Energy Supply Chains Planning: Risk-based Optimization

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The planning of an Energy Supply Chain (ESC) aims at maximizing the benefits of the ESC agents, while satisfying the demands of the customers (Stadtler (2005); Shiyu et al. (2020)). Demand variability and supply disruption, originating from the connectivity between supply and demand, can disturb the agents interactions and impair the agents management (Govindan et al. (2017)). In this study, we propose a risk-based optimization approach for the management of ESC. We introduce a Conditional Value at Risk (CVaR) measure with the purpose of measuring and controlling the risk to the ESC management. A multi-objective optimization based by the Non-dominated Sorting Genetic Algorithm (NSGA-II) is performed to search for the solution optimal with respect to the maximization of the ESC total profit and the minimization of the risk under uncertainties. For demonstration, an application is carried out considering a specific oil&gas ESC model with five layers, including crude oil producers, storages, refineries, terminal storages and retailers. Results show that the optimization approach enables the trade-off between the ESC optimal planning and the source of risk that it is subjected to.

Keywords: Energy Supply Chain (ESC), Agent-based Modeling (ABM), risk-based optimization, CVaR, NSGA-II, uncertainty.

1. Introduction

An Energy Supply Chain (ESC) is made up of a number of agents interacting with each other. The agents in the ESC, such as crude oil producers, refineries, storages are physically and functionally heterogeneous, and organized in a hierarchy such that what happens to one agent can easily spread through the ESC and affect other agents (Zio (2016)). In such environment, agents are required to maximize the benefits, while satisfying the demands of the customers(Stadtler (2005); Shiyu et al. (2020)). Therefore, modeling and optimizing of ESCs become important for its planning.

This paper studies the planning problem of ESC under uncertainties and risks. Demand, production and supply uncertainties, related to product characteristics, are the major sources of uncertainties (Ho et al. (2005)). Besides these uncertainties, consideration must be given also to supply chain risks of two types: disruption risk and operational risk (Kleindorfer and Saad (2005); Tang (2006)). The disruption risks are related to circumstances such as natural disaster, terrorist attacks and labor strikes, whereas operation risks are caused by high uncertainty and unbalance between supply and demand (Lockamy III and McCormack (2010); Sreedevi and Saranga (2017)). These risks influence the ESC function (Heckmann et al. (2015)).

To address this problem, we propose a simulation-based optimization method which consists of a simulation module and an optimization module. For the simulation former, we rely on Agent-based Modeling (ABM), which is a powerful technique for modelling large interconnected systems (Bonabeau (2002)). The oil companies, factories, producers, customers in the ESC are functionally described as agents who can interact with each other(Farmer and Foley (2009)).

In this ESC model, the demand and supply

uncertainties, and the disruption risks are considered. Demand and supply uncertainties change the plant operations and consequently the production planing. To consider these problems, we correspondingly define the objective functions.

For the multi-objective optimization module, the objective functions are the total profit and the Conditional Value at Risk (CVaR). On one hand, the profit is a most crucial factor for oil companies. On the other hand, we consider CVaR to measure the "tail risk" of an investment portfolio, which is widely used in supply chain portfolio optimization. For example, Carneiro et al. (2010) uses CVaR as a risk measure constraint to maximize returns with risk constraints. Soleimani and Govindan (2014) applies CVaR as a risk evaluator to study design and planning of a reverse supply chain network in a two-stage stochastic programming framework. Qiu et al. (2014) studies a robust inventory decision problem by applying the CVaR risk measure under discrete demand distribution uncertainty. Thus, it can be seen that CVaR is an effective tool to manage risk. Hence, we apply CVaR to measure the disruption risk in the ESC. Finally, the multi-objective problem defined is solved by applying a simulation-based genetic algorithm optimization method.

The rest of the paper is organized as follows. In Section 2, we present the Agent-Based ESC model. Section 3 introduces the ABM-MOO formulation and solution framework. Section 4 illustrates the case study and the results of the ESC's profit and CVaR optimization under disruption risk and uncertainties. A discussion is given in Section 5.

