A Neural Network Model for Natural Gas Price Prediction

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ABSTRACT

The model explores using machine learning technic to perform deep learning on natural gas industry trends and consumer demands, and predict natural gas future prices movement. It experiments the possibility to use advanced computer algorithm in structural modeling to predict human behavior, such as the pricing of a cyclical commodity. It will also compare the model result from different machine learning algorithms, along with statistical modeling.

1. INTRODUCTION

Natural gas future price has historically been very volatile due to seasonal demand and supply imbalance, the extreme weather conditions, as well as the speculation on the uncertainties of the future demand and consumption needs. However, the future contracts have expiry dates and few speculators are willing to take physical deliveries, so the effect of speculation will cancel out overtime. Economic activities play a key role in determining the price movement of natural gas futures in the mid-term and over decades. For example, due to the shale gas boom, natural gas has been in a downtrend for over a decade although more and more natural gas has been used in electric power generation.

Natural gas is mainly methane, a strong greenhouse gas. It cannot be released into the atmosphere directly due to strict government regulations and industry standards. When the current price level makes natural gas producers uneconomical to transport the natural gas for sale, it has to be burned at well sites because CO2 produces less greenhouse effect than methane. Neither can natural gas be transported overseas easily. There are only limited port and LNG ship capacities to send natural gas over the Pacific and the Atlantic ocean. The current capacity is at maximum 11-13Bcfs per day, versus 100+ Bcf production per day. Global surplus or shortage has limited impact in local market prices.

For the reason, natural gas has been contained in a closed container since extraction from the site, either a transportation pipe, or on site or underground storages, before it is burnt in a residential household or a power plant. It can be accounted for and we can build a decent picture of when and where the natural gas is used over multiple decades. A model can be built to investigate the small imbalance between demand and consumption and predict the price movement in the market.

Machine learning models are able to solve complicated non-linear regression problems with great success. Artificial neural networks(ANNs) has performed remarkably in pattern recognition and data analysis.

1.1 Natural Gas Industry

Natural gas is a naturally occurring hydrocarbon, a class of organic compounds. Raw natural gas from the wells also contain non-energy components that have to be removed in processing plants before the natural gas is marketed and placed into pipelines. In the past, natural gas was a byproduct of oil production. During recent years, while natural gas production from conventional wells has been gradually depleting, natural gas production from unconventional sources, such as shale gas supplies, has increased substantially. As a result, annual U.S. Lower 48 natural gas production increased from 55.1 Bcf/d in Jan 2000 to 99.6 Bcf/d in Dec 2020. Shale gas now accounts for over 70% of Lower 48 natural gas production.

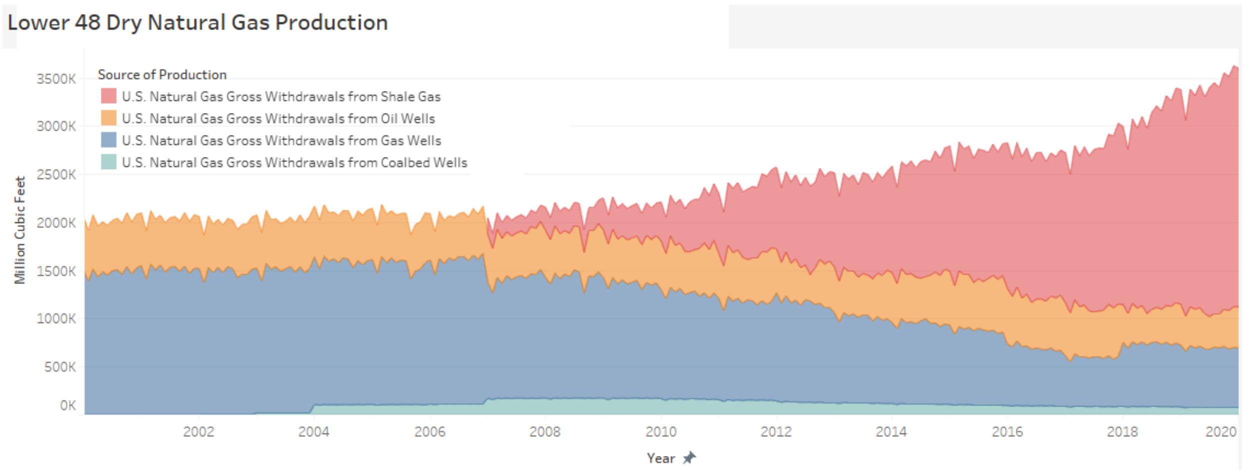


Figure 1 Dry Natural Gas Gross Withdrawals in Lower 48 States by Production Type

The main uses of natural gas are industrial, residential and power generation. Industrial users often use natural gas as a source of heat. Natural gas furnaces ignite and turn off quickly, comparing to coal furnace. Residential households use natural gas for home heating in the winter, as well as furnaces and water heaters. Power plants are the fastest growing users of natural gas because natural gas is more environmental friendly than coal or oil-based plants. In June 2021, 58% of natural gas production was used in power generation. It accounted for 40% of the electricity generated that month.

