8-2012

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Strategic Analysis of Technology and Capacity Investments in the Liquefied Natural Gas Industry

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Tepper Working Paper 2008-E43
August 2012

Abstract

Energy plays a fundamental role in both manufacturing and services, and natural gas is rapidly becoming a key energy source worldwide. Facilitating this emergence is an expanding network of ocean-going vessels that enable the matching of natural gas supply and demand on a global scale. This is achieved through the transportation of liquefied natural gas (LNG) for eventual regasification at its destination. Until very recently, only one type of technology had been available for transporting and regasifying LNG: Conventional LNG vessels coupled with land based LNG regasification. But it is now possible to transport and regasify LNG onboard special LNG vessels. Companies such as Excelerate Energy and Höegh LNG are currently developing LNG supply chains based on this new technology. Motivated by these developments, we engaged executives at Excelerate Energy to facilitate an investigation of issues related to strategic technology selection, as well as choices around technology configuration and capacity for the incumbent and emerging technologies. The resulting analysis brings to light managerial principles delineating the impact of alternative LNG throughput models on decisions regarding how to deploy each technology option and how to configure and size their capacity. Our findings have additional potential relevance beyond our industry specific analysis.

1. Introduction

Energy is fundamental to any manufacturing and service activity, and natural gas is rapidly acquiring a prominent role as a source of energy worldwide (Geman 2005, Chapter 10). However, due to local imbalances, matching the supply to the demand for natural gas requires its transportation from locations with excess supply to locations with excess demand. Over short distances natural gas transportation is done by pipelines; over longer distances natural gas is transported in the form of liquefied natural gas (LNG) by ocean-going vessels (Tusiani and Shearer 2007). Such vessels are instrumental in the LNG industry’s current development on a global scale (EIA 2003, Jensen 2003).

LNG must be regasified before it can be consumed as natural gas. Until very recently, there existed only one type of LNG regasification technology. In this incumbent technology (onshore
terminal-based regasification), LNG is regasified at a land-based terminal after being unloaded from conventional LNG vessels. In contrast, new regasification technology (onboard regasification) allows special LNG vessels to regasify LNG onboard without requiring a costly onshore terminal. This new technology is relatively cheap and fast to build, but has the drawback of a lower unloading rate compared to the incumbent technology. It is currently being commercially deployed by companies such as Excelerate Energy and Höegh LNG.

As a result, companies investing in the development of new LNG supply chains now face the challenge of selecting between the incumbent and emerging LNG regasification technologies. In addition, these technologies can be deployed using different configuration and capacity levels, leading to different operational and financial performance. Motivated by these challenges, our objective is to conduct a strategic analysis of the technology selection, technology configuration, and capacity choices, comparing the incumbent and emerging regasification technologies. In particular, our goal is to elucidate the impact of alternative models of LNG throughput on these strategic choices. To do so, we develop, structurally analyze, and apply to data an integrated analytic model. In the process, we have engaged with executives at Excelerate Energy; they have validated our strategic analysis, and used our results to support strategic choices at their company.

Our integrated model chooses the resource levels that maximize the net present value (NPV) generated by an LNG network, for each technology option, at any given LNG throughput requirement. We utilize both stochastic (closed queueing network and simulation) and deterministic models to calculate the throughput rate that can be sustained by given resource levels. The use of different throughput models allows us to investigate the sensitivity of strategic decisions, i.e., the technology selection, technology configuration and capacity decisions, to operational (throughput) modeling choices. It also enables us to assess the managerial relevance of modeling uncertainty in processing times when making these decisions.

The structural analysis and application to data of our integrated analytic model provide insights into the following strategic decisions: (1) the selection of LNG regasification technology, (2) the configuration of the onboard technology, if selected, and (3) the capacity sizing of an LNG supply chain.

We characterize the regasification technology selection decision according to two factors: The desired throughput rate and the lead time difference (LTD) in revenue generation (LTD arises due to the shorter development time of the new onboard technology compared to a land-based regasification terminal). Specifically, we find that the throughput and LTD space can be partitioned into three regions; two where one of the two technologies dominates over the other, and one region
where no clear dominance arises. This partitioning appears robust to the type of throughput model used. In cases of dominance, the preferred technology option does not seem to depend in a critical manner on the type of throughput model used, i.e., deterministic or stochastic. But, in the third, sizable, region the preferred technology choice may depend on the type of throughput model used, and possibly other factors, e.g., available vessel specifications. Our characterization of the dominance and no dominance regions challenges the current view that the onboard technology is well suited only for low throughput requirements (Jensen 2003, Smith et al. 2004), as this view appears to have overlooked the possibility of configuring this technology with multiple unloading buoys. This characterization provided important strategic guidance to executives at Excelerate Energy.

We also find that an LNG supply chain based on the onboard technology should be configured using only special LNG vessels, rather than a mix of conventional and special regasification ships utilizing transshipment from conventional to special LNG ships. The latter is a configuration being considered for adoption by companies such as Excelerate Energy and Höegh LNG to improve the profitability of the onboard technology, as a special vessel is more expensive than a conventional vessel (Bryngelson 2007). This configuration decision is largely insensitive to the type of throughput model used. This finding also proved to be managerially significant for executives at Excelerate Energy in terms of assessing the benefit of the transshipment based configuration.

Our analysis of the capacity choice reveals that this choice is nontrivial, as the chosen resource levels can depend on the type of model used to compute throughput. Moreover, the resulting differences can be managerially significant: Choosing resource levels for the onboard technology by relying on a deterministic model of throughput can yield up to a 13% ($12 billion (B)) NPV shortfall compared to the NPV obtained from a stochastic model of throughput that assumes exponentially distributed service times. This shortfall is 6.96% ($6.47B) when a stochastic model with less variable, likely more realistic, service times are used (these stochastic models are discussed by Koenigsberg and Lam 1976). For the onshore technology these figures are 7.86% ($5.5B) and 4.1% ($4.25B), respectively. In addition, the NPV obtained by determining the resource levels for the onboard technology assuming exponential service times is no more than 0.39% ($275 million (M)) lower than the NPV obtained by assuming the less variable service times proposed by Koenigsberg and Lam (1976). This figure for the onshore technology is 0.34% ($250M). These findings reveal that ignoring uncertainty in service times when sizing the capacity of LNG networks can be significantly costly, whereas the cost of overestimating the uncertainty, and consequently over-provisioning capacity can be relatively smaller.
While our focus is on a specific segment of the LNG industry, our findings have potential implications for strategic technology decisions, as well as technology configuration and capacity choices in other settings. Likewise our insights into the importance of accurately modeling processing time uncertainty when supporting these strategic decisions potentially offer guidance in other settings. Specifically, this accuracy issue is important because lack of data, a typical issue especially when evaluating emerging technologies, may prevent managers from developing accurate operational models, leading to misspecification and potentially wrong and costly choices in technology and capacity levels. In some cases, even if the data were available, managers may prefer simpler models with fewer parameters (Little 1970, Hax et al. 1980, Gino and Pisano 2008, Browning 2009). In our LNG setting, we know ex-ante what the accurate throughput model is. So we benchmark against it to measure the impact of using other simpler models of throughput. This leads to the following generic conclusions:

- For technology selection, accurate operational models may not be needed for extreme values of the relevant performance metrics, but otherwise they can be, as deterministic and stochastic operational models with different levels of processing time variability can lead to different choices. In this case, failing to accurately model the uncertainty in the processing times can lead to erroneous and costly conclusions as to when to deploy an emerging technology.

- Advanced configurations of an emerging technology that seek to reduce capital cost by employing a mix of resources with different cost structures may not pay off, due to the cost associated with complicating the process flow structure.

- Making good capacity investment decisions requires using stochastic models of throughput. Exaggerating the uncertainty in processing times by using exponential models, widespread in academic research, is far less harmful than ignoring this uncertainty using simpler deterministic models. In many cases, especially for emerging technologies, it is crucial to ensure sufficient capacity is present so as to be able to capture all of the potential revenue, even at the cost of possibly over-provisioning the system.

Our findings should be of interest to operations management researchers concerned in developing models for technology choice and capacity investment, as well as to operations managers involved in making these decisions in practice.

Our modeling approach may have other potential applications within the energy industry. For example, it may be used to evaluate other technology innovations in the LNG industry, such as
It may also be used to compare technologies in other industries; in particular in settings where one type is cheaper and requires a shorter time to install, but can sustain a lower production rate. Companies often face such tradeoffs when developing new technologies, both in manufacturing and service industries. One example occurs in emerging markets: A company can typically start manufacturing using cheaper and labor-intensive systems producing at a lower rate, or can enter the market with a more expensive automated system that sustains a higher production rate.

The remainder of this paper is organized as follows: We review the related literature in §2. We discuss the LNG networks based on the technology options we compare in §3. Section 4 presents our models. We conduct our structural analysis using our deterministic models of throughput in §5. Section 6 presents our numerical analysis and the insights it generates into the issues we investigate. We conclude in §7 by summarizing our findings and discussing further research avenues. Appendix A provides the proofs of the results established in §5.

