DECISION SCIENCES INSTITUTE

A Simulation Model for Comparing the Robustness of Alternative Liquefied Natural Gas (LNG) Annual Delivery Programs (ADPs)

Authors: Fatih Mutlu[*], Hakan Yildiz[+], Erkut Sonmez[#], Shaligram Pokharel[*]

[*] *Qatar University, Mechanical and Industrial Engineering Department, Doha, Qatar*
[+] *Michigan State University, Eli Broad College of Business, East Lansing, MI, USA*
[#] *Boston College, School of Management, Boston, MA, USA*

ABSTRACT

An ADP is a production and delivery plan LNG suppliers to fulfill contractual requirements. It is subject to random disturbances during the implementation, which may increase the planned costs. We develop a model simulating the ADP implementation along with contingency plans, and compare alternative ADPs using the model.
KEYWORDS: LNG supply chain, simulation, robustness, maritime logistics

INTRODUCTION

Natural gas, the source of one quarter of the global energy demand (BP Statistics, 2014), can be distributed from source to distant markets in liquid form, which is known as liquefied natural gas (LNG). Thanks to the liquefaction technology, which enables compressing the volume at an approximate ratio of 600-to-1, large volumes of natural gas can be loaded into specialized vessels in the form of LNG and sold globally. Both the liquefaction and delivery of LNG have very high capital and operational expenses. Thus LNG investments can economically be feasible with long-term sales and delivery contracts. This brings along challenging logistics problems for the LNG suppliers that necessitate an integrated plan of production, inventory, and delivery of LNG over the course of a year. Such a plan is typically referred to as the annual delivery program (ADP) in the LNG industry. In recent years, a growing body of literature focuses on preparing a cost efficient ADP has emerged (Halvorsen-Weare and Fagerholt, 2013a; Rakke et al., 2011; Stålhane et al., 2012; Goel et al., 2012, 2015; Shao et al., 2015; Mutlu et al., 2016a,b).

ADP is a tactical level plan, spanning approximately a set of year long operations, and to our knowledge, vast majority of the studies aiming at cost optimization assume deterministic problem parameters. However, there are many random elements inherent to the LNG logistics operations, the most prevalent of which is the vessel cruise times. Due to weather conditions, altering regulations for maritime transportation, and other factors such as marine pirates and breakdowns, cruise times can be longer than planned. In this case, the vessel can be late for its next delivery, which will affect the rest of the ADP including inventory levels at the liquefaction (production) port, and delivery times and volumes. This will result in increased costs as the LNG supplier has to speed-up its vessels, charter-in additional vessels, or cancel cargoes. In this regard, the robustness of a given ADP against uncertainties is an important dimension for LNG suppliers in order to keep the costs low and satisfactorily ensure delivery of customer contracts with minimal changes.

The literature that addresses the robustness of ADPs is very limited. Halvorsen-Weare et al. (2013b) consider cruise time uncertainties and modifies the ADP formulation in Halvorsen-

Weare and Fagerholt (2013a) by adding a constant slack to all of the travel times and adding penalty costs for the deviations from target inventory level at the liquefaction port and target loading berth use. They compare the solutions of pure cost minimization model to their modified formulation. Mutlu et al. (2016c) propose a multi-objective model with a second objective to improve the ADP flexibility by incorporating slackness into the model and present trade-off curves, which suggest that significant flexibility can be introduced into the plan at a relatively small incremental cost.

In this paper, we develop a simulation model that tests the robustness of a given ADP against vessel cruise time uncertainty. Several contingency actions, similar to the re-planning decisions in practice, are incorporated into the model. Our proposed model quantifies the sensitivity of the performance metrics of the ADP and the resulting penalty costs. Halvorsen-Weare et al. (2013b) also develops a simulation model, in which, rerouting decisions are made by solving the remaining subproblem as a mixed integer programming formulation. Our simulation model does not require an optimizer, and thus it has lower solution times. Moreover, our model is capable of simulating ADPs that allow for split deliveries. In a more general sense, our model simulates integrated production, inventory, and maritime routing solutions with heterogeneous vessels and delivery time windows.