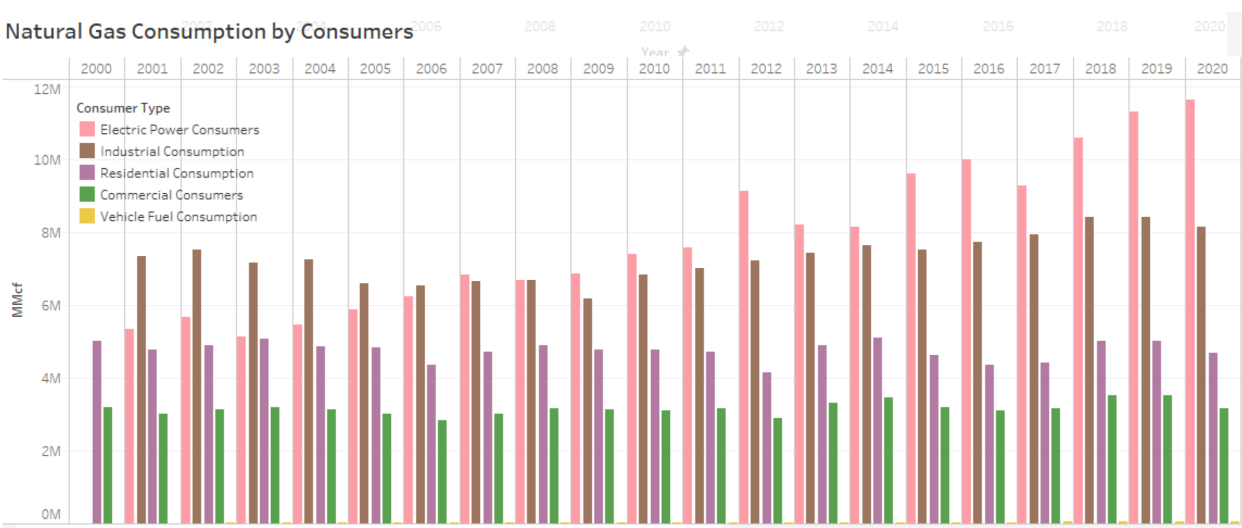


Figure 2 Annual Natural Gas Consumptions in Lower 48 States by Consumer Type

In the most of past 40 years, U.S. imported natural gas by pipeline from Canada to fill the gap between consumption and production. With the growth in domestic shale gas supplies, U.S. has become a net exporter of natural gas since 2017. In Oct 2021, U.S. net exports 10 Bcf/d, mostly due to net LNG exports to European and Asian markets.

1.2 Natural Gas Marketplace

The domestic natural gas marketplace has highly active spot markets and derivative markets. Across continental U.S. and Canada, brokers and others buy and sell natural gas for physical delivery in local delivery points. The benchmark price for North American natural gas is the Henry Hub, located in southern Louisiana. It is interconnected with 13 different interstate pipelines. When quoted by a trader, the price is the difference between the Henry Hub price and that location's price, called the basis price.

Future contracts are traded in both NYMEX and ICE. NYMEX mainly trades Henry Hub futures. A NYMEX natural gas futures contract requires the seller to deliver and the buyer to take the delivery. Futures trading in NYMEX has grown substantially since its inception in 1990. ICE trades futures on major spot hubs (including Henry Hub) through its U.S. Energy Division (IFED). ICE futures are cash settled based on the monthly price published by NYMEX (Henry Hub) and FERC (other major hub futures). However the open interests in all ICE natural gas future products are often 4 times larger than the open interests in NYMEX.

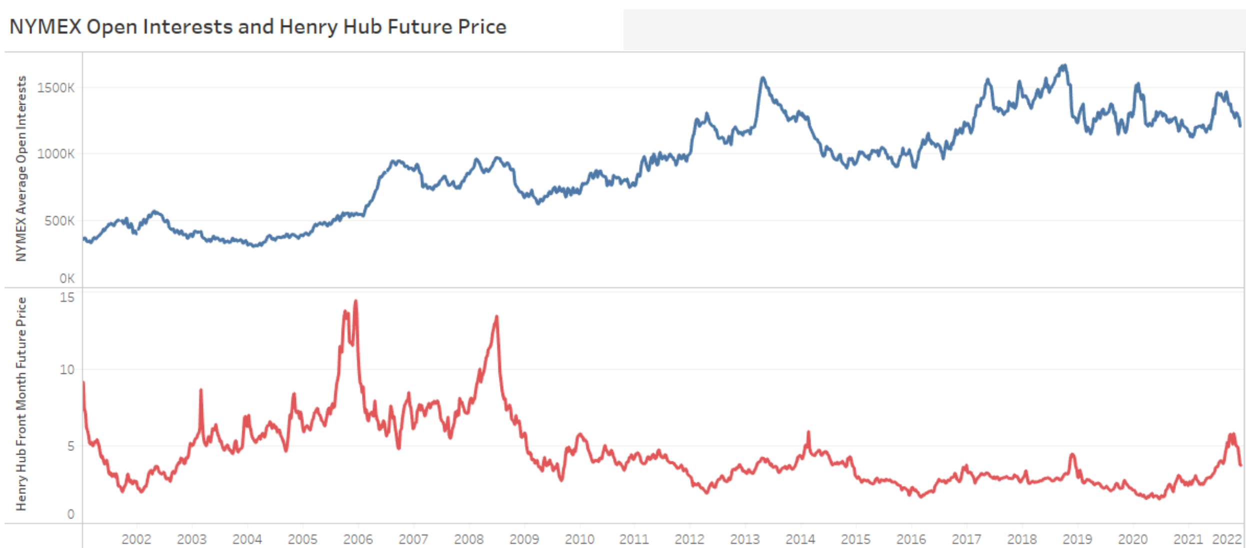


Figure 3 Weekly NYMEX Henry Hub Future Open Interests and Front Month Future Prices

2. METHODOLOGY

The presented method is to predict month end henry hub future price by the industry activities and climate change. Specifically, it investigates the production of natural gas, the consumption of natural gas by different consumer types, the import and export during the period, the storage movement, the weather data and the market speculation level to predict month over month price changes. As with other machine learning methodologies, the process consists of three main steps: data collection, data preprocessing and feature extraction, and regression prediction.

