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Liquefied natural gas inventory routing problem under uncertain weather conditions

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ABSTRACT

We study the liquefied natural gas (LNG) production-inventory control and vessel routing problem under disruptive weather conditions. If extreme weather is expected to strike an LNG plant, all planned LNG loading operations should be rescheduled to prevent expected safety accidents. We propose two mathematical optimization models to cope with the potential disruptions. The first model is formulated as a two-stage stochastic mixed integer program to maximize the overall expected revenue while minimizing the cost caused by the uncertain impact of weather disruptions. The second model is a decision maker's preference model that reflects a decision maker's evaluation of risk. This model enables a decision maker to have a 'what-if' analysis by varying the level of preference for risks. The two proposed mathematical models can be reduced to a vehicle routing problem which is an NP-hard combinatorial optimization problem. Therefore, two computational techniques have developed to improve the optimization performance. First, a probing-based preprocessing technique is developed to reduce the solution space by eliminating obvious infeasible or non-optimal solutions. Second, an optional logical inequality is developed to generate an upper bound for the optimal solution only if an LNG carrier visits one or two customers in a single tour. Computational results indicate our proposed models and computational techniques are well suited to solve the problem within a reasonable time.

1. Introduction

In the last decade, there has been a remarkable upward trend in the LNG industry (Finley, 2014). To meet the growing international demand, North America has significantly increased its production of shale gas (U.S. Department of Energy, 2005; U.S. Energy Information Administration, 2014). Since February 2016, the U.S. began exporting LNG for the first time. This meant that the US, the world's largest natural gas consumer and importer, was now turning into a natural gas exporter.

Generally, natural gas is transported to customers either through pipelines or by a fleet of LNG carriers. The trade of natural gas through the pipeline is convenient and economical up to 2500 km. However, as shipping distances increase above this maximum, maritime transportation of natural gas in liquid form become more economical (Hartley et al., 2013; Hartley, 2014). LNG demand has been mostly identified from well-determined long-term contracts which have 20–30 year durations which guarantee stable supply and demand relations. Therefore, an annual delivery program was considered to fulfill a set of long-term contracts (Rakke et al., 2011). In recent years, however, there has been an increasing trend for spot-demand and short-term contracts. Traders are willing to trade at short notice when there is an increasing risk of holding surplus LNG unsold under long-term contracts. This trend change is similar to the global market for crude oil seen in the 1970s (Von Hirschhausen and Neumann, 2008).

The LNG value chain is composed of three phases as shown in Fig. 1 (Tusiani and Shearer, 2007). First, once natural gas is produced, it is stored in a storage tank in a liquid form at a temperature of −160 °C. The volume of natural gas in the liquefied state is 1/600 of the volume of the natural gas in its gaseous state. Second, LNG is transported from a production site to a consumer site by an LNG carrier. Usually, a certain amount of LNG is vaporized during the marine transportation. This boil-off gas (BOG) is considered a loss that cannot be delivered to consumers. Third, when an LNG carrier arrives at a consumer site, LNG is transformed back to its original gaseous state for ground transportation and distribution (Thomas and Dawe, 2003). The cost structure of each phase related to the LNG value chain is as follows: exploration & production ($0.60–1.2 per one million British thermal units, or MMBtu),

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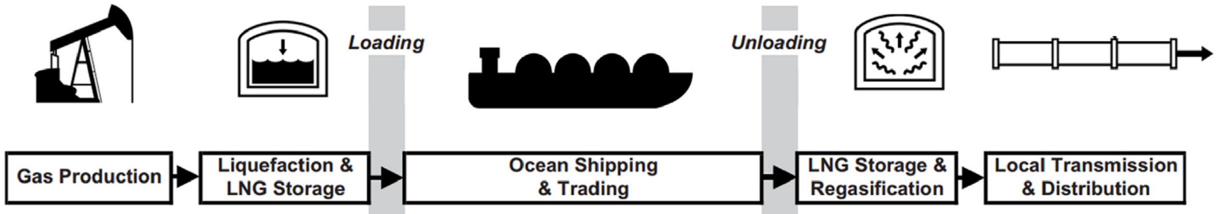

Fig. 1. LNG value chain.

liquefaction ($0.90–1.30/MMBtu), shipping ($0.50–1.80/MMBtu), storage & regasification ($0.40–0.60/MMBtu). The LNG value chain can be directly or indirectly affected by the following performance indicators: daily production rate, daily minimum and maximum regasification rate, initial inventory, storage capacity, volume loaded/discharged by ship, travel time between two terminals, demands, number of berths at a terminal, penalty for unmet demand at a terminal, penalty for lost production/stockout at a terminal, daily boil-off rate, LNG carrier operating cost, and port/terminal fees (Michot Foss, 2007; Goel et al., 2012, 2015; Andersson et al., 2010). This study covers the first and second phases of the LNG value chain to optimize LNG production, storage and LNG shipping scheduling at the same time, and this problem is classified as an LNG inventory routing problem (IRP).