Using our simulation model, we compare two alternative multi-objective ADP formulations, for which the first objective is to minimize the total operating and contractual penalty costs. The first formulation is suggested by Mutlu et al. (2016c), which aims to make the deliveries to the contracts as early as possible within the delivery time window of the contract as a second objective. This approach aims at increasing the flexibility of the plan. Flexibility and redundancy are identified as two main risk mitigation strategy types in the supply chain risk management literature (Rice and Caniato, 2003; Sheffi and Rice Jr, 2005; Talluri et al., 2013). Second multi-objective formulation we propose aims to incorporate redundancy by maximizing the idle times of the vessels between consecutive deliveries as a second objective.

The genetic algorithms-based solution approach suggested by Mutlu et al. (2016c) can effectively generate a frontier of Pareto-optimal plans. We simulate all of these plans at the optimal frontier and investigate their robustness.

The contribution of this paper is two-fold. First, we introduce a model, which is capable of simulating ADPs that are generated using various methods. The model helps LNG suppliers test the robustness of their ADPs. Second, we build several realistic recourse actions in order to relieve the side-effects of vessel delays. Delivery time of LNG using maritime transportation, especially to overseas, is highly affected by the weather and maritime traffic conditions; and without effective contingency planning, LNG supplier may fail to fulfill the his contractual requirements. Our experimental analysis indicates that the suggested recourse actions can effectively eliminate potential delays and/or cancellations in future deliveries.

The next section summarizes the model that is used in the ADP formulation. Section 2 describes the logic of the simulation model. In Section 3, we describe the problem instances for our computational study and present a comparison of alternative multi-objective formulation approaches. The paper concludes in Section 4 with the managerial takeaways derived from this study and future research directions.

THE SIMULATION MODEL

We study the integrated liquefaction, inventory, and delivery operations of An LNG supplier having one liquefaction facility accompanied by a loading port with multiple berths and delivering to a set of long-term contracted customers located around the globe. Each customer has a set of delivery requirements, which we refer to as a contract, throughout the time horizon of the ADP. Each contract has a desired volume and a time window for delivery. Typically, a contract's delivery volume would exceed the capacity of a single vessel; therefore multiple vessel deliveries have to be made to fulfill the contract requirements. Contract offers various levels of flexibility to the supplier on both delivery volume and time.

The simulation model's major input is an ADP, which includes several pieces of information such as the daily liquefaction rates, times of departure from the liquefaction port and arriving at the customer ports and delivery volumes at each visit for all the vessels. Each round trip tour of a vessel starting from the liquefaction port and delivering to a single or multiple customer ports is named as a cargo. A cargo contains the information of (i) its assigned vessel, (ii) departure time from the liquefaction port, (iii) arrival time(s) to the customer port(s), (iv) delivery volume at each visited port, and (v) return date according to the ADP. We note that a cargo may contain deliveries to multiple customer ports. Therefore, a vessel may visit several customer ports throughout its tour and deliver part of its load at each port. This phenomenon is known as ``split-deliveries." Cargo information is stored in a list of scheduled cargoes of its departure day from the liquefaction port. In the simulation, travel times of vessels between ports are assumed to be stochastic. To model the travel time uncertainty, we adopt the approach suggested in Halvorsen-Weare et al. (2013), which is discretization of a log logistic probability distribution. In this approach, the probability distribution of sailing times of LNG vessels is approximated by a log logistics distribution based on an empirical study on sailing times of vessels by Kauczynski (1994).