2.1 Data Collection

Data were collected through multiple government agencies' archives and publications. The production breakdowns, the consumption breakdowns, the inventory data, the import and export data are collected through EIA's historical archives. Heating Degree Days(HDD) information was collected through NOAA's archives. Historical henry hub future price were using NYMEX Henry Hub Future daily closing prices. The market speculation level was using CFTC's weekly Commitment of Traders (COT) report. The full data descriptions were included in Appendix I.

2.2 Data Preprocessing

Because natural gas usually has very large price swing year over year and month over month. All the price movement has been converted to log-normal returns in the prediction variable before the training starts. In testing phase, the predictions are again using natural exponential function to convert them into price returns.

Natural gas future price movement has strong seasonality. Each observation set is only relevant to the month it is observed. However, it is either mark the month to 1 – 12 numerical value or Jan – Dec Categorical value will lose important information such as, January is one month after December, April and June are only two months apart, or January and July are opposite months. The model use solar calendar to mark each month. Each month is represented by two variables, one for location and one for direction.

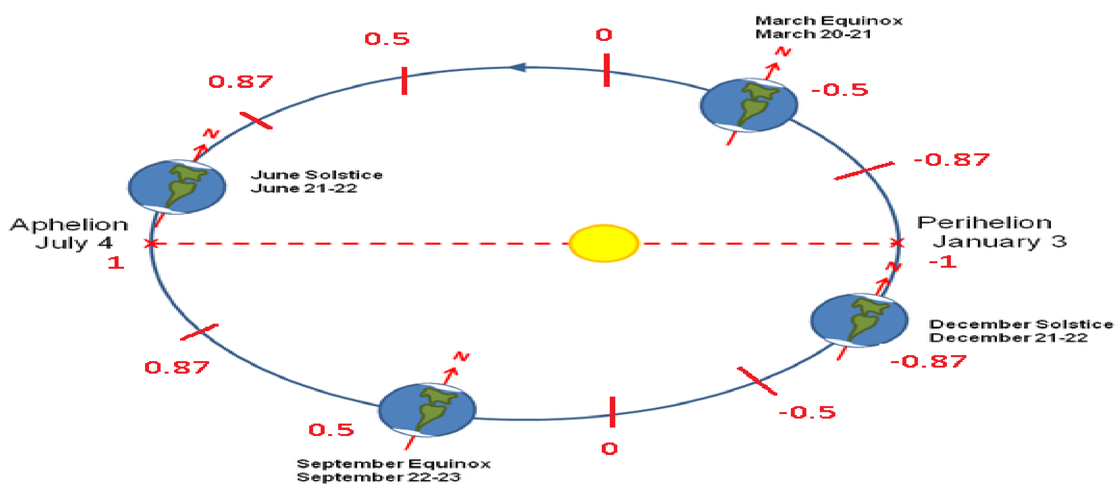


Figure 4 Mark 12 months as a circle of a year for Deep Learning Purpose

Location is a sine function of the earth's angle to the sun, using April as 0 degree and October as 180 degrees. The direction is the change of sine from current month to the next month, so April is marked as [0, 0.5], July is marked as [1, -0.13], and October is marked as [0, -0.5].

Before the factors were presented to the model, all factors were transformed to a standard range to help the deep learning process to optimize the network faster. The standardization process scales each input variable by separately subtracting the series mean and dividing by the standard deviation to shift the distribution.

2.3 Machine Learning Process

Artificial Neural Networks(ANN) is a basic architecture of a neural network, which consists of layers of neurons connected densely. This type of networks is also known as Multi-layer Perceptrons(MLP), or the "vanilla" neural networks. An MLP neural network is a feed-forward multilayer network architecture that consists of three types of layers, an input layer, multiple hidden layers and an output layer. Except for the input nodes, each neuron in other nodes has its own non-linear activation function. MLP utilizes a supervised learning technique called backpropagation algorithm to train the network.

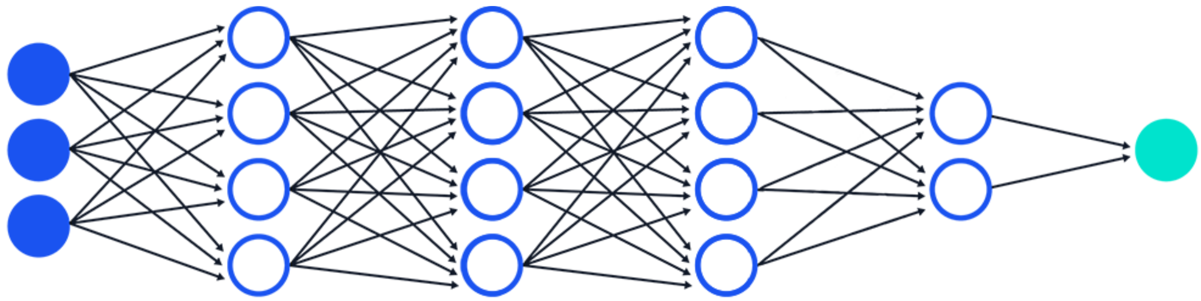


Figure 5 Multi-Layer Perceptron Neural Network Architecture

The input layer has 32 neurons, corresponding to 32 input dimensions. The output layer has one neuron, it predicts the price movement of the month. The learning process takes place in 4 hidden layers. Each neuron in the hidden layer is connected to all the neurons in the previous layer. Each neuron is an individual cell and calculates its own output from all outputs in the previous layer,

