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Incorporating Game Theory in the Life Cycle Optimization of Decentralized Supply Chains

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In this paper, we propose a novel modeling framework to account for multiple strategic decisions in the shale gas supply chain, including the well drilling schedule, water management, installation of gathering pipelines, allocation, capacity and design of processing plants, and selection of processing contract. We incorporate a leader-follower game theory and the life cycle optimization method into a holistic modeling framework, which enables us to simultaneously address the trade-offs between conflicting objectives as well as the interactions between different players. In this supply chain, the shale gas producer is identified as the leader. Due to the key role of leader in a game, the producer not only enjoys the priority to make decisions first, but senses the responsibility to mitigate the life cycle greenhouse gas (GHG) emission embedded in the final product. The midstream player shale gas processor is identified as the follower, who will take actions rationally according to the leader's decisions to pursue its own profit. The resulting problem is a multiobjective mixed-integer bilevel linear programming problem and solved by a novel projection-based reformulation and decomposition algorithm. Based on a case study of Marcellus shale play, the leader's net present value ranges from \$ 29.2 M to \$ 50.7 M, and the corresponding total GHG emissions range from 329 kt CO_2-eq to 367 kt CO_2-eq.

1. Introduction

In the past decade, accompanying the rapid development of shale gas energy systems (Gong, 2015), concerns are raised regarding the environmental impacts of shale gas production (Hurley et al., 2016), among which the greenhouse gas (GHG) emissions is of special interest to both academia and industry (He et al., 2016). There have been a huge body of literature focusing on evaluating the life cycle GHG emissions of shale gas, most of which are based on life cycle assessment methodology (Weber et al., 2012). Meanwhile, some publications focus on optimization of shale gas supply chains; issues such as process design (He et al., 2014), process intensification (Gong et al., 2017), water management (Yang and Grossmann, 2014), uncertainties (Gao et al., 2015a), and GHG emissions (Gao et al., 2015c) were addressed. Although a centralized model is used in the existing literature (Emara et al., 2016), a shale gas supply chain is normally decentralized and run by different entities. Consequently, the optimal strategy obtained from a centralized model can be practically infeasible (Yue et al., 2014). Therefore, there is an urgent need to properly address the non-cooperative relationship between multiple stakeholders in the life cycle optimization of a shale gas supply chain (Garcia et al., 2015).

To address this challenge, we propose a leader-follower game-based Life Cycle Optimization (LCO) model, which integrates both the leader-follower Stackelberg game and LCO framework. A "cradle-to-gate" system boundary is chosen covering the whole shale gas production system from upstream shale sites to midstream processing plants and distribution facilities. A three-echelon shale gas supply chain superstructure is given in Figure 1. The major novelties of this work are summarized as follows:

- A leader-follower game-based life cycle optimization framework addressing trade-offs between multiple objectives as well as interactions between multiple players;
- Simultaneous optimization of decisions for well drilling, water management, allocation, capacity, and process design of processing plants, and processing contracts.
- A specific case study in Marcellus region is considered to compare the results with the centralized model.

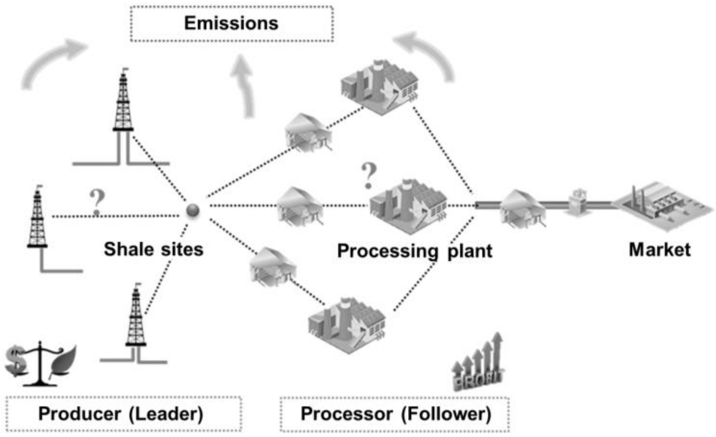

Figure 1: Superstructure of a shale gas supply chain

2. Problem statement

As mentioned in the previous section, the stakeholders in the shale gas supply chain here are classified into two players, identified as the producer, indicating the shale sites, and the processor, indicating the processing plants and corresponding gathering and distributional facilities. Since the producer initiate the shale gas supply chain and is able to control the overall shale gas production, we consider the producer as the leader in this game that makes decisions first, which include:

