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Tackling Uncertain Performances of Multiple Stakeholders in the Design and Optimization of Decentralized Supply Chains

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Supply chains are normally managed in a decentralized way by multiple stakeholders pursuing distinct objectives. However, most existing supply chain studies rely on centralized models and neglect the uncertain behaviors of stakeholders in the decision-making process. In this work, a novel game theory based stochastic model is proposed that integrates two-stage stochastic programming with a single-leader-multiple-follower Stackelberg game scheme. The aim is to address the optimization problem of decentralized supply chains considering multiple stakeholders under uncertainty. The resulting model is formulated as a stochastic mixed-integer bilevel nonlinear program, which can be further reformulated into a tractable single-level stochastic mixed-integer linear program by applying KKT conditions and Glover's linearization method. To illustrate the applicability of proposed modeling framework, a case study of a large-scale shale gas supply chain is presented, which demonstrates the advantages of the proposed modeling framework and efficiency of the solution algorithm.

1. Introduction

Most existing supply chain design and optimization studies rely on centralized models (Garcia and You, 2015). In other words, a single decision maker is assumed to oversee the whole supply chain (Aiello et al., 2017) All the decisions can be implemented successfully to pursue a single objective (Asala et al., 2017). However, supply chains in practice are normally managed by multiple stakeholders, and each stakeholder may pursue different objectives. The conflict of interest may eventually lead to compromised solutions that are not in favour of any single stakeholder (Cachon and Netessine, 2004). Consequently, the optimal solutions obtained from centralized models can be suboptimal or even infeasible in a decentralized supply chain. To explicitly address the interest of each stakeholder in supply chain optimization problems, multiple game theoretic models are developed (Gao and You, 2017a). For instance, there are models for the optimization of cooperative multi-enterprise supply chains based on the generalized Nash bargaining solution approach (Yue and You, 2014a). On the other hand, optimization models integrating game theories of Stackelberg game and Nash-equilibrium are proposed for the design and operations of noncooperative supply chains (Gao and You, 2017b). However, one important assumption made in these models is that the information among stakeholders is deterministic. In other words, all the stakeholders make decisions based on perfect information of the supply chain (Yue and You, 2014b). This assumption may not hold in real-world applications since there are always time delays between the decisions, and uncertainties are ubiquitous in the supply chain decision making process (Yue and You, 2017). Different uncertainty realizations may significantly affect the rational behaviors of stakeholders. Therefore, it is considered imperative to develop a holistic game theoretic model for systematic optimization of supply chains with different stakeholders considering their uncertainty behaviors.

Motivated by this knowledge gap, a novel modeling framework is proposed in this work, where the leader-follower Stackelberg game (Stackelberg, 2010) is integrated with two-stage stochastic programming approach to formulate a holistic game theoretic model. Compared with traditional game theoretic models, this modeling framework allows consideration of uncertain behaviours associated with different stakeholders. Following the sequence of two-stage stochastic programming approach, decision variables for both the leader and the followers can be classified into design decisions that must be made "here-and-now" and operational decisions that are postponed to a "wait-and-see" mode after the realization of uncertainties (Gao and You, 2015a). In the

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first stage, both players will interact with each other to determine their optimal design strategies. Then, uncertainties associated with the leader and followers are realized. Based on the perceived uncertainty knowledge as well as the predetermined design decisions, both types of stakeholders need to determine their optimal operational decisions. The uncertainties are depicted with discrete scenarios with given probabilities following the stochastic programming approach. The leader and the followers all strive to maximize their own expected net present values. The resulting problem can be formulated as a stochastic mixed-integer bilevel programming (MIBP) problem. Specifically, the upper-level problem is formulated as a mixed-integer nonlinear programming (MINLP) problem corresponding to the leader's optimization problem; the lower-level problems are formulated as linear programs corresponding to the optimization problems of the followers. By replacing the lower-level problems with their equivalent Karush-Kuhn-Tucker (KKT) conditions, we can reformulate this MIBP problem into a single-level mixed-integer nonlinear programming (MINLP) problem. To further improve the tractability of the resulting MINLP problem, the Glover's linearization approach is applied to reformulate it into an equivalent MILP problem (Glover, 1975). A large-scale case study of shale gas supply chains based on Marcellus Shale is presented to illustrate the applicability of the proposed modeling framework and solution strategy. Based on the optimization results, we can conclude that both players tend to choose more conservative strategies when considering the uncertainties in the noncooperative supply chain optimization problem.