$$z = \mathrm{b} + \sum_{i=1}^{n} w_i x_i \qquad \text{, where}$$

$x = input\ to\ neuron$

$w = weights$

$b = bias$

$n = the\ number\ of\ inputs\ from\ the\ previous\ layer$

Each neuron makes its own decision through an non-linear activation function called Exponential Linear Units(elu). Compared to other activation functions, elu function graduately dims in the network and provide a smooth transition in the regression modeling.

Activation	*linear*	*relu*	*elu*
Function	$R\{z, m\} = \{z \times m\}$	$R(z) = \begin{Bmatrix} z & z > 0 \\ 0 & z \leq 0 \end{Bmatrix}$	$R(z) = \begin{Bmatrix} z & z > 0 \\ \propto (e^z - 1) & z \leq 0 \end{Bmatrix}$

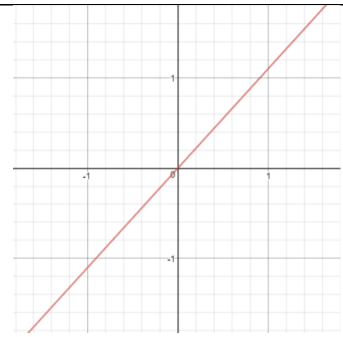
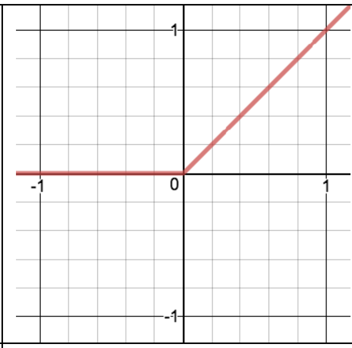
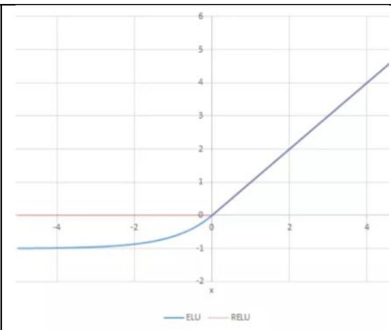
Graph			
Pros	•It gives a range of activations	•Avoids and rectifies vanishing gradient problem •Less computationally expensive	•Smooth slowly until its output equal to −α •Can produce negative outputs
Cons	•Derivative is constant •Constant gradient descent	•Some neuron dies. •Gradient will be 0 when x<0 •For x>0, it can blow up the activation	•For x>0, it can blow up the activation

Table 1 Comparison of Activation Functions in Regression Models

Learning is achieved through the backpropagation algorithm. The backpropagation algorithm calculates the cost of the network in each example, and uses gradient descent to minimize the cost function and optimize the network. This model uses mean squared error as the cost function for all the hidden layers. The optimization process applies gradient descent to optimize the weights and biases in each neuron. The backpropagation evaluates the derivatives of the cost function from the last layer backwards through the whole network, computes the gradient at each layer, and simultaneously optimize the whole network to minimizes the error. The learning completed when the loss of the network has been reasonably minimized at a low level.

2.4 Training and Validation

The process splits the data into pre-2020 set and post-2020 set distinctively for training and testing purpose. It uses complete 20 year history from Jan-2000 to Dec-2019 as the training set to train the neural network and use the observations of month over month price changes since Jan-2020 to test the model. The neural network has no information of the upcoming black swan event, a virus was going to swipe through human societies in two months and cause significant psychological shift in the market and complicated economic impacts in the next two years.

3. RESULTS AND EVALUTION

The training process runs 1000 cycles (epochs). Usually the neural network is able to minimize the loss in its stochastic gradient descent and finish optimization within the first 20 epochs. The longest observed run took about 40 epochs to finish optimizing the network. Using training data set, we observed the mean squared error(MSE) and correlation coefficient between the output and the observations after each optimization,

Epochs	Mean Squared Error	Correlation Coefficient
001	0.013	32%
003	0.012	42%

004	0.012	46%
007	0.011	42%
008	0.011	40%
009	0.010	41%
010	0.010	43%
011	0.009	45%
027	0.008	62%

Table 2 Model Optimization in Training Data

After the training, the model is used to predict the month end henry hub natural gas future price from the beginning of 2020 to the end of 2021.