2. The ESC Model

The ESC is described by ABM, which considers the logical rules of the agents behavior and interactions (Macal and North (2005)). The model allows simulating the ESC transaction processes in an uncertain, dynamic and time-dependent environment (Labarthe et al. (2007); Julka et al. (2002); Parunak et al. (1998); Farmer and Foley (2009)). In our model, we take into account the demand and supply uncertainties, and the disruption risk.

2.1. *Modeling of Agents Uncertain Behavior*

We consider an ESC with L layers and each l-th layer consists of V_l agents, $a_{l,1}, a_{l,2}, ..., a_{l,v}, ..., a_{l,V_l}$ (Figure 1). In the ESC, the orders sent from the demanders of Layer 1 flow layer-by-layer to the end layer L, whose V_L agents are suppliers that send the supply backward to the demanders.

An agent $a_{l,v}, v = 1, 2, ..., V_l$, in the l-th layer, is assigned with behaviors, which allow the agent to adaptively interact with the others. The details of the model are described in the following.
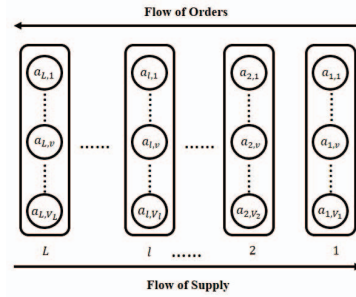

Fig. 1. The ABM-ESC model

2.1.1. *Sending Orders*

The process of sending orders of an agent $a_{l,v}$ in the l-th layer (Fig.2) is as follows:

(a) $a_{l,v}$ chooses the supplier $a_{l+1,v'}$ in the upper layer $l+1$, based on capacity and cost of satisfying the order.

(b) $a_{l,v}$ sends orders to $a_{l+1,v'}$.

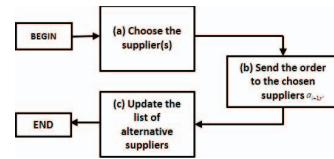(c) $a_{l,v}$ updates the list of alternative suppliers, taking into account the capacity of supply.

Fig. 2. The process of sending orders

2.1.2. *Receiving Orders and Choosing Demanders*

The process of an agent $a_{l,v}$ receiving orders and choosing demander(s) is shown in Fig.3:

(a) $a_{l,v}$ receives the order from $a_{l-1,v''}$ in the lower layer $l-1$.

(b) $a_{l,v}$ checks whether the received order is empty:

- If yes, $a_{l,v}$ does not choose demanders.
- Otherwise, (c) $a_{l,v}$ checks whether it has available productions that satisfy the received orders.

  – If yes, (d) $a_{l,v}$ checks whether the received orders exceed the existing production limitation $U_{l,v}(t)$ defined as:

$$U_{l,v}(t) = S_{l,v}(t) - S_{l,v}^*(t) \qquad (1)$$

where $S_{l,v}$ is the storage of $a_{l,v}$ and $S_{l,v}^*$ is the back-up safety storage of $a_{l,v}$.

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* If yes, (e) $a_{l,v}$ refuses the order from $a_{l-1,v''}$ demanded with the lowest bid price, and returns to (d).
* Otherwise, (f) the agent $a_{l,v}$ accepts the order and makes a contract with $a_{l-1,v''}$. Then, the existing oil production limitation of the agent $a_{l,v}$ (Eq.(2)) updates for the next time $t+1$:

$$U_{l,v}(t+1) = U_{l,v}(t) - \sum_{v'',v''\in\{v_a\}} x_{l,v}^{l-1,v''}(t) \tag{2}$$

where, $x_{l,v}^{l-1,v''}(t)$ is the amount of orders accepted by the agent $a_{l,v}$ which are sent by the agent $a_{l-1,v''}$

– Otherwise, (g) $a_{l,v}$ sends a response back to the demander $a_{l-1,v''}$.