2. Problem Statement

As mentioned in the previous section, the proposed modeling framework integrates the leader-follower Stackelberg game with two-stage stochastic programming approach. The aim is to simultaneously optimize the design and operations decisions of different stakeholders under uncertainty. Specifically, the upstream shale gas producer is regarded as the leader in this shale gas supply chain, and the midstream shale gas processors are identified as the followers. As the leader in this Stackelberg game, the shale gas producer seeks to optimize its design and operational decisions to maximize its expected NPV. The leader's major decisions include:
First-stage design decisions:

- Exploration of candidate shale sites;
- Scheduling of drilling activities at each shale site;
- Design of gathering pipeline network;
- Selection of processing contracts offered by processors.

Second-stage operational decisions:

- Amount of freshwater acquired for drilling and hydraulic fracturing in each time period;
- Amount of wastewater handled by different types of water management options in each time period;
- Amount of raw shale gas produced at each shale well in each time period;
- Amount of raw shale gas transported from shale sites to processing plants in each time period;
- Amount of raw shale gas sold to markets directly in each time period.

Once observing the leader's decisions, the followers react rationally to maximize their own NPVs. In this study, the fee-based processing contracts are considered between the shale gas producer and the processors. In other words, the processing plants will offer a fixed fee for unit processing capacity to the shale gas producer in each time period. Depending on the raw shale gas output, the producer may choose to sign processing contracts of varying processing capacities with the processors. The followers' major decisions include:
First-stage design decisions:

- Unit processing fee for their processing contracts.

Second-stage operational decisions:

- Amount of shale gas processed in each time period;
- Amount of natural gas and natural gas liquid sold to the market.
- These decisions are made according to the following information:
- Actual shale well productivity of each shale site in each scenario;
- Composition of raw shale gas from each shale site;
- Cost data on capital investment and operating cost associated with different design and operational decisions;
- Actual performance ratio of processing plants in each time period;
- Demand and price of natural gas and natural gas liquids at the market;
- Planning horizon of this project.

The resulting problem is a multi-period decentralized supply chain optimization problem under uncertainty. There are uncertainties associated with leader and followers, namely the uncertain shale well productivity in each time period and the uncertain performance ratio of processing plants in each time period. The uncertainty associated with shale well productivity accounts for the production fluctuations of active shale wells, and the uncertainty of performance ratio describes the uncertain processing performance of existing processing facilities. Therefore, both types of stakeholders need to consider the uncertain performances of other stakeholders before making their design and operational decisions.

3. Model Formulation and Solution Algorithm

The general model formulation is presented as follows.

$$\min \ TEP^{leader} = \mathrm{E}_{\xi}\left[TP^{leader}\left(x^u, y^u, x^l, \xi\right)\right] \tag{1}$$

$$\text{s.t. } A_R\left(\xi\right)x^u + A_Z\left(\xi\right)y^u + B_R\left(\xi\right)x^l < r\left(\xi\right) \tag{2}$$

$$x^u \in R_+^{m_R},\ y^u \in Z_+^{m_Z}$$

where x^l solves:

$$\min \ TEP_p^{follower} = \mathrm{E}_{\xi}\left[TP_p^{follower}\left(x^l, \xi\right)\right], \quad \forall p \in P \tag{3}$$

$$\text{s.t. } Q_R\left(\xi\right)x^u + Q_Z\left(\xi\right)y^u + P_R\left(\xi\right)x^l < s\left(\xi\right) \tag{4}$$

$$x^l \in \mathbb{R}_+^{n_R}$$

x^u and y^u indicate the continuous variables and discrete variables corresponding to the leader's decisions, respectively. x^u involves decisions including the shale gas production rate at each shale site in each time period, the amount of shale gas transported from shale sites to processing plants, capacity of gathering pipelines, amount of freshwater required for each shale site, and amount of wastewater treated by different technology options. y^u involves discrete decisions on the number of wells drilled at certain shale site in each time period, and whether a gathering pipeline should be installed or not. x^l indicates the continuous variables corresponding to follower's decisions, including the unit processing fee of processing contracts, processing schedule of shale gas, and amount of natural gas and NGLs extracted from raw shale gas.

