Dynamic Inventory Management and Profitability Analysis in Natural Gas Trading: A Computational Approach

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Abstract

This paper presents a comprehensive computational model for managing natural gas inventories and analyzing profitability in a dynamic trading environment. The model integrates time series forecasting, inventory tracking, and financial analysis to provide a holistic view of natural gas trading operations. By incorporating factors such as storage costs, transportation expenses, and market price fluctuations, this study offers insights into optimal inventory management strategies and their impact on profitability in the natural gas sector.

1. Introduction

The natural gas market is characterized by high volatility, seasonal demand patterns, and complex logistical considerations. Effective inventory management in this sector requires sophisticated tools that can handle multiple variables and provide actionable insights. This study introduces a computational model that addresses these challenges by combining price forecasting, detailed inventory tracking, and comprehensive profitability analysis.

2. Methodology

2.1 Data Preparation and Price Forecasting

The model begins with historical natural gas price data, which is processed and analyzed using the Seasonal and Trend decomposition using Loess (STL) method. This decomposition allows for the separation of trend, seasonal, and residual components, facilitating more accurate price forecasting.

```
stl = STL(nat_gas_prices['Prices'], seasonal=13, robust=True)
result = stl.fit()
trend = result.trend
seasonal = result.seasonal
```

A linear regression model is then applied to the trend component to generate future price predictions:

```
lin_reg = LinearRegression()
lin_reg.fit(time_index, trend.dropna())
predicted_trend = lin_reg.predict(extended_time_index)
```

2.2 Inventory Management System

The core of the model is an inventory management system that tracks purchases, sales, and withdrawals of natural gas. This system employs a First-In-First-Out (FIFO) methodology to accurately account for the cost of goods sold and remaining inventory.

Key functions in this system include:

1. `log_purchase`: Records new purchases of natural gas, updating storage availability.
2. `update_storage_availability`: Recalculates storage availability after changes in inventory.
3. `update_purchase_log_with_sales`: Updates the purchase log when sales occur, calculating the cost of sales.

2.3 Profitability Analysis

The model incorporates a sophisticated profitability analysis function, `check_valuation`, which considers various costs associated with natural gas trading:

- Storage costs (per month)
- Transportation costs (per withdrawal)
- Injection costs (per purchase)
- Withdrawal costs

This function calculates the profitability of each withdrawal, taking into account the weighted average cost of the gas, storage duration, and all associated expenses.

3. Results and Analysis

The model was tested with sample data to demonstrate its capabilities. The results are presented in the following tables:

3.1 Sales Log

Table 1: Sales Log with Cost of Sale

Sale_ID	Sale_Date	Price_per_MMBtu	Amount_MMBtu	Sale_Proceeds	Cost_of_Sale
SALE_1	2025-01-30	13.091609	5,000,000	65,458,050	57,985,000
SALE_2	2025-02-01	13.089175	1,300,000	17,015,930	15,145,000

3.2 Valuation Summary

As of the initial request date, the valuation for all unsold units was:

- Total Remaining Units: 3,000,000 MMBtu
- Average Cost of All Unsold Units: $11.73 per MMBtu

3.3 Withdrawal Log

Table 2: Withdrawal Log

Withdrawal Date	Requested Units	Average Cost	Total Storage Costs	Total Cost	Price per MMBtu	Sales Proceeds	Net Profit
2025-02-05	1,000,000	11.69	463,333	12,266,670	13.078567	13,078,570	811,900

Withdrawal Date	Requested Units	Average Cost	Total Storage Costs	Total Cost	Price per MMBtu	Sales Proceeds	Net Profit
2025-02-12	1,500,000	11.743333	468,889	18,210,000	13.060003	19,590,000	1,380,004