– If yes, the agent $a_{l,v}$ stops sending the order plan.
– Otherwise, (d) the agent $a_{l,v}$ updates its demands,

$$y_{l,v}^{l+1,v'}(t+1) = y_{l,v}^{l+1,v'}(t) - \sum_{v',v'\in\{v_a\}} x_{l+1,v'}^{l,v}(t) \tag{3}$$

where, $y_{l,v}^{l+1,v'}(t)$ is the amount of orders sent by the agent $a_{l,v}$ which are received by the agent $a_{l+1,v'}$ at time t, $x_{l+1,v'}^{l,v}(t)$ is the amount of orders accepted by the agent $a_{l+1,v'}$ which are sent by the agent $a_{l,v}$ at time t.
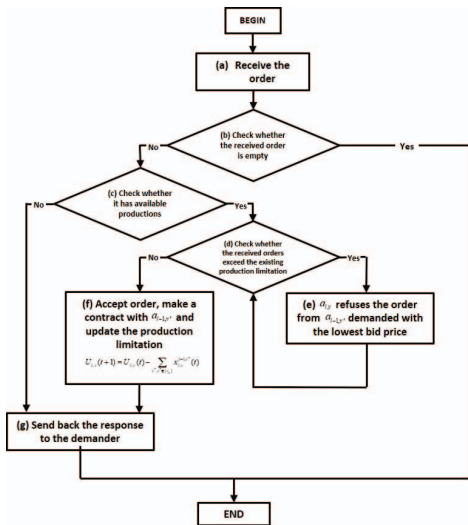And, (e) send orders (as discussed in Section 2.1.1) again.

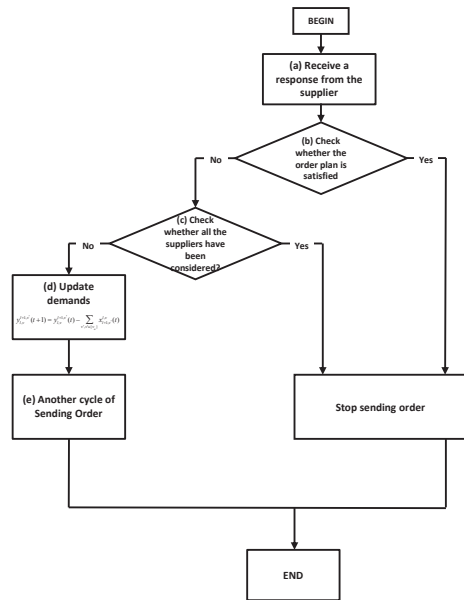Fig. 3.   The process of receiving orders and choosing demander(s)

Fig. 4.   The process of response

2.1.3. *Response*

One demander $a_{l,v}$ may negotiate with its supplier $a_{l+1,v'}$, in case of receiving a response from $a_{l+1,v'}$. This process is shown in Fig.4 and described as follows:

(a) The agent $a_{l,v}$ receives a response from the supplier $a_{l+1,v'}$.
(b) Check whether the order plan is satisfied:

* If yes, $a_{l,v}$ stops sending the order plan.
* Otherwise, (c) $a_{l,v}$ checks whether all the alternative suppliers have been considered:

2.1.4. *Selling Production*

An agent $a_{l,v}$ should sell productions after accepting an order plan. This process is shown in Fig.5 and defined as follows:

(a) $a_{l,v}$ checks whether it stores enough productions satisfying the accepted order plan:

* If yes, (b) sells the productions to the demander $a_{l-1,v''}$ and updates the set of accepted orders and the storage for the next time $t+1$ (Eq.(4)):

$$S_{l,v}(t+1) = S_{l,v}(t) - \sum_{v'',v'' \in \{v_a\}} z_{l,v}^{l-1,v''}(t)$$

(4)

where $S_{l,v}$ is the production storage of $a_{l,v}$ and, $z_{l,v}^{l-1,v''}(t)$ is the amount of the production sold by $a_{l,v}$ to $a_{l-1,v''}$.