- Drilling schedule at each shale site;
- Water management strategy at each shale site;
- Installation of gathering pipelines from shale sites to gathering nodes;
- Amount of raw shale gas transported to potential processing plants at each time period;

The shale gas processor provides shale gas processing service to the producer in the supply chain, who is assumed follower in this game that reacts rationally according to the leader's decisions. The processor's decisions include:

- Selection of location and capacity for each potential processing plant;
- Type of processing contract signed with the producer;
- Specific process design adopted at processing plant;
- Processing planning at processing plant at each time period.

The producer cares about not only its economic performance, but the life cycle environmental performance embedded in the final products. To be more specific, the objectives of the producer include:

- Maximizing its total net present value (NPV);
- Minimizing the total life cycle GHG emissions.

Meanwhile, the processor takes action after the leader and tends to only care about its own profit. Thus, after the realization of the producer's decisions, the processor will react accordingly to optimize its own objective:

- Maximizing its total NPV.

3. Model formulation and solution method

According to the problem statement in the previous section, a multiobjective mixed-integer bilevel linear programming (MIBLP) model is developed to address the sustainable design and operations of non-cooperative shale gas supply chain networks. A general form of this MIBLP problem is presented as follows denoted as (P0).

Economic Objective: $$\max_{x^u, y^u, x^l, y^l} \quad TP^{leader} = c_R^t x^u + c_Z^t y^u + d_R^t x^l + d_Z^t y^l \tag{1}$$

Environmental Objective: $$\min_{x^u, y^u, x^l, y^l} \quad TE = e_R^t x^u + e_Z^t y^u + f_R^t x^l + f_Z^t y^l \tag{2}$$

$$\text{s.t.} \quad A_R x^u + A_Z y^u + B_R x^l + B_Z y^l \le r \tag{3}$$

(P0) $$\left(x^l, y^l\right) \in \underset{x^l, y^l}{\operatorname{argmax}} \quad \mathrm{TP}^{follower} = w_R^t x^l + w_Z^t y^l \tag{4}$$

$$\text{s.t.} \quad Q_R x^u + Q_Z y^u + P_R x^l + P_Z y^l \le s \tag{5}$$

$$x^u \in \mathbb{R}_+^{m_R}, y^u \in \mathbb{Z}_+^{m_Z}, x^l \in \mathbb{R}_+^{n_R}, y^l \in \mathbb{Z}_+^{n_Z}$$

TP^{leader} denotes the producer's total NPV, which can be calculated using the following equation.

$$TP^{leader} = TR^{leader} - TC^{leader} \tag{6}$$

TR^{leader} indicates the total revenue of the producer obtain from sales of natural gas and NGL as well as the remaining value of shale well at the end of planning horizon.

$$TR^{leader} = \sum_{t\in T} \frac{png_t \cdot \left(TNG_{c_1,t} + \varphi \cdot TNG_{c_2,t} + TNG_{c_3,t}\right)}{\left(1+dr\right)^t} + \sum_{k\in K}\sum_{t\in T} \frac{pnl_{k,t} \cdot \left(TNL_{c_1,k,t} + \varphi \cdot TNL_{c_2,k,t}\right)}{\left(1+dr\right)^t} + \sum_{i\in I}\sum_{t\in T} psgd \cdot \left(NN_{i,t} \cdot eur_i - SP_{i,t}\right) \tag{7}$$

TC^{leader} denotes the total cost incurred by the producer's activities, including drilling wells, gas production, water management, gas processing, transportation, and royalty payment.