2. Related Literature

Energy has long been an active area of research in both operations management and operations research. Durrer and Slater (1977) review the operations research literature that deals with petroleum and natural gas production. As demand for LNG increases worldwide, the recent literature has witnessed an increased amount of research on optimizing LNG supply chains both at the strategic and tactical planning levels.

Strategic planning typically involves decisions regarding investment in physical assets, such as LNG vessels, liquefaction and regasification terminals, and contractual terms and conditions, such as duration, volume, and destination clauses (Anderson et al. 2010). Özelkana et al. (2008) use a deterministic optimization model to analyze the design of LNG terminals. Rodríguez (2008) develops a real option optimization model to value the delivery flexibility embedded in long-term LNG contracts. Abadie and Chamorro (2009) use Monte Carlo simulation to value natural gas investments, including an LNG plant. Lai et al. (2011) develop a real option model to value LNG storage at regasification terminals that use the incumbent technology we discuss. Our paper adds to this growing literature by analyzing strategic and novel problems of technology selection, technology configuration, and capacity choice in LNG supply chains.

Tactical planning involves decisions such as fleet schedules, routes, and annual delivery programs. Kaplan et al. (1972), Koenigsberg and Lam (1976), and Koenigsberg and Meyers (1980) represent the shipping stage of an LNG supply chain using closed queueing networks and simulation.
models, capturing the uncertainties in the processing times. In this paper, we use the models of Koenigsberg and Lam (1976) to evaluate the throughput of some configurations of the incumbent and emerging LNG regasification technologies, and also develop original models to analyze the transshipment configuration of the emerging technology.

A recent stream of research focuses on the combined vessel routing and inventory management problem in LNG supply chains, extending the classical maritime scheduling and routing literature (reviewed by Ronen 1983, Ronen 1993, and Christiansen et al. 2004). Grønhaug and Christiansen (2009) introduce the LNG inventory routing problem (LNG-IRP). This problem consists of designing profit maximizing LNG vessel delivery routes and schedules, LNG production and regasification plans, and terminal inventory targets. These authors present both an arc-flow and a path-flow formulation of LNG-IRP. Grønhaug et al. (2010) propose a branch-and-price method for the same problem. Fodstad et al. (2010) develop a mixed-integer optimization model for a richer version of LNG-IRP, and discuss the implementation of LNGScheduler decision support software. Rakke et al. (2011) and Halvorsen-Weare and Fagerholt (2010) develop a rolling horizon heuristic and a decomposition based method, respectively, for solving simplified versions of LNG-IRP. All these papers assume given technology types and configurations, as well as fleet and port capacities. We complement these studies by developing and applying an integrated analytical model for the strategic optimization of LNG technology and capacity choices, which have significant influence on tactical scheduling and routing decisions.

Our research is also related to the literature that examines the impact of alternative uncertainty modeling choices on strategic supply chain planning in various industries. Zimmermann (2000) suggests an approach to determine, in a context dependent manner, a suitable method to model uncertainty in applications, such as inventory planning. Henn and Ottomanelli (2006) analyze how uncertainty affects the drivers’ route choice process in traffic assignment models and discuss the adequacy of deterministic and stochastic models in supporting traffic assignment calculations. Shutz et al. (2009) examine how the use of stochastic models of demand influences strategic capacity and location decisions in a meat processing supply chain as compared to using a deterministic model. In the context of a call center application, Bassamboo et al. (2009) discuss the impact of relaxing the assumption of exponentially distributed interarrival and service times on capacity choice and customer routing modeling. We add to this literature by assessing the impact of alternative service time distributions on the strategic analysis of technology selection and capacity investment decisions in LNG supply chains.

Our results also contribute to the practice-based literature in operations management and opt-
erations research by providing data-driven managerial principles (Fisher 2007, p. 374) illustrating
the drivers of the selection of LNG regasification technology and related configuration and capacity
choices, and offering specific guidance to executives making such decisions.

3. LNG and Regasification Technologies

LNG is natural gas that has been converted temporarily to liquid form for efficient storage and
economical transportation over long distances. The journey of LNG begins when natural gas,
extracted from underground reservoirs, is sent to a liquefaction facility through a pipeline. At the
liquefaction plant, the natural gas is cooled to minus 260 degrees Fahrenheit transforming it into
LNG. LNG takes 600 times less space than natural gas, thereby making it feasible to transport over
long distances. LNG vessels load LNG at the liquefaction facility and transport it to regasification
terminals at remote demand locations. At these import terminals, LNG is warmed back to its
natural gas state. It is then pumped into pipelines feeding the target market.

(a) Option OS: Incumbent onshore terminal based regasification.

(b) Option OB: Emerging onboard regasification without transshipment.

Figure 1: LNG networks based on the OS and OB options.

In this paper, we study the following three regasification technology and configuration options
currently available, or under examination, for LNG supply chains: Incumbent onshore-terminal
technology based system (option OS), emerging onboard technology based system without trans-
shipment (option OB), and onboard technology based system with transshipment (option OBT).
We describe each of these below.

We first contrast the LNG chains based on options OS and OB in Figure 1. In both systems,
ships load LNG at the loading port, transit to the unloading facility, unload their cargos, and transit
back to the loading port. However, in option OS (Figure 1(a)), conventional LNG carriers (LNGCs)
unload their LNG cargo, still in liquid form, to the storage tanks of the land-based terminal. LNG
in the tanks is then regasified by the regasification unit and pumped into the local natural gas
pipeline. In contrast, option OB (Figure 1(b)) has special LNG vessels (LNG regasification vessel – LNGRV) that can regasify LNG onboard at an offshore deepwater port location: When an LNGRV arrives at an offshore deepwater port, it connects to a submerged unloading buoy, vaporizes the LNG onboard, and subsequently delivers it to shore through a subsea pipeline.

Figure 2 displays the third option for the LNG chain that features a transshipment based configuration along with the emerging onboard technology (option OBT). In this configuration two types of ships are used: LNGCs and LNGRVs. Both types of ships sail toward each other, LNGC from the loading port and LNGRV from the deepwater port, until the two meet. Upon meeting, the LNGC transfers its cargo onto the LNGRV. After the cargo transfer is completed, the LNGRV sails back to the deepwater port to regasify the cargo, while the LNGC sails back to its loading port. The process then repeats for the next cycle. This type of a transshipment network may bring potential savings in capital investment by allowing the more expensive LNGRVs to dedicate more time to regasification, rather than transportation. The latter is conducted with cheaper LNGCs.

The vast majority (more than 90 %) of the global LNG trade is comprised of point-to-point networks with one liquefaction plant as the source of supply and one regasification facility at the demand location, with LNG vessels dedicated to this chain. Such networks are governed by long-term contracts specifying constant LNG throughput requirement rates. In other words, these supply chains are static and the demand rate is constant. This is due to the intensive capital investment required for the facilities and vessels (Tusiani and Shearer 2007, p. 200). Furthermore, due to long
lead times required for building the facilities and vessels, technology and capacity choice decisions are made at the outset of the LNG projects. Thus, in this paper we focus on this type of LNG supply chain.

When modeling these three LNG network options, we make the following modeling assumptions: (1) We do not include storage in our analysis, as (natural gas) storage could be available for both systems, at a roughly equal price. For the onboard technology, one could store natural gas after the LNG regasification step, for example in underground storage facilities. For the onshore technology, the regasification terminal allows for some storage, but natural gas, as opposed to LNG storage, offers the ability to store supply for longer times. Thus, we do not think incorporating storage would affect our conclusions. (2) In our models, we assume that there is sufficient storage capacity at the liquefaction plant and the onshore terminal so vessels will not be delayed at the loading and unloading ports due to storage constraints. In practice, systems are typically managed to ensure this case. (3) In our models, we ignore the maintenance time of vessels when comparing different options. This should not bias our comparisons, as we could incorporate the time spent on vessel repairs/maintenance by simply suppressing the monetization of throughput for some periods of time, i.e., those corresponding to maintenance, during the project lifetime.

4. Models

In this section we explain the models developed to conduct our strategic analysis of the technology selection and configuration and capacity decisions. In §4.1, we describe the models developed to calculate the throughput obtained at given resource levels for each of the LNG network options. In §4.2, we discuss the computation of the net present value (NPV) generated for given resource levels and throughput requirement. In §4.3, we present the optimization model employed to select the resource levels that maximize NPV for a given technology configuration and throughput requirement.

4.1 Throughput Models

We use both stochastic and deterministic models to calculate the throughput at given resource levels. These are discussed sequentially.

4.1.1 Stochastic Models

OS and OB options. We model the systems corresponding to options OS and OB in two different ways, in order to incorporate different levels of variability in the processing times.
The first model represents options OS and OB as product-form closed queueing networks (CQN)s, following Koenigsberg and Lam (1976), Koenigsberg and Meyers (1980), Wang (2008), and Lai et al. (2011); see Figure 3. We model the loading and unloading processes as FCFS exponential queues, and the transit processes as ample-server (AS) stations with service time distributions having rational Laplace transforms. Under these assumptions, each CQN has a closed product-form stationary distribution (Baskett et al. 1975).