- Otherwise, (c) $a_{l,v}$ sells the productions to the demander who makes its income highest, and, then, updates the set of accepted orders and the storage $S_{l,v}(t+1)$.
  (d) Check whether the storage or the set of accepted orders is empty.
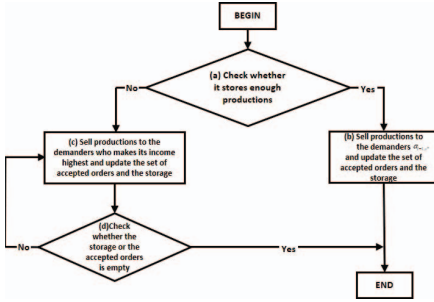
  – If not, repeat (c).
  – Otherwise, end.

Fig. 5.   The process of selling production

2.1.5. *Receiving Production*

An agent $a_{l,v}$ receives the oil production from the upstream agents $a_{l+1,v'}$ and updates its storage $S_{l,v}(t+1)$ for the next time $t+1$:

$$S_{l,v}(t+1) = S_{l,v}(t) + w_{l,v}^{l+1,v'}(t) \cdot k_{l,v}$$

(5)

where $w_{l,v}^{l+1,v'}(t)$ is the amount of the oil production sent by the the agent $a_{l,v}$ which are received by the agent $a_{l+1,v'}$ time t, $k_{l,v}$ is the production capacity of $a_{l,v}$,

2.2. *Uncertainty and risk assessment*

In this study, we use the Conditional Value-at-Risk (CVaR) to measure the risk in the cost of supply (Carneiro et al. (2010); Qiu et al. (2014); Gebreslassie et al. (2012); Zhang and Zhang (2019); Saghaei et al. (2020); Snoeck et al. (2019)). The definitions of VaR and CVaR are shown as follows:

$$VaR_\alpha(X) = \inf\{Z \in R : F_X(Z) > \alpha\}$$

(6)

where X is the loss, F_X is the discrete approximation of the probability distribution of the loss X, α is the α-percentile for the function F_X, Z is the smallest value of loss whose probability is greater than α.

$$CVaR_\alpha(X) = E(X|X \geq VaR_\alpha(X))$$

(7)

where X is the loss and $E(X)$ is the expected value of X which is larger than $VaR_\alpha(X)$ defined in 6.

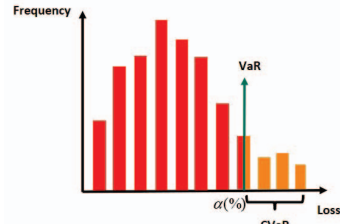In order to understand the CVaR in a comprehensive view, we draw a graphical definition in Fig.6.

Fig. 6.   Distribution of sending production loss

Fig.6 shows that VaR is the smallest value of the loss for a confidence level α of the probability distribution. Although the VaR has been widely used in measuring risk, it also presents some deficiencies (Carneiro et al. (2010)).

CVaR is the expected value of the loss given that the loss is greater than or equal to the $VaR_\alpha(X)$. The definitions and properties of CVaR are given in detail in (citerockafellar2006generalized,rockafellar2002conditional).

The ESC planning problem under risk and uncertainty is described in Section 2.3.

2.3. *MOO problem formulation*

In the ESC, every agent wants to maximize its profit. Here, we assume that the main income is from selling oil production and the main cost is in buying oil production.

Eq.(8) defines the ESC total profit P over a time horizon T:

$$P = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{v=1}^{V_l} (A - B - C - D)$$

(8)

A is related to the income from selling the oil production to the customer, expressed as:

$$A = \sum_{v''=1}^{V_{l-1}''} p_{l,v}^{l-1,v''} z_{l,v}^{l-1,v''}(t)$$

(9)

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where $p_{l,v}^{l-1,v''}$ is the unit price of the agent $a_{l,v}$ when selling the oil production to the agent $a_{l-1,v''}$, $z_{l,v}^{l-1,v''}(t)$ is the production sent by the agent $a_{l,v}$, which is received by the agent $a_{l-1,v''}$ at time t.

