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Optimal dynamic allocation of mobile plants to monetize associated or stranded natural gas, part II: Dealing with uncertainty

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ABSTRACT

Using the Bakken shale play as a case study, the previous part of this two-part series demonstrated how small-scale mobile plants could be used to monetize associated or stranded gas effectively. Here, we address the issue of uncertainty in future supply, demand and price conditions. To this end, we modified our multi-period optimization framework to a stochastic programming framework to account for various scenarios with different parameter realizations in the future. The maximum ENPV (expected net present value) obtained was $2.01 billion, higher than the NPV obtained in the previous part. In addition, the value of the stochastic solution was 0.11% of the optimal ENPV, indicating that the flexible nature of mobile plants affords them a great advantage when dealing with uncertainty.

1. Introduction

The first part of this series [1] introduced the concept of small-scale, mobile modular plants and their potential to shift the current paradigm away from large capital expenditures and one fixed location for investments in the oil and gas industry. We considered two technologies at the small scale, namely GTL (gas-to-liquids) conversion and LNG (liquefied natural gas) production. A small-scale, modular plant for either GTL or LNG involves pre-manufacturing each process unit as compartmentalized, individual modules which can then be shipped to the site of interest and assembled together in minimal time to form the entire plant. Additionally, plants can be quickly disassembled into their individual modules and redeployed at other sites, affording them the benefit of mobility. This mobility allows them to respond quickly to changes in conditions that might affect their profitability.

Operating plants in a small-scale, mobile fashion offers several benefits. First, it offers access to stranded sources of gas which arise as a consequence of a lack of accessibility or of insufficient volumes for larger-scale monetization technologies. Second, it offers lower financial risk due to the smaller capital outlay, shorter development times, and the ability to continuously redeploy operations to more profitable locations over time. Thirdly, it allows oil resources to be produced without the environmental impacts of flaring associated gas.

Prior to this work, there had been no objective and quantitative framework with which these plants and associated technologies could be analyzed. Therefore, the first part of this series [1] involved the development of an optimization framework which determined the optimal purchase, sales, operation and relocation of these plants under time-varying conditions of supply, demand and prices over multiple time periods. The framework was then applied to a case study of the Bakken shale play, where the short-lived availability of associated gas at different drilling sites made it appropriate to consider the application of mobile plants. The main conclusion from the case study was that these technologies offered a very profitable route to monetizing associated gas. In addition, the profitability of the optimal strategy was largely enabled by the flexibility to continuously redeploy the plants to different gas sources over time [1].

In this second part of this series, we add to the complexity of the problem at hand by introducing uncertainty into various parameters that would ultimately affect the profitability of the entire undertaking. Sahinidis [2] provided a review on optimization under uncertainty. Specific to this study, a stochastic programming framework was implemented. Readers are referred to Shapiro [3] for a comprehensive reference on stochastic programming.

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For a sense of continuity, we provide a brief review of articles which have appeared in *Energy* in recent years where stochastic programming frameworks have been implemented to solve energy-related problems. A two-stage stochastic MILP (mixed-integer linear programming) approach was implemented by the following authors. Cristóbal et al. [4] determined the optimal timing of investments and operation of a CO_2 capture system under uncertainty in CO_2 allowance prices. Osmani and Zhang [5] studied a multi-feedstock lignocellulose-based supply chain under uncertainties in switchgrass yield, crop residue purchase price, bioethanol demand and sales price. Tajeddini et al. [6] maximized the expected profit of a virtual power plant under uncertainties of solar photovoltaic and wind power output and day-ahead market prices. Shabani et al. [7] optimized the production planning of a forest biomass power plant under supply uncertainty.

Azadeh et al. [8] used a multi-stage stochastic linear programming approach to optimize the design and operation of a biofuel supply chain under uncertainty in biofuel demand and prices and biomass supply. Seddighi and Ahmadi-Javid [9] used a multi-stage stochastic MILP approach to plan power generation and transmission expansion with sustainability aspects under uncertainty of electricity demand, fuel prices, greenhouse gas emissions and power supply disruptions. Ottesen and Tomasgard [10] used a multi-stage stochastic MILP approach to operate an energy system in a building under intermittent supply, load and energy prices uncertainties.

Currently, there is a relatively small number of papers published in the general literature which apply optimization under uncertainty to shale gas. Yang et al. [11] optimized water management operations during shale gas production to maximize profits under the uncertain availability of water. Bistline [12] explored how uncertainties in natural gas prices and future climate policies impacted economic and environmental outcomes in the U.S. power sector.

We now identify the specific sources of uncertainty in our case study which might have significant influence on the final profitability of the project. First, typically complicating the decision process is the considerable uncertainty in the EUR (estimated ultimate recovery) of gas from wells being drilled. As mentioned by the U.S. EIA (Energy Information Administration) [13], this problem is significantly acute for the case of unconventional resources where the data collected on production patterns thus far are not sufficient to estimate reliably production rates far into the future. In addition, this uncertainty in EUR also impacts the predictions of drilling patterns of future wells in the play.

