Computers & Industrial Engineering 158 (2021) 107410

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

An agent-based approach for project-driven supply chain problem under information asymmetry and decentralized decision-making

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ARTICLE INFO

Keywords:
Project scheduling
Multi-agent system
Supply chain coordination
Contracting

ABSTRACT

In a project-driven supply chain, the project schedule and material supply influence one another. The effective decision-making process between the project manager and the suppliers can promote the flexibility and competitiveness of supply chains. However, due to their incompatible objectives, the suppliers are reluctant to disclose private information. By incorporating information asymmetry, we build a model to describe the decentralized decision-making process. The project manager does not know the lead time and the production/transportation cost of the material suppliers accurately. To build an effective alliance in the supply chain, different contracts are considered to provide a positive or negative incentive for the suppliers, including a non-financial incentive contract with continuous orders. Then, we present a framework that integrates the agent-based approach and evolutionary algorithm. In the framework, the agents not only negotiate with each other to complete a solution but also jointly evaluate the solutions generated by the evolutionary algorithm. Finally, an experiment is conducted to compare the agent-based approach and the classical NSGA-II under information symmetry. The results show that the gap between the algorithms is acceptable, especially for a large project. The results also show that the non-financial incentive contract is beneficial to all the players in the supply chain.

1. Introduction

Effective supply chain management is critical for projects, because it can avoid time and cost overruns. In construction projects, building materials alone can constitute up to 60% of the total project cost, and the management of materials affects 80% of the project schedule (Safa et al., 2014). If a supply chain is not controlled properly, it will ultimately result in project failure (Shojaei and Haeri, 2019). The Boeing 787 project was postponed for two years due to material shortage or late delivery, which damaged its credibility and cost billions of dollars. The supply chain which ultimately delivers a customized capital project is referred to as a project-driven supply chain (Wu, 2014). As shown in Fig. 1, in a project-driven supply chain, the project is the single customer and generally orders materials in batches during the project execution, especially for a large project with a limited site (Ghisolfi et al., 2017). The project purchases materials based on its inventory, which depends on the requirement of the relevant activities and the delivery status of the associated suppliers; if the inventory is less than the minimum requirement, the project will be suspended for a lack of materials. There exist intertwined relationships in the project-driven supply chain: the demand quantity and the demand cycle are defined by the project schedule, while the implementation progress of the project is constrained by the actual deliveries of different suppliers. If we schedule activities or purchase materials separately, both plans are generally inexecutable and make the project difficult to respond to various disruptions flexibly.

Integrated project planning can help to define these relationships and to enhance the project performance (Wu, 2014; Mello et al., 2017). On the one hand, the project manager can timely adjust the schedule due to a potential delay or a limited capacity of suppliers. The adjusted schedule partly reduces the negative effect of the material shortage. On the other hand, the selection of suppliers throughout the project progress can increase productivity and reduce costs (Chen et al., 2018). The uniqueness of the project leads to a discontinuous and uncertain nature of demand for the suppliers and entails supplier identification (Shishodia et al., 2019). The same project in a separate batch may raise different requirements for the suppliers as well. For example, in the event of time pressure, the project manager prefers the supplier with a faster delivery rather than that with a lower price. The current research on the project scheduling or the project procurement assumes information symmetry

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https://doi.org/10.1016/j.cie.2021.107410
Received 2 October 2020; Received in revised form 9 February 2021; Accepted 19 May 2021
Available online 21 May 2021

and is conducted through a centralized decision-making process (e.g., heuristics-based methods, mathematical programming, multi-objective algorithm). This assumption implies that the information of all the players in supply chain is completely public; this decision-making process requires that all the players concentrate on the common objectives, and all the plans are executed firmly without consideration of personal loss. However, in practice, suppliers prefer to keep some information private to increase their competitive advantage even in a collaborative environment; thus, the objectives of the players are generally conflicting. Therefore, the project-driven supply chain resolved via a centralized decision-making process may lead to unreliable information, inattentive execution and unsatisfactory outcomes (Chen and Lee, 2017).

On another dimension, as shown in Fig. 1, the players in the project-driven supply chain are closely connected by contracts, which outline the expectations for the goods and stipulate the payment to the suppliers. Each type of contract differs in the specific terms about incentives. From the perspective of the project manager, an effective contract can propel the suppliers to deliver goods on time, and reduce the schedule slippage in a cost-efficient way. The literature about the contracts for project procurement is scarce. To the best of our knowledge, only Chen and Lee (2017) proposed a time incentive contract in a simplified project network. Although the mutual effect between the project scheduling and the material procurement was not considered, they proved that channel coordination was achieved in a decentralized decision-making process. The existing research on contracting in the whole field of project management mainly focuses on financial incentive contracts that directly use money to produce a negative or positive incentive (Kwon et al., 2010b; Kerkhove and Vanhouckev, 2017; Palit and Brint, 2020). Moreover, the incentive strength in the financial incentive contract, such as the ratio of down payment, is always assumed to be exogenous. However, in practice, incentives are represented in various forms, not restricted to financial factors; the project manager can adjust the incentive strength according to the order quantity and the delivery date for different orders.

This paper deals with the decentralized decision-making process in the project-driven supply chain and improves the interface between site activities and the supply chain under information asymmetry. This paper makes two main contributions. First, we propose a decentralized decision-making framework integrating the agent-based approach and evolutionary algorithm. The agents collectively resolve resource conflicts via negotiations or evaluations, and no sensitive information is disclosed during the resolution. Second, except for two types of financial incentive contract, we adopt a non-financial incentive contract as a link between the players. This non-financial incentive contract takes a future work opportunity as an incentive. In these contracts, the project manager is entitled to change the contractual requirements according to the market competition and the project condition, such as the delivery cycle and the incentive strength.

This paper is organized as follows. Section 2 provides a brief review of the related literature. A mathematical programming model for the project manager and material suppliers is presented in Section 3. An evolutionary algorithm to integrate with agents is proposed in Section 4. Section 5 presents the agent-based approach. Section 6 discusses several experiments performed in various supply chain situations to verify the