B is the purchase cost, which includes the procurement cost plus other costs like the transportation cost, the labor cost and so forth:

$$B = \sum_{v'=1}^{V'} (p_{l+1,v'}^{l,v} + o_{l,v}^{l+1,v'}) w_{l,v,}^{l+1,v'}(t) \quad (10)$$

where $p_{l+1,v'}^{l,v}$ is the unit price of the agent $a_{l+1,v'}$ for selling the oil production to agent $a_{l,v}$, $o_{l,v}^{l+1,v'}$ is the unit price for the other costs, $w_{l,v,t}^{l+1,v'}$ is the amount of the oil production sent by the agent $a_{l+1,v'}$ and which is received by the agent $a_{l,v}$.

The item C accounts for the storage cost:

$$C = c_{l,v}^{S} S_{l,v}(t) \quad (11)$$

where $c_{l,v}^{S}$ is the agent $a_{l,v}$ storage unit cost, $S_{l,v,t}$ is the production storage of the agent $a_{l,v}$ at time t.

Finally, D is the penalty for supply shortage:

$$D = \alpha_{l,v} \sum_{v''=1}^{V_{l-1}''} (x_{l,v}^{l-1,v''}(t) - z_{l,v}^{l-1,v''}(t)) \quad (12)$$

where $\alpha_{l,v}$ is the unit penalty cost, $x_{l,v}^{l-,v''}(t)$ is the amount of orders accepted by the agent $a_{l,v}$ which are sent by the agent, $z_{l,v}^{l-1,v''}(t)$ is the amount of oil production sent by the agent $a_{l,v}$, which are received by the agent $a_{l-1,v''}$ at time t.

Then, the total cost at time t could be defined as:

$$E(t) = \sum_{l=1}^{L} \sum_{v=1}^{V_l} (B + C + D) \quad (13)$$

The general MOO problem is, then, formulated as:

$$\max P(\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L}, p_{2,1}^{1,1}, ...,$$
$$p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}) \quad (14)$$

$$\min CVaR(\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L},$$
$$p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}})$$
$$= CVaR_\alpha(\sum_{l=1}^{L} \sum_{v=1}^{V_l} E_{l,v}(t)) \quad (15)$$

s.t.

$$\bar{y}_l^{\min} \leq \bar{y}_{l,v,t} \leq \bar{y}_l^{\max} \quad (16)$$

$$p_l^{\min} \leq p_{l,v}^{l-1,v''} \leq p_l^{\max} \quad (17)$$

Eq.14 maximizes the total profit and Eq.15 minimizes the risk, simultaneously. The constraint 16 and the constraint 17 give the feasible region for the average orders and the price.

3. The ABM-MOO Framework

GA is used to search a set of feasible solutions optimal with respect to the objective functions. These solutions (chromosomes, in GA terminology) are input in the simulation model. Fig.7 shows the framework of the hybrid simulation-based optimization process.
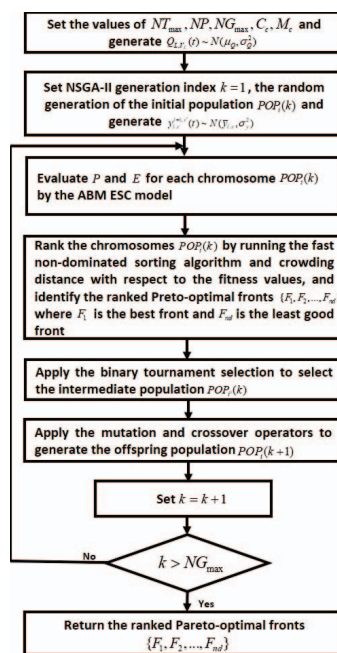

Fig. 7. The flowchart of the ABM-MOO framework

A set of Pareto solutions is, eventually, identified and a best-compromised solution can be chosen among them by the Min-Max method (Marseguerra et al. (2005); Belegundu and Chandrupatla (2019)). Given the Pareto solutions $H \equiv (P, CVaR)$ the relative deviations of P and CVaR are defined, respectively:

$$z_P = \frac{|P - P^{\min}|}{P^{\max} - P^{\min}} \quad (18)$$

where $P^{\min}$ and $P^{\max}$ are the minimum and maximum of the fitness values P, respectively.

$$z_{CVaR} = \frac{|CVaR - CVaR^{\min}|}{CVaR^{\max} - CVaR^{\min}} \quad (19)$$

where $CVaR^{\min}$ and $CVaR^{\max}$ are the minimum and maximum of the fitness values $CVaR$, respectively.

