Predicting Natural Gas Spot Prices Using Artificial Neural Network

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Abstract—**Natural gas is a major global energy commodity. Gas prices around the world face substantial volatility, inducing major downside market risks. Forecasting accuracy is thus a major concern for the consumers. Traditional econometrics models do not perform well due to inherent nonlinear and nonstationary gas price data. We thus propose an Autoregressive Neural Network (ARNN) model for forecasting daily spot gas prices. The model is benchmarked against the traditional Autoregressive Integrated Moving Average (ARIMA) model. Using a cross validation study, the ARNN model showed an improvement of around 33% over ARIMA in terms of mean squared error. This improvement is significant when price forecasts are used in gas purchase decisions.**

Keywords-Natural gas; spot prices; forecasting; ARIMA; artifical neural network; nonlinear autoregressive neural network

I. Introduction

Natural gas, alongside oil and coal, is considered a major commodity for driving global economy. Its application ranges from domestic use such as in heating and cooking to industrial use such as in electricity generation and as an input to fertilizer and fabrics industry. The scale of this use is significant where e.g., in United States alone, it makes up to 30% of its annual energy requirements (22.8 trillion ft^3) [1]. This trend is consistent around the world and is in fact on the rise. Since 2010, for instance it has seen a global growth of 3%, which is driven by an increase in gas consumption by major economies such as China (15% rise in 2017 alone). This is also substantiated by a corresponding increase in global gas production and an advancement in its long haul transportation via LNG (Liquified Natural Gas) ocean tankers [2].

In terms of price, natural gas consumers face significant volatility. These fluctuations are exemplified by the variations in its spot prices on all major global exchanges including the US Henry Hub exchange (considered to be a global benchmark), which in 2018 alone showed daily spot price variations ranging between -34% to 28% [3]. The significant economic impact of this is obvious given the present largescale use of natural gas at both the domestic and industrial levels. Similar to oil, these price fluctuations are driven by several factors including its supply and demand imbalances [4], current inventory levels, weather changes, political events, as well as changes in the related local economic conditions [5-7]. The situation complicates further in the presence of its limited global sources, which leads to price impacts by international transportation costs, geopolitical situation as well as variations in the world oil prices [8, 9].

Under such complexity, pure price mechanism is arguably very hard to determine. Despite this, the ability to accurately predict gas prices is vital, especially for the economic wellbeing of its largescale customers. This is due to their inherent dependency on the natural gas for their respective businesses, where they need to make decisions on the appropriate quantities of spot purchases of gas – at the right times. Furthermore, medium and longer-term futures contracts are also considered, where a competitive price has to be determined and negotiated in the corresponding contracts and options. In fact, the rise of the futures is attributed to the inability of the users to forecast the spot price accurately, which then has to be compensated by hedging tools against this price driven downside market risks i.e., longer term contracts and options. This inclination was observed by [10] for the US market. They analyzed seven different forecasting models showing that futures forecasts are more accurate than spots price forecasts, where spot price forecasts have large variances as well as prediction biases. While the hedging ability of futures against market (or price) risk is obvious, heavy dependency on these alone is problematic. This is as for many users the demand of natural gas itself remain uncertain, which makes futures less effective due to shifting the market risk towards company specific or demand (or underutilization) risk. [11].

To deal with the counteracting risks situation (i.e., market and demand risks), it is essential for a consumer to have good forecasting ability for either the spot or futures prices. Interestingly, compared to oil, which has several common price drivers, less academic work is evident when it comes to natural gas. This is perhaps due to oil's long-lasting domination on energy markets. Related to crude oil spot prices, several traditional econometric models including timeseries ARIMA, ARCH and GARCH family models, causal or regression-based models, financial models, and structural models were proposed [12]. These models, due an inherent nonlinear and nonstationary structure of the data, turned out be less effective i.e., showing limited forecasting accuracy [13]. Consequently, substantial works started proposing machine learning models – mainly artificial neural networks; their variants; support vector machine models; as well as their hybrid forms [13-16].