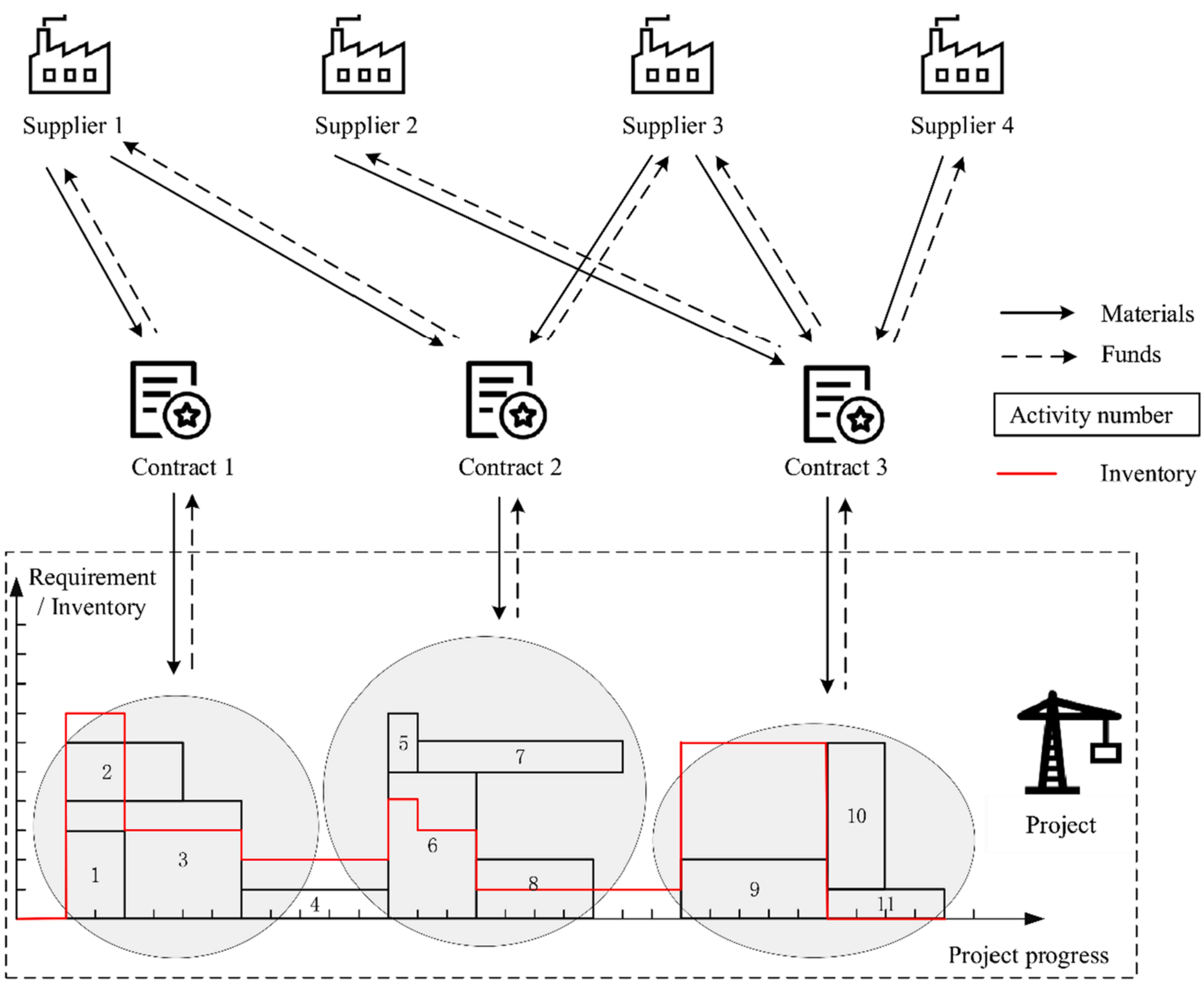

Fig. 1. Project-driven supply chain.

algorithm effectiveness. Finally, some conclusions are drawn. All the proofs and pseudocodes are presented in the Appendixes.

2. Related literature

In a project-driven supply chain, the procurement plan is integrated with the project schedule, and the coordination between the project manager and the suppliers is mainly ensured by a contract. The study is related to the following research streams: (1) project integrated scheduling and (2) contracting in project management.

2.1. Project integrated planning

The project integrated planning includes project scheduling, material ordering, supplier selection, etc. There is similar research in the field of production integrated planning (Chen, 2010; Viergutz and Knust, 2014; Cui, 2016). For the integrated problem of project scheduling and material ordering, Tabrizi and Ghaderi (2016) proposed a mixed-integer programming model for project scheduling and material procurement, subject to the risks of activity durations and execution costs. Considering the price discount, an order is put for each activity. Zoraghi et al. (2017) extended the model by including mode selection for project scheduling and assumed that the material procurements are exposed to the total quantity discount policy. The integrated problem was further studied with consideration of supplier selection. Chen et al. (2018) considered supplier selection and final quality inspection for concurrent projects in construction. The projects were independent in operation but subject to shared suppliers. They assumed that each project chooses one single supplier for each resource. In consideration of the risks of material delivery, Xu et al. (2016) presented a dynamic programming model for a recurrent project with random material delays to jointly optimize safety-stock decisions in material supply chains and crashing decisions in projects. They simplified the project into a sequence of critical tasks and assumed that the supply chains of different activities were operated independently. Habibi et al. (2019) proposed a mathematical model to determine the activities schedule, the material ordering time and quantity, and the supplier selection that maximize the project's Net Present Value and the environmental and social benefits of its suppliers. As shown in Table 1, the above studies all adopt centralized methods, in which the project manager (or the contractor) and the suppliers collaborate perfectly. These approaches typically require sensitive strategic information from business partners. Project integrated planning cannot be realized exactly in practice because the different players in the supply chain are always self-interested and maximize their profits without considering others.

We acknowledge that no single player can determine the schedules for the whole supply chain. Therefore, we consider the supplier's trade-off model separately from the project manager's planning model. The project manager cannot know the sensitive information of the suppliers accurately due to information asymmetry. Then, we resolve the integration problem via a decentralized approach—an agent-based approach.

2.2. Contracting in project management

The incentives in supply chain management take the form of a contract so that all parties internalize the full system-wide costs and benefits associated with their decisions, such as a profit-sharing contract (Shang et al., 2016). Four types of contracts in project management are common when a project manager can observe the completion time or the actual operating cost for the contract. 1) Under a fixed-price contract, the project manager pays the contractor a fixed price upon project completion with no incentives. 2) Under a time incentive contract, the payment for the contractors is a decreasing function of the delivery time to impel the contractor to complete the project earlier. 3) Under a cost incentive contract, the payment depends on the actual cost incurred by the contractor plus an incentive to restrain the cost, e.g., cost plus a fixed fee contract. 4) Under a quality incentive contract, better quality/scope performance brings the contractors more gains, and the quality/scope evaluation mostly uses key performance indicators or balanced scorecard techniques. Our paper concentrates on time incentive contracts due to the time risks in a project-driven supply chain.

In the literature on project management, most studies, except for the mentioned work of Chen and Lee (2017), consider a contractual relationship between a general contractor and several subcontractors. Kwon et al. (2010a) compared a delayed contract and a no-delayed contract based on the suppliers' work rates. They analysed the contracts' impact on each supplier's effort level and on the manufacturer's net profit in equilibrium. This study assumed that the contractor outsources parallel activities to identical subcontractors and considered the payment amounts as exogenous parameters. Kwon et al. (2010b) additionally considered the uncertain completion time and compared three types of project contracts commonly used in practice, namely, fixed price contract, time incentive contract and cost incentive contract. Chen et al. (2015) focused on a set of serial activities and nonhomogeneous subcontractors and incorporated the payment amounts as decision variables. They also studied an incentive payment contract and examined the impact on the project client's expected profit and the schedule performance of serial stochastic projects. Wang et al. (2017) investigated the impact of a time incentive contract for a serial project consisting of two activities, each performed by a subcontractor. They characterized the project makespan as an uncertain variable that depends on the subcontractor's unobservable effort. Based on the above framework, Dawande et al. (2019) derived multiple types of optimal

Table 1
Overview of literature on project integrated planning.