The best-compromised solution is determined as

$$z_H = \min[\max\{z_P, z_{CVaR}\}] \quad (20)$$

4. Case Study

An ESC ABM of five layers is considered. This includes retailers (Layer1), terminal storages (Layer2), refineries (Layer3), storages (Layer4) and crude oil producers (Layer5). In Layer1, Layer2 and Layer3, there are 3 agents respectively. In Layer4 and Layer5, there are 2 agents in each layer. In this ESC, we assume that there is 10% probability that the refinery 3 is disrupted. When it is disrupted, it is not able to send oil production to down stream demanders.
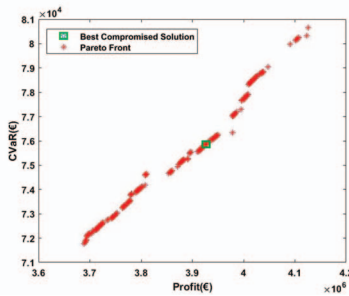
Fig. 8.   The Pareto front with the best-compromised solution

Fig.8 shows the Pareto front which reflects that the CVaR increases when the ESC total profit tends to be large. Then increasing CVaR means increasing risk: if the agents want to get more profit they have to face larger risk which makes sense because high profit are always accompanied by high risk. According to Eq.(20) discussed in Section 3, the best compromised solution is identified, and the total profit P equals to €3924956.04 and $CVaR$ equals to €75851.93.

Fig.9 shows the cost frequency distribution in the normal state which is optimized in the literature (Shiyu et al. (2020)). Fig.10 shows the cost frequency distribution with disruption risks if we do not take any measure to control them. Fig.11 shows the cost frequency distribution with disruption risk if the ESC is optimized.

Fig.9 shows that if the ESC is without disruption risk, the cost is distributed in the range from
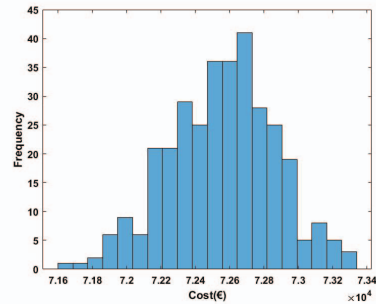
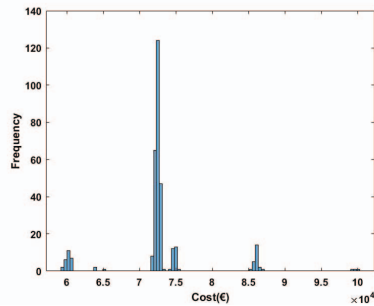Fig. 9.   The cost frequency distribution under the ESC normal state

Fig. 10.   The cost frequency distribution with the ESC disruption risk
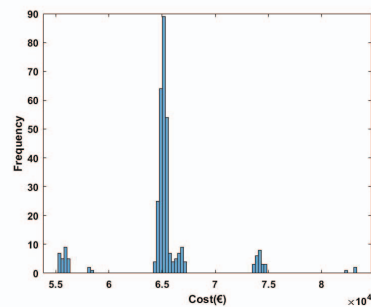
Fig. 11.   The cost frequency distribution with the ESC disruption risk after optimization

€7.16×10^4 to €7.34×10^4 which is a relatively concentrated range. Comparing Fig.9 with Fig.10 and Fig.11, the range of the cost distribution increases, because the disruption risks cause the refinery storage cost and shortage penalty to increase. On the other hand, after the disruption happens, some oil production has to be stored in Refinery 3. When the ESC goes back to normal, Refinery 3 does not need to order new oil produc-

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tion from up stream storage, so the procurement cost is decreasing, which further increases the range of the cost distribution. In Fig. 10, the 95% confidence level on the right-hand of the cost is €88650. In Fig. 11, the 95% confidence level on the right-hand of the cost is €75851.93. Comparing Fig. 10 with Fig.11, the proposed ABM-MOO framework is effective to decrease the CVaR related to the risk disruption.