$$\begin{aligned} TC^{leader} &= TC^{drill} + TC^{prod} + TC^{water} + TC^{proc} + TC^{tran} + TC^{royal} \\ &= \sum_{i\in I}\sum_{t\in T} sdc_i \cdot NN_{i,t} + \sum_{i\in I}\sum_{t\in T} \frac{spc_i \cdot SP_{i,t}}{\left(1+dr\right)^t} + \sum_{i\in I}\sum_{t\in T} \frac{fwc \cdot FW_{i,t}}{\left(1+dr\right)^t} + \sum_{i\in I}\sum_{w\in W}\sum_{t\in T} \frac{wtc_w \cdot WW_{i,w,t}}{\left(1+dr\right)^t} + \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} \frac{vp_c \cdot STP_{i,p,c,k,t}}{\left(1+dr\right)^t} \\ &+ \sum_{i\in I}\sum_{p\in P}\sum_{r\in R} tpri_{r-1} \cdot XP_{i,r} \cdot lsp_{i,p} + \sum_{i\in I}\sum_{p\in P}\sum_{r\in R} \left(TCP_{i,r} - tprc_{r-1} \cdot XP_{i,r}\right) \cdot \left(\frac{tpri_r - tpri_{r-1}}{tprc_r - tprc_{r-1}}\right) \cdot lsp_{i,p} \\ &+ \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} \frac{vtcs \cdot lsp_{i,p} \cdot STP_{i,p,c,k,t}}{\left(1+dr\right)^t} + \sum_{c\in C}\sum_{t\in T} \frac{vtcm \cdot lpd \cdot TNG_{c,t}}{\left(1+dr\right)^t} + \sum_{k\in K}\sum_{t\in T} \frac{vtcl \cdot lpm \cdot \left(TNL_{c_1,k,t} + TNL_{c_2,k,t}\right)}{\left(1+dr\right)^t} + \frac{\sum_{i\in I}\sum_{t\in T} \gamma_i \cdot psg_{i,t} \cdot SP_{i,t}}{\left(1+dr\right)^t} \end{aligned} \tag{8}$$

TE denotes the total "cradle-to-gate" life cycle GHG emissions in this shale gas supply chain generated in different processes.

$$\begin{aligned} TE &= TE^{drill} + TE^{prod} + TE^{water} + TE^{proc} + TE^{tran} \\ &= \sum_{i\in I}\sum_{t\in T} esd_i \cdot NN_{i,t} + \sum_{i\in I}\sum_{t\in T} esp_i \cdot SP_{i,t} + \sum_{i\in I}\sum_{t\in T} efw \cdot FW_{i,t} + \sum_{i\in I}\sum_{w\in W}\sum_{t\in T} ewt_w \cdot WW_{i,w,t} + \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} epc_k \cdot STP_{i,p,c,k,t} \\ &+ \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} est \cdot lsp_{i,p} \cdot STP_{i,p,c,k,t} + \sum_{c\in C}\sum_{t\in T} emt \cdot lpd \cdot TNG_{c,t} + \sum_{c\in C}\sum_{k\in K}\sum_{t\in T} elt \cdot lpm \cdot TNL_{c,k,t} \end{aligned} \tag{9}$$

$TP^{follower}$ denotes the processor's total NPV, which are given in the following equations.

$$\begin{aligned} TP^{processor} &= TR^{processor} - TC_{fix}^{processor} - TC_{var}^{processor} \\ &= \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} \frac{vp_c \cdot STP_{i,p,c,k,t}}{\left(1+dr\right)^t} + \sum_{t\in T} \frac{png_t \cdot (1-\varphi) \cdot TNG_{c_2,t}}{\left(1+dr\right)^t} + \sum_{k\in K}\sum_{t\in T} \frac{pnl_{k,t} \cdot \left[(1-\varphi) \cdot TNL_{c_2,k,t} + TNL_{c_3,k,t}\right]}{\left(1+dr\right)^t} \\ &+ \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} \frac{vpx \cdot \left(PC_{p,k} - STP_{i,p,c,k,t}\right)}{\left(1+dr\right)^t} - \sum_{p\in P}\sum_{k\in K}\sum_{r\in R} pri_{k,r} \cdot YP_{p,k,r} - \sum_{i\in I}\sum_{p\in P}\sum_{c\in C}\sum_{k\in K}\sum_{t\in T} \frac{vpo_{c,k} \cdot STP_{i,p,c,k,t}}{\left(1+dr\right)^t} - \sum_{k\in K}\sum_{t\in T} \frac{vtcl \cdot lpm \cdot TNL_{c_3,k,t}}{\left(1+dr\right)^t} \end{aligned} \tag{10}$$