TEP^{leader} denotes the leader's total expected NPV, which equals the leader's second-stage NPV minus the leader's first-stage cost. The leader's first-stage cost accounting for various "here-and-now" capital investments, including the following terms:

- Shale well drilling and completion cost;
- Gathering pipeline installation cost;
- Processing contracts cost.

The leader's second-stage NPV comprises the following terms:

- Revenue from sales of natural gas and natural gas liquids (NGLs);
- Salvage value of shale wells at the end of planning horizon;
- Income from sales of raw shale gas;
- Shale gas production cost;
- Water management cost;
- Transportation cost;
- Royalty payment.

The leader's objective is optimized subject to the following constraints:

- Economic constraints calculating the costs associated with leader's design and operational decisions.
- Mass balance constraints describing the input-output balance relationships associated with the upstream shale sites;
- Capacity constraints describing the capacity limits of different processes, including water management, drilling activity, shale gas production, gas processing, gas transportation, and market demand;
- Logic constraints addressing the basic assumptions and logical relationships of major decisions, especially those regarding shale well drilling, pipeline installation, processing contract selection, and technology selection.

$TEP_p^{follower}$ denotes the follower *p*'s total expected NPV, which equals the follower's first-stage income from processing contracts minus the second stage operating cost for their shale gas processing service. The follower's objective is optimized subject to the following constraints:

- Economic constraints calculating the costs associated with follower's design and operational decisions;
- Mass balance constraints describing the input-output balance relationships associated with the midstream processing plants;

- Capacity constraints describing the capacity limits of shale gas processing, gas transportation, unit processing fees, and market demand.

As can be observed, the leader's and the follower's decisions variables appear in both the upper level problem and the lower level problem. This indicates that the leader's optimization problem is partially dependent on the follower's decisions, and the follower's optimal strategy will be determined based on the leader's decisions. The final optimum of such a bilevel program follows the solution concept of Nash equilibrium. The resulting problem is a two-stage stochastic MIBP problem, where the upper-level problem is an MINLP problem with bilinear terms formulated as products of a continuous variable and a binary variable, and a set of lower-level LP problems are involved in the constraints. We note that such a stochastic MIBP problem can be computationally challenging to solve using off-the-shelf mathematical programming solvers. Therefore, by replacing the lower-level optimization problems with their equivalent KKT conditions, the original bilevel problem is reformulated into an equivalent single level MINLP problem with bilinear terms. To further improve the computational efficiency, the Glover's linearization approach is adopted to reformulate this single level MINLP problem into an equivalent MILP problem (Glover, 1975), which can be solved directly by MILP solver CPLEX 12.6.3.