Total Net Profit: $2,191,905.10

3.4 Purchase Log

Table 3: Purchase Log

Purchase Date	Price per MMBtu	Amount MMBtu	Purchase Cost	Sold Status	Remaining Units	Sale IDs	Request IDs	Storage Availability
2024-09-04	11.54	1,500,000	17,310,000	Yes - FULL	0	SALE_1		15,000,000
2024-09-10	11.60	2,000,000	23,200,000	Yes - FULL	0	SALE_1		15,000,000
2024-09-15	11.65	3,000,000	34,950,000	Yes - FULL (Request)	0	SALE_1 SALE_2	REQUEST_1	15,000,000
2024-09-20	11.70	1,000,000	11,700,000	Yes - FULL (Request)	0		REQUEST_1 REQUEST_2	15,000,000
2024-09-25	11.75	1,800,000	21,150,000	Yes - PARTIALLY (Request)	500,000		REQUEST_2	14,500,000

4. Mathematical Formulas

The following formulas explain the key calculations performed in the code:

4.1 Price Forecasting

The price forecasting uses a combination of STL decomposition and linear regression:

1. STL Decomposition:
   $Y_t = T_t + S_t + R_t$
   where
   - Y_t is the observed price,
   - T_t is the trend component,
   - S_t is the seasonal component, and
   - R_t is the residual.
2. Linear Regression for Trend:
   $T_t = \beta_0 + \beta_1 t + \epsilon_t$
   where β_0 is the intercept, β_1 is the slope, and ϵ_t is the error term.

4.2 Profit Calculation

For each withdrawal, the profit is calculated as follows:

1. Total Cost per Withdrawal:
   $TC_w = (U_w \times AC_u) + SC + \sum PT_c + WT + \sum IC + WC$
   where:
   - TC_w is the total cost per withdrawal
   - U_w is the number of units withdrawn
   - AC_u is the average cost per unit
   - SC is the storage cost
   - PT_c is the purchase transport cost
   - WT is the withdrawal transport cost
   - IC is the injection cost
   - WC is the withdrawal cost
2. Sales Proceeds:
   $SP = U_w \times P_w$
   where P_w is the price per MMBtu at the time of withdrawal
3. Net Profit:
   $NP = SP - TC_w$

4.3 Storage Cost Calculation

The storage cost for each withdrawal is calculated as:

$SC = \frac{\sum_{i=1}^{n}(U_i \times D_i)}{U_w} \times C_m$

where:
- U_i is the number of units from purchase i
- D_i is the storage duration in months for purchase i
- U_w is the total number of units withdrawn
- C_m is the storage cost per month

4.4 Average Cost Calculation

The average cost of all unsold units is calculated as:

$AC_{unsold} = \frac{\sum_{i=1}^{n}(U_i \times P_i)}{\sum_{i=1}^{n} U_i}$

where:
- U_i is the number of remaining units from purchase i
- P_i is the purchase price per MMBtu for purchase i

5. Discussion

The model's strength lies in its ability to integrate multiple aspects of natural gas trading into a single, cohesive system. By combining price forecasting with detailed inventory tracking and cost analysis, it provides a nuanced understanding of profitability in this complex market.

Key insights from the model include:

1. The impact of storage duration on profitability, highlighting the importance of efficient inventory turnover.
2. The significance of various costs (storage, transportation, injection, withdrawal) in overall profitability.
3. The potential for optimizing purchase and sale timing based on price forecasts and inventory levels.

6. Limitations and Future Work

While the model provides valuable insights, there are several areas for potential improvement:

1. Price Forecasting: The current linear regression approach could be enhanced with more sophisticated time series models or machine learning techniques.
2. Dynamic Cost Modeling: Incorporating variable costs that change with market conditions could improve accuracy.
3. Risk Analysis: Adding features for risk assessment and scenario analysis would provide a more robust decision-making tool.
4. Market Dynamics: Incorporating broader market factors such as supply-demand dynamics and regulatory changes could enhance the model's predictive capabilities.

Future work could focus on integrating these elements to create a more comprehensive and adaptive trading strategy optimization tool.

7. Conclusion

This study presents a novel computational approach to natural gas inventory management and profitability analysis. By integrating price forecasting, detailed inventory tracking, and comprehensive cost analysis, the model provides a powerful tool for decision-making in natural gas trading operations. While there is room for further refinement, this approach lays a solid foundation for more sophisticated and data-driven strategies in the natural gas market.

References

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