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While we refer readers to the above works for oil forecasting models, corresponding natural gas models are limited. In this direction, [17] presented a single day ahead forecast models for the gas prices in UK electricity generation market based on linear regression, GARCH, extended Kalman filter, particle filter, and various their combinations. Their results show improvements made by the hybrid models as compared to others. Using normalized mean squared error (NMSE) as the error measure, and random walk as the benchmark model (NMSE=0.176), the best performing model turned out to be the Adaptive GARCH model with NMSE=0.154. As compared, [18] proposed a hybrid model for the US gas price data. The model uses a multilayered feedforward neural network (trained using Levenberg-Marquardt method (LMM)), and a linear moving average model. Using mean squared error (MSE), the model was tested for various number of neurons in the single hidden layer (i.e., 5, 10, ..., 30 neurons). Their results suggest 20 neurons model to be the best with MSE=0.073. The worst performing model being the 5 neurons one with MSE=0.083. A multilayered feedforward neural network was proposed by [19], which was calibrated using gamma test analysis. The model was tested using the US Henry Hub spot price (daily, weekly and monthly) data. The results for the next day forecast indicate an MSE of 0.29 and 0.13 with the linear and dynamic regression models and 0.11 with the neural network model. Similar trend was evident for the weekly and monthly data. [20] presented a seasonality-adjusted, support vector machines model (SVM) that is compared with a feedforward neural network (trained using LMM) and the traditional ARIMA models for US Henry Hub spot prices as well. Using mean absolute percentage error and root mean squared error measures (RMSE), their results indicate comparable performance of the ARIMA and neural network models with a slight improvement with the SVM model. Most recently, [21] proposed models that are based on least square SVM, genetic programming, feedforward neural network (trained with LMM and conjugate gradient), ARIMA and a heuristic combination of the above four. For the country gas price dataset used, the last model showed RMSE reduction of 18.3%-28.3% by the hybrid model over the individual models.

In other related works, [7] presented a vector autoregressive model tested over German gas market spot price data. This model aimed at separating the impacts of various fundamental influences during three major supply disruptions evident within the considered period. The results suggested that oil and coal prices have a long-term effect, while weather, storage and supply shortfalls have short-term effects on gas prices. [22] presented a cointegration model for city-gate vs residential retail prices of natural gas prices in US states. The results indicate cointegration in all the 50 states data used.

While the tilt towards machine learning forecasting is obvious due to nonlinearity and nonstationary present in the gas prices, we see predominant reliance on the feedforward neural network models probably due to their general ability to approximate nonlinear functions [23]. In case of energy prices, we here refer to the well-known cyclical patterns in the prices [24], which are attributed to information and market decision/action lags happening with the price changes. These cycles are evident in the gas spot prices as well (Fig. 1). Considering this phenomenon, it is reasonable to believe that the price change has a substantial autoregressive structure where several earlier prices drive, with a delay or lag, the future gas prices. This assumption is also supported by extensive use of ARIMA models in the cited works, which despite being linear in form performed reasonably well. Therefore, we suggest a closed loop (nonlinear) autoregressive neural network (ARNN) model, which allows various lagged prices as input to the model (detail in section III).

As with the cited works, we benchmarked the performance of the proposed ARNN model with the ARIMA model due to their similar autoregressive structures. In terms of error measure, we mainly rely on MSE, which is also used in several of the cited studies. Both the models were tested using the Henry Hub natural gas daily spot price data available for over a 20 years period. The performance was cross-validated using an average daily performance of the model for a period of around 1 ½ years (i.e., 546 days). We also note that [19] also uses the same dataset and MSE as the error measure. Hence, their results for their feedforward neural network model was also compared. The results suggest that ARNN showed an overall improvement of over 33% over ARIMA. ARNN also outperfomred the neural network model of [19], showing an improvement of 58%.

The rest of the paper is organized as follows. In section II, we present the details of dataset used, followed by methodology and experimentation in sections III and IV respectively. Finally, we present conclusions in section V.

II. DATA

In this work, we consider Henry Hub daily natural gas spot price ($/Mil-Btu), made available via Energy Information Administration website [3]. The timeseries is shown in Fig. 1, which covers daily spot prices between January 07, 1997 and October 01, 2018 i.e., it includes 5470 daily price values for a period of over 20 years. The descriptive statistics of the timeseries in shown in TABLE I. Here the minimum and the maximum prices for the date range is shown to be 1.05 and 18.48 $/Mil-Btu (a price range of $17.43), where the average price turned out to be 4.34 $/Mil-Btu.