4. Application to a Shale Gas Supply Chain

To illustrate the applicability of the proposed modeling framework and solution approach, a case study of a decentralized shale gas supply chain based on Marcellus Shale is presented. A shale gas producer is considered as the leader, who oversees five potential shale sites. Each shale site allows for drilling of up to four to eight shale wells. The wastewater can be handled by three different water management options, including underground injection into Class-II disposal wells, centralized wastewater treatment (CWT), and onsite treatment and recycling with multi-stage flash, multi-effect distillation, or reverse osmosis technologies (Gao and You, 2015b). The produced raw shale gas can be transported to three shale gas processing plants. Alternatively, the raw shale gas can be sold directly to the market. Each processing plant represents a follower, who will charge the producer for their processing service based on the processing contracts (Gao and You, 2017c). Specifically, three types of fee-based processing contracts are considered, corresponding to 50 %, 75 %, and 100 % of total processing capacity in a shale gas processing plant. A 10-year planning horizon is considered, which is divided into 10 time periods. Each time period represents one year. There are two types of uncertainties in this shale gas supply chain, namely the uncertain productivity of a shale well at a certain time period and the uncertain processing capacity that can be provided by the processing plants. Normal distributions are assumed for both uncertainties. By applying sampling approximation approach, the number of scenarios is finalized as 200 scenarios with 98 % confidence interval (Shapiro and Homem-de-Mello, 1998). After the reformulation steps mentioned above, the resulting single level MILP problem has 341 integer variables, 115,016 continuous variables, and 65,557 constraints. All the models and solution procedures are coded in GAMS 24.7.3 on a PC with an Intel® Core™ i7-6700 CPU and 32GB RAM.

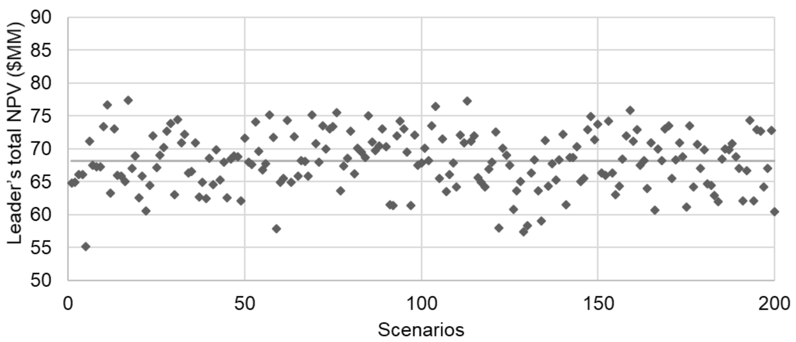

Figure 1: Leader's total NPV in 200 scenarios

By solving this optimization problem, the optimal expected NPV for the leader is $ 68.9 MM. The three followers corresponding to three processing plants are expected to achieve $2.57 MM, $ 3.39 MM, and $ 1.21 MM NPVs, respectively. In Figure 1, the leader's NPVs in 200 scenarios are summarized to demonstrate the impact of uncertainties on the overall economic performance of stakeholders. Each point in this figure indicates a specific solution point associated with a scenario. All the solution points share the same first-stage design decisions obtained from the two-stage stochastic MIBP model. The straight line indicates the expected NPV throughout the 200 scenarios considered in this case study.

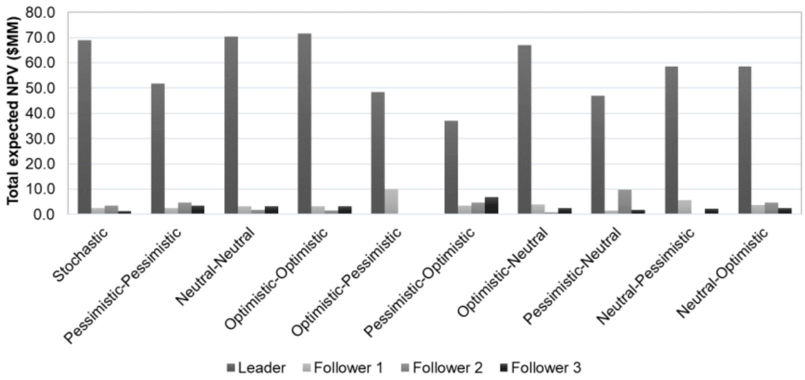

Figure 2: Optimal expected NPVs of the leader and followers in different game theoretic models

To demonstrate the advantage of this two-stage stochastic MIBP model, the optimal results obtained in the proposed two-stage stochastic game theoretic model are compared with those of the deterministic game theoretic models. Notably, in the deterministic game theoretic model, each stakeholder makes decisions based on its deterministic expectation of other stakeholders instead of considering all the possibilities. Consequently, when the leader and the followers have different perspectives on the others' performances, there may be a significant discrepancy in the resulting optimal strategies obtained in the deterministic game theoretic models. In this case study, distinct cases are considered to address this issue. To be more specific, the leader may hold optimistic, neutral, or pessimistic expectations toward the follows' actual performance, and vice versa. The optimistic expectation corresponds to 150 % expectation. The neutral corresponds to 100 % expectation. The pessimistic corresponds to 50 % expectation. The optimal expected NPVs of the leader and the followers associated with these nine cases are summarized in Figure 2.