Let $I$ be the total number of blocks (four blocks in Figure 3). Each block consists of the servers and queues at each station (loading, unloading, and transit). We denote the number of ships in block $i$ as $s_i$. The state of the shipping system is the array $s := (s_i, i = 1, \ldots, I)$, and satisfies $\sum_{i=1}^{I} s_i = S$, where $S$ is the total number of ships. Let $\lambda_i$ and $\mu_i$ be the mean arrival and service rate of block $i$, respectively. Denote by $\pi(s)$ the steady state probability that the system is in state $s$. Following Baskett et al. (1975), $\pi(s) = \Gamma \prod_{i=1}^{I} \gamma_i(\lambda_i, \mu_i, s_i)$, where $\Gamma$ is a normalizing constant chosen to make these probabilities sum to 1 and $\gamma_i(\cdot)$ is computed as follows:

$$\gamma_i(\lambda_i, \mu_i, s_i) := \begin{cases} \left(\frac{\lambda_i}{\mu_i}\right)^{s_i}, & \text{if block } i \text{ is FCFS}, \\ \frac{1}{s_i!} \left(\frac{\lambda_i}{\mu_i}\right)^{s_i}, & \text{if block } i \text{ is AS}. \end{cases}$$

In an OB system, there can be multiple unloading buoys/subsea-pipelines at the unloading port to enable unloading multiple vessels at the same time. In this case, station 1 (the unloading port in Figure 3) has multiple servers (buoys/subsea-pipelines), and $\gamma_1(\lambda_1, \mu_1, s_1)$ becomes $\left(\frac{\lambda_1}{\mu_1}\right)^{s_1}/\prod_{a=1}^{s_1} y(a)$, where $y(a)$ is the rate of service at station 1 when there are $a$ vessels at this
station relative to the service rate when there is only one vessel at this station. If there are $B$ servers at station 1, then

$$y(a) := \begin{cases} a, & 1 \leq a \leq B, \\ B, & a > B. \end{cases}$$

Let $S$ denote the set of all possible states of the system. Denote by $S'$ the set of states in which at least one ship is in station 3 (loading port), i.e., $S' := \{ s \in S : s_3 > 0 \}$. Then, denoting by $c$ the cargo size of a ship, the throughput rate is

$$X = c\mu_3 \sum_{s \in S'} \pi(s). \quad (2)$$

The only difference between the OS and OB systems is the service rate of the unloading block, $\mu_1$; due to onboard regasification, an LNGRV unloads its cargo at a slower rate than an LNGC.

In the product-form CQN model explained above, we must assume exponentially distributed service times for the FCFS loading and unloading stations (For expositional convenience, we refer to this product-form model as the exponential model in the following sections). But the coefficient of variations (CVs) of the actual service times often fall in the 0.15-0.25 range (these CV values are reported by Koenigsberg and Lam 1976, and, according to Lane 2008, they are consistent with empirically observed CVs). To account for this feature, we use our second model to compute the throughputs of the OS and OB systems; a Monte Carlo simulation with normally distributed service times and all their CVs equal to 0.15 or 0.25 and negative service times reset to zero (Koenigsberg and Lam 1976) (when truncated at zero, the change in CV values is negligible, less than $10^{-5}$). We built our model using the ARENA simulation software following the process flow chart in Figure 3. We select the simulation run times and number of replications such that the throughput rate becomes insensitive to the simulation length and the half-width of a 95% confidence interval is at most 0.5% of the mean.

**OBT option.** We likewise calculate the throughput of the onboard technology based system with transshipment (option OBT) with a Monte Carlo simulation assuming different levels of service time variability (all exponential distributions or all truncated normal distributions with CVs equal to 0.15 or 0.25). Figure 4 displays the flow chart for this system. An entity representing an LNGRV or an entity representing an LNGC flow into a match block immediately after they leave the unloading deepwater port or the liquefaction plant, respectively. When an entity arrives at the match block, it is placed in one of two associated queues, one for each vessel type. Entities remain in their
respective queues until a match occurs. We record this waiting time in the match block queue to obtain the distance traveled by the matching vessel before the match occurs.

Once a match occurs, one entity from each queue is released. After the vessels leave the match block, they flow into a batch block to form a single entity representing the paired vessels that will transship. Batched entities are delayed in the transit-to-meet block for the remaining time required to meet, which is equal to half the difference between the one way transit time and the previously recorded time waited in the match block. Then, the batched entity is delayed in the transshipment block for the time required by the ship-to-ship LNG transfer. When this transfer is completed, the batched entity is separated into its component entities in the separate block. Upon leaving the separate block, the entities representing the LNGRV and the LNGC are delayed in their respective transit blocks for the time required for sailing from the location where transshipment was performed to the deepwater port or the liquefaction plant, respectively.

We use the ARENA simulation software to calculate the throughput of the OBT option, following the same approach described earlier to select the simulation run times and number of replications.

4.1.2 Deterministic Models

OS and OB options. Let $c_i$ represents the capacity of station $i$ in the OS and OB based networks in Figure 3, $i = 1, \ldots, I$. For the FCFS stations ($i = 1, 3$), $c_1 = B\mu_1$ and $c_3 = \mu_3$; and for the
AS stations \((i = 2, 4), c_i = S\mu_i\). The bottleneck capacity of the LNG network is then \(K := \min(c_i, i = 1, \ldots, I)\). Let \(D\) denote the demand rate of ships in the system: \(D := S/\sum_{i=1}^{I} 1/\mu_i\).

The throughput rate of the deterministic OS and OB networks is the cargo size of a ship, \(c\), times the minimum of the bottleneck capacity and the demand rate:

\[X_d = c \min(K, D).\]  \hfill (3)

**OBT option.** Figure 5 represents the process flow of a deterministic onboard system with transshipment (option OBT). One can think of this system as two conjoined loops that are coupled via the transshipment block. Let \(S_1\) and \(S_2\) be the number of LNGRVs and LNGCs in loops 1 and 2, respectively, and \(\tau\) be the travel time between the unloading and loading ports: \(\tau := 1/\mu_2 + 1/\mu_6 = 1/\mu_4 + 1/\mu_7\). In this network, since uncertainty in the processing times is eliminated and the ships sail until they meet, the transhipment point must be fixed, either between the unloading and loading ports, at the unloading port, or at the loading port, depending on the number of vessels of each type, \(S_1\) and \(S_2\), and the service rates, \(\mu_i, i = 1, \ldots, 7\). If the transhipment point is between the unloading and loading ports, then loops 1 and 2 are perfectly coordinated: No ship will ever wait to transship. In this case, the demand rate of the network is simply the total number of available ships divided by the sum of the processing times in the network: \((S_1 + S_2)/(2(\tau + 1/\mu_3) + 1/\mu_1 + 1/\mu_5)\). If the transhipment point is at the unloading port,
then LNGCs wait until LNGRVs complete regasifying LNG to conduct the LNG transfer. In this case, the demand rate of the network is the demand rate of the bottleneck loop 1: \( S_1/(1/\mu_1 + 1/\mu_3) \). Similarly, if the transshipment point is at the loading port, the demand rate of the network is the demand rate of the bottleneck loop 2: \( S_2/(1/\mu_5 + 1/\mu_3) \). The demand rate of the ships in the network is then
\[
D^{OBT} := \min\left(\frac{S_1 + S_2}{2(\tau + 1/\mu_3) + 1/\mu_1 + 1/\mu_5}, \frac{S_1}{1/\mu_1 + 1/\mu_3}, \frac{S_2}{1/\mu_5 + 1/\mu_3}\right). \tag{4}
\]

Let \( K^{OBT} \) denote the bottleneck capacity of the network: \( K^{OBT} := \min(c_i, i = 1, \ldots, 7) \). The throughput rate of the deterministic OBT network is the cargo size of a ship times the minimum of the bottleneck capacity and the demand rate:
\[
X_d^{OBT} = c \min(K^{OBT}, D^{OBT}). \tag{5}
\]

### 4.2 Valuation Model

The NPV generated by given resource levels at a given throughput requirement is defined as the present value of the obtained revenue stream minus the present values of the operational and capital investment costs incurred during the project lifetime. We compute NPV using a risk neutral valuation approach (Smith 2005, Luenberger 1998, Ch. 13). Assuming that the capital investment costs are incurred at time zero, we discount the cash flows over the project lifetime using a constant annual risk-free rate. To calculate the revenue, we use New York Mercantile Exchange (NYMEX) natural gas futures prices. That is, we monetize the throughput during each month in the project lifetime at the respective futures price. Since the futures prices capture the current market view of future supply and demand conditions, this approach takes into account uncertainty in future natural gas supply and demand. We assume that regasified LNG can be sold on the natural gas spot market at the prevailing market price at the time of regasification, i.e., the amount of natural gas that is vaporized and pumped into the local natural gas pipeline system does not affect the natural gas price. Given that we assume LNG is regasified in the U.S. (see §6.1), this is a reasonable modeling choice.

