Natural Gas Storage Valuation

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Background and Context

Energy trading involves physically handling energy commodities like oil, natural gas, coal, etc. Energy conversion assets enable physical handling activities. These assets are facilities that take energy commodities as input and produce energy commodities as outputs through a conversion process.

The conversion process can be physical, temporal, or spatial. Oil refining is an example of physical conversion, where crude oil is converted into petroleum products. Another example is oil tankers that resemble both temporal and spatial conversion.

Collectively, conversion assets comprise what is called an energy trading network that matches global supply and demand. These assets are the backbone of the energy trading network. Hence, properly managing these assets' operational capacity constraints is crucial in energy trading.

From an asset operator's perspective, the problem is to decide on the optimal operating policy that maximizes profits. Given how commodity prices evolve, this is achieved by managing the assets' capacity limits. This perspective is referred to in the literature as *merchant operations* (Secomandi & Seppi, 2014).

An energy merchant company would actively adjust/optimize the conversion asset's operating policy to support its trading activity. The ability to adjust an asset's conversion level as the commodity price evolves relates to managerial flexibility or, more formally, *real options*. This flexibility/optionality is crucial in the valuation of commodity conversion assets.

In the energy trading industry, it is not uncommon to partially lease the capacity of a conversion asset, such as leasing a pipeline or a storage facility capacity for a future date. An energy merchant company would need to properly assess the value of that conversion asset capacity to be leased.

A static valuation measure, such as the NPV based on the current futures curve, would mostly undervalue the conversion asset. This valuation method ignores the embedded optionality in these assets and measures only the intrinsic value.

However, an energy merchant would take advantage of the embedded optionality in these conversion assets, i.e., the managerial flexibility to adjust operational levels, given how the futures curve evolves. This is referred to as the extrinsic value of the asset.

Having said that, incorporating extrinsic value in an asset's valuation is a difficult task. It entails modeling the evolution of energy commodity prices and stochastic optimization of the conversion operations. This thesis is based on the integration of finance and operations management disciplines.

Literature Review

In the inventory management literature, the warehouse problem has been well-known for a long time (Cahn, 1948). The problem was defined as follows; for a given warehouse with fixed capacity, i.e., storage space, and fluctuating prices and costs, what is the optimal pattern for purchase (production), storage, and sales?

This formulation assumes that the warehouse can be filled or emptied without restrictions. In reality, however, storage facilities are restricted by both space and flow capacity constraints.

To demonstrate this point, (Secomandi, 2010) developed a natural gas storage valuation model incorporating injection/withdrawal constraints. He showed that trading and operational decisions can not be decoupled. These results were confirmed using simulations and actual data. The computations showed that ignoring the flow capacity constraints resulted in significant losses due to uncoordinated trading and operational activities. This is a significant result for practitioners.

Another important result from (Secomandi, 2010) related to the role of inventory level on optimal policy. He argues that under capacity constraints formulation, the optimal policy is nontrivial. This is due to the effect of intertemporal linkages of the inventory level in deciding on optimal policy. In other words, commodity spot prices alone are not enough to derive the optimal policy, given that the storage facility is bounded by flow constraints that need to be considered.

In practice, energy commodity traders perform valuations using commercial solvers based on heuristic algorithms. However, these heuristics don't provide upper or lower bounds of storage valuations, i.e., performance guarantees.

To benchmark the performance of these algorithms, (Lai et al., 2010) developed a novel approximation method for natural gas storage valuation and provided upper/lower bounds to benchmark these practice-based heuristics.

Their results showed that these heuristics were fast in computation, yet they provided a low estimation for the intrinsic value of storage while not accounting for the extrinsic value. On the other hand, their approximation method provided more accurate valuations, albeit at the expense of higher computational costs.

With the expansion of global liquified natural gas (LNG) trading, new problems arise in the valuation of the conversion assets in this growing sector. (Lai et al., 2011) examined the valuation problem of LNG storage and regasification facility, i.e., LNG supply chain downstream terminal. The main contribution of their paper was an approximation method that combined the LNG supply chain, natural gas price model, and LNG regasification and sale.