The simulation runs at daily steps. Each day, two stages of checks are made: First, for each cargo scheduled to be shipped on that day, whether its assigned vessel is available or not is checked. If the assigned vessels are not available, they are delayed to next day, or assigned to another available vessel, or moved to a charter vessel. In the second stage, scheduled cargoes with available vessels are checked if they can be shipped. At this stage, berth and inventory availability at the liquefaction port are checked. The cargoes that cannot be shipped are delayed or cancelled. We next present a more detailed flow of the simulation logic:

The Simulation Logic

1. For each day *t*
   1.1. For each cargo *c* in the set of *vessel waiting cargoes - t*

      - If there is an available vessel at the liquefaction port, assign an available vessel to cargo *c* and move it to the set of *scheduled cargoes – t*
      - Else:
        - If cargo *c* can be delayed by one day, move it to the set of *vessel waiting cargoes – t+1*
        - Else: assign cargo *c* to a chartered vessel and move it to *scheduled cargoes – t*

   1.2. For each cargo *c* in set of *scheduled cargoes – t*

- If the assigned vessel of cargo c is at the liquefaction port: add cargo *c* to the set of *cargoes to be shipped - t*
- Else:
  - If the cargo can be on hold till the next day without changing its assigned vessel: move cargo *c* to set of *scheduled cargoes – t+1*.
  - Else:
    - If cargo *c* can be assigned to another compatible vessel, chance its assigned vessel and add cargo *c* to the set of *cargoes to be shipped – t*
    - Else:
      - If cargo *c* can be delayed one day, move cargo *c* to the set of *vessel waiting cargoes* - *(t+1)*.
      - Else: assign cargo *c* to a chartered vessel and move it to *scheduled cargoes – t*

1.3. Rank the cargoes in the *cargoes to be shipped – t*, according to their criticality

1.4. For each cargo *c* in the ranked list of *cargoes to be shipped – t*

- If there is a free berth and sufficient inventory: send cargo *c*
- Else:
  - If cargo *c* can be delayed by one day, move it to the set of *scheduled cargoes cargoes – t+1*
  - Else: cancel cargo *c*
  -

2. Compare the ADP and the actual deliveries and it computes the deviations from the plan. The deviations are
   i. *Delays:* the sum of the days the cargoes are delayed;
   ii. *Charters:* the total number of chartered vessels;
   iii. *Volume:* difference between the planned and actual delivery volumes. Delivery volumes to the contracts may change due to two potential reasons. If a cargo is assigned to another vessel with a different capacity than its originally assigned vessel, the delivery volume for the cargo may change. In addition, we assume that delivery volume to the intended contract is zero if a cargo is cancelled.
   iv. *Penalty Costs:* the difference between the total actual and planned contractual penalty costs.

The verification of the model is done through our discussion with the logistics planners of one of the LNG suppliers in Qatar. For the validation of the model, we ran the simulation by removing the travel time uncertainty. In this case, the actual deliveries should match the plan without any deviations. We tested over 400 different plans for various problems and obtained an exact match in each case.

The model aims to simulate a given ADP, which is a one-year long plan, and then compares the deviations from that plan. Therefore, no warm-up period is used and each simulation run spans a period of 360 days.

COMPUTATIONAL STUDY

There are two objectives of the computational study: (i) to evaluate the impact of the contingency actions, and (ii) to compare robustness of alternative ADPs using the simulation model. Adding flexibility and redundancy to the supply chain plans are identified as two main risk mitigation strategies in supply chain risk management. In the ADP preparation context, risk mitigation is very critical as the implementation of the program is subject to many disturbances. An emerging trend in the ADP literature is to employ multi-objective optimization and introduce alternative objectives that aim to maximize the flexibility and redundancy of the plan. In our study, we compare the robustness of alternative ADPs, developed by Mutlu et al (2016c).

To do so, we study five problem instances generated by Mutlu et al. (2016a). First three problems are representative of a small-to-medium scale LNG providers and the last two are representative of large scale LNG providers. The selected problems also vary according to the total annual demand to total production capacity ratio. This ratio is low in the first two problems compared to the others. In the first four problems, contractual demands are almost evenly distributed throughout the planning horizon. On the contrary, the last one has higher demand seasonality. Parameters of each problem are presented in Table 1. In this table, ρ^P is the demand to production capacity ratio and DS is the coefficient of variation of monthly demand.