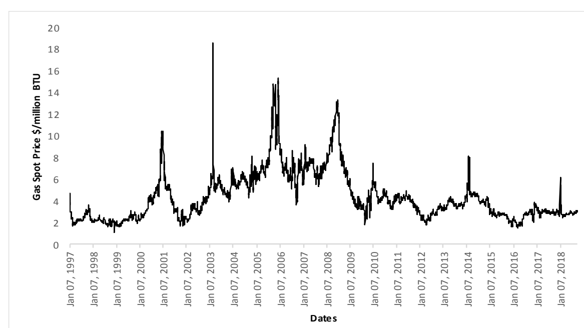

Figure 1: Henry Hub Natural Gas Spot Price ($/Mil-Btu)

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TABLE I: DESCRIPTIVE STATISTICS FOR PRICE DATA

Statistic	Value
Mean	4.337
Standard Error	0.029
Median	3.72
Mode	2.88
Standard Deviation	2.213
Sample Variance	4.896
Kurtosis	3.047
Skewness	1.547
Range	17.43
Minimum	1.05
Maximum	18.48

III. METHODOLOGY

For forecasting, we suggested (section I) using the Autoregressive Neural Network model. However, we also suggested using ARIMA model to benchmark its performance. To do so, we first tested the data for stationarity i.e., via modified Dicky fuller test (model: Autoregressive; significance: 5%; Test Statistic: Standard t statistic) [25]. Autocorrelation function (ACF) plot was also generated. Expectedly, the data turned out to be non-stationary with a unit root present (TABLE II). The ACF plot also show significant autocorrelation even after 20 lags (Fig. 2(a)). We thus took the first difference and tested it again – which turned out to be stationary (TABLE II and Fig. 2(b)). Consequently, we evaluated the standard ARIMA model, which we first describe in the following section III-A. We then discuss the structure of proposed ARNN model in section III-B. Following our discussion on the ARIMA and ARNN models, we also discuss the error measure used in the section III-C, which we use to test and compare the performance of both models.

TABLE II: MODIFIED DICKEY FULLER UNIT ROOT TEST

Series	Null	p-Value	Test-Stat.	Critical Value
Price	Accepted	0.0716	-1.7794	-1.9416
Price Diff	Rejected	1.00E-03	-64.3388	-1.9416

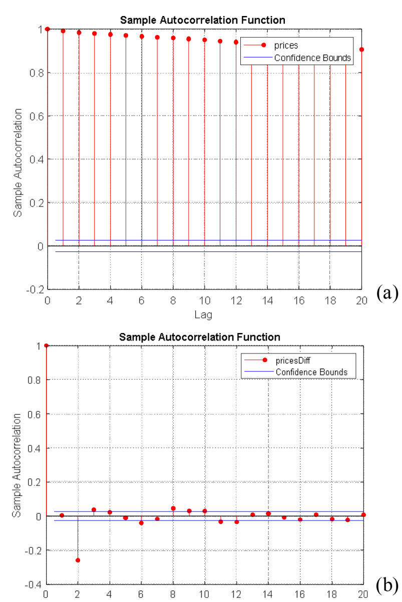

Figure 2: Gas Price ACF Plot (a); Price First-Difference Plot (b)

A. *ARIMA Model*

As we define ARIMA model [26], we first describe the basic ARMA model in (1), which is formed of the Autoregressive AR(p) model with p lagged prices, and the moving average MA(q) model with q lagged error terms ε_{t-j}.

$$y_t = c + \varepsilon_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_i \varepsilon_{t-j} \tag{1}$$

Here (1) shows p lagged price terms y_{t-i} and q lagged price errors $\varepsilon_i = y_t - \hat{y}_t$, where the error is simply the difference between the forecasted and the actual values during period t. Also, c, α_i, and β_i are model parameters. Now considering the lag operator $Ly_t = y_{t-1}$, the AR and MA models can be rewritten as $\varepsilon_t = \alpha(L) y_t$ and $y_t = \beta(L)\varepsilon_t$. So, ARMA model will simply be $\alpha(L) y_t = \beta(L)\varepsilon_t$ where $\alpha(L) = 1 - \sum_{i=1}^{p} \alpha_i L_i$ and $\beta(L) = 1 + \sum_{j=1}^{q} \beta_i L_j$.

The above model works only when the timeseries are stationary. When non-stationarity is present, the timeseries is made stationary by doing finite number of difference [26]. In this case, the ARIMA (p,d,q) model is used that considers d differencing to be done with the timeseries. The model is presented in (2) below. Note that for d=0, the model reduces to standard ARMA (p,q) model.

$$\left(1 - \sum_{i=1}^{p} \alpha_i L_i\right)(1-L)^d y_t = \left(1 + \sum_{j=1}^{q} \beta_i L_j\right)\varepsilon_t \tag{2}$$

B. *Autoregressive Neural Network (ARNN)*

For ARNN, we first define the nonlinear ARMA model as $y_t = h(y_{t-1}, y_{t-2}, \ldots, y_{t-p}; \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q},) + \varepsilon_t$ (where $h(.)$ being some nonlinear function). For the ARNN, $h(.)$ is a feedforward neural network with input, hidden and output layers (Fig. 3). The input layer takes the p lagged price terms as input. For any hidden layer, certain number of neurons exist, each with $X = (x_1, x_2, \ldots, x_n)$ and $W = (w_1, w_2, \ldots, w_n)$ as value input and weight vector and $f(X, W)$ as activation function. For the closed loop ARNN, the output also loops back as input. For this network, various training algorithms can be used. We used Bayesian Regularization algorithm which works well with noisy data as compared to LMM.