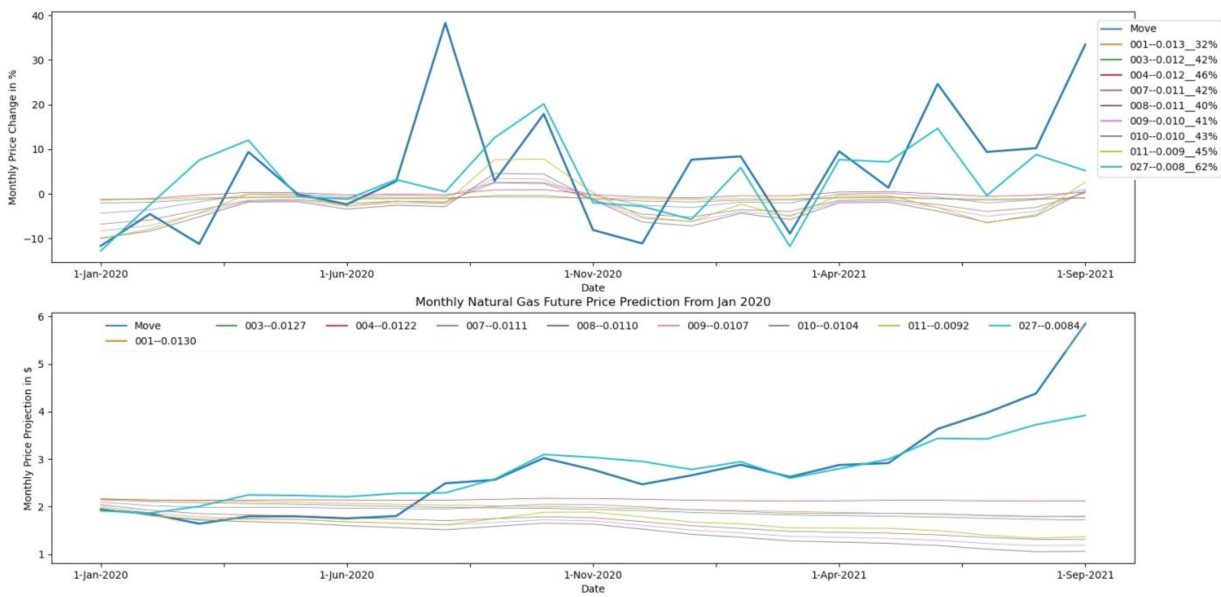


Figure 6 Model Prediction on Front Month Henry Hub Future Price Since 2020

3.1 Result Analysis

The navy line was the observed month end future price in NYMEX. The line marked from 001 to 027 reflected the prediction outcome from different stages in the learning process. 001 curve represents the beginning of the learning process when the neural network was poorly trained. 027 curve marks the completion of the learning process when the network is well optimized and finalized.

The predicted price change curves at the top of Figure 5 demonstrated, the 1st two learning outcomes 001 and 003 have barely discovered the key factors determining the future price. In the third optimization, 004 correctly identified the seasonality in the future price movement that natural gas future price usually rise before the winter and drop in the spring (it has no knowledge what a spring or winter is). After 004, the learning curve accelerated. The neural network was able to reinforce the knowledge and identified more key factors. The neural network was compiled to use mean squared error (MSE) as the evaluation metric. There is an interesting finding in the learning process. The MSE has been declining from 004 to 009 while the correlation coefficients between the observations and the outputs were also declining. Using the curves in testing results as guidance, the algorithm optimized into the right direction. Instead of estimating the direction of each price movement correctly, the algorithm tries to better understand the factors behind the large price movements. After identifying the factors in large price movements, the correlation between observation and output resumes to rise when the optimization continues. After 011, it took another 16 epochs for the algorithm to find the next gradient descent direction and dive into the local bottom on 027.

The cyan color curve at the top of Figure 5 is the prediction made by finalized and fully trained neural network model. Comparing it to the navy color curve which is actual observation of month over month price movement, the neural network correctly predicted most of large price jumps and dips over the two year period.

The cyan color curve at the bottom of Figure 5 is the cumulative price movement on top of actual price on Dec 2019. It represents the model predicted price level on continuous projections. Comparing it to the navy color curve which is actual observations of the henry hub future prices, the neural network was able to constantly predict reasonable natural gas price all the way to late 2021.