Table 1: Problem Instances

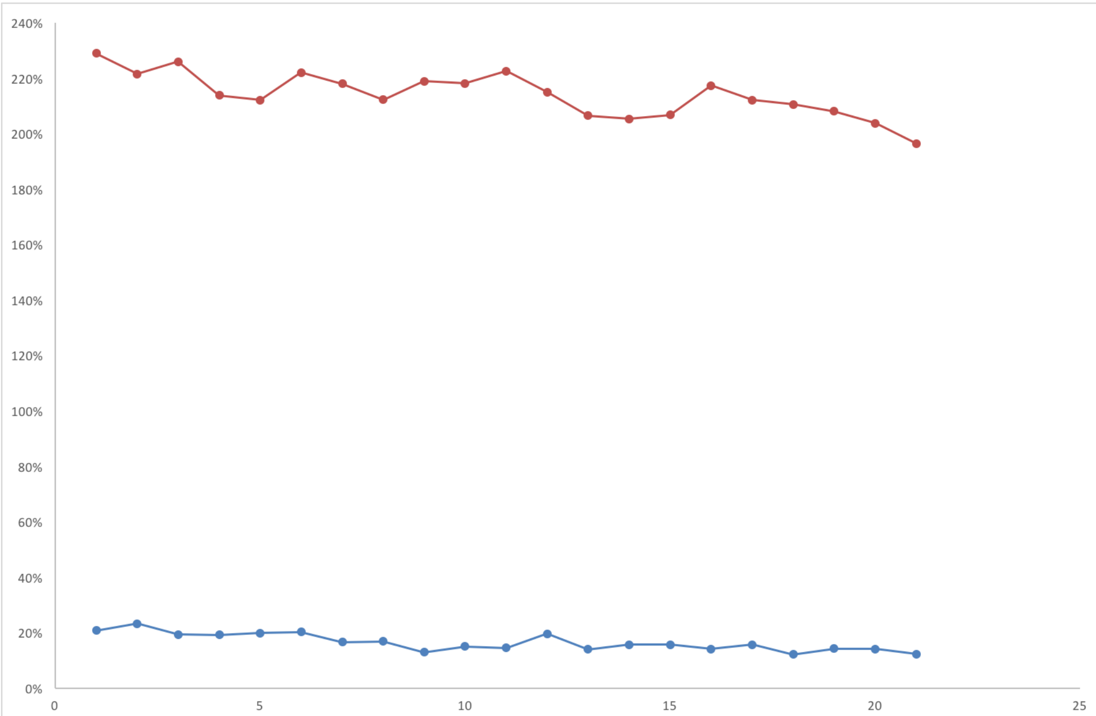
Class	|V|	|P|	|C|	B	DS	ρ^P
P1	20	8	65	3	0.02	0.65
P2	20	8	65	3	0.02	0.75
P3	20	8	65	3	0.02	0.95
P4	40	16	111	5	0.05	0.95
P5	40	16	111	5	0.2	0.85

Simulation run times are rather short; thus we took a conservative approach and selected a large number of replications in order to ensure that the total simulated costs between two adjacent ADPs are different according to the one-sided hypothesis testing using 95% significance level. 100 independent simulation runs were enough for this.

RESULTS

For first objective of the computational study, we have prepared a similar version of the simulation model, which does not contain any of the contingency actions. In this version, if the assigned vessel of a scheduled cargo has not arrived on the planned day, the cargo is simply delayed until the last date it can be delivered; otherwise it is cancelled. Figure 1 displays the percentage increases from the planned costs under the absence and existence of contingency actions for alternative ADPs for P1. When there is no contingency plan, the cost increases reach above 200% but with the simple contingency plans we suggested, the increases are less than 20%. This shows the effectiveness of the simply implemented contingency plans.

Figure 1: Percentage Increase in Planned Costs for No-Action and Contingency Planning - P1



The second objective is to compare the robustness of alternative ADPs. For this purpose, we first plot the total planned and actual costs under travel time uncertainty. Figure 2 shows this comparison for P2. We note that the ADPs are ranked on the horizontal axis according to increasing order total planned cost and total planned vessel idle times. In other words, the plans on the left hand side of plot are better in terms of planned costs and the ones on the right hand side have more redundancy. We observe that, even the latter plans have higher planned costs, the actual total costs after experiencing the travel time delays and their consequences are almost the same as those of cost optimal plans. This indicates the effectiveness of vessel idle times on mitigating travel time delays. The conclusion is even stronger as the production capacity to demand ratio increases. In Figure 3, one can observe a decreasing trend in actual costs for the first 12 ADPs.