### 4.3 Optimization of Resource Levels

In this section, we present our optimization model that selects the resource levels at the outset of the project lifetime to maximize NPV for a given technology configuration and throughput requirement. Our model is an integer program. We employ the following additional notation to formulate our model:
\( N := (S_1, S_2, B) \): nonnegative integer valued resource level array (decision variable). This array is equal to \((0, S_2, 1)\), \((S_1, 0, B)\), and \((S_1, S_2, B)\) for options OS, OB, and OBT, respectively;

\( J := \{ \text{OS, OB, OBT} \} \): set of technology options, indexed by \( j \);

\( \mathcal{N}^j \): feasible resource level array set for option \( j \); \( \mathcal{N}^{\text{OS}} := \mathbb{Z}_+ \), \( \mathcal{N}^{\text{OB}} := \mathbb{Z}_+^2 \), \( \mathcal{N}^{\text{OBT}} := \mathbb{Z}_+^3 \);

\( t^{\text{OS}} \): investment cost of regasification terminal in option OS;

\( b \): investment cost of an unloading buoy/pipeline structure in options OB and OBT;

\( v_1 \): capital cost of an LNGRV;

\( v_2 \): capital cost of an LNGC;

\( h^j \): present value of operating cost of a vessel in option \( j \);

\( C_1^j(N) \): present value of investment and shipping costs in option \( j \) given the resource level array \( N \). This is defined as \( C_1^{\text{OS}}(N) = t^{\text{OS}} + S_2(v_2 + h^{\text{OS}}) \), \( C_1^{\text{OB}}(N) = Bb + S_1(v_1 + h^{\text{OB}}) \), and \( C_1^{\text{OBT}}(N) = Bb + S_1(v_1 + h^{\text{OBT}}) + S_2(v_2 + h^{\text{OBT}}) \);

\( X^j(N) \): throughput rate of option \( j \) obtained by the resource level array \( N \) according to one of the models described in §4.1;

\( X^T \): LNG throughput rate requirement;

\( R^j(X^T) \): present value of the revenue generated in option \( j \) at the \( X^T \) throughput requirement rate;

\( C_2^j(X^T) \): present value of the liquefaction and regasification costs in option \( j \) at the \( X^T \) throughput requirement rate;

\( V^j(X^T, N) \): NPV generated in option \( j \) at the \( X^T \) throughput requirement rate by the resource level array \( N \). This is defined as \( V^j(X^T, N) := R^j(X^T) - [C_1^j(N) + C_2^j(X^T)] \).

The optimization model for option \( j \in J \) is

\[
\begin{align*}
\text{max} & \quad V^j(X^T, N) \\
\text{s.t.} & \quad X^j(N) \geq X^T.
\end{align*}
\]
The objective function of this model is the NPV generated by option \( j \) when the throughput rate requirement is \( X^T \) and the resource level array \( N \) is deployed at the beginning of the project. The constraint on \( N \) imposes integrality restrictions on the resource level array. The constraint on \( X^j(N) \) ensures that the resource level array \( N \) is chosen to sustain the desired throughput rate \( X^T \) (\( X^j(N) \) is an average).

5. Structural Analysis with Deterministic Models

As discussed in §4.1, the throughput of an LNG supply chain can be calculated using stochastic or deterministic throughput models. When stochastic (CQN and simulation) throughput models are used, this throughput cannot be obtained as a closed form function of the resource levels (see §4.1.1). This situation restricts our ability to derive analytical expressions for the optimal resource levels under each technology options and analyze the comparative merits of these options when they are optimally capacitated. This section characterizes the optimal resource levels for each technology option and the selection among these options when deterministic throughput models are used.

Proposition 1 presents closed form expressions for the optimal resource levels under deterministically computed throughput. We define \( N^{j,*} := (S^{j,*}_1, S^{j,*}_2, B^{j,*}) \) as the array of these optimal resource levels for technology option \( j \in J \). We let \( \alpha^j \) denote the sum of the processing times for option \( j \) and define by \( \beta_1 \) and \( \beta_2 \) the sum of the transshipment time and the unloading time and the transshipment time and the loading time, respectively, that is: \( \beta_1 = 1/\mu_3 + 1/\mu_1 \) and \( \beta_2 = 1/\mu_3 + 1/\mu_5 \) for the OBT option discussed in §4.1.2. Furthermore, we denote by \( \lceil x \rceil \) the smallest integer larger than or equal to \( x \).

Proposition 1. (Optimal resource levels) It holds that

(i) \( N^{OS,*} = (0, \lceil \frac{X^T}{c} \alpha^{OS} \rceil, 1) \),

(ii) \( N^{OB,*} = \left( \lceil \frac{X^T}{c} \alpha^{OB} \rceil, 0, \lceil \frac{X^T}{c\mu_1} \rceil \right) \),

(iii) \( N^{OBT,*} = \left( \lceil \frac{X^T}{c} \beta_1 \rceil, \max \left( \lceil \frac{X^T}{c} \alpha^{OBT} - \lceil \frac{X^T}{c} \beta_1 \rceil \rceil, \lceil \frac{X^T}{c} \beta_2 \rceil \right) \right) \).

The expressions in cases (i), (ii), and (iii) are the minimum resource levels that satisfy the constraints of the optimization model in §4.3 when the throughput \( X^j(N) \) is calculated using deterministic models. Using these expressions, we calculate the optimal NPVs under each technology option, which enable us to characterize the choice among these options in Propositions 3 and 4 below. They are also used in our numerical analysis in §6.2 and §6.3, and support the comparison in §6.4 of the optimal capacity levels obtained using stochastic and deterministic throughput models. Case (iii) reveals an important insight into the optimal fleet composition of the OBT.
option: LNGRVs should be used only as floating regasification terminals, while LNG should be transported by cheaper LNGCs. That is, transshipment should be conducted as close as possible (due to the integrality of the resource levels) to the unloading buoy at the demand location. This insight continues to hold in our numerical analysis conducted in §6.3 using stochastic models of throughput.

Proposition 2 compares the optimal resource levels established in Proposition 1.

**Proposition 2.** (Comparison of optimal resource levels) Under deterministic models of throughput:

(i) the optimal fleet size under the OB option is always no smaller than it is under the OS option: \( S_{OB,*} \geq S_{OS,*} \);

(ii) the optimal fleet size under the OBT option is always no smaller than it is under the OB option: \( S_{OBT,*} + S_{OBT,*} \geq S_{OB,*} \);

(iii) the OB and OBT options require the same number of unloading buoys: \( B_{OB,*} = B_{OBT,*} \).

The relationship in case (i) is due to the extra time required for onboard regasification. The ordering in case (ii) is due to the extra time required for transshipment. The equality in case (iii) arises from the LNG unloading rate being the same under the OB and OBT options. This equality is specific to deterministic throughput models: It may fail to hold when using the stochastic throughput models. We use these relationships to explain the insights obtained from our numerical analysis discussed in §6.

Proposition 3 characterizes the dependence of the choice between the OB and OS options on the throughput requirement rate and LTD when throughput is computed with deterministic models.

**Proposition 3.** (Selection between the OB and OS options) Suppose that the deterministic models of throughput are used. The throughput requirement and LTD space can be partitioned into at most three regions: Two where one of the OB and OS options dominate, and a third where no dominance arises between the two technologies.

The proof of Proposition 3 is based on the analysis of the difference between the optimal NPVs achieved under the OB and OS options at a given throughput requirement. Our technology choice analysis in §6.2 shows that the stated partitioning of the throughput requirement and LTD space appears robust to the type of throughput model used (deterministic versus stochastic).

Proposition 4 characterizes the choice between the OB and OBT options under deterministically computed throughput.
Proposition 4. (Selection between the OB and OBT options) Suppose that the deterministic models of throughput are used. The choice between the OB and OBT options oscillates as the throughput requirement changes.

The proof of Proposition 4 relies on the analysis of the difference between the optimal NPVs achieved under the OB and OBT options for a given throughput requirement. The result is a consequence of the non-monotone step function structure of this difference; it can take positive or negative values based on the tradeoff between the capital investment savings obtained by replacing expensive LNGRVs with cheaper LNGCs and the capital and operating costs of extra vessels required under the OBT option. In §6.3 we see that the conclusions of Proposition 4 persist when using stochastic models of throughput.

6. Numerical Analysis

We apply our models to conduct a field study integrating financial and operational data. Some of the parameter values used in our study were determined in consultation with the managers of Excelerate Energy, while others are based on the existing LNG literature. Table 1 reports the relevant units of measurement and conversion factors.

