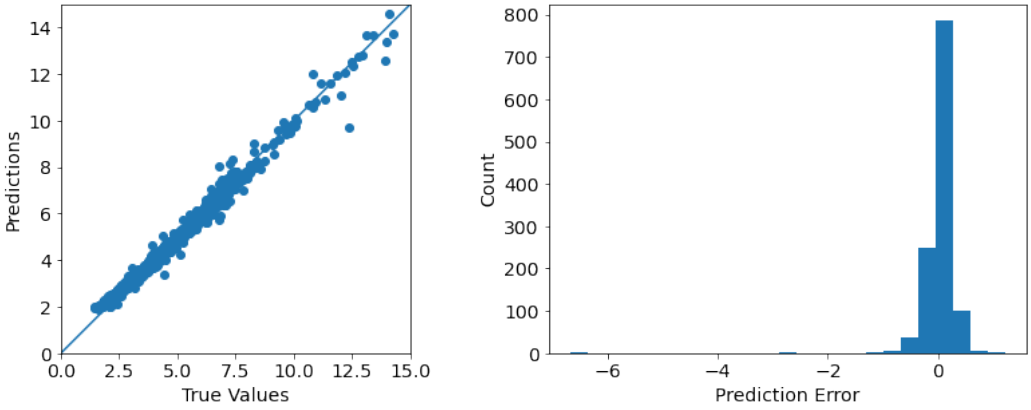
4 Feedforward Neural Network with 1 Lag

We now look at the performance of the same model using 1 lag now. Observe, the loss function is very similar to one above.

Figure 6



The next set of plots show the model predictive capabilities,

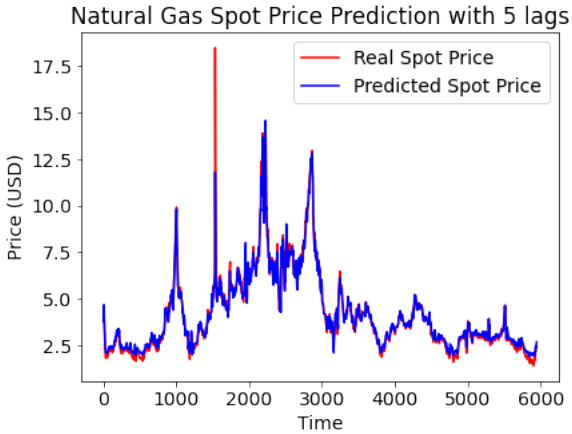


(a) (b)

Figure 7

The model with 1 lag is doing reasonably well. However, the next plot shows the model underestimates the volatility in the prices

Figure 8



which is not a surprise since it is predicting using a single past observation.

Looking at the Train and Test MSE

Train MSE	Test MSE
0.176	0.170

Again, we can see the model is fitting well.

We again illustrate a prediction using the past observation of [2.52] whose real value is 2.46. The model predicts 2.68.

5 Conclusion

Forecasting spot prices for natural gas using deep learning is reasonable. Both models were able to fit the data well and not overfit. However, both models tend to underestimate the prices and are sensitive to outliers, especially the model using 1 lag. Despite that, these models can be used to find the general movement in the prices and the amount of volatility.