Figure 2: Planned vs. Actual Costs - P2

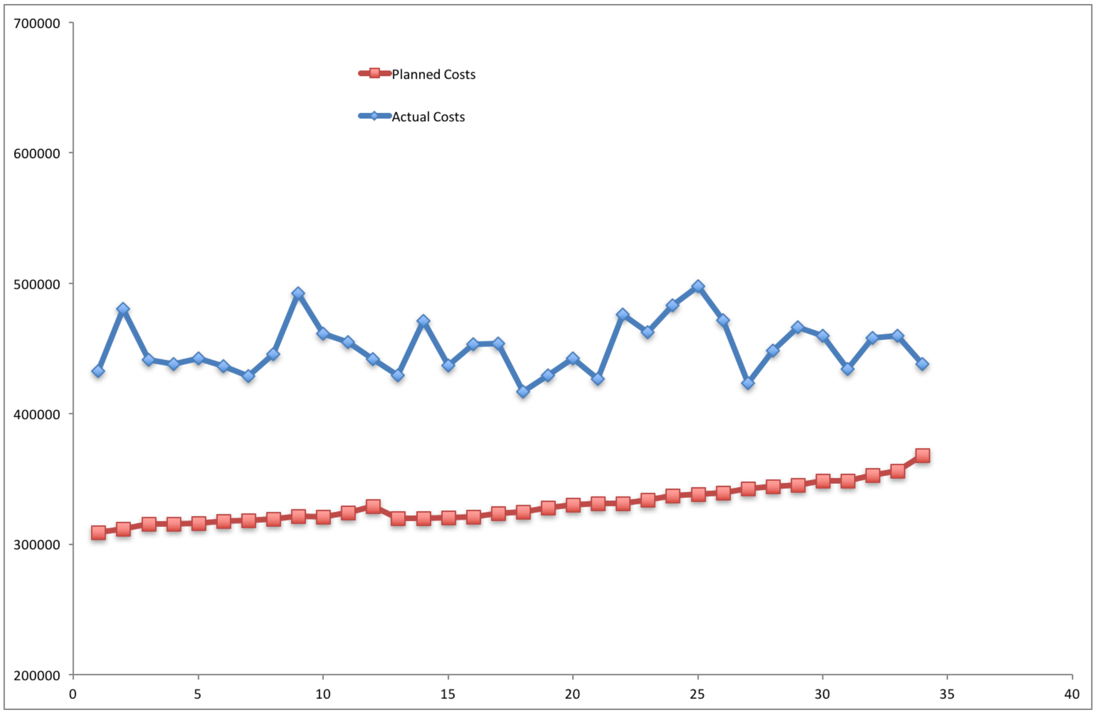
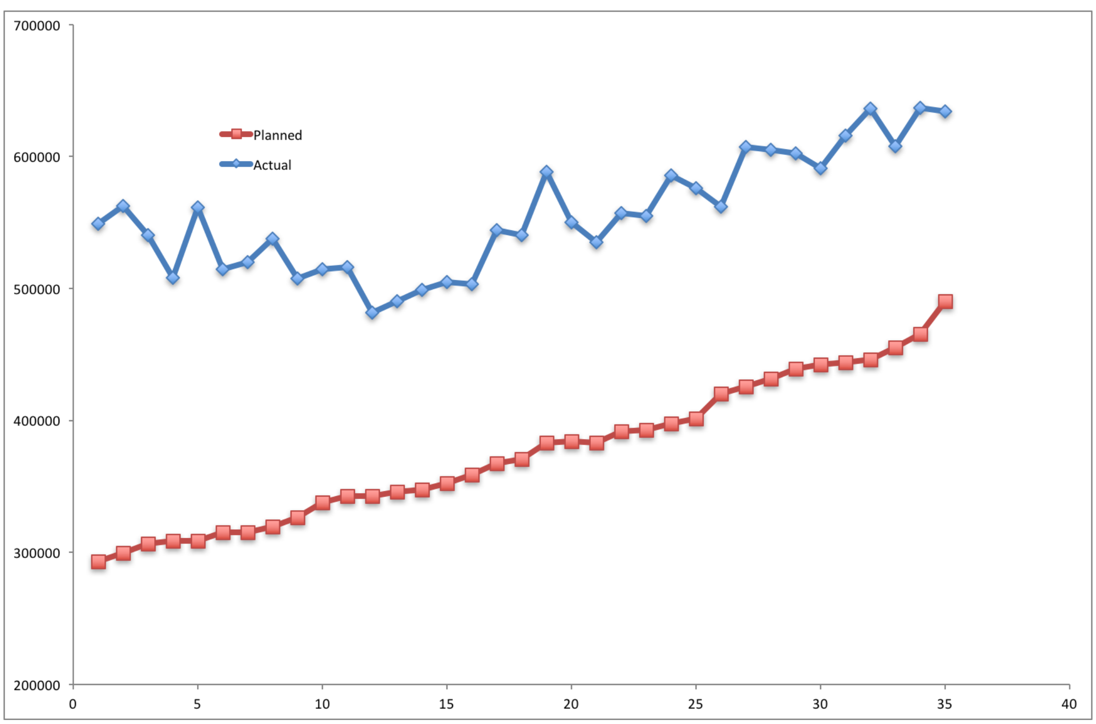