Research	Project scheduling				Material procurement	Supplier selection	Characteristic of procurement		Approach
	Single mode	Multi-mode/Crashing	Multi-project	Multi-objective			Uncertain delivery	Procurement contract	
Tabrizi and Ghaderi (2016)			√	√	√				Multi-objective algorithm
Zoraghi et al. (2017)		√		√	√				Multi-objective algorithm
Chen et al. (2018)			√		√	√			Mathematical programming
Xu et al. (2016)		√	√		√	√	√		Dynamic programming
Habibi et al. (2019)	√			√	√	√			Multi-objective algorithm
This paper	√			√	√	√	√	√	Agent-based approach

contracts for series–parallel projects, which induces the agents to exert optimal effort and a penalty. As shown in Table 2, the above studies are mainly conducted via the Stackelberg model and Principal-Agent model, while some studies are conducted via the Nash bargaining model (Palit and Brint, 2020). There is another solution using optimization methods. Kerkhove and Vanhoucke (2016) constructed a quantitative framework for the contract design problem, using incentive items for cost, duration and scope simultaneously. Kerkhove and Vanhoucke (2017) proposed a multi-objective scatter search heuristic to solve it. Aouam and Vanhoucke (2019) formulated the owner's model of determining the optimal parameters of a linear incentive contract as a bi-level program, considering that the contractor's effort influences the duration and cost of activities.

Our research addresses the contracting problem between the project manager (on behalf of the owner) and the material suppliers, which is different from the contractual relationship between a general contractor and several subcontractors. We analyse different types of time incentive contracts in the supply chain under information asymmetry, especially a non-financial incentive contract. Moreover, the incentive strength serves as a decision variable in the financial incentive contract, which is expressed by the incentive parameter. The suppliers are entitled to refuse the contract under an assumption of bounded rationality.

3. Mathematical formulation

We build models for the players in the supply chain due to their conflicting objectives. As shown in Fig. 2, the first model simulates the repeated ordering and the coordinated scheduling process from the perspective of project managers. The project manager makes a project schedule and develops procurement contracts to minimize the project costs. Three variables (the order quantity, the incentive parameter and the due date of delivery) are determined in the contract, and another variable (the order date) is also associated with it.

Another model is on behalf of the material suppliers. If a supplier accepts the contract, a *mode* of production & transportation will be selected to balance the lead time and the costs. The *mode* is introduced to describe the lead time of suppliers, which is influenced by the differences in the production techniques, the means of transportation or the distance to the project (Dotoli et al., 2017). When the actual delivery time exceeds the due date, the delay time will incur backorder cost.

The information asymmetry is twofold. First, the mode of the supplier is not revealed to the project manager. The project manager cannot know the actual lead time but only estimates it. Under a given contract, the suppliers tend to select the cheapest mode to maximize profits. The cheapest mode may lead to a late delivery and negatively affect the project schedule. Second, the project manager does not know the most favourable parameters of a contract for himself, which can be agreed upon by the suppliers as well. If the project manager is self-centred to determine the parameters, the suppliers may deny the contract because of no profits.

3.1. Project manager's model

The project network is described by a directed graph ($\mathscr{V}$, $\mathscr{G}$) defined over the node set $\mathscr{V} = \{0, 1, \cdots N, N+1\}$, where 0 and $N+1$ indicate dummy source activity and dummy sink activity, respectively. The set $\mathscr{G}$ collects the arcs representing the finish-start precedence relationships with zero time lag. We consider only one type of material but several optional suppliers. Once an activity starts, the required materials are consumed instantly. Material procurement is repeated several times, and the project manager is dominant at the orderings. The due date of delivery and the order quantity are determined based on a project schedule. A late delivery should be prevented due to the backorder cost. The notations are listed in Table 3.

The objective of the project manager is to minimize $TC^{contract}$. The expression of the discounted cash flow is expressed as in the study of Homberger and Fink (2017). The model can be formulated as follows.

$$\min TC^{\mathbf{fc}} = \sum_{l\in[L]}\sum_{g\in[G]}\left[MC_{g,l}(1+\alpha)^{-AD^{e}_{g,l}} + BC_{g,l}\right] \tag{1}$$

s.t.

$$\sum_{t\in[T]} t \times x_{i,t} \geq \sum_{t\in[T]} (t + d_j) x_{j,t} \forall (i,j) \in \mathscr{G} \tag{2}$$

$$x_{00} = 1 \tag{3}$$

$$\sum_{i\in w_t} r_{i,k} \leq R_k \forall k \in [K], \forall t \in [T] \tag{4}$$

$$I_t = I_{t-1} + \sum_{(g,l):AD^{e}_{g,l}=t} q_{g,l} - \sum_{i\in[N]} n_i x_{i,t} \forall t \in [T] \tag{5}$$

$$I_0 = I_T = 0 \tag{6}$$

$$0 \leq I_t \forall t \in [T] \tag{7}$$

$$ld^{\min} < D_g - O_g \leq ld^{\max} \forall g \in [G] \tag{8}$$

$$D_g < O_{g+1} \forall g \in [G-1] \tag{9}$$

$$AD^{e}_{g,l} = \max\left(O_g + ld^{e}_l, D_g\right) \forall g \in [G], \forall l \in [L] \tag{10}$$

$$\sum_{j\in[g]:AD^{e}_{j,l} > O_g} q_{j,l} \leq MQ_l \forall g \in [G], \forall l \in [L] \tag{11}$$

Table 2
Overview of literature on contracting in project management.

Research	Fixed price contract	Time incentive contract	Cost incentive contract	Quality incentive contract	Non-financial incentive contract	Project stage	Approach
Kwon et al. (2010a)	√	√				Construction	Game theory
Kwon et al. (2010b)	√	√	√			Construction	Game theory
Chen et al. (2015)	√	√				Construction	Game theory
Wang et al. (2017)		√				Construction	Game theory
Dawande et al. (2019)		√				Construction	Game theory
Palit and Brint (2020)		√				Construction	Game theory
Kerkhove and Vanhouckev (2016)		√	√	√		Construction	N/A
Kerkhove and Vanhouckev (2017)		√	√	√		Construction	Multi-objective algorithm
Aouam and Vanhoucke (2019)			√			Construction	N/A
Chen and Lee (2017)	√	√				Procurement	Game theory
This paper	√	√			√	Procurement	Agent-based approach