x^u and y^u indicate the continuous variables and discrete variables in the upper-level problem, respectively. x^u involves decisions including the amount of shale gas production at each shale site, the capacity of gathering pipelines from shale sites to gathering nodes, the water management planning, and the processing planning at each time period. y^u involves decisions on drilling schedule and installation of corresponding infrastructures. Correspondingly, x^l and y^l indicate the continuous variables and discrete variables in the lower-level problem, respectively. x^l addresses decisions regarding detailed processing operations, capacity of processing plants, and the sales and distribution activities. y^l addresses the construction decisions of processing plants, the selection of different process designs, and the type of processing contract signed with producer. The constraints for both the leader and follower can be classified into five parts, namely the mass balance constraints, environmental constraints, economic constraints, capacity constraints, and logic constraints.

The resulting problem is a multiobjective MIBLP problem, which cannot be solved using any off-the-shelf solvers directly (Chu et al., 2014). Thus, a tailored optimization algorithm is presented to tackle this complex problem efficiently. We first reformulate the original MIBLP into an equivalent generalized semi-infinite program, which is further reformulated into a projection-based single-level optimization problem. In order to boost the computational efficiency, a decomposition approach is implemented based on the single-level reformulation. By iteratively solving one master problem (MP) and two subproblems (SP1 and SP2), a Karush-Kuhn-Tucker (KKT)-condition-based cut is generated in each iteration and added to the master problem. Thus, the lower bound and upper bound can be updated correspondingly.

4. Case study

To illustrate the application of the proposed modelling framework and solution algorithm, we consider a case study based on Marcellus shale play. In this case study, the producer plans to develop with 3 potential shale sites, each of which can drill up to 4-8 shale wells at maximum. Meanwhile, the producer also needs to determine the optimal water management strategy. There are 3 water management options considered here, including injection into disposal wells, treated by centralized wastewater treatment (CWT) facilities, and onsite treatment (Gao and You, 2015b). We further consider 3 different onsite treatment technologies, namely the multi-stage flash (MSF), multi-effect distillation (MED), and reverse osmosis (RO) (Al-Nory et al., 2014). In addition, according to the drilling schedule, the producer needs to properly design the gathering pipelines to transport the raw shale gas from shale sites to gathering nodes and then further sent to processing plants. As to the midstream processor, there are 3 potential processing plants to choose from, for which 3 capacity ranges are considered (He and You, 2015). Moreover, for each processing plant to be built, the processor will determine the specific process scheme and processing contract to adopt. We consider 3 different NGL recovery process schemes, including the gas sub-cooled process (GSP), recycle split-vapor process (RSV), and enhanced NGL recovery process (IPSI-1). Each process scheme has distinct economic and environmental performances. Besides, we consider 3 types of contracts that are mainly employed by shale gas processors, namely fee-based (FB) contracts, percentage of proceeds (POP) contracts, and keep-whole (KW) contracts. The total planning horizon is 10 y, which is divided into 10 time periods, i.e. one year per time period. The compositions of the shale gas are taken from those reported in (Gao and You, 2017).

The resulting multiobjective MIBLP problem is solved using the proposed optimization algorithm and 10 Pareto optimal solutions are obtained, which form the Pareto-optimal curve shown in Figure 2. The x-axis represents the total life cycle GHG emissions generated. The y-axis represents the leader's total NPV. The total NPV increases as the total life cycle GHG emissions increase, which explicitly shows the trade-off between the economic and environmental objectives in the leader's problem. In addition, we use pie charts above the Pareto curve to illustrate the cost breakdowns for producer, and the corresponding emission breakdowns are illustrated by the bars over the Pareto curve.

