Commodity Storage Contract Pricing: A Comprehensive Analysis

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Abstract

In an era defined by energy volatility, precise forecasting of gas prices and strategically pricing storage contracts have become paramount for energy companies, investors, and policymakers alike. This quantitative project embarks on a multifaceted mission: the creation of a cutting-edge forecasting model, poised to drive strategic trading decisions but also the construction of a robust pricing model for natural gas storage contracts. This project unveils groundbreaking insights into the future of gas pricing and storage contract management, empowering stakeholders to make informed decisions in a rapidly changing energy ecosystem. As we present our findings, you'll discover the tools and strategies that promise to reshape the energy industry.

1) Introduction

In the dynamic realm of commodities trading, where fortunes can turn on a dime, precision and insight are the bedrock of success. In the context of natural gas, the ability to forecast price trends accurately and strategically price storage contracts hold the key to capitalizing on seasonal market dynamics. This quantitative research project stands at the intersection of financial innovation and strategic trading, with a primary goal: to empower traders with a comprehensive pricing model that not only values storage contracts but also forecasts future gas prices with remarkable precision.

Driven by the urgent need to seize the imminent opportunities presented by a colder-than-expected winter, our collaboration with a forward-thinking trading desk is fueled by innovation and a commitment to delivering actionable insights. Central to this endeavor is the development of a cutting-edge forecasting model, meticulously designed to unravel the intricacies of natural gas price movements. Leveraging advanced statistical techniques, machine learning algorithms, and historical data, this model transcends traditional forecasting methods, considering not only market dynamics but also the profound influence of climate trends and geopolitical factors.

However, our mission extends beyond forecasting alone. In the world of commodity storage contracts, value hinges on a delicate balance between buying and selling prices, while factoring in a multitude of costs, from storage fees to injection/withdrawal expenses and transportation charges. Our pricing model offers a holistic view of contract valuation—a fair estimate that harmonizes the interests of the trading desk and the client, forming the cornerstone of strategic trading decisions.

As we embark on this transformative journey, our aim is not only to develop a script or a model but to reshape the trading landscape, redefining the art of seasonal trading. Beyond this research phase, we anticipate seamless collaboration with engineering, risk management, and model validation teams, ensuring that our innovations are integrated into production code, empowering traders with the precision and confidence needed to navigate the volatile world of natural gas trading.

Dates	**Prices**
10/31/2020	$10.10
11/30/2020	$10.30
12/31/2020	$11
1/31/2021	$10.90
2/28/2021	$10.90
3/31/2021	$10.90
4/30/2021	$10.40
….	….
3/31/2024	$12.70
4/30/2024	$12.10
5/31/2024	$11.40
6/30/2024	$11.50
7/31/2024	$11.60
8/31/2024	$11.50
9/30/2024	$11.80

Table 2.1 – Partial historical data

2) Historical Data

The dataset utilized in this paper comprises monthly gas price records in the USA spanning from October 31, 2020, to September 30, 2024. A partial representation of this dataset is presented in Table 2.1, while Figure 2.1 provides a visual depiction of gas prices over this time frame. An analysis of Figure 2.1 reveals distinct seasonal patterns in pricing, correlated with the months of the year.

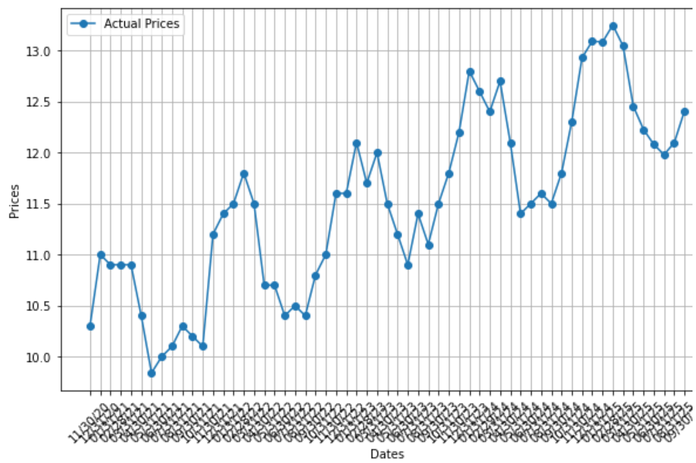

Figure 2.1 – Historical Gas Price Visualization

Notably, the data showcases a price upswing commencing in August and extending through January, potentially attributed to the commencement of the school year and the culmination of annual festivities such as Thanksgiving, Christmas, and New Year's Eve. Conversely, a price decline becomes evident from February to July. To gain deeper insights into these patterns, Figure 2.2 offers an advanced seasonal decomposition of gas prices, effectively illustrating the trend, seasonality, and residual components.