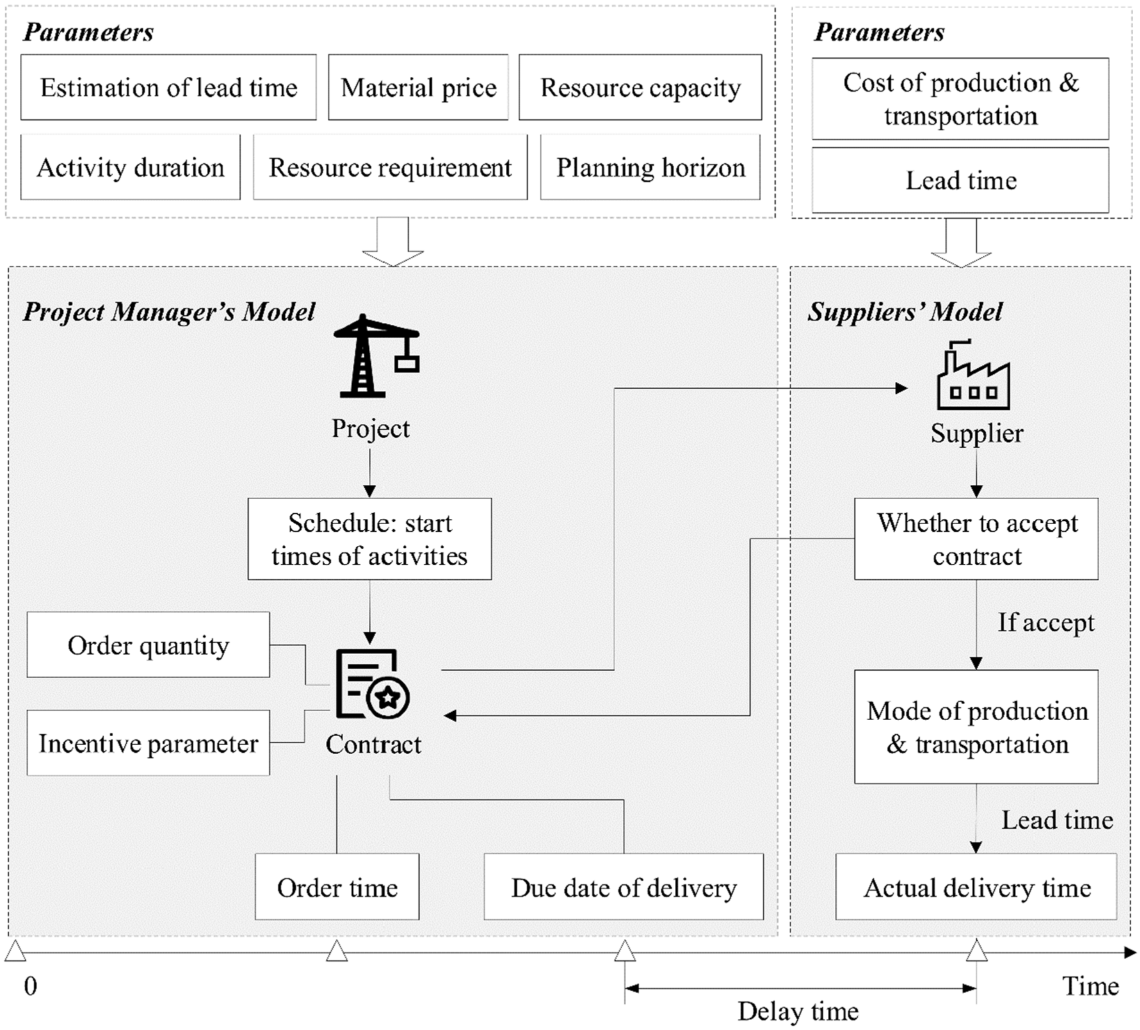

Fig. 2. Relation between project manager's model and suppliers' model.

$$\begin{array}{ll} x_{i,t} \in \{0,1\} & \forall i \in \mathscr{V}, \forall t \in [T] \\ D_g, q_{g,l} \in \mathbb{N} & \forall g \in [G], \forall l \in [L] \\ f_{g,l}, pn_{g,l} \in (0,1) & \forall g \in [G], \forall l \in [L] \end{array} \tag{12}$$

Expression (1) shows that the project manager pays the material suppliers a fixed price upon material delivery under a fixed-price contract. The total cost comprises the material price and a backorder cost. Constraint (2) shows that the precedence relations between activities need to be taken into consideration. Each activity should start after all immediate predecessors are completed. Constraint (3) requires that the dummy source activity starts at time 0. Constraint (4) describes that the requirement for renewable resources at any time is below the relative resource availability. A state transition equation is constructed to monitor the inventory level over the planning horizon in Constraint (5). Constraints (6) and (7) show that the initial inventory and ultimate inventory are both 0 and the inventory is non-negative at any time. Constraint (8) shows that the due date minus the order time is in a semi-closed interval of the shortest (estimated) lead time and the longest (estimated) lead time. The interval ensures the order contract is executable. D_g is generally earlier than the next order time for$g < G$ in Constraint (9). Constraint (10) indicates that the (estimated) delivery time is a maximum of the (estimated) material arrival time and the due date of delivery. The material arrival time is defined as the order time plus the lead time. Early delivery is also not allowed due to limited storage. Constraint (11) shows that at the order time O_g, the order quantity that is not delivered cannot exceed the capacity of each supplier. The materials with $AD^e_{j,l} > O_g$ are ordered at the jth order but not delivered. Constraint (12) defines the domains of decision variables.

3.2. Suppliers' model

For a given contract, the suppliers are entitled to deny it, if they cannot benefit from the business. Under an established contract, the suppliers will decide the most profitable mode for themselves. The mode is arranged in ascending order of the cost of production & transportation. Suppose that there is a negative correlation between the cost of production & transportation and the lead time. Moreover, we assume that the cost of production & transportation arises at the middle of the lead time. We define the notations of suppliers in Table 4.

From Table 4, the (actual) *material arrival time* of supplier l is a specific value with respect to the mode m. It is different from the (estimated) *material arrival time* in the project manager's model. The project manager thinks the lead time as ld^e_l, an estimation of the material lead time of supplier l, because the project manager cannot know it accurately. In this paper, we focus on the coordinative approach even when ld^e_l obviously differs from $ld_{l,m}$, irrespective of the predication techniques of the lead time.

Supplier l maximizes the discounted profit $\sum_{g\in[G]} y_{g,l} SP^{contract}_{g,l}$. Under a fixed-price contract (**fc**), the project manager pays the material suppliers a fixed price upon material delivery. The objective function is shown in Expression (13). Constraint (14) reveals that the supplier l can select

Table 3
Notations for the project manager's model.