6.1 Numerical Values for the Relevant Parameters

We consider an integrated LNG chain with a 25 year lifetime, the length of a typical LNG project (Flower 1998). Our LNG chain has one liquefaction facility and one regasification facility. With the incumbent technology, we assume that the regasification terminal is located at Lake Charles, Louisiana, which indeed hosts an onshore LNG terminal operated by Trunkline LNG. We also assume that the offshore facility is located nearby; for example, Excelerate Energy’s Gulf Gateway offshore deepwater port is located 100 miles off the Louisiana coast. We assume that the liquefaction plant is located in Egypt, one of the major LNG exporters (Smith et al. 2004, Lai et al. 2011). The distance between Egypt and Lake Charles is approximately 7,000 NMs.

We use the following parameters in our study.

Shipping. We consider a homogeneous ship cargo size of 3 bcf, which is common in the LNG industry (Flower 1998). We assume a shipping speed of 19 knots (Cho et al. 2005, Flower 1998, p. 100). With this assumption, a one-way trip between the regasification facility and the liquefaction plant takes approximately 15 days, on average.

Liquefaction Plant. Following Wang (2008) and Lai et al. (2011), we consider the mean service
Table 1: Units of measurement and conversion factors

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>bcf</td>
<td>Billion Cubic Feet</td>
</tr>
<tr>
<td>cm</td>
<td>Cubic Meter</td>
</tr>
<tr>
<td>bcf/d</td>
<td>Billion Cubic Feet per Day</td>
</tr>
<tr>
<td>MMTPA</td>
<td>Million Tons per Annum</td>
</tr>
<tr>
<td>MMBTU</td>
<td>Million British Thermal Units</td>
</tr>
<tr>
<td>NM</td>
<td>Nautical Mile</td>
</tr>
<tr>
<td>1 Knot</td>
<td>= 1 NM per Hour</td>
</tr>
<tr>
<td>1 bcf</td>
<td>= 1,100,000 MMBTU</td>
</tr>
<tr>
<td>1 MMTPA</td>
<td>= 0.128 bcf/d</td>
</tr>
<tr>
<td>1 cm</td>
<td>= 0.0000215 bcf</td>
</tr>
</tbody>
</table>

time at the liquefaction plant (loading port) to be 1 day. This is the time required by a vessel for entering the loading port, loading 3 bcf of LNG, completing the required paperwork, and leaving the port.

**Onshore Terminal.** We assume that the regasification capacity of the onshore terminal is 2 bcf/d, which is consistent with the capacity of some of the onshore terminals in the U.S., including Lake Charles. We set the mean service time at the onshore terminal (entering the port, unloading 3 bcf of LNG into the storage tanks, completing the required paperwork, and leaving the port) as 1 day (Koenigsberg and Lam 1976). Following Lane (2008), we let the LNGC capital cost be $250M.

The capital cost of an onshore terminal varies considerably depending on factors such as storage and vaporization capacity, cost of real estate, geological structure, local labor and construction costs, and marine environment (Tusiani and Shearer 2007). Thus, varying cost figures are reported in the literature. For instance, Smith et al. (2004) state that a 1 bcf/d regasification terminal costs $0.5B, and EIA (2003) states that the cost of a terminal can range from $0.1B to $2B depending on its regasification capacity. In our base case, we set the onshore terminal cost to be $1.5B (Lane 2008). We also conducted an analysis including the cost of the onshore terminal as a function of its regasification capacity, consistent with these cost figures. In §6.2, we explain how our conclusions change when we use this cost function, instead of a $1.5B fixed cost for all throughput levels.

Tusiani and Shearer (2007) report that the construction time for an LNG terminal does not generally vary with the size of the facility. Rather, it is determined by the construction schedule for the storage tanks, the most time-consuming and expensive components of a terminal, and is typically take between 2 and 5 years. As our base case, we assume that it takes 5 years to construct the onshore terminal. In §6.2 we explain how our conclusions change with a shorter terminal construction time.

**Deepwater Port.** We assume that the LNG regasification rate of an LNGRV is 0.5 bcf/d (En-
ergy Bridge Fact Sheets 2008), so we set the mean service time at the deepwater port (mooring, connecting with the submersed buoy, vaporizing 3 bcf of LNG, and leaving the port) as 7 days (Lane 2008). We let the capital cost of an LNGRV be $275M (Lane 2008). We assume that each buoy/subsea-pipeline structure (each server) at the deepwater port costs $70M, and that it takes 1 year to construct the deepwater port (Gulf Gateway Fact Sheets 2008), independent of the number of buoys in the deepwater port. The LNG transshipment service time is taken to be 2 days on average (Lane 2008).

**Operational Cost.** This cost has three components: Liquefaction, shipping, and regasification. Following Wang (2008) and Lai et al. (2011), we assume that the liquefaction plant operating cost is $8M per MMTPA. According to Lane (2008), the shipping cost is $47.851M per ship per year (this includes fuel and crew costs). We take the regasification variable cost as $0.0285 per MMBTU with a 1.69% fuel loss (Wang 2008, Lai et al. 2011).

**Revenue.** We use NYMEX natural gas futures prices as of 8/8/2008 (Figure 6) for calculating the relevant revenue figures. For each trading day, NYMEX futures prices are available for maturities of 148 months in the future. To estimate the futures prices for the months beyond the last available maturity, we replicate the prices of the last 12 available months. We set the annual risk-free interest rate as 1.7%, the three-month U.S. Treasury rate as of 8/8/2008. Recall that we use a risk a neutral valuation approach.

![Figure 6: NYMEX natural gas futures prices as of 8/8/2008.](image)
6.2 Technology Selection: Comparing OB and OS

In this subsection we analyze technology selection, comparing the OB and OS systems. To evaluate the sensitivity of this choice, we compare the two technologies employing both the stochastic and deterministic models of throughput detailed in §4.1. In our comparison, the LNG networks using each technology option are optimally resourced given a target throughput requirement, as discussed in section §4.3. We vary the target throughput requirements up to and including 2 bcf/d with a grid of at least 10,000 evaluation points.

We first report our findings obtained using the throughput formula (2), which assumes exponentially distributed service times for loading and unloading, and transit time distributions with rational Laplace transforms. The dashed line in Figure 7 shows the difference obtained by subtracting the total capital and operating costs of the OS system from those of the OB system under the parameters reported in §6.1. The jittery pattern is caused by the integer-valued fleet size difference between the OB and OS systems: The magnitude of each peak corresponds to the capital and operating cost of an additional vessel required by the OB system compared to the OS system to sustain the throughput interval in which the peak occurs. The dashed cost difference line shows that for “low” throughput levels – less than 0.5 bcf/d – the OB system’s cost is lower than that of the OS system, due to the lower capital investment required to build the offshore deepwater port compared to the land based terminal for the OS option. However to sustain higher throughput levels, the OB system needs several unloading buoys and more vessels than the OS system (consis-
tent with case (i) of Proposition 2, which is based on deterministic throughput models), due to its lower unloading rate. This requires a level of additional capital and operating costs that diminish the cost advantage of the OB system. Soon the total cost of the OB system becomes significantly larger than that of the OS system for “high” throughput levels – more than 0.5 bcf/d.

But this cost difference is not the entire story: The solid line in Figure 7 displays the difference obtained by subtracting the NPV of the OS system from the NPV of the OB option. This line shows that for all throughput levels the OB system generates significantly more NPV than the OS system, even though the cost of the OB system is much higher for high throughput levels. This result arises due to the shorter time required to build an onboard regasification facility compared to an onshore terminal (recall that we assume it takes one year to complete the deepwater port and five years to construct the onshore terminal). That is, due to its four year LTD, the OB system starts generating revenue four years earlier than the OS option. As a result, as shown in Figure 7, the OB system is more profitable than the OS system even though its total cost may be greater than that of the OS system for high throughput requirements.

Clearly, the NPV difference displayed in Figure 7 is specific to the parameters reported in §6.1. In practice, LTD and the magnitude of the NPV advantage it generates for the OB system can vary with operational parameters and market conditions, such as the permit approval process, facility construction time, vessels availability, LNG supply, natural gas futures prices, and interest rates. For instance, due to idiosyncrasies in the LNG industry, building LNGRVs, which are used in the
OB option, may take longer than the one year we assumed, decreasing the LTD. Moreover, the natural gas future prices or the interest rate that will be employed in actual technology selection analyses might be lower than the levels used in our analysis, which would likewise reduce the NPV advantage for the OB option. In all of such cases, the slope of the NPV difference curve would be lower than that displayed in Figure 7, rotating the curve clockwise as illustrated in Figure 8.

(a) High LTD.          (b) Medium LTD.          (c) No LTD.

Figure 9: Technology selection for different LTD cases.