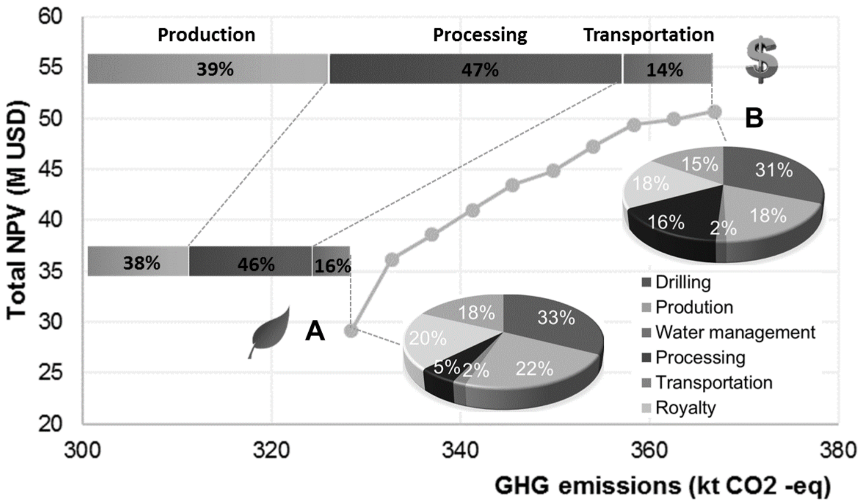

Figure 2: Pareto-optimal curve of the case study with cost breakdowns

From the Pareto-curve, we identify the most sustainable solution point A with the lowest GHG emissions of 329 kt CO_2-eq and the lowest NPV of $29.2 M. Meanwhile, the processor's total NPV is $ 71.0 M. By contrast, point B has the highest NPV of $ 50.7 M and the highest GHG emissions of 367 kt CO_2-eq. The corresponding processor's NPV is $ 69.1 M. For the producer, the major cost include the drilling cost, production cost, processing cost, transportation cost, and the royalty cost. For the processor, the major cost comes from the drilling, accounting for about one third of the total cost. The shale gas production and processing are recognized as the major GHG emission sources, which account for 46 % and 38 % of the total GHG emissions, respectively. Transporation activities accounts for about 16 % of the total GHG emissions.

The detailed optimal drilling schedule as well as corresponding shale gas production profile for both point A and point B are summarized in the following Figure 3. As can be seen, at point A when the uptream producer minimizes the total life cycle GHG emisison, a total of 13 wells are drilled, resulting in a relatively stable shale

gas production profile. For the point B where the producer maximizes its NPV, a total of 17 shale wells are drilled, and more production fluctuations can be observed as a reflection of the natural gas and NGL price fluctuation. Addtionally, the specific wells chosen to be drilled at each time period are different as well due to their distinct shale gas compositions.
Since the objective of processor is to maximize its NPV regardless of the producer's preference, the processor will stick to the most profitable strategy. In this case study, all the shale sites are wet ones that produce shale gas with higher than 15 % NGL composition. Considering the much higher price of NGL, processor is inclined to choose the KW contract and POP contract to gain more revenue. For the KW contract, processor will retain title of the separated NGLs and return identical amount of pipeline-quality sales gas to the producer that equals the heating value of raw shale gas feedstock stream. As to the POP, in addition to a processing fee, processor will get a certain percentage (25 % here) of the proceeds of the sale of natural gas and NGL for compensation. It is interesting to note that due to price variability in the future year, the contract selection decisions vary significantly. From Figure 3 we observe that for point A, the processor holds the KW contract for 7 y and the POP contract for 3 y. While for point B, POP contract is preferred that lasts for 9 y due to the relatively lower gas price of that year. The optimal process design for NGL recovery turns out to be the IPSI-1 scheme, which features lower capital and operting cost, higher NGL recovery rate, and less carbon footprint. Although the natural gas recovery rate is lower, the loss will be compensated by sales of NGL.