The IRP is an integration of the production-inventory problem and the vehicle routing problem (VRP). The very first IRP was formulated as a mixed integer program to manage industrial gases at customer locations (Bell et al., 1983). Major applications of IRP are usually in the oil and gas industries because of the maritime shipping environment. From the perspective of ship routing and scheduling, the problems can be categorized into four basic models: 1) network design, 2) fleet deployment, 3) tramp cargo routing and scheduling problem and 4) maritime IRP for a single product (Christiansen et al., 2013). The fourth model is the focal point of this research.

Ship routing and production-inventory planning in the LNG business is a representative maritime IRP. While optimizing inventory and production levels within a given time horizon, a fleet of LNG carriers must be properly assigned to a path between a liquefaction terminal and a single or multiple regasification terminals.

There has been an increasing trend of research on LNG IRP since 2009. One of the earliest approaches reported in the literature was a mixed integer programming (MIP) model considering LNG cargo ships shuttling from a liquefaction plant to a regasification plant. These were formulated in an arc-flow and a path-flow model considering inventories at liquefaction and regasification terminals (Grønhaug and Christiansen, 2009). Subsequent models have evolved to become more realistic and progressive, with additional considerations such as sailing conditions, contract types and classes of LNG carriers (Andersson et al., 2010; Fodstad et al., 2010). Yet, a drawback of their studies is that they are limited to serving one customer in a tour. Traditional LNG demand is mostly identified from well-determined long-term contracts, and so an annual delivery program (ADP) was considered with a limited number of berths, and a heterogeneous fleet of LNG ships to fulfill a set of long-term contracts (Rakke et al., 2011). However, this model is not suitable when considering spot-demand and short-term contracts.

Because the LNG IRP is a complex optimization problem under various conditions, existing studies on optimization were focused on developing exact and approximate algorithms to reduce computational time to find a solution. For example, the Lagrangian relaxation technique was used to solve an LNG IRP with 800,000 variables and 200,000 constraints with the optimality gap of 0.5% (Bell et al., 1983). Other useful exact algorithms include branch-and-price (Grønhaug et al., 2010), branch-price-and-cut (Engineer et al., 2012; Coelho and Laporte, 2013), decomposition (Papageorgiou et al., 2014), and approximate dynamic programming (Papageorgiou et al.). A number of efficient heuristic approaches have also been proposed for the problem such as iterative heuristic search algorithm (Goel et al., 2015), multi-start construction and improvement heuristic (Stålhane et al., 2012), a route construction heuristic (Vidović et al., 2014), and a rolling horizon heuristic (Rakke et al., 2011).

In practice, the LNG IRP is significantly affected by various uncertainties. One of the most challenging problems is accurately forecasting uncertain demand. A simple way to approximate demand is to average recent customers' inventory levels as a constant (Bell et al., 1983), or to consider the demand as a random element (Federgruen and Zipkin, 1984). Even if the demands are known, disruptions from the supplier side can still make a value chain unstable (Baghalian et al., 2013). Another issue is volatile market prices which influences the production-inventory decisions (Arvesen et al., 2013). In maritime transportation, sailing time is inherently uncertain because of changing weather conditions (Halvorsen-Weare et al., 2013; Zhang et al., 2015).

Due to a constantly changing external environment during marine transport, LNG is randomly vaporized (Cho et al., 2014a). Since the vaporizing gas increases the pressure inside the storage tank, it is usually discharged to the outside for safety purposes. As an LNG carrier loses a fraction of gas during the voyage, the LNG supplier should consider both the amount of LNG to be delivered to the customer and the expected loss of random BOG generation at the time of determining the amount of LNG to be loaded on an LNG carrier. In an early stage of research, the focus was on discovering the characteristics of BOG in a partially filled tank and developing mathematical foundations (Chatterjee and Geist). In addition, the occurrence and the effect of BOG on the LNG value chain have been examined dividing the time phases into three categories: loading, unloading and marine transportation (Dobrota et al., 2013). Numerous environmental factors influence the degree of BOG generation. However, since the exact prediction of the BOG is too complex, it is often considered as a constant (Grønhaug et al., 2010; Zhang et al., 2015; Cho et al., 2014b).

Uncertain weather conditions disrupt LNG loading operations frequently. When severe weather is imminent, all port operation schedules related to LNG shipping, loading, production, and storage should be delayed or accelerated altogether to avoid safety accidents (Halvorsen-Weare et al., 2013; Zhang et al., 2015).

The literature review reveals that there is a clear need to study the impact of uncertain weather conditions on LNG IRP more carefully. Especially, no mathematical optimization models have been developed to minimize the impact of uncertain weather disruptions on the LNG value chain. To address this gap in the literature, we propose two mathematical optimization models to minimize the impact of extreme weather on the LNG value chain. The LNG IRP models generally include a very large number of variables, and require a significant computational time in order to solve the medium- and large-size instances to the global optimality. Therefore, we propose an approach that is computationally efficient to solve the optimization models in a reasonable time. Contributions of this paper can be highlighted as follows:

- A two-stage stochastic LNG IRP (TSS) model has been developed considering the uncertain occurrence time of bad weather which disrupts LNG production, storage, and shipping schedules. In a previous study, boil-off-rate (BOR) was considered as a random element (Cho et al., 2014b). However, BOR is set as a constant to