To further illustrate the impact of LTD on technology selection, we analyze three scenarios: High, medium, and no LTD. In each of these scenarios, we vary the year when the OB system starts generating revenues (high LTD – year 1, medium LTD – year 3, and no LTD – year 5), while fixing the completion time for the onshore terminal at year 5. All the other parameter values remain as reported in §6.1. Figure 9 illustrates the technology choice for each of these LTD cases. Under the high LTD scenario (Figure 9(a)), the OB option is the preferred choice for all throughput requirements, due to the factors explained earlier. Under medium LTD (Figure 9(b)), three regions appear. At either extreme end of the throughput requirement, low (less than 0.5 bcf/d) and high (more than 1.75 bcf/d), the OB and OS options are preferred, respectively. However, at the remaining throughput levels (0.5-1.75 bcf/d), neither technology dominates the other. In this no-dominance region, the preferred technology option oscillates as the throughput requirement changes. This is due to the jittery pattern of the NPV differences between the two technology options caused by integral fleet sizes. Finally, when there is no LTD (Figure 9(c)), again three regions result. For low throughput requirements (less than 0.5 bcf/d), OB is the preferred option. At higher throughput levels (more than 0.6 bcf/d), OS is the better choice. The no-dominance region still appears, but it is much smaller compared to the medium LTD case in Figure 9(b). This shows that LTD can play an important role in the selection of LNG regasification technology.

We replicate our analysis employing the alternative stochastic and deterministic throughput
models explained in §4.1. Figure 10 displays technology choice as a function of throughput requirement and LTD, when various types of throughput models (exponential, normal with all CVs equal to 0.15 or 0.25, and deterministic) are employed. As established in Proposition 3, the throughput requirement and LTD space is partitioned into three regions when using deterministic models of throughput; two where one of the two technologies dominates over the other, one region where no dominance arises between the two technologies. We observe the same finding under all the stochastic throughput models utilized. Furthermore, we observe that the boundaries of the no-dominance region vary only slightly, but the preferred technology option in this region may change with the type of model utilized. However, in the overlapping dominance regions, the preferred technology option remains the same. Hence, in these regions technology selection is insensitive to the model type, but otherwise this may not be the case.

In the no-dominance region the preferred technology oscillates as the throughput requirement changes, due to the cost of under-utilized shipping capacity arising with integral fleet sizes. In practice, companies can adjust the specifications of their vessels (e.g., engine size, cargo capacity, speed) to mitigate these integrality effects. However, as they have access to only a limited set of specification options, the integrality effects typically cannot be eliminated. Hence, the no-dominance region poses a formidable challenge for technology selection, requiring further analysis in which other factors, such as the available vessel specification options, have to be evaluated.
Moreover, as shown earlier, the technology choice in this region is sensitive to the throughput model used, and making an error can be quite costly: Figure 8 suggests that the cost of a wrong technology choice in this region can be as high as $1.21B (the height of a peak when the NPV difference oscillates around the throughput axis, reflecting the total capital and operating costs of a vessel).

On the other hand, in regions where one technology option dominates the other, the preferred option remains the same even when the vessels can be specified to sustain full-utilization. In other words, the technology selection in these dominance regions is relatively robust compared to the choice in the no-dominance region. To support this claim, we replicated our analysis on technology selection by relaxing the integrality constraint on fleet size: We compute the throughput with the deterministic throughput equation (3), allowing the number of vessels, $S$, to take fractional values to achieve full utilization of the shipping capacity at a given throughput requirement. This mimics the best case scenario in which companies can adjust vessel specifications such that all vessels are fully utilized. Figure 11 presents the resulting NPV differences. Compared to our earlier analysis, we observe that the preferred technology options in the dominance regions remain the same, and the no-dominance region disappears.

In summary, our technology selection analysis reveals conditions under which each technology should be adopted as a function of the throughput requirement and LTD. We find that:

- If the throughput requirement is low, an OB system is always more profitable than an OS
system, due to the OB system’s lower capital investment cost.

- As the throughput requirement increases, the technology adoption choice depends on LTD: Although the OB system’s total cost is greater than that of the OS system for high throughput requirement levels, the extra NPV that may be obtained by the OB system, due to faster revenue generation, may make it more profitable than the OS system.

The former finding is consistent with the literature (Jensen 2003, Smith et al. 2004). However, the latter finding contrasts with those obtained by Jensen (2003) and Smith et al. (2004): These authors state that the emerging onboard technology is well-suited for seasonal and occasional usage, i.e., the low throughput case; they also report that the incumbent onshore technology is more profitable than the emerging onboard technology in the high throughput case. In contrast, our models demonstrate that the onboard technology can be the preferred choice at high throughput requirements, provided the NPV advantage arising from LTD is great enough.

At first glance, it is surprising that the onboard technology, which features a longer time for vessel unloading, outperforms the onshore technology even at high throughput levels. The reason for this apparently counterintuitive result is the possibility of configuring the onboard technology using multiple unloading buoys, a factor that the extant literature and practitioners have seemingly ignored. Optimizing the number of buoys and fleet size overcomes the onboard technology’s disadvantage of slower unloading rate. This, together with the NPV advantage arising due to the LTD, may enable the onboard technology to outperform the onshore technology at high throughput requirements. Thus, our analysis challenges the LNG industry to think differently about the emerging onboard technology, and can help in promoting the adoption of this emerging technology.

In §6.1, we explained that the capital cost of an onshore terminal may vary considerably. Therefore, we analyze the sensitivity of our technology choice findings by modeling the capital cost of the onshore terminal as a function of the terminal’s regasification capacity: We assume that capital cost of the onshore terminal increases by $0.5B for every 0.5 bcf/d increase in throughput requirement. (These figures are consistent with those reported in the literature, as explained in §6.1.) Compared to our earlier analysis, we observe that the OS system may be more profitable than the OB system for some throughput intervals in the low throughput region. However, for high throughput requirements, our findings on technology choice remain robust: The technology choice depends on LTD in a similar manner to the case with fixed terminal cost. The LTD and throughput space has the same partitioning as in Figure 10, but the no-dominance region expands.
6.3 The Benefit of Configuring the Emerging Technology with Transshipment: Comparing Options OB and OBT

In this subsection we compare the OB and OBT options to study the merit of ship-to-ship LNG transshipment, a configuration that companies such as Excelerate Energy and Höegh LNG are exploring to improve the profitability of the OB option. Transshipment allows a firm to configure a fleet of ships as a mix of the cheaper LNGCs and more expensive LNGRVs. Such a configuration can potentially reduce capital investment costs at the expense of introducing an additional processing step in the LNG network: The ship-to-ship LNG transfer. It also partially decouples the transportation from the storage and regasification processes, which in turn leads to higher utilization of the regasification capacity of the more expensive LNGRVs. In other words, while incurring additional processing time in the network, transshipment enables the LNGRVs to dedicate more time to regasification rather than transportation. We examine this tradeoff by computing the *net benefit of transshipment* in terms of improved profitability of an OB based system. We also evaluate how this configuration impacts our technology selection insights presented in §6.2.

Figure 12 displays the difference obtained by subtracting the NPV of the system with transshipment from the NPV of the system without transshipment assuming exponential service times. (In Figure 12, the NPV difference starts at 0.079 bcf/d, because one LNGRV is sufficient to sustain this level. Thus, there is no need for transshipment.) This figure quantifies the stated tradeoff between the capital investment savings obtained by replacing the expensive LNGRVs with the cheaper...
LNGCs, and the capital and operating costs of extra vessels required due to the additional transshipment activity. For most throughput levels, the OB option generates significantly more NPV than the OBT option. This arises since an OBT system typically requires more vessels than an OB system to sustain a given throughput requirement (as also suggested by case (ii) of Proposition 2), due to the additional time required for the ship-to-ship LNG transfer and the synchronization of the ships. The capital and operating costs of these extra ships far exceed the savings resulting from using the cheaper LNGCs. Only at some throughput intervals less than 0.5 bcf/d, does transshipment pay off in terms of NPV. But as seen in Figure 12, even in these cases the benefit is marginal.

We replicated our analysis using a deterministic throughput model and normal models with CVs equal to 0.15 or 0.25. This yields NPV difference curves that are very similar to the one in Figure 12 (this finding is also implied by Proposition 4, when deterministic throughput models are used). Hence, the OB technology configuration choice seems to be robust to the model type.

In summary, our analysis indicates that LNG supply chains based on the OB regasification technology should be developed, when possible, using only dedicated LNGRVs, rather than both vessel types. The use of transshipment should only be considered as a way to circumvent capacity restrictions if the availability of LNGRVs is limited. This finding provides an answer to the process configuration and fleet structure questions faced by LNG companies planning to use, or already using, the emerging OB technology (Bryngelson 2007). The costs associated with transshipment may overcome its benefits, which is also emphasized by the literature on transshipment in retail industry (Çömez et al. 2012). Our analysis also reveals that the insights on technology selection presented in §6.2 are not affected by the potential deployment of the OB technology using transshipment.

6.4 Capacity Sizing

In this subsection we compare the optimal resource levels prescribed by stochastic and deterministic throughput models for each of our technology options. Obviously, the optimal resource levels computed by utilizing stochastic throughput models, which account for uncertainty in processing times, are higher than those obtained in Proposition 1 when using deterministic throughput models. What is less obvious is the magnitude of this difference and its consequence on the throughput achieved and the NPV realized. We quantify these effects.