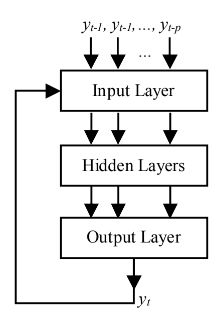

Figure 3: ARNN Structure

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C. Accuracy Measures

To measure the accuracy of forecast models, several measures exists [27]. These measure focus on various aspects i.e., scale dependent and scale independent errors measurement etc. In our case, we make use of the Mean Squared Error or MSE, which is also used by several earlier cited works (section I). MSE is one of the standard error measures used, which is scale dependent and thus easy to interpret. Furthermore, as the performance of the model may change overtime, analysis base on a single period could be quite misleading. To deal with the situation Hyndman [27] suggested the strategy of cross-validation i.e., where the model is recursively or sequentially updated and tested for performance as the new data is revealed. We thus make use of the same approach, where we updated and retested the model using the data of over 1 ½ year or 546 days (10% of data points).

IV. EXPERIMENTATIONS

As discussed earlier (section III), we first calibrated the ARIMA (*p,d,q*) model, which is to be used as a benchmark with the ARNN model. The model fitting is performed using the Econometrics Modeler toolbox available with the MATLAB R2018b. As the data turned out to be non-stationary, we performed differencing, where after the first difference the data turned out to be stationary. Consequently, we calibrated for ARIMA (*p*,1,*q*) model. In fact, we fitted ARIMA (*3*,1,*3*) and ARIMA (*2*,1,*2*) models, the results of which are presented in TABLE III and TABLE IV respectively. Clearly, the results, indicate that ARIMA (*2*,1,*2*) model is to be used which has all terms significant except the constant term.

For the ARNN fitting, MATLAB R2018b NARNET or nonlinear autoregressive model from the neural network toolbox is used. For the model, we test various configurations with different number of hidden layer neurons and delays. Finally, we used the model shown in Fig. 4. The model has 1 hidden layer with 10 neurons and with 3 lags. The training algorithm used is Bayesian Regularization, which takes longer to train but performs better with noisy data as compared to LMM.

TABLE III: ARIMA (3,1,3) MODEL

Parameter	Value	Standard Error	t-Statistic	p-value
Constant	0.00	0.01	0.01	0.97
AR(1)	-0.30	0.86	-0.35	0.73
AR(2)	-0.18	0.20	-0.91	0.37
AR(3)	-0.06	0.13	-0.45	0.66
MA(1)	0.31	0.86	0.36	0.72
MA(2)	-0.07	0.21	-0.36	0.72
MA(3)	0.04	0.10	0.38	0.70
Variance	0.08	0.00	240.33	0.00

TABLE IV: ARIMA (2,1,2) MODEL

Parameter	Value	Standard Error	t-Statistic	p-value
Constant	0.00	0.01	0.02	9.87E-01
AR(1)	-0.22	0.03	-8.07	6.82E-16
AR(2)	-0.12	0.04	-2.88	4.00E-03
MA(1)	0.23	0.03	8.57	1.05E-17
MA(2)	-0.13	0.04	-3.22	1.30E-03
Variance	0.08	0.00	243.38	0.00E+00

With the cross-validation strategy, we made use of the 4924 data points for the initial model fitting purposes, while the remaining 546 data points are used for testing Fig. 5. During the testing, with this strategy, each time a period is forecasted, MSE is recorded and then the model is recursively updated with the new actual value, for which the forecasted value is tested again for the next period. The residual plots for the ARIMA and the ARNN models from this exercise are presented in Fig. 6 and Fig. 7 below.

The MSE plots over the same test data is shown in Fig. 8 and Fig. 9. Average MSE over the test period turned out to be 0.039 for the ARIMA model and 0.026 for the ARNN model. This is an improvement of 33.4% with ARNN over ARIMA. Mainly, large errors appear using both models for the two price shocks shown in test data in Fig. 5, which is understandable due to their unpredictable form. Other than these two major shocks, the model performed quite well.