Notations	Description
Indices	
i	Index of activities, $i \in \mathscr{V}$.
k	Index of type of renewable resources, $k \in [K]$.
l	Index of material suppliers, $l \in [L]$.
t	Time index, $t \in \{0, 1, \cdots, T\}$, where T is a planning horizon.
g	Index of order, $g \in [G]$.
Parameters	
d_i	Duration of activity i.
r_{ik}	Quantity of renewable resource k required by activity i.
n_i	Quantity of material required by activity i.
R_k	Availability of renewable resource k per period.
BN	Per-period backorder cost rate of the material price.
α	Discount rate of cash flow, $\alpha \in (0, 1)$.
ld_l^e	Estimation of material lead time of supplier l.
MP_l	Material price per unit of supplier l.
MQ_l	Material capacity of supplier l for each order.
$\mathscr{H}_g$	Preference set for selecting suppliers at the gth order.
$ld^{\max}$	Longest lead time of all suppliers.
$ld^{\min}$	Shortest lead time of all suppliers.
contract	Contract type, *contract* $\in \{\mathbf{fc}, \mathbf{ic}, \mathbf{pc}, \mathbf{nc}\}$. **fc**, **ic**, **pc** and **nc** denote fixed-price contract, instalment contract, penalty contract and non-financial incentive contract, respectively.
Decision variables	
$x_{i,t}$	If activity i starts at time t, $x_{i,t} = 1$; otherwise $x_{i,t} = 0$.
D_g	Delivery due date specified in the contract for the gth order.
$q_{g,l}$	Order quantity of supplier l at the gth order.
$f_{g,l}$(optional)	Down payment rate of the material price agreed with supplier l at the gth order under **ic**.
$pn_{g,l}$(optional)	Per-period penalty rate of the material price agreed with supplier l at the gth order in case of material delivery beyond the due date under **pc**.
Other variables	
$TC^{contract}$	Discounted total cost under a *contract*.
w_t	A set of activities in progress at time t, $w_t = \{i \mid x_{i,t-\delta} = 1, \delta = 1, \cdots, d_i\}$.
I_t	Remainder of material at time t.
O_g	Order time for the gth order.
$AD_{g,l}^e$	Estimation of delivery date of supplier l at the gth order.
$MC_{g,l}$	Material price paid to supplier l at the gth order, $MC_{g,l} = MP_l \times q_{g,l}$.
$DP_{g,l}$	Default penalty submitted by supplier l at the gth order, $DP_{g,l} = pn_{g,l} \times MC_{g,l}\left(AD_{g,l}^e - D_g\right)^+$.
$BC_{g,l}$	Discounted backorder cost of material l at the gth order in case of delay in delivery, $BC_{g,l} = \sum_{t \in [AD_{g,l}^e - D_g]} BN \times MC_{g,l}(1+\alpha)^{-(D_g+t)}$.

Table 4
Notations for the suppliers' model.

Notations	Description
Indices and Parameters	
m	Index of mode of production & transportation, $m \in [M]$.
$ld_{l,m}$	Material lead time of supplier l in mode m.
$SC_{l,m}$	Per-unit cost of production & transportation of supplier l in mode m.
Decision variables	
$z_{g,l,m}$	$=1$ if supplier l selects mode m at the gth order; 0 otherwise.
$y_{g,l}$	$=1$, supplier l award the gth contract if $SP_{g,l}^{\mathbf{contract}} > 0$; 0 otherwise.
Other variables	
$SP_{g,l}^{contract}$	Discounted profit of supplier l under a *contract* at the gth order.
$AD_{g,l}$	Actual delivery date of supplier l at the gth order, $AD_{g,l} = \max\left(O_g + \sum_{m \in [M]} ld_{l,m} z_{g,l,m}, D_g\right)$.
$DC_{g,l}$	Discounted cost of production & transportation of supplier l at the gth order, $DC_{g,l} = \sum_{m \in [M]} z_{g,l,m} SC_{l,m} q_{g,l}(1+\alpha)^{-(AD_{g,l}+O_g)/2}$.

only one mode to produce and transport materials. Constraint (15) defines the domains of decision variables.

$$\max \sum_{g \in [G]} y_{g,l} SP_{g,l}^{\mathbf{fc}} = \sum_{g \in [G]} y_{g,l}\left[MC_{g,l}(1+\alpha)^{-AD_{g,l}} - DC_{g,l}\right] \tag{13}$$

s.t.

$$\sum_{m \in [M]} z_{g,l,m} = 1 \forall g \in [G] \tag{14}$$

$$z_{g,l,m}, y_{g,l} \in \{0,1\} \forall g \in [G], \forall m \in [M] \tag{15}$$

Proposition 1.. *The supplier selects the optimal mode m^* for $\max_m SP_{g,l}^{\mathbf{fc}}$. 1) If $\max_m ld_{l,m} \le D_g - O_g$, $m^* = 1$. 2) If $\min_m ld_{l,m} \ge D_g - O_g$, $m^* = \operatorname{argmax}_m \{\eta(\eta MP_l - SC_{l,m})\}$. 3) If the above conditions are invalid, we define the optimal mode m_1 for $\max_{O_g + ld_{l,m} \le D_g} SP_{g,l}^{\mathbf{fc}}$ and the optimal mode m_2 for $\max_{O_g + ld_{l,m} > D_g} SP_{g,l}^{\mathbf{fc}}$. If $MP_l\left[(1+\alpha)^{-D_g} - \vartheta^2\right] + (\rho_2 - \rho_1)\vartheta + \rho_1\left[\vartheta - (1+\alpha)^{-D_g/2}\right] \ge 0$, $m^* = m_1$; otherwise, $m^* = m_2$. Let $\eta = (1+\alpha)^{-ld_{l,m}/2}$, $\vartheta = (1+\alpha)^{-(ld_{l,m_2}+O_g)/2}$, $\rho_1 = SC_{l,m_1}(1+\alpha)^{-O_g/2}$ and $\rho_2 = SC_{l,m_2}(1+\alpha)^{-O_g/2}$.*

3.3. Objectives under incentive contracts

We consider three types of incentive contracts: instalment contract (**ic**), penalty contract (**pc**) and non-financial incentive contract (**nc**). Under each contract, the constraints of both the project manager's model and the suppliers' model remain.

In the case of the instalment contract, a down payment is paid in advance, and the balance is deferred until material delivery. A down payment rate $f_{g,l}$ is defined as an incentive parameter. Expressions (1) and (13) are replaced by

$$\min TC^{\mathbf{ic}} = \sum_{l \in [L]} \sum_{g \in [G]} \left[BC_{g,l} + f_{g,l} MC_{g,l}(1+\alpha)^{-O_g} + \left(1 - f_{g,l}\right) MC_{g,l}(1+\alpha)^{-AD_{g,l}}\right] \tag{16}$$

and

$$\max \sum_{g \in [G]} y_{g,l} SP_{g,l}^{\mathbf{ic}} = \sum_{g \in [G]} y_{g,l}\left[f_{g,l} MC_{g,l}(1+\alpha)^{-O_g} + \left(1 - f_{g,l}\right) MC_{g,l}(1+\alpha)^{-AD_{g,l}} - DC_{g,l}\right] \tag{17}$$