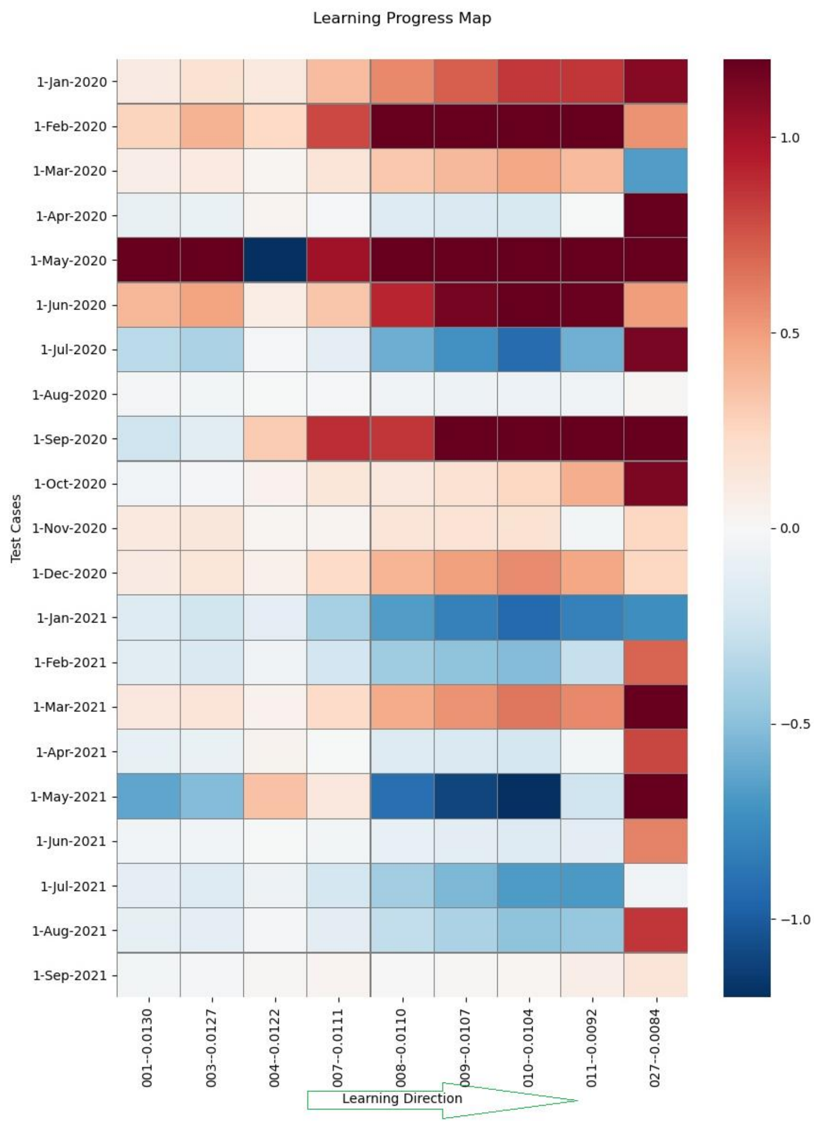


Figure 7 Neural Network Learning Progress Map

Figure 6 demonstrates how the neural network is making progress in its learning curve. The warm color represents an observed return and a predicted return are in the same direction, predicted rise with actual rise, or predicted drop with actual drop. The cold color represents a predicted return are in the wrong direction from an observed return. The colorfulness (color saturation) represents how close the predicted return is to the observed return. If the predicted return is far apart from the observation, the box will be mostly blank. For simplicity, if a predicted return overshoots an observation, it will still be filled with dark color, for the indication that the model has stronger bias of the market direction than the market actually was.

Starting from the left when the learning begins, most of boxes are near blank colors. It indicates the neural network knows little of the price return. As the learning progresses, the color becomes darker and darker. The neural network has stronger and stronger bias how the return will be like, right or wrong. When the learning completed, 17 out of 21 predictions are warm color, meaning the predictions and the observations are in the same direction. 14 predictions are in darker color, indicating the predictions are more and less close to the observations.

3.2 Model Limitations

The artificial neural network is one of supervised learning algorithms. It can only predict outcomes based on the information that was fed to the model. If the required information is not present in the input, the model will not be able to predict reasonable outcome.

For example, there are a few months the model predicts little price change during the month. However, the actual price jumped/dropped dramatically. One of the months is August 2020. The neural network, no matter how we train it, what stages of the training it is in, has an inconvincible confidence that there should be little price movement in the month. However, in reality, the future price jumped more than a third, from 2.4 to 3.2 month over month. There is a reason why model had the wrong perception of the reality. In August 2020, EIA reported that more than 60% of natural gas production in July was used for power generation. It was a historical record. Natural gas has become the biggest fuel source for power generation, accounting for more than 36% of the electricity generated in July. There were other news feeding the rally. The expectation of upcoming vaccine increased market optimism that pandemic would end in the end of 2020. And also, oil price recovered from -33 and stabilized in mid 30s. The market sentiment changed in August without any extraordinary activities the model can observe in the data set. However, what neural network read in August was, the consumption in power generation peaked in July at 1300Bcf and dropped 30% to a total of 1000Bcf in August. It is negative information and there is nothing to be excited for that month.

In another month, Jan 2021 month end, the neural network unanimously predicted the price should drop, while the actual price zigzagged and ended the month with 10% increase. In January 2021, there were sudden stratospheric warmings. However, by the end of January, meteorologists had warned a polar vortex was coming. The actual future price dropped to a low in the mid of January and quickly recovered in month end on renewed weather forecasts. However, the neural network, read the monthly average HDDs, which had been averaged by the warmer days, have no information of weather pattern change and predicted price drop due to the warmer weather, lower residential consumptions and less storage withdrawals.

This neural network model, also constantly underestimate the human greed level and how parabolic a price movement can be. Every training that is able to predict 2005 and 2008 paraboric price movements turned out to be poorly trained model in overall predictions. Every well trained model that is able to predict price movement before and after 2020 most of the time, is very “shy” in predicting 2005 and 2008. While the real movement reached 50% change month over month, the model only predicts 25% or 30%. So does the model predict the future price in Sept 2021. The model agrees the price ought to rise, but not like that. The data set may lack a better market sentiment measure to reflect once/twice-in-a-decade market frenzy. Or we shall respect an artificial neural network’s view on the craziness of real neural networks.

4. MODELS COMPARISON AND DISCUSSION

The figure below compares the outcome from neural network model with other popular machine learning algorithms, as well as the traditional linear regression model, point by point in each month end.