5. Conclusions

The objective of this study is to manage the production planning problem in Energy Supply Chains (ESCs), where the agent interaction behavior is uncertain and the ESC faces disruption risk. In order to address this problem, we propose a simulation-based multi-objective optimization framework which enables decision making on planning production, including the price and the amount of purchased oil production. Firstly, we use Agent-based Modeling (ABM) to model and simulate the agent behaviors and the ESC transaction processes. Secondly, we use Non-dominated Sorting Genetic Algorithm (NSGA-II) to get the optimal solutions that maximize the ESC total profit and minimize the disruption risk. An oil ESC model with five layers, including crude oil producers, storages, refineries, terminal storages and retailers is presented to demonstrate the methodology.

For future research, we think that the cooperative and competitive relationships among agents can be considered in the ESC optimization problem.

Acknowledge

Appendix A. Nomenclature

$\{v_a\}$: The set of the agent indexes whose orders are accepted.
$a_{l,v}$: The v-th agent in the layer l.
$k_{l,v}$: The production capacity of agent $a_{l,v}$.
$\alpha_{l,v}$: The unit penalty cost.
ε_P: An arbitrary large number for total profit.
ε_E: An arbitrary large number for uncertainty.
$p_l^{\min}$: The minimum for the unit price.
$p_l^{\max}$: The maximum for the unit price.
$\bar{y}_l^{\min}$: The minimum for the average orders.
$\bar{y}_l^{\max}$: The maximum for the average orders.
$r(t)$: The number of agents who get a loss after the oil production transaction.
$Q_{L,V_L}(t)$: The amount of productions, which are produced by the agents in the last layer at time t.
$U_{l,v}(t)$: The residual oil production limitation of the agent $a_{l,v}$ at time t.
$S_{l,v}(t)$: The storage of the agent $a_{l,v}$ at time t.

$S_{l,v(t)}^*$: The back up safety storage in the agent $a_{l,v}$ at time t.
$x_{l,v}^{l-,v''}(t)$: The amount of orders accepted by the agent $a_{l,v}$, which are sent by the agent $a_{l-1,v''}$ at time t.
$y_{l,v}^{l+1,v'}(t)$: The amount of orders sent by the agent $a_{l,v}$, which are received by the agent $a_{l+1,v'}$ at time t.
$z_{l,v}^{l-1,v''}(t)$: The amount of the oil production sent by the agent $a_{l,v}$, which are received by the agent $a_{l-1,v''}$ at time t.
$w_{l,v}^{l+1,v'}(t)$: The amount of the oil production sent by the the agent $a_{l+1,v'}$, which are received by the agent $a_{l,v}$ at time t.
$o_{l,v}^{l+1,v'}$: The unit price for the other cost.
$p_{l,v}^{l-1,v''}$: The unit price of the agent $a_{l,v}$ by selling the oil production to the agent $a_{l-1,v''}$.
$c_{l,v}^S$: The agent $a_{l,v}$ storage unit cost.
μ_l: The mean of agents profits in the layer l.
σ_l: The standard deviation of agents profits in the layer l.
μ_Q: The mean of agents production amount $Q_{L,V_L}(t)$.
σ_Q: The standard deviation of agents production amount $Q_{L,V_L}(t)$.
$\bar{y}_{l,v}$: The amount of average orders sent by the agent $a_{l,v}$ at time t.
σ_y: The standard deviation of agents orders $y_{l,v}^{l+1,v'}(t)$.
NT_{max}: The total transaction time.
NG_{max}: Maximum number of GA generations.
NP: GA population size.
C_c: Crossover coefficient.
M_c: Mutation coefficient.

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