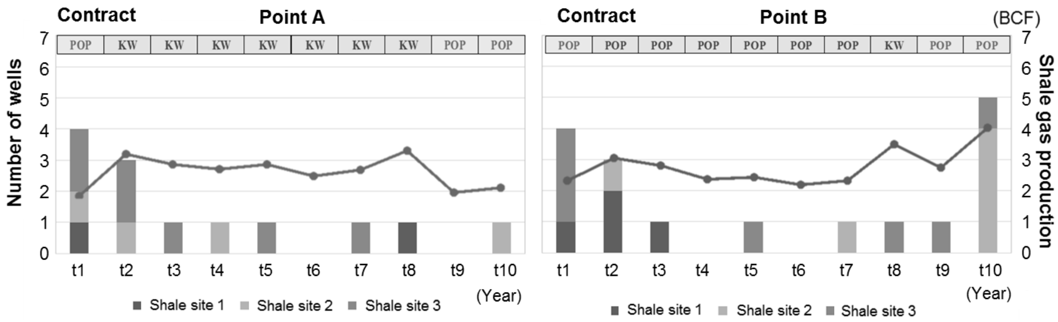

Figure 3: Optimal drilling schedule in different solutions

In order to demonstrate the impact of non-cooperative perspective in the life cycle optimization of shale gas supply chain, we further consider two extra centralized models maximizing the producer's NPV and total life cycle GHG emissions, respectively. The corresponding results are summarized and compared with those of game theory-based models as shown below.

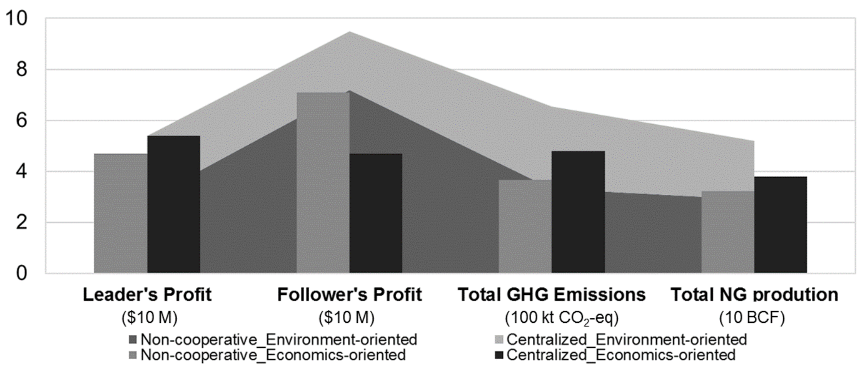

Figure 4: Performance comparison between centralized models and non-cooperative models (economics-oriented models given in columns; environmental-oriented model given in areas)

As can be seen in Figure 4, on one hand, by comparing the economics-oriented model and environmental model, we come to the conclusion that in order to minimize the overall GHG emissions in the shale gas supply chain, the producer has to adjust its strategy by sacrificing its own profit to achieve this goal. The reduction in producer's profit can be up to 40 %. In return, the total GHG emissions can be reduced by about 10-30 %. Meanwhile, due to the adjustment of production strategy of the producer, the processor has the chance to gain more profit as an individual player. On the other hand, the comparison between the centralized model and the proposed non-cooperative model illustrates the drawback of the former one. For both economics-oriented model and environmental-oriented model, the producer in the centralized model can obtain about 30-40 % more profit due to its absolute control over the shale gas supply chain. As a consequence, the processor will have 40-70 % less profit in the centralized model. For the GHG emissions reduction, the centralized model also leads to over-optimistic results that may not be realized in practice.

5. Conclusions

In this work, we propose a leader-follower game-based MIBLP model to demonstrate the interactions among different players and trade-offs between conflicting objectives in a non-cooperative shale gas supply chain. Multiple decisions with respect to shale well drilling schedule, water management, installation of gathering pipelines, allocation, capacity and design of processing plants, and selection of processing contract are considered. In order to solve the resulting multiobjective MIBLP problem, we present a novel projection-based reformulation and decomposition algorithm. A case study based on Marcellus shale play was also presented.

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