Proposition 2.. *The supplier selects the optimal mode m^* for $\max_m SP_{g,l}^{\mathbf{ic}}$. 1) If $\max_m ld_{l,m} \le D_g - O_g$, $m^* = 1$. 2) If $\min_m ld_{l,m} \ge D_g - O_g$, $m^* = \operatorname{argmax}_m \left\{\eta\left[\eta\left(1 - f_{g,l}\right) MP_l - SC_{l,m}\right]\right\}$. 3) If both conditions are invalid, we define the optimal mode m_1 for $\max_{O_g + ld_{l,m} \le D_g} SP_{g,l}^{\mathbf{ic}}$ and the optimal mode m_2 for $\max_{O_g + ld_{l,m} > D_g} SP_{g,l}^{\mathbf{ic}}$. If $\left(1 - f_{g,l}\right) MP_l\left[(1+\alpha)^{-D_g} - \vartheta^2\right] + (\rho_2 - \rho_1)\vartheta + \rho_1\left[\vartheta - (1+\alpha)^{-D_g/2}\right] \ge 0$, $m^* = m_1$; otherwise, $m^* = m_2$. Let $\eta = (1+\alpha)^{-ld_{l,m}/2}$, $\vartheta = (1+\alpha)^{-(ld_{l,m_2}+O_g)/2}$, $\rho_1 = SC_{l,m_1}(1+\alpha)^{-O_g/2}$ and $\rho_2 = SC_{l,m_2}(1+\alpha)^{-O_g/2}$.*

In the case of the penalty contract (**pc**), if the delivery date is beyond the due date specified in the contract, the project manager imposes a penalty on the supplier as liquidated damages. The default penalty $DP_{g,l}$ for supplier l at the gth order is paid for the case of $AD_{g,l} > D_g$. The penalty rate $pn_{g,l}$ is also an incentive parameter. Expressions (1) and (13) are replaced by

$$\min TC^{\mathbf{pc}} = \sum_{l\in[L]}\sum_{g\in[G]}\left[BC_{g,l} + MC_{g}(1+\alpha)^{-AD_{g,l}} - DP_{g,l}(1+\alpha)^{-AD_{g,l}}\right] \tag{18}$$

and

$$\max\sum_{g\in[G]} y_{g,l}SP^{\mathbf{pc}}_{g,l} = \sum_{g\in[G]} y_{g,l}\left[MC_{g,l}(1+\alpha)^{-AD_{g,l}} - DP_{g,l}(1+\alpha)^{-AD_{g,l}} - DC_{g,l}\right] \tag{19}$$

Proposition 3.. *The supplier selects the optimal mode m^* for $\max_m SP^{\mathbf{pc}}_{g,l}$. 1) If $\max_m ld_{l,m} \leq D_g - O_g$, $m^* = 1$. 2) If $\min_m ld_{l,m} \geq D_g - O_g$, $m^* = \operatorname{argmax}_m \left\{\eta^2 MP_l\left[1 - pn_{g,l} \times \pi(m)\right] - \eta SC_{l,m}\right\}$. 3) If both conditions are invalid, we define the optimal mode m_1 for $\max_{O_g+ld_{l,m}\leq D_g} SP^{\mathbf{pc}}_{g,l}$ and the optimal mode m_2 for $\max_{O_g+ld_{l,m}>D_g} SP^{\mathbf{pc}}_{g,l}$. If $MP_l\left[(1+\alpha)^{-D_g} - \vartheta^2\right] + (\rho_2 - \rho_1)\vartheta + \rho_1\left[\vartheta - (1+\alpha)^{-D_g/2}\right] + \vartheta^2 pn_{g,l} \times \pi(m_2) \geq 0$, $m^* = m_1$; otherwise, $m^* = m_2$. Let $\eta = (1+\alpha)^{-ld_{l,m}/2}$, $\pi(m) = \left(O_g + ld_{l,m} - D_g\right)^+$, $\vartheta = (1+\alpha)^{-(ld_{l,m_2}+O_g)/2}$, $\rho_1 = SC_{l,m_1}(1+\alpha)^{-O_g/2}$ and $\rho_2 = SC_{l,m_2}(1+\alpha)^{-O_g/2}$.*

In the case of the non-financial incentive contract (**nc**), the on-time delivery is not motivated through a bonus, an incentive fee or penalties, but possible future work (Rose and Manley, 2011). If the materials are delivered on time at the previous orderings, the project manager will give a priority to this supplier. The priority implies that the supplier is a candidate for suppling materials at the next ordering. Once the supplier violates the contract at a certain ordering, the priority will be withdrawn. Let $\mathscr{H}_g$ denote the preference set at the gth order. The suppliers are selected randomly from $\mathscr{H}_g$ under the material requirement is satisfied. The objective function of the project manager or the supplier is still as Expression (1) or (13) shows.

Proposition 4.. *Assuming that the suppliers are completely conservative and consider the worst case of the future, the supplier selects the optimal mode m^* as proposition 1 shows.*

4. Evolutionary algorithm

We employ an evolutionary algorithm to generate new solutions and integrate it with the agent-based approach to search for satisfactory solutions. The reasons are twofold. First, the model of the project manager is built based on the classic model of the resource-constrained project scheduling problem (RCPSP), which is a well-known NP-hard combinational optimization problem. Second, the evolutionary algorithm is effective and efficient for RCPSP (Xiao et al., 2016; Kadri and Boctor, 2018; Zaman et al., 2020) and project ordering problem (Zhang et al., 2019). Thus, the evolutionary algorithm is applicable for solving the models in this paper, which is an extension of the models of RCPSP and project ordering problem.

4.1. Generic framework

A generic framework is used to integrate the agent-based approach and an evolutionary algorithm. It can be extended to the other decentralized decision-making problem using agents. There are mainly two types of integration. On one hand, the agents take actions based on a part of a solution. The agents not only coordinate the interests of players but also complete the solution. For example, in multi-project environment, when the activities are scheduled and the resource requirements are collected, the project agents start to compete for the shared resources (Adhau et al., 2013). The solution sent to the agents is generally formed by a heuristic algorithm but not an exact algorithm, because it may be incomplete or will be partly replaced. It is difficult to find satisfactory solutions globally with the heuristic algorithm, because the objective function value hardly impacts the form of the partial solution. On the other hand, as Homberger and Fink (2017) mentioned, the agents can bid for a set of complete solutions, which are approximately Pareto-optimal solutions. Each agent evaluates the existing solutions for its own interest. It spends much time searching for the Pareto set, because the agents cannot quantitatively describe their requirements or criteria. In this paper, we design a framework that combines the two types.

From Fig. 3, the initial population is divided into two subpopulations: **archive** and **routine**. The suppliers' objective function value is permitted to be negative to expand the search space. The H_2 solutions with the best $TC^{contract}$ are reserved in the archive, supposing that the project manager leads the contract negotiation with the suppliers. The other H_1 solutions are selected randomly to constitute the routine. As the first type of integration described, the solutions in the archive will be further adjusted via agent negotiation. In the second type, the agents evaluate the solutions in both the routine and the offspring. The offspring contains H_1 solutions generated by the evolutionary algorithm. After this evaluation, only H_1 solutions are reserved to form a mixed population with the archive. Then, the agents evaluate the mixed population again: the best H_2 solutions are used to update the archive, and the other solutions are used to update the new routine. The update operators require the agents to evaluate the old subpopulation and the new solutions. The program terminates within the finite iterations.