Figure 3: Planned vs. Actual Costs - P3



The costs show here are the summation of operating costs and penalty costs according to the contractual volumes and delivery times. Same cost parameters are also used while preparing an ADP. However, once an ADP is prepared, the supplier negotiates this plan with the customers. Intuitively, after this stage, the customers expect that the actual deliveries match the ADP. Hence, al alternative measure of robustness is the changes in delivery volumes and delivery times. By associating the same unit penalty rates for early- and late-delivery penalties, and under- and over- delivery penalties, we computed the % increases in the penalty costs. the percentage increase in the actual costs can be used as one measure of robustness. Figure 4 and Figure 5 show the percentage increases for P4 and P5, respectively. For both problems, a decreasing trend in percentage increase in penalty costs can be observed as the total vessel time of the plans increase. The trend is stronger when seasonal variation of demand is higher.

Figure 4: Percentage Increase In Penalty Costs - P4

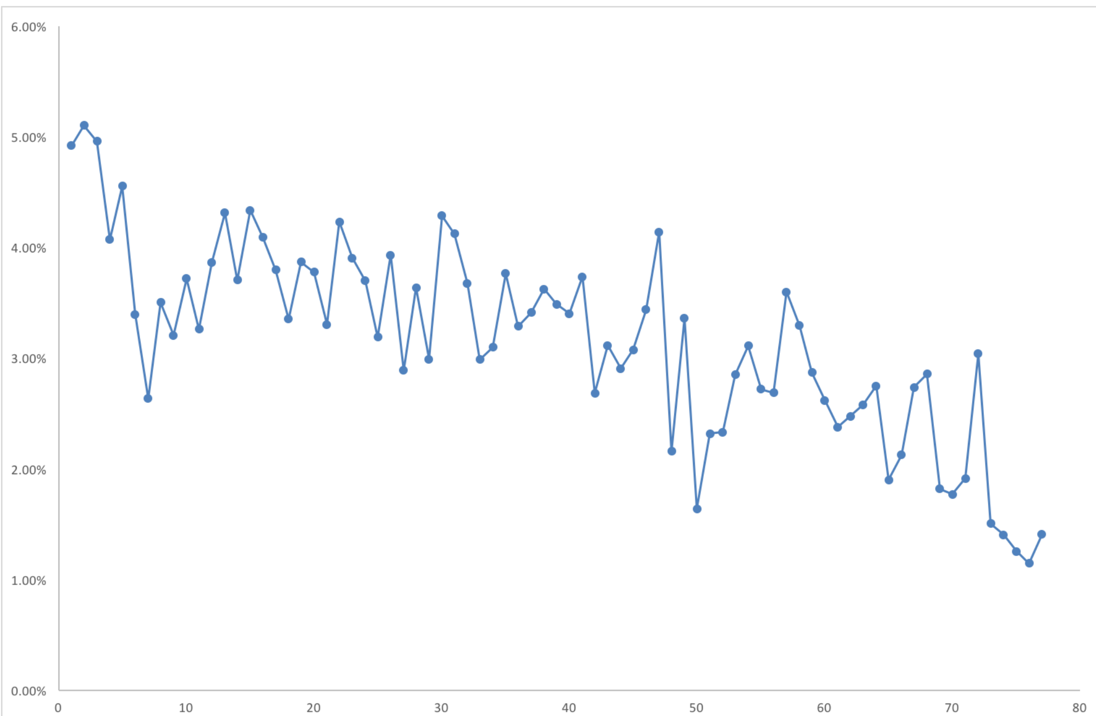
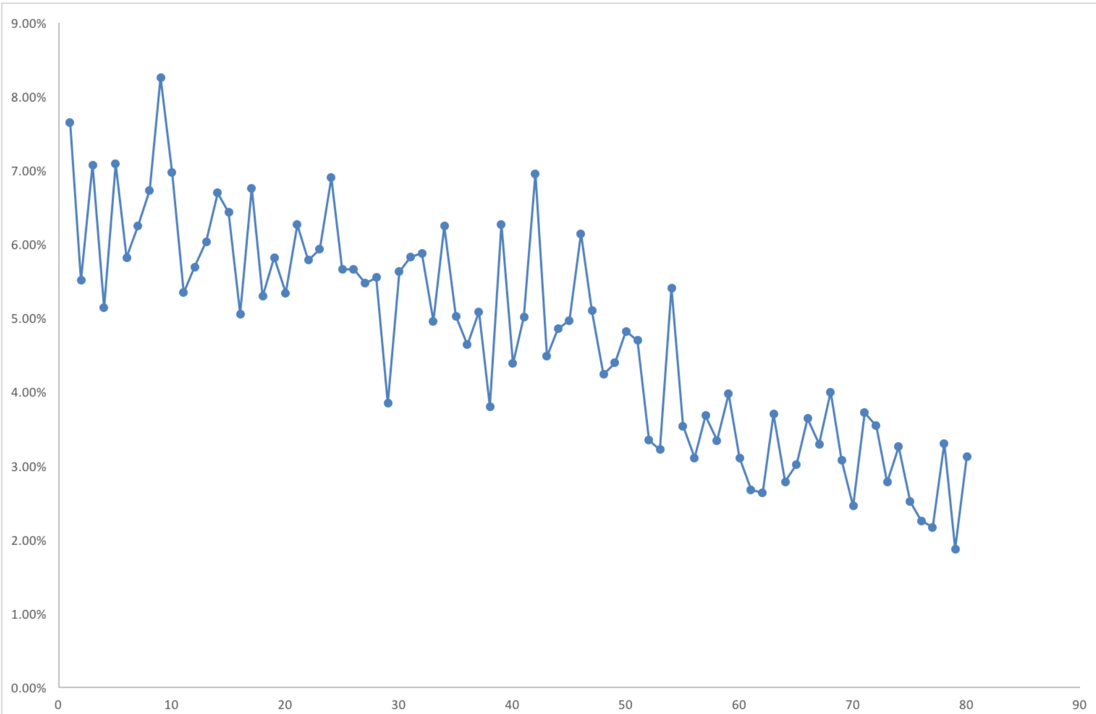