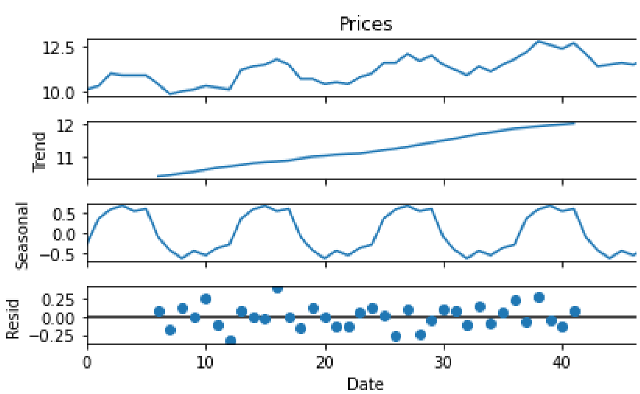

Figure 2.2 – Seasonal decomposition

3) Times Serie Model

3.1) Stationary

At its essence, a time series is a sequence of data points collected or recorded at regular intervals over time, and these models aim to extract patterns, trends, and dependencies from such data. This enables us to make informed predictions and forecasts about future values, all while considering the historical context of the data. Time series models are a formidable tool in the realm of data analysis, offering a unique lens through which we can examine and interpret data points over time. Unlike traditional statistical analyses, which treat data as independent and unrelated, time series models are designed explicitly for data sequences where each observation is not only influenced by its past but is also temporally linked to the preceding and subsequent data points.

Common times series model includes an autoregressive, Moving Average, autoregressive moving average, and seasonal autoregressive moving average. Before building a time series model, we need to check if the data is stationary, if not we will perform a modification called Differencing. There are different methods to check if we have stationary data, however in this paper we will use the Dickey-Fuller-Test.

The null hypothesis for this test posits that the data lacks stationarity, while the alternative hypothesis suggests that the data exhibits stationarity.

```
ADF Statistic: 0.21807686170000343
p-value: 0.9732574388448695
Critical Values:
   1%: -3.6209175221605827
   5%: -2.9435394610388332
   10%: -2.6104002410518627
```

The computed p-value, which stands at 0.97 and exceeds the significance level of 0.05, compellingly suggests the presence of a non-stationary time series. Consequently, a necessary step is to introduce differencing, a method involving the subtraction of each current observation from its predecessor. This differential approach serves to stabilize the mean within the time series data, we proceed with first-order differencing, successfully transforming the data into a stationary time series.

```
ADF Statistic: -6.844773557477349
p-value: 1.7541696852940399e-09
Critical Values:
   1%: -3.6209175221605827
   5%: -2.9435394610388332
   10%: -2.6104002410518627
```

3.2) ARIMA Model

ARIMA stands for Auto Regressive Integrated Moving Average and is a class of models that explains a given time series based on its own past values. It is specified with three parameters p, q and d. where p=number of autoregressive terms, d= number of non-seasonal differences integrated and q= number of lagged forecast error in the equation. After conducting extensive parameter tuning, we have identified the optimal configuration for this dataset as ARIMA (12, 0, 0). This refined model will be employed to project gas prices for the next 12 months into the future.

3.3) Forecasting Results

As illustrated in Table 3.1 and Figure 3.1, the forecasted gas prices, and the updated visualization span from November 30, 2020, to September 30, 2025. Remarkably, it becomes evident that the model has adeptly assimilated insights from the historical data, seamlessly aligning with the pronounced seasonality inherent in gas prices.