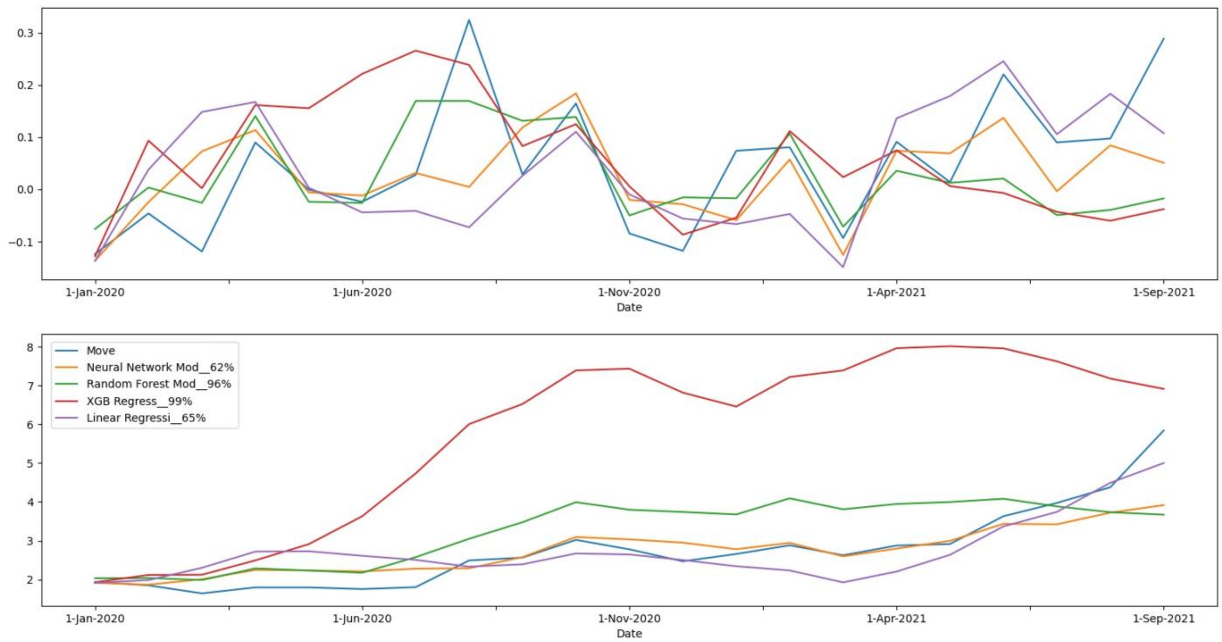


Figure 8 Comparison of Machine Learning and Statistical Models

The results are interesting. The simpler machine learning models failed to make better predictions. Instead, either traditional linear regression models, or ANN with 3-4 hidden layers, were able to better predict the trend from 2020 to 2021. Especially, random forest model and XGB regressor model both were able to fit the training data so well that the correlation coefficient between the outputs and the observations reached higher than 90% in the training process. When they were applied to the test data set, the outcome is nowhere near the statistic accuracy it claimed it has achieved. Linear regression model and ANN model, although only able to achieve some 60% correlation in the training, performed better in the prediction.

One possible explanation is that this model is essentially learning the balance sheet operation of EIA. The natural gas production has to meet the demand, or it has to be in storage somewhere. When demand outpaces production, more natural gas will be imported from Canada to fill the gap. When production outpaces demand, more LNG port will be built in both coasts to export overseas. The demand, Supply, import/export and storage are linear relationships in the equation. The pricing of natural gas serves as a facilitator to shift one curve closer to the other to reach equilibrium. A linear regression model may achieve better results than some machine learning algorithms.

One interesting observation to note is XGB regressor model has been most efficient and 99% correlated to the training set. It would have been a perfect model for risk simulation purpose. When it is used to predict the price movement since the pandemic began, it underperformed all other models. The analysis is beyond the scope of this document.

A comparison between linear regression model and neural network model indicates, both models accurately project the trends of natural gas future price movement. It seems the linear regression projects smoother outcomes over long term, while the neural network model is more sensitive to inter-period volatilities. Longer term testing period may be necessary to validate the findings.

5. CONCLUSION

A neural network model usually requires a very large data set to perform deep learning process. However, in pricing model, too much information may add additional irrelevant noise into the process. In the model, it picks 20 year history of natural gas industry data from 2000 – 2019, only 240 samples. At the same time, the data were condensed to 32 factors to reduce the complexity in the training process. The result shows that deep learning process was able to quickly pick up key factors determining natural gas future price and produce impressive predictions on natural gas future prices than traditional modeling methods and other machine learning algorithms.

APPENDIX I. DATA DESCRIPTION

Data Field	Source	Description
Last Future	NYMEX	Last Period Front Month Future Price
Dry Production	EIA	The process of producing consumer-grade natural gas. Natural gas withdrawn from reservoirs is reduced by volumes used at the production (lease) site and by processing losses. Volumes used at the production site include (1) the volume returned to reservoirs in cycling, repressuring of oil reservoirs, and conservation operations; and (2) gas vented and flared. Processing losses include (1) nonhydrocarbon gases (e.g., water vapor, carbon dioxide, helium, hydrogen sulfide, and nitrogen) removed from the gas stream; and (2) gas converted to liquid form, such as lease condensate and plant liquids. Volumes of dry gas withdrawn from gas storage reservoirs are not considered part of production. Dry natural gas production equals marketed production less extraction loss.
Residential Consumption	EIA	Gas used in private dwellings, including apartments, for heating, air-conditioning, cooking, water heating, and other household uses.
Commercial Consumption	EIA	Gas used by nonmanufacturing establishments or agencies primarily engaged in the sale of goods or services. Included are such establishments as hotels, restaurants, wholesale and retail stores and other service enterprises; gas used by local, State, and Federal agencies engaged in nonmanufacturing activities.
Industrial Consumption	EIA	Natural gas used for heat, power, or chemical feedstock by manufacturing establishments or those engaged in mining or other mineral extraction as well as consumers in agriculture, forestry, and fisheries. Also included in industrial consumption are generators that produce electricity and/or useful thermal output primarily to support the above-mentioned industrial activities.
Electric Power Consumption	EIA	Gas used as fuel in the electric power sector
Δ(Dry Production)		The change of Dry production over the last period
Δ(Residential Consumption)		The change of residential consumption over the last period
Δ(Commercial Consumption)		The change of natural gas deliveries to commerical consumers over the last period
Δ(Industrial Consumption)		The change of industrial consumption over the last period
Δ(Electric Power Consumption)		The change of natural gas deliveries to electric power consumers over the last period
Pipeline Imports	EIA	Natural Gas received in the Continental United States (including Alaska) from a foreign country.
Pipeline Exports	EIA	A continuous pipe conduit, complete with such equipment as valves, compressor stations, communications systems, and meters, for transporting natural and/or supplemental gas from one point to another, usually from a point in or beyond the producing field or processing plant to another pipeline or to points of use. Also refers to a company operating such facilities.
Liquefied Exports	EIA	Natural gas (primarily methane) that has been liquefied by reducing its temperature to -260 degrees Fahrenheit at atmospheric pressure.
Working Storage	EIA	The volume of total natural gas storage capacity that contains natural gas available for withdrawal.
Net Withdraws	EIA	Monthly withdrawals/surplus(-) from the storage facilities.
Δ(Pipeline Imports)		The change of net pipeline imports over last period.
Δ(Pipeline Exports)		
Δ(Liquefied Exports)		
Δ(Working Storage)		
Δ(Net Withdraws)		