Figure 5: Percentage Increase In Penalty Costs - P5



DISCUSSION AND CONCLUSIONS

In this study, we develop a novel simulation model that can simulate the implementation of an LNG ADP under various uncertainties. The simulation model is generic enough to simulate any single depot integrated production, inventory, and delivery routing plan with demand time windows. It also proposes recourse actions in case of vessel delays.
Our simulation model can be used to compare alternative ADPs. We demonstrate this by simulating Pareto-optimal solutions for a multi-objective LNG ADP formulation proposed by Mutlu et al. (2016c). Their multi-objective formulation aims to maximize vessels' idle times in between cargo delivery jobs. Our simulation results indicate that Pareto-optimal plans obtained from this formulation are highly robust against uncertainties. The model developed in this study can be utilized by LNG suppliers to test robustness of their annual delivery plans under various scenarios.

A future research avenue is to enhance the simulation model in order to make it sufficiently generic so that it can be used to compare solutions for a larger class of integrated production, inventory, and delivery routing problems.

ACKNOWLEDGEMENTS

This research was made possible by a NPRP award NPRP 4-453-5-059 from the Qatar National Research Fund (a member of The Qatar Foundation). The statements made herein are solely the responsibility of the authors.

REFERENCES

BP Statistics, D. (2014). Bp statistical review of world energy june 2014. Technical report, British Petroleum.

Goel, V., Furman, K. C., Song, J.-H., and El-Bakry, A. S. (2012). Large neighborhood search for lng inventory routing. Journal of Heuristics, 18(6), 821-848.

Goel, V., Slusky, M., van Hoeve, W.-J., Furman, K., and Shao, Y. (2015). Constraint programming for lng ship scheduling and inventory management. European Journal of Operational Research, 241(3), 662-673.

Halvorsen-Weare, E. E., & Fagerholt, K. (2013). Routing and scheduling in a liquefied natural gas shipping problem with inventory and berth constraints. *Annals of Operations Research*, *203*(1), 167-186.

Halvorsen-Weare, E. E., Fagerholt, K., and R□onnqvist, M. (2013). Vessel routing and scheduling under uncertainty in the lique_ed natural gas business. Computers & Industrial Engineering, 64(1), 290-301.

Kauczynski, W. (1994). Study of the reliability of the ship transportation. In Proceeding of the international conference on ship and marine research, page 15.

Mutlu, F., Msakni, M. K., Yildiz, H., Sonmez, E., and Pokharel, S. (2016a). A comprehensive annual delivery program for upstream liquefied natural gas supply chain. European Journal of Operational Research, 250(1), 120-130.

Mutlu, F., Yildiz, H., Sonmez, E., and Pokharel, S. (2016b). A genetic algorithm based approach to the liquefied natural gas annual delivery planning problem. Manuscript Submitted for Publication.

Mutlu, F., Yildiz, H., Sonmez, E., and Pokharel, S. (2016c). Multi-objective optimization for the liquefied natural gas annual delivery problem. Working Paper.

Rakke, J. G., Stalhane, M., Moe, C. R., Christiansen, M., Andersson, H., Fagerholt, K., and Norstad, I. (2011). A rolling horizon heuristic for creating a liquefied natural gas annual delivery program. Transportation Research Part C, 19, 896-911.

Rice, J. B. and Caniato, F. (2003). Building a secure and resilient supply network. Supply Chain Management Review, 7(5), 22-30.

Shao, Y., Furman, K. C., Goel, V., and Hoda, S. (2015). A hybrid heuristic strategy for liquefied natural gas inventory routing. Transportation Research Part C: Emerging Technologies, 53, 151-171.

Sheffi, Y. and Rice Jr, J. B. (2005). A supply chain view of the resilient enterprise. MIT Sloan management review, 47(1), 41.

Stälhane, M., Rakke, J. G., Moe, C. R., Andersson, H., Christiansen, M., and Fagerholt, K.

(2012). A construction and improvement heuristic for an lng inventory routing problem. Computers & Industrial Engineering, 62, 245-255.

Talluri, S. S., Kull, T. J., Yildiz, H., and Yoon, J. (2013). Assessing the efficiency of risk mitigation strategies in supply chains. Journal of Business logistics, 34(4), 253-269.