A second major source of uncertainty lies in the prices and demand for the finished products, as they directly impact the revenue generated from the decision maker's activities. As the markets for the finished products are very large, the decision maker is essentially a price taker. Predicting the future prices and demand for oil and gas-based products is extremely difficult and as can be seen from past experience, can be very inaccurate. An example would be the flurry of activity a decade ago to increase LNG import capacity with the expectation of future shortages of domestic natural gas production, as reported by White [14]. Hence, the decision maker has to live with the uncertainty with regards to prices and demand and make his or her decisions under such conditions.

A stochastic programming framework can be used to identify optimal solutions in the presence of parametric uncertainty. In this framework, several price, supply and demand scenarios are projected for the future. The decision variables are partitioned into two sets: the “here-and-now” decisions, which have to be made before the scenarios are realized, and the “wait-and-see” decisions, which are made once a particular scenario has been realized. The objective function for the stochastic program would typically be to maximize the ENPV (expected net present value) of the project, which is the sum of the net present value of every scenario weighted by its associated probability.

This paper provides a novel, timely, and necessary addition to the first part of the study. Rarely are strategies adequately justified to be put into practice without the explicit consideration of uncertainties which might have significant impact on the ultimate profitability. In addition, the application of optimization under uncertainty to small-scale mobile plants has not been performed before, to the best of the authors' knowledge.

2. Stochastic formulation

A complete description of the problem can be found in Part I [1]. Here, we modify the formulation in order to account for parametric uncertainty. We retain the previous indices: time stages $t \in \{0,\dots,T\}$, gas sources $i \in \{1,\dots,I\}$, plant type $j \in \{1,\dots,J\}$, markets $k \in \{1,\dots,K\}$ and products $l \in \{1,\dots,L\}$. We then introduce a new index for scenarios $s \in \{1,\dots,S\}$.

The optimization decisions are:

1. Decision to allocate plant of type j to source i at time t of scenario s, denoted by $y_{ij}^{ts} \in \{0,1\}$.
2. Indicator of the presence of a gas gathering system at source i at time t of scenario s, denoted by $z_i^{ts} \in \{0,1\}$.
3. Gas feed rate to plant of type j at source i at time t of scenario s, denoted by $x_{ij}^{ts} \in \mathbb{R}_+$.
4. Product delivery rate of product l from source i to market k at time t of scenario s, denoted by $w_{ikl}^{ts} \in \mathbb{R}_+$.
5. Number of plants of type j purchased at time t of scenario s, denoted by $Buy_j^{ts} \in \mathbb{Z}_+$.
6. Number of plants of type j which originally arrived in inventory at time $0 \le \tau < t$ of scenario s, sold at time t, denoted by $Sell_{j\tau}^{ts} \in \mathbb{Z}_+$.
7. Inventory of plants of type j at time t of scenario s, arriving in inventory at time $0 \le \tau \le t$, denoted by $Inv_{j\tau}^{ts} \in \mathbb{Z}_+$.

Essentially, to each constraint in Part I, we replace it with its stochastic counterpart simply by requiring that each constraint holds for each individual scenario. For brevity, we directly list the constraints here and refer the reader to Part I for detailed explanation of each set of constraints.

$$z_i^{ts} \le z_i^{t+1,s}, \quad \forall i,s, \quad \forall 0 \le t < T. \tag{1}$$

$$y_{ij}^{ts} \le z_i^{t-\mathcal{T}_g,s}, \quad \forall i,j,s, \quad \forall t \ge \mathcal{T}_g, \quad \text{and} \tag{2}$$

$$y_{ij}^{ts} = 0, \quad \forall i,j,s, \quad \forall t < \mathcal{T}_g. \tag{3}$$

$$\begin{aligned} &Inv_{j\tau}^{ts} = Buy_j^{t-\mathcal{T}_j,s}, \quad \forall j,s, \quad \forall t \ge \mathcal{T}_j, \quad \forall \tau = t, \quad \text{and} \\ &Inv_{j\tau}^{ts} = 0, \quad \forall j,s, \quad \forall t < \mathcal{T}_j, \quad \forall \tau = t. \end{aligned} \tag{4}$$

$$Inv_{j\tau}^{ts} = Inv_{j\tau}^{t-1,s} - Sell_{j\tau}^{ts}, \quad \forall j,t,s \quad \forall \tau < t. \tag{5}$$

$$\sum_i y_{ij}^{ts} \le \sum_{\tau=0}^{t} Inv_{j\tau}^{ts}, \quad \forall j,t,s. \tag{6}$$