First, we compare the optimal resource levels calculated using the exponential and deterministic throughput models, (2) and (3). Figure 13 illustrates the optimal number of buoys and vessels for the OB system. This figure shows that the resulting fleet sizes are often similar, but using the
Figure 13: Optimal resource levels calculated with the deterministic and exponential throughput models - OB.

The exponential model typically yields a higher number of unloading buoys: When it needs to increase throughput, the optimization model first chooses to install an additional buoy, since the capital and operating cost of an additional vessel is far higher than the cost of an unloading buoy. When adding an extra buoy can no longer boost throughput, this model adds an extra ship. This increases the throughput dramatically, so the target throughput can be met with fewer buoys. (In Figure 13, when the number of buoys decreases, this always coincides with an increase in fleet size.)

Figure 14(a) displays the throughput levels achieved when the optimal resource levels computed using the deterministic throughput model are evaluated using the exponential throughput model. This yields a gap between the targeted and achieved throughput levels, which indicates a potential inefficiency.

Figure 14: Throughput and NPV shortfalls resulting from deterministic analysis - OB.
throughput shortage relative to the targeted level when a deterministic model is used for resource planning. This gap can be as large as 17.29%. Figure 14(b) quantifies the analogous NPV shortfall. The NPV shortfall can be as large as $12B, or, equivalently, 13% of the total NPV generated. These figures reflect the potential errors that may result from a deterministic analysis.

Figures 15 and 16 are analogous to Figures 13 and 14, respectively, but pertain to the OS system. Although the throughput and NPV shortfalls due to employing the deterministic throughput model are still present and can be as large as 7.86% and $5.5B (8.4% of the total NPV), they are smaller than in the OB option case due to the shorter vessel unloading times. (The negative valued

Figure 15: Optimal fleet size calculated with the deterministic and exponential throughput models - OS.

Figure 16: Throughput and NPV shortfalls resulting from deterministic analysis - OS.
peaks in the NPV shortfall graphs 14(b) and 16(b) arise due to the integral fleet size; sometimes the deterministic model chooses fewer vessels, and ultimately misses the throughput target, but is more profitable. The throughput requirements where the NPV shortfall is negative, however, would never be chosen as targets in practice, since more NPV can be generated by targeting either lower or higher throughput rate levels, for both the OB and OS options.)

We also compare the results obtained with the deterministic and exponential models with those obtained using the normal models with CVs equal to 0.15 or 0.25. In other words, we quantify the potential errors due to ignoring and magnifying the variability in the service times that has been observed empirically, using the normal models as benchmarks.

First, we evaluate the optimal resource levels computed with the deterministic throughput models (presented in Proposition 1) against the normal benchmark model. For the OB system, the throughput and NPV shortfalls are as large as 6.31% and $4.95B (5.3% of total NPV) when the CV is 0.15, and 8.9% and $6.47B (6.96% of total NPV) when the CV is 0.25. For the OS system, the throughput and NPV shortfalls are as large as 3.89% and $3.62B (3.44% of total NPV) when the CV is 0.15; and 4.47% and $4.25B (4.1% of total NPV) when the CV is 0.25. These figures underscore our earlier result that the throughput and NPV shortfalls resulting from the deterministic analysis are substantial, even when the CV of the service times is smaller than one (the exponential case).

Next, we compare the exponential and normal models to investigate the cost of over estimating uncertainty. For both the OB and OS systems, the exponential model prescribes at most one more vessel than the normal models (5.5% and 6.25% of the fleet sizes). The capital cost of an extra vessel is $275M and $250M (0.39% and 0.34% of total NPV) for the OB and OS systems, respectively. These figures suggest that the cost of over-provision due to overestimating uncertainty in service times is much lower than the cost that arises when uncertainty is ignored. Thus, it is crucial to ensure sufficient capacity to capture all of the potential throughput (and the subsequent revenue), even at the risk of possibly over provisioning the system.

These findings show that capacity sizing is delicate, as the chosen resource levels depend on the type of model used to compute throughput. Our analysis reveals that modeling uncertainty in service times is important when sizing the capacity of an LNG supply chain: Using deterministic models may result in substantial throughput and NPV shortfalls. On the other hand, overestimating the capacity by assuming exponential service times changes the NPV generated by a smaller amount.
7. Conclusions

We analyze LNG regasification technology selection, as well as technology configuration and capacity choices, motivated by recent developments in the LNG industry. Our strategic analysis brings to light conditions under which a specific regasification technology and its configuration are appropriate for adoption, and also provides insights into how to size the capacity of an LNG supply chain. We conduct our analysis using different operational models of LNG throughput, to assess the sensitivity of these strategic decisions to the modeling of uncertainty. Some of our insights attribute a different role to the emerging technology than currently envisioned; others offer new perspectives on pressing issues encountered by companies that are currently deploying this technology on a commercial scale: Our findings provided useful guidelines to executives at Excelerate Energy for their strategic-level planning of capital investments and operating decisions. Overall, our research sheds new light on the impact of alternative operational models of throughput on strategic decisions regarding technology selection and capacity investments.

Our results also have potential relevance for other companies developing new LNG supply chains, as well as for supporting related choices in other settings. In particular, our findings suggest the following insights: (1) Simple deterministic models of throughput may be adequate to support strategic technology adoption choices in extreme cases where one technology clearly dominates the other, but are unlikely to be so otherwise. (2) The value of advanced configurations of an emerging technology should be evaluated against the cost of complicating the process flow structure in the supply chain, since this cost may overcome the associated benefits. (3) Especially in the deployment of emerging technologies, it is crucial to ensure sufficient capacity is present so as to be able to capture all of the potential revenue, even at the cost of possibly over-provisioning the system. This requires modeling the uncertainty in processing times when making capacity investment decisions. However, how this uncertainty is modeled may be less critical.

Our work could be extended in several directions. In this paper, we focus on technological innovations in the regasification and transportation of LNG. Increased global LNG demand has also led to several technological innovations in the upstream portion of LNG supply chains; for example, floating offshore liquefaction facilities (FOLFs). Companies that are seeking alternatives to conventional onshore natural gas liquefaction plants have expressed growing interest in FOLFs (Chazan 2009, Tusiani and Shearer 2007, Ch. 5). These facilities can offer greater flexibility and lower cost and capacity installation time as compared to onshore liquefaction plants (Loo 2009). One could adapt our models to study the selection of technology for natural gas liquefaction.
In this paper, we analyze the profit of an integrated LNG chain. However, LNG chains may include multiple parties that manage different stages of the chain, such as LNG producers, shippers, and merchants; these players may have conflicting objectives. In such a case, our models could be extended to include the perspectives of different parties within a game-theoretic framework. These models could then be used to analyze the impact of ownership and contractual terms on the design of an LNG supply chain.

Due to competition between LNG import markets, some LNG importers have recently experimented with diverting their cargoes to those markets with the greatest profit margins, such as the U.K., Spain, and Japan. Our models could be extended to assess the value of this delivery flexibility (Rodríguez 2008), and to support the development of practical vessel routing policies.

Acknowledgments

The authors thank Captain Mark K. Lane, Vice President-Operations at Excelerate Energy, for his help and support in determining the operational parameters in our numerical study. The authors also thank the entire review team whose constructive feedback led to a significantly improved version of this paper.

A. Proofs

For each technology option $j \in J$, the generic optimization model (6)-(7) formulated in §4.3 can be specified as explained below when using the deterministic models of throughput presented in §4.1.2. This optimization model for the OS option is

$$\max_{S_2 \in \mathbb{Z}^+} \quad R^{OS}(X^T) - C^{OS}_2(X^T) - t^{OS} - (v_2 + h^{OS})S_2$$

s.t. $$c \frac{S_2}{\alpha^{OS}} \geq X^T.$$  

This optimization model for the OB option is

$$\max_{S_1,B \in \mathbb{Z}^+} \quad R^{OB}(X^T) - C^{OB}_2(X^T) - hB - (v_1 + h^{OB})S_1$$

s.t. $$cB \mu_1 \geq X^T,$$

$$c \frac{S_1}{\alpha^{OB}} \geq X^T.$$
This optimization model for the OBT option is

\[
\begin{align*}
\max_{S_1, S_2, B \in \mathbb{Z}_+} & \quad R^{OBT}(X^T) - C_2^{OBT}(X^T) - bB - (v_1 + h^{OBT})S_1 - (v_2 + h^{OBT})S_2 \\
\text{s.t.} & \quad cB\mu_1 \geq X^T, \quad (A.7) \\
& \quad \frac{S_1 + S_2}{\alpha^{OBT}} \geq X^T, \quad (A.8) \\
& \quad \frac{S_1}{\beta_1} \geq X^T, \quad (A.9) \\
& \quad \frac{S_2}{\beta_2} \geq X^T. \quad (A.10)
\end{align*}
\]

**Proof of Proposition 1.** The objective function (A.1) strictly decreases when increasing the value of \( S_2 \). It is thus optimized at the minimum integer value of \( S_2 \) that satisfies the constraint (A.2):

\[ S^{OBT,*}_2 = \lceil \frac{X^T\alpha^{OS}}{c} \rceil. \]