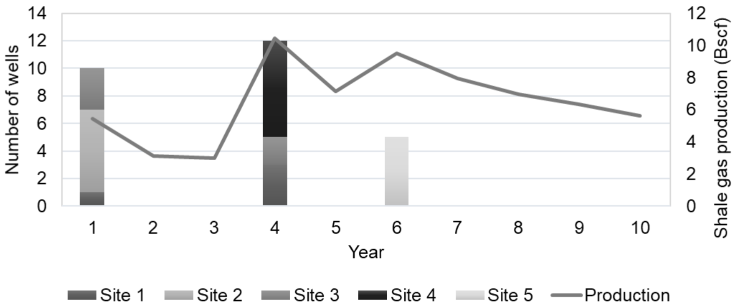

Figure 3: Optimal drilling schedule and average shale gas production profiles at shale sites

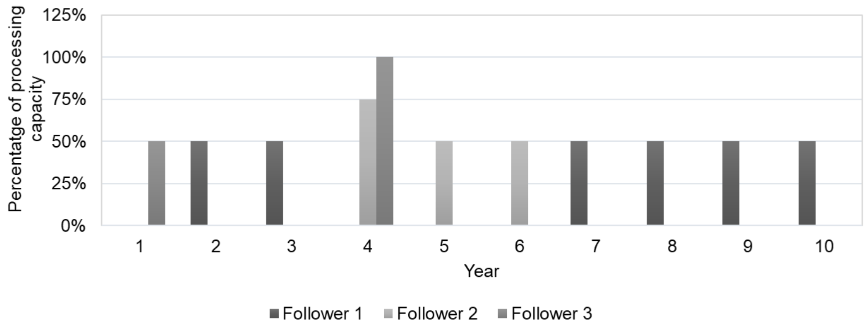

Figure 4: Optimal drilling schedules of solution points A and B

Figure 3 presents the optimal drilling schedule determined by the leader. The corresponding average shale gas production profile is included as well. A total of 27 shale wells are drilled within the 10-year planning horizon.

Specifically, 10 shale wells are drilled in the beginning at shale sites 1, 2 and 3 to satisfy the initial natural gas demand. Later, based on the forecasted price of natural gas, there will be a price increase in the fourth year. As a result, the leader determines to drill 12 extra shale wells at shale sites 1, 3, and 4 to make more profit. Due to the decreasing feature of productivity of shale wells, 5 more shale wells are drilled in the sixth year to compensate for the production decrease. The leader's optimal strategy on selection of processing contracts is presented in Figure 4. In most years, the leader performs conservatively to sign a processing contract with only one processing plant, and 50 % of the total processing capacity is considered enough. Since different processing plants have distinct processing capabilities, the leader may switch to other processing plants when production fluctuation is encountered. In the fourth year, with 12 extra shale wells being developed, additional processing capacity is required, so the leader signs contracts with both processing plants 2 and 3.

5. Conclusions

A novel modeling framework is proposed that integrates the leader-follower Stackelberg game with two-stage stochastic programming approach into a holistic model. This modeling framework enables us to investigate the optimal design and operations of decentralized supply chains involving multiple stakeholders with uncertain behaviors. To illustrate the application, a case study of Marcellus shale gas supply chain is presented. Based on the optimization results, it is concluded that stakeholders tend to choose more conservative strategies when considering uncertainties in decentralized supply chains. Although the conservativeness may affect the overall performance of stakeholders to some extent, it effectively hedges against the risk of extreme cases when stakeholders wrongly anticipate others' behaviors.

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