These models can be extended to other energy commodities as they share similar problem structures. For a recent and broader literature review on the interface of finance and operations in the energy industry, kindly refer to (Nadarajah & Secomandi, 2022).

Research Methodology

This section will present a high-level overview of the approach used in formulating and solving the problem of energy commodity conversion asset valuation problem. The material presented is based on the work of (Secomandi & Seppi, 2014) and (Nadarajah, 2014).

There is a vast literature on the usefulness of modeling managerial flexibility as real options. The idea is that a conversion asset's input and output energy commodities are traded in financial markets. Hence, these commodities' prevailing spot and futures prices influence the cash flows from operational decisions.

Real options and financial options valuations share the same theoretical foundations. However, real options for energy merchant operations differ from financial options in the following ways: (1) decisions at multiple dates, (2) intertemporal linkages across decisions, (3) multiple underlying variables, (4) payoffs determined by operational costs and contractual provisions, (5) engineering-based constraints on operational decisions, and (6) quantity decisions rather than binary exercise/no-exercise decisions.

The problem has three distinctive features. The first is dynamic decisions; we solve an optimization problem in discrete times. Secondly, we have operational constraints; decisions must satisfy capacity constraints or flow requirements. Additionally, decisions are coupled over time, so it is not feasible to solve each decision independently, as each decision in the past affects our decisions in future states. Thirdly is uncertainty; decisions at each state depend on exogenous factors that are unknown and uncontrollable.

It is helpful to model this problem as a markov decision process. In this formulation, we have the following variables:

- N stages $i \in I := \{0, \ldots, N-1\}$
- Endogenous state: $x_i := \{x_{i,1}, \ldots, x_{i,L}\} \in \mathcal{X}$ (inventory)
- Exogenous state: $F_i := \{F_{i,i}, F_{i,i+1}, \ldots, F_{i,N-1}\} \in \mathcal{X}$ (forward/demand curve)
- Action $a_i(x_i, F_i)$ belongs to the discrete set $\mathcal{A}_i(x_i)$ (feasible actions)
- Reward function: $r_i: (a_i, x_i, F_i) \mapsto \mathbb{R}$
- Transition rule:
    - Endogenous: $x_{i+1} = x_i - a_i$
    - Exogenous: transition from F_i to F_{i+1} is determined by the model of uncertainty

The optimization problem aims to maximize the cumulative rewards $r_i(a_i, x_i, F_i)$, given the transition rules for the state variables across N stages. This approach entails solving a stochastic dynamic optimization model. The general structure is shown in the equation below.

$$V_i(x_i, F_i) = \max_{a \in \mathcal{A}_i(x_i)} r(a, x_i, F_i) + \delta \mathbb{E}\left[V_{i+1}\left(x_i - a, \tilde{F}_{i+1}\right) | F_i\right]$$

This is called the value function for each stage i, given the current inventory level and futures curve, x_i and F_i respectively. We seek to find the optimal action a at each stage i from the set of feasible actions $\mathcal{A}_i(x_i)$. This formulation uses risk-neutral valuation; hence δ is a discount factor for future expected rewards $V_{i+1}(.)$. Finally, $\tilde{F}_{i+1}$ is the stochastic futures curve for the next stage conditioned on the current futures curve F_i.

Given the large stage-state space and unknown reward function, this problem is difficult to solve due to the so-called curse of dimensionality. Therefore it is imperative to resort to approximations as this problem is computationally intractable. This requires the following, (1) approximation of the reward function, (2) estimation of upper/lower bounds to evaluate the optimality gap of the proposed approximation.

This approach allows us to develop a lower-dimension approximation function that we can compute, referred to as basis functions. The reason that we resort to approximation is that it allows us to compute heuristic policy. This policy is not necessarily optimal but close to optimality. Then we can calculate lower and upper bounds that guarantee the performance of our heuristic policy.

There are three methods for approximating dynamic programs, Monte Carlo-based regression, approximate linear programs, and reinforcement learning. The choice of which approximation approach primarily depends on the problem structure with respect to the number of endogenous and exogenous states and the choice of basis functions.

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