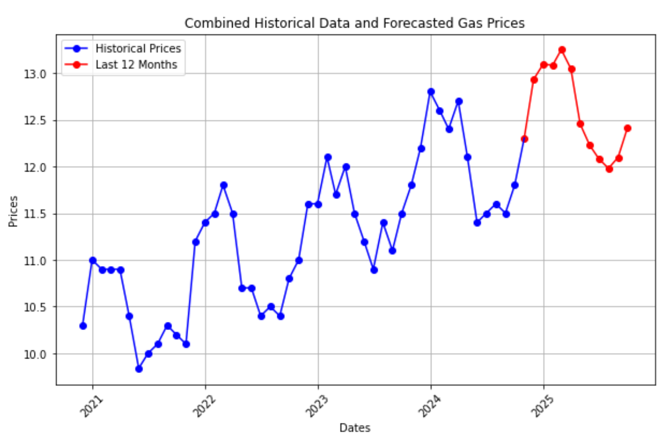

Figure 3.1- Updated visualization of gas prices

Dates	Predicted prices
10/31/2024	12.304345
11/30/2024	12.928941
12/31/2024	13.092917
1/31/2025	13.083218
2/28/2025	13.249333
3/31/2025	13.046063
4/30/2025	12.454838
5/31/2025	12.226229
6/30/2025	12.080187
7/31/2025	11.979482
8/31/2025	12.097390
9/30/2025	12.409549

Table 3.1 – Predicted dates and prices

4) Storage Contract Pricing

Following the construction of our ARIMA model and the derivation of predicted prices, we can now harness these forecasts to inform our pricing strategy for gas storage contracts. In anticipation of a potentially colder-than-expected winter, we contemplate procuring gas in advance for storage and subsequent sale during the winter season to capitalize on the anticipated surge in gas prices. The value of any trade agreement hinges on the spread between the selling and purchasing prices, with adjustments made for associated expenses. Within the scope of this study, we introduce several supplementary costs, encompassing transportation, injection/withdrawal fees, and monthly storage charges.

The model's operation can be succinctly outlined as follows: Suppose I acquire 100 MMBtu of gas on September 30, 2023, at a rate of $11.5 per unit, amounting to a purchase cost of $1,150 million. This initial cost is augmented by transportation and injection fees, collectively referred to as "Expenses." Subsequently, I plan to vend 80 MMBtu on December 31, 2023, at a price of $12.8 per unit, resulting in revenue of $1024 million. This revenue, in turn, is subject to deductions for transportation and injection costs, constituting the "Revenue" phase. Finally, the model addresses the remaining 20 MMBtu, which we intend to retain until December 30, 2024, at an expected gas price of $13.09 per unit. This yields an asset valuation of $261.8 million, net of total monthly storage cost since the initial injection.

To compute the net cash flow (NCF) associated with the storage contract, we employ the formula:

NCF = Asset + Revenue - Expenses.

This comprehensive approach encapsulates the financial dynamics of the storage contract, encompassing both acquisition and disposition, and aligns with our strategic objective of optimizing returns in response to market fluctuations. The next cash flow here is our estimated contract value.

The Python code for this project is readily available, allowing readers and future researchers the flexibility to customize and enhance the pricing model to accommodate more intricate scenarios such as multiple injection, withdrawal, and variables.

5) Conclusion

In summary, this study has illuminated the intricate interplay between data-driven forecasting and strategic decision-making in the realm of gas price dynamics and storage contracts. Leveraging the ARIMA model and historical data, we achieved robust gas price projections, effectively capturing seasonality and trends. Beyond prediction, we explored the practical application of these forecasts, emphasizing the importance of proactive decision-making in response to market shifts, such as the potential impact of colder winters. By incorporating comprehensive cost considerations, encompassing transportation, injection/withdrawal fees, and storage charges, we provided a holistic framework for evaluating storage contract profitability. Our analysis introduced a multifaceted approach to assessing net cash flows, spanning from acquisition to disposition, empowering stakeholders with a versatile tool for optimizing financial outcomes. In essence, this research underscores the potential of data-driven insights to navigate dynamic commodity markets, fostering more informed and lucrative choices within the gas storage and trading arena.

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