4.2. Initialization

The solution is encoded by three parts. **Part 1** is a priority vector (**PR**), which is a priority rule representation to determine the start order of each activity under constraints. The PR ensures feasibility easily after the various operators in the evolutionary algorithm. **Part 2** is an order-delivery vector. The vector includes G pairs, each of which describes the time interval between the order times and the due dates. The time interval is tractable for the crossover operator in the evolutionary algorithm. The first pair in the vector describes $(0, D_1)$ at the first order ($O_1 = 0$); the gth ($g > 1$) pair indicates $\left(O_g - D_{g-1}, D_g - O_g\right)$ at the gth order. **Part 3** consists of three $G \times L$ dimensional matrices. Each element in the first matrix indicates the order quantity from supplier l at the gth order. The second matrix is the decisions of the material suppliers, and each element is the selected mode, namely, $\sum_m m \times z_{l,g,m}$ of supplier l at the gth order. The third matrix is employed only under the instalment contract (**ic**) or the penalty contract (**pc**). Each element indicates the incentive parameter for supplier l at the gth order. The pseudocodes of the coding and the decoding (modified SSGS) are presented in the Appendixes E and F.

The coding process for initialization is designed from the perspective of the project manager. Let LS_i be the latest start time of activity i. The process includes four steps to generate the three parts of a complete code. The main content is the third step to generate the order quantity: first, we randomly define the number of suppliers for ordering, denoted $assa_g$; then, the order quantity is randomly determined according to Constraint (11) for these suppliers.

The code is transformed into a schedule using a modified SSGS. Let DS indicate the set of unscheduled activities with all immediate predecessors being scheduled. We need to schedule each activity in the set DS under the precedence relations and the available resources. During the decoding process, "repair the solution" is activated when the project makespan reaches the deadline due to insufficient material. It changes part 2 of the code, namely, the order date and the due date: if the current time $t \in \left(O_g, D_g\right]$ or $\left(D_{g-1}, O_g\right]$, we set $D_g = t - 1$, and O_g is regenerated randomly based on Constraints (8) and (9).

4.3. Evolutionary algorithm

The evolutionary algorithm is composed of parent selection and bi-

Fig. 3. Framework for the agent-based approach and the evolutionary algorithm.

level recombination to generate offspring. First, for each pair of parents, the first individual is randomly selected from the archive, while the second is chosen randomly from the routine.

Second, the bi-level recombination is executed to search for satisfactory solutions effectively. The first-level recombination handles part 1 and part 2 of the code, and consists of three steps: two crossover operators and a mutation operator. First, a hybrid two-point/electromagnetism crossover operator (Xiao et al., 2016) is used to generate the first-part code of the two offspring. The second step is a traditional one-point crossover operator for the second-part code. A crossover point is generated randomly between 1 and G. The elements of the offspring before a crossover point come from the father, and the other elements are inherited from the mother; the parents are changed for another offspring (Bargaoui et al., 2017). Third, a simple mutation operator is employed for the g^*th pair of the second-part code. The element is increased or decreased by a time unit with a half chance.

The first-level recombination generates only two children, but the second-level recombination will produce $H_1/2$ solutions for each. The second-level recombination handles part 3 of the code and includes a one-point crossover operator and a mutation operator. First, a crossover point is generated randomly between 1 and G. Taking the crossover point as a cut-off point, the third part of the code, namely, the three matrices, originates from the father or the mother. Then, a simple mutation operator is adopted: the positive order quantity q_{g^*,l_1} of supplier l_1 is decreased by one unit, and another positive order quantity q_{g^*,l_2} increases by one unit ($l_1 \neq l_2$).

5. Agent-based approach

The agent-based approach is characterized by distributed computation and information processing and is regarded as a valid technique for supply chain management (Pan et al., 2009). The competing or interfering agents make their decisions independently without considering the constraints of other agents or global performance, which is also termed the multi-agent scheduling problem (Perez-Gonzalez and Framinan, 2014). This approach has been widely applied to solve various problems, such as smart cities (Buzachis et al., 2020), supply chain scheduling (Aminzadegan et al., 2019), decentralized multi-project scheduling (Homberger and Fink, 2017), parallel machine scheduling (Choi and Park, 2017) and cloud manufacturing (Wang et al., 2020). The agent-based approach aims to balance the interests of the involved players considering asymmetric information and strategic behaviour.

The main difficulty of the proposed models is the coordination between the players. If a supplier rejects the contracts, the project manager may take various actions: selecting another supplier, adjusting the schedule to reduce the requirement, or conceding in the incentive parameter to the supplier. Moreover, the decisions of the suppliers are private and self-interested. Therefore, we employ an agent-based approach. Three types of agents are employed: L supplier agents (SAs), one project agent (PA), and one mediator (MA). They are assigned different works at the negotiation and the evaluation.

5.1. Agent negotiation

With a specific order time and delivery date, the negotiation progress is shown in Fig. 4. First, the PA sends the contract type, the requirements and the incentive parameter to all supplier agents. The best and worst incentive parameters among the suppliers are set as the initial value and the current bound, respectively. Each SA decides whether to receive the contract and submits this decision to the mediator; if the SA receives the contract, it should select a proper mode as propositions 1 ~ 4 show. If the requirement of the PA matches the supplies of the SAs, the mediator can end this order and return to the upper algorithm; otherwise, the MA judges whether the sum of the supply quantities exceeds the requirement quantity. On one hand, if the requirement can be satisfied completely, the MA will select the appropriate candidates for the PA to form a new supplier list. The PA decides whether to receive the list based on the objective function. On the other hand, if the total requirement is dissatisfied or the PA refuses the supplier list sent by the MA, the PA changes the incentive parameter for a desired supplier or reschedules the relevant activities.

5.1.1. Negotiation about the incentive parameter

The incentive parameters are initialized equally for all suppliers. The SA rejects the contract if it cannot benefit from the contract. If required, the parameter changes in a beneficial way for the suppliers. The incentive parameter before (after) the change is described with the superscript $bf(af)$. Thus, the down payment rate after the change is $f_{g,l}^{af} = f_{g,l}^{bf}(1 + \Delta f)$, and the penalty rate after the change is $pn_{g,l}^{af} = pn_{g,l}^{bf}(1 - \Delta pn)$. Δf and Δpn are specified parameters.