Furthermore, as we argued for ARNN over typical feedforward neural network structure used in the literature, we compared our results with [19] who also used the same dataset with a typical feedforward neural network model. Using MSE to measure error with their model for first period forecast, ARNN shows an improvement of approximately 58%.

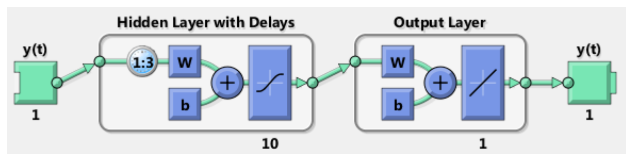

Figure 4: ARNN Model Configuration

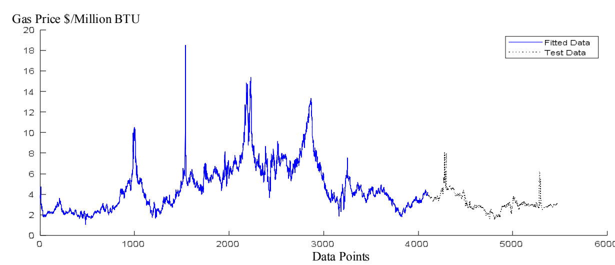

Figure 5: Initial Training and Testing Data Sets

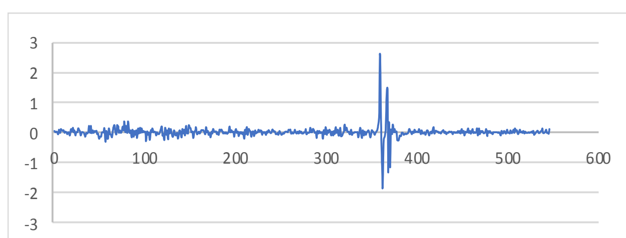

Figure 6: Residual Plot for the ARIMA Model during Cross-Validation

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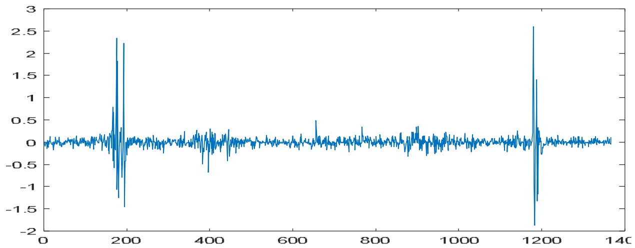

Figure 7: Residual Plot for the ARNN Model during Cross-Validation

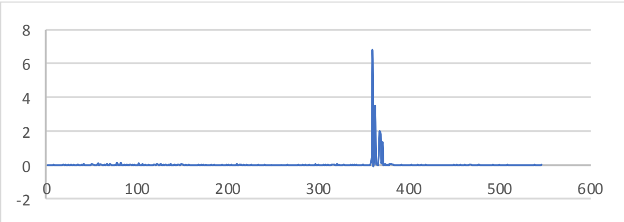

Figure 8: MSE Plot for the ARIMA Model during Cross-Validation

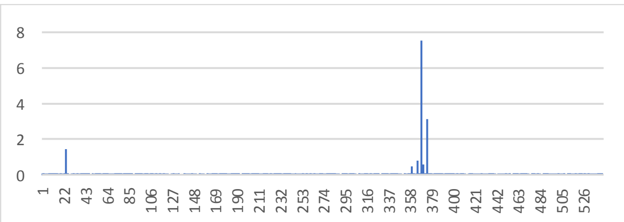

Figure 9: MSE Plot for the ARNN Model during Cross-Validation

V. Conclusions

In this paper we suggested using ARNN model to predict gas prices. The model was benchmarked against the linear ARIMA model. ARNN performed well and showed a performance improvement of around 33.4% over the ARIMA model. We also compared our result with the typical feedforward neural network structure proposed in [19]. In their work, the model was tested using the same dataset i.e., Henry Hub daily spot prices. The improvement reported in our work with MSE as an error measure is approximately 58%.

Clearly, such an improvement is significant in terms of basing spot gas purchase decisions. This is also important in determining longer term contracts and option prices where the underlying instrument is the spot price. However, the model is only tested for the single period case – as is with most of the other works. Hence, in terms of future research, the real benefit of this approach lies when the method is extended and tested for the case of multi-step (or multi-period ahead) forecasting. These results can be especially be useful for decision makers who require longer time horizon forecasts. In this case, perhaps a hybrid approach is needed where daily, weekly and/or monthly data can be coherently used for better longer-term and multi-period predictions.

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