Non-Comm Net Stded	CFTC	
Δ(Non-Comm Net)		
HDD CONUS	NOAA	Monthly Average Heating Degree Days(HDD) in lower 48 states
Δ(HDD CONUS)		Change of Monthly Average HDD
Month		Calendar reporting month of the year corresponding to above economic data period

The correlation matrix is visualized in the map below.

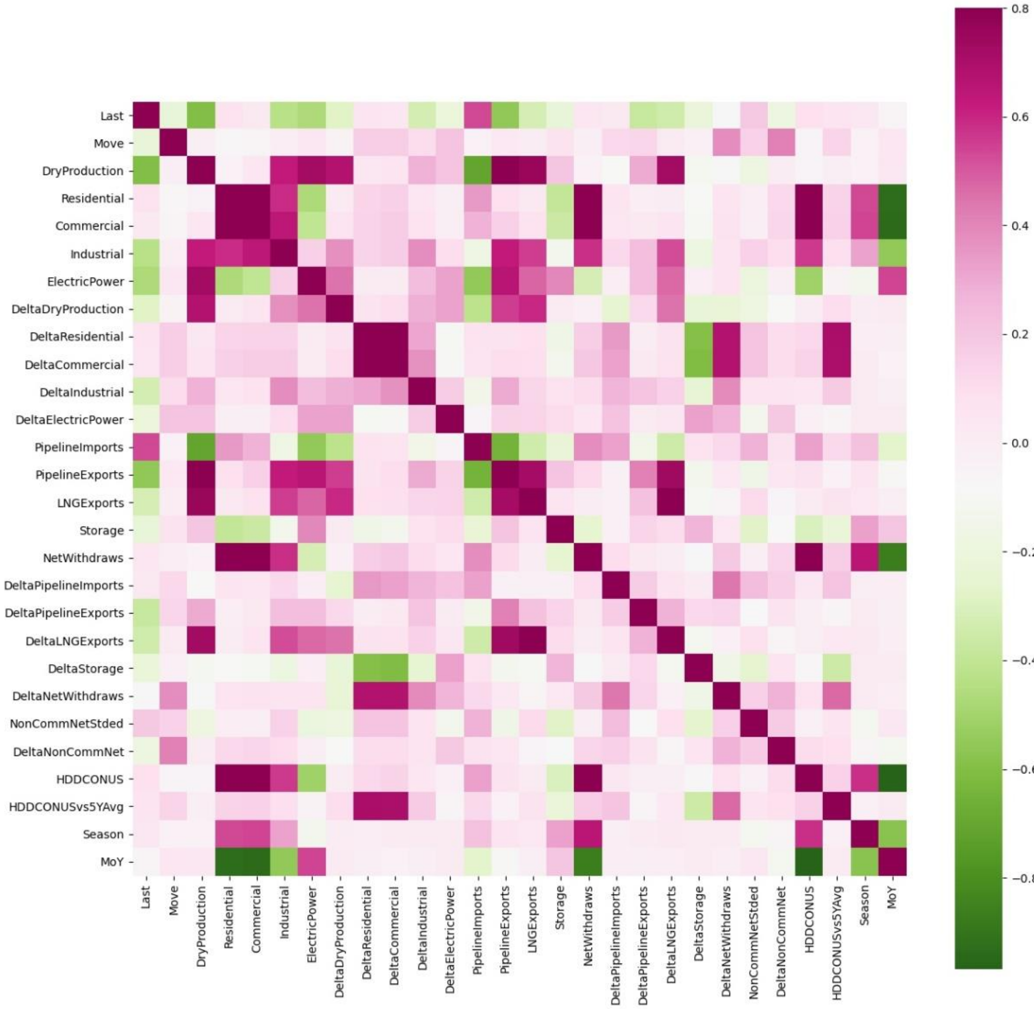


Figure 9 The Correlation Matrix of Input Parameters

Visually, residential, commercial and industrial consumption are all correlated to storage withdrawals and heating needs. Gross dry production is correlated to LNG and pipeline exports. Price movements are not significantly correlated to any individual factors.

SOURCE LINK

https://github.com/jinghuacao/NN.4.NG

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