The objective function (A.3) strictly decreases when increasing the values of both \( S_1 \) and \( B \). Thus, the optimal number of buoys is the minimum integer value of \( B \) that satisfies the constraint (A.4):

\[ B^{OBT,*} = \lceil \frac{X^T}{c\mu_1} \rceil. \]

The objective function (A.6) strictly decreases when increasing the value of \( B \). Thus, the optimal number of buoys is the minimum integer value of \( B \) that satisfies the constraint (A.7):

\[ B^{OBT,*} = \lceil \frac{X^T}{c\mu_1} \rceil. \]

The objective function (A.6) also strictly decreases when increasing the values of \( S_1 \) and \( S_2 \). Since \( v_1 > v_2 \), it follows that \( S^{OBT,*}_1 = \lceil \frac{X^T\alpha^{OB}}{c} \rceil \), which is the minimum integer value of \( S_1 \) that satisfies the constraint (A.9), and \( S^{OBT,*}_2 = \max(\lceil \frac{X^T\alpha^{OB}}{c} \rceil, \lceil \frac{X^T\beta_2}{c} \rceil) \), which is the minimum integer value of \( S_2 \) that satisfies both the constraints (A.8) and (A.10). \( \square \)

**Proof of Proposition 2.** Case (i) follows from the inequality \( \alpha^{OS} < \alpha^{OB} \). Consider case (ii). If \( \lceil \frac{X^T\alpha^{OBT}}{c} \rceil - \lceil \frac{X^T\beta_2}{c} \rceil \geq \lceil \frac{X^T\beta_1}{c} \rceil \), then it follows that \( S^{OBT,*}_2 = \lceil \frac{X^T\alpha^{OB}}{c} \rceil \). We then have

\[
S^{OBT,*}_1 + S^{OBT,*}_2 = S^{OBT,*}_1 + \lceil \frac{X^T\alpha^{OBT}}{c} \rceil - S^{OBT,*}_1 \quad \text{(since } S^{OBT,*}_1 \in \mathbb{Z}_+) \\
= \lceil \frac{X^T\alpha^{OBT}}{c} \rceil \\
= \lceil \frac{X^T\alpha^{OB}/c + 2X^T/(c\mu_3)}{c} \rceil \quad \text{(since } \alpha^{OBT} = \alpha^{OB} + 2/\mu_3) \\
\geq \lceil \frac{X^T\alpha^{OB}}{c} \rceil \\
\geq S^{OB,*}_1.
\]

If \( \lceil \frac{X^T\alpha^{OBT}}{c} \rceil - \lceil \frac{X^T\beta_2}{c} \rceil < \lceil \frac{X^T\beta_1}{c} \rceil \), it then follows that \( S^{OBT,*}_2 = \lceil \frac{X^T\beta_2}{c} \rceil \). This leads \( S^{OBT,*}_1 + S^{OBT,*}_2 \geq S^{OBT,*}_1 + \lceil \frac{X^T\alpha^{OB}}{c} \rceil - S^{OBT,*}_1 \). The rest of the proof proceeds in an analogous
manner to the proof of the previous case. It is thus omitted for brevity. Case (iii) is an immediate consequence of cases (ii) and (iii) in Proposition 1. □

**Proof of Proposition 3.** Define by $\Delta V^{OB-OS}(X^T)$ the difference between the optimal NPVs corresponding to the OB and OS technology options as a function of the throughput requirement $X^T$ given that deterministic throughput models are used:

$$\Delta V^{OB-OS}(X^T) := V^{OB}(X^T, N^{OB,*}) - V^{OS}(X^T, N^{OS,*}) = \left[R^{OB}(X^T) - C^{OB}_{2}(X^T) - R^{OS}(X^T) - C^{OS}_{2}(X^T)\right] + t^{OS} - b[X^T/c\mu_1] + (v_2 + h^{OS})[X^T\alpha^{OS}/c] - (v_1 + h^{OB})[X^T\alpha^{OB}/c].$$

Since $[R^{OB}(X^T) - C^{OB}_{2}(X^T)] - [R^{OS}(X^T) - C^{OS}_{2}(X^T)]$ is a linear function of $X^T$ and $t^{OS} - b[X^T/c\mu_1] + (v_2 + h^{OS})[X^T\alpha^{OS}/c] - (v_1 + h^{OB})[X^T\alpha^{OB}/c]$ is a non-monotone step function of $X^T$, $\Delta V^{OB-OS}(X^T)$ is a non-monotone discontinuous piecewise linear function of $X^T$. This function strictly increases when increasing LTD, since $V^{OB}(X^T, N^{OB,*})$ and $V^{OS}(X^T, N^{OS,*})$ strictly increase and decrease, respectively, when LTD increases, that is, when the OB and OS options' installation times decrease and increase, respectively. To emphasize the dependence of the function $\Delta V^{OB-OS}(X^T)$ on a given LTD level we write $\Delta V^{OB-OS}(X^T; LTD)$.

When LTD equals 0, we have $\Delta V^{OB-OS}(X^T; 0) = t^{OS} - b[X^T/c\mu_1] + (v_2 + h^{OS})[X^T\alpha^{OS}/c] - (v_1 + h^{OB})[X^T\alpha^{OB}/c]$. In this case there exist at most two throughput values $X^T_1(0)$ and $X^T_2(0)$, with $X^T_1(0) \leq X^T_2(0)$, such that if $X^T < X^T_1(0)$ then $\Delta V^{OB-OS}(X^T; 0) > 0$ and if $X^T > X^T_2(0)$ then $\Delta V^{OB-OS}(X^T; 0) < 0$. In words, when the throughput requirement $X^T$ is less than $X^T_1(0)$ the OB option dominates the OS option, and when this requirement exceeds $X^T_2(0)$ then the OS option dominates the OB option. Moreover, there is no dominance relationship between these options when $X^T \in [X^T_1(0), X^T_2(0)]$. If it holds that $t^{OS} - b > v_2 - v_1$ then $X^T_1(0) \geq c/\alpha^{OB}$ and $X^T_2(0) \leq t^{OS}c\mu_1/b$. Otherwise, we define $X^T_1(0)$ to be equal to 0 and it holds that $X^T_2(0) = 0$ if $t^{OS} - b < v_2 - v_1$ and $X^T_2(0) > c/\alpha^{OB}$ if $t^{OS} - b = v_2 - v_1$.

Since $\Delta V^{OB-OS}(X^T; LTD)$ strictly increases when increasing LTD, given a positive LTD value there exist at most two throughput levels $X^T_1(LTD)$ and $X^T_2(LTD)$, with $X^T_1(LTD) \leq X^T_2(LTD)$, such that if $X^T < X^T_1(LTD)$ then $\Delta V^{OB-OS}(X^T; LTD) > 0$ and if $X^T > X^T_2(LTD)$ then $\Delta V^{OB-OS}(X^T; LTD) < 0$. Moreover, both $X^T_1(LTD)$ and $X^T_2(LTD)$ weakly increase when increasing LTD. In other words, the OB and OS throughput requirement dominance intervals weakly expand and contract when increasing LTD. Thus, at some LTD value $LTD$ the OB option may dominate the OS option for all throughput requirements (in this case we define $X^T_1(LTD)$ and
When this occurs, the same relationship holds for all LTD values greater than LTD. □

**Proof of Proposition 4.** Define by ΔS := S_{1OBT,*} + S_{2OBT,*} − S_{1OB,*} the difference between the optimal fleet sizes under the OB and OBT options and by h := h^{OB} = h^{OBT} the present value of the operating cost of a vessel under these options (h^{OB} = h^{OBT} since these options have the same installation times). Denote by ΔV_{OB−OBT}(X^T) the difference between the optimal NPVs corresponding to the OB and OBT options given the throughput requirement X^T and that deterministic throughput models are used. We have

\[
ΔV_{OB−OBT}(X^T) = V^{OB}(X^T, N^{OB,*}) - V^{OBT}(X^T, N^{OBT,*})
\]

\[
= v_1S_{1OBT,*} + v_2S_{2OBT,*} - v_1S_{1OB,*} + hΔS
\]

\[
= v_1(S_{1OBT,*} + S_{2OBT,*} - S_{1OB,*}) - (v_1 - v_2)S_{2OBT,*} + hΔS
\]

\[
= (v_1 + h)ΔS - (v_1 - v_2)S_{2OBT,*}.
\]

The quantity ΔV_{OB−OBT}(X^T) is a non-monotone step function of the throughput requirement X^T, since the terms ΔS and S_{2OBT,*} are non-monotone step functions of this requirement and v_1 > v_2. This quantity is positive, and hence the OB option is preferred over the OBT option, when and only when ΔS > (v_1 - v_2)S_{2OBT,*}/(v_1 + h). Since the terms ΔS and S_{2OBT,*} are non-monotone step functions of the throughput requirement X^T, the choice between the OB and OBT options oscillates as X^T changes. □

**References**


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