5.1.2. Rescheduling

When the total supply quantity at the gth order is less than the total

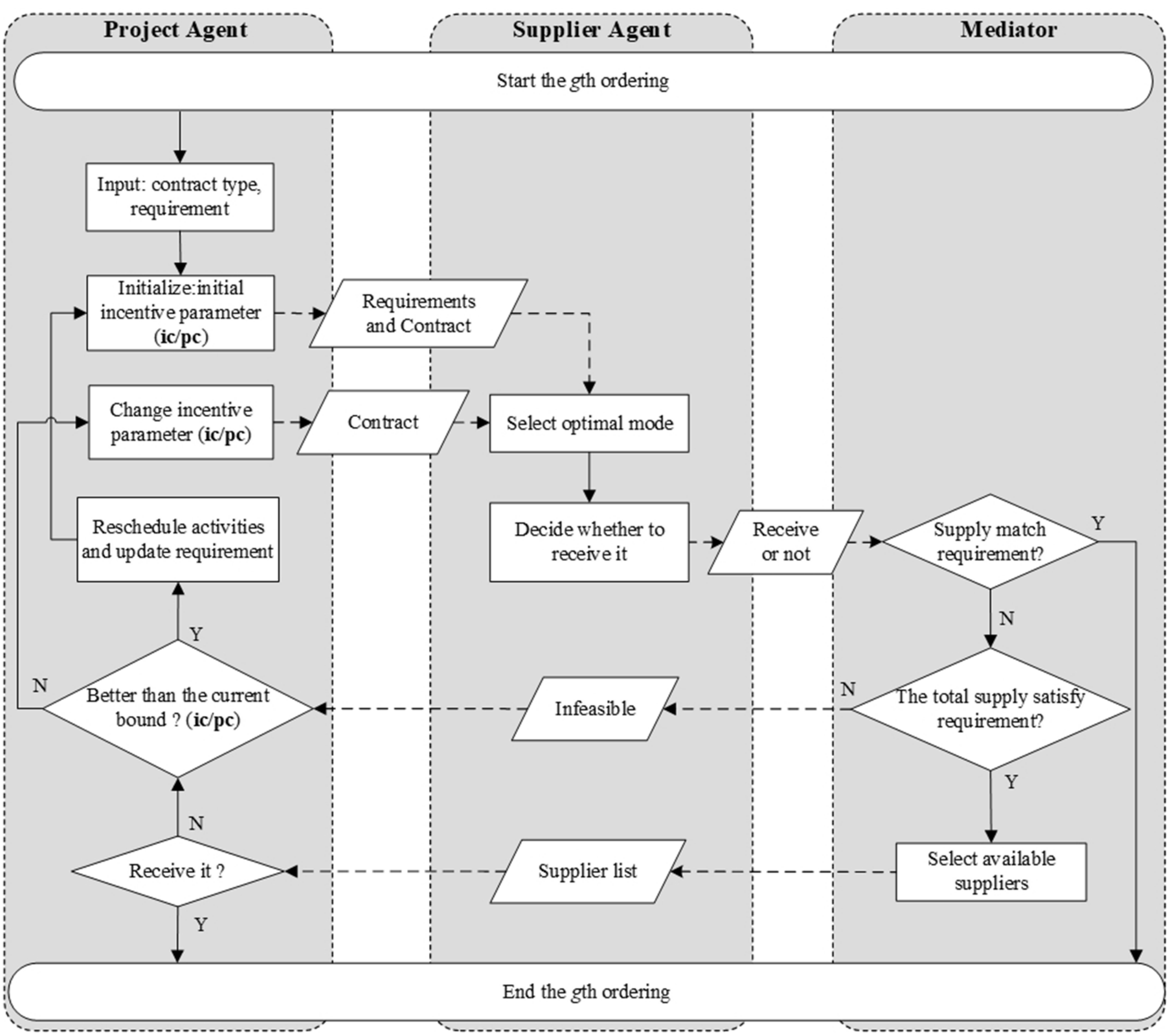

Fig. 4. Flowchart of the agent-based approach.

order quantity, the PA should reschedule activities that start after the due date D_g under the available resources. The order quantity is redetermined based on the total supply quantity. Moreover, the order quantity should ensure the feasibility of Constraints (7) and (11). If Constraint (7) is violated, we randomly select a supplier and determine an order quantity randomly within the available capacity. This selection is repeated until the gap between the supply and the requirement is filled. Constraint (11) only provides the available capacity of each supplier.

5.2. Agent evaluation

The SA and PA evaluate the solutions according to their own interest. Each agent computes the objective function value of the solutions privately. The PA ranks them in the ascending sequence, and the SA ranks them in the descending sequence. Then, we summarize the sequence numbers. The solution with a smaller sum is better. For example, a PA and two SA need to evaluate three solutions (denoted by A, B and C). They ranked them as "A C B", "C B A" and "A C B", respectively. The sum values of A, B and C are 5, 8 and 5. Solutions A and C are better. If we only want to keep one solution, solution A or C is reserved with a half chance. During the evaluation, the agents only expose the preference sequence of the solutions, not the definitive objective function values.

6. Numerical experiments

6.1. Instance parameters

The parameters of the instances include two parts: the project and the material ordering. The project parameters are available in PSPLIB, an open collection of resource-constrained project instances, to evaluate the proposed algorithm. The instances comprise 30, 60, or 90 non-dummy activities, which are denoted by sets J30, J60 and J90, respectively. We choose 120 instances from the three sets, namely, 40 instances from each set. As described in Kolisch and Sprecher (1997), the network complexity $\mathrm{NC} \in \{1.5, 1.8\}$ and the resource strength of the renewable resources $\mathrm{RS} \in \{0.2, 0.5\}$. There is one type of material and three types of renewable resources for each instance. The project procures materials with $G = 3$ for J30 instances, $G = 4$ for J60 instances and $G = 5$ for J90 instances. The down payment rate and the per-period penalty rate are in the range of $(0.2, 0.6]$ and $(0, 0.1]$, respectively. At each round of negotiation, $\Delta f = 0.1$ and $\Delta pn = 0.05$. In addition, the per-period backorder cost rate BN is 0.3, and the discount rate α equals 0.2%.

On the other hand, the suppliers are $3 \le L \le 5$ to simulate the competitive market and reduce the number of objectives. The majority of the material ordering parameters are generated at random. Supplier l' s supply capacity MQ_l is assumed to round up the maximal material requirement and follows a uniform distribution in $[10, 13]$ for J30 instances, $[24, 27]$ for J60 instances and $[32, 43]$ for J90 instances. The per-unit material price MP_l from supplier l follows a uniform distribution as MP_l $U[400, 500]$. There are five modes ($M = 5$) for each supplier's selection. For the production & transportation of supplier l in mode m, the unit cost $SC_{l,m}$ follows a uniform distribution as $SC_{l,m}$ $U[100, 250]$. Suppose that the material lead time $ld_{l,m}$ follows a Poisson distribution in a bounded interval $[4, 30]$, as $ld_{l,m}$ $\pi(l\lambda_{l,m})$. $l\lambda_{l,m}$ follows a uniform distribution as $l\lambda_{l,m}$ $U[7, 16]$. The lead time $ld_{l,m}$ $(m \in \{1, 2, \cdots, M\})$ varies inversely with the unit cost $SC_{l,m}$ for supplier l.

6.2. Results analysis

6.2.1. Information asymmetry vs. symmetry

To evaluate the algorithm performance, we compare the mixed algorithm with the classic NSGA-II under the fixed-price contract (**fc**). NSGA-II is a very effective algorithm in the literature for the resource-constrained project scheduling problem (Zoraghi et al., 2017; Habibi et al., 2019). We employ the same initialization (Section 4.2) and evolutionary algorithm (Section 4.3) in NSGA-II. There are two main differences in the program: (1) The NSGA-II is a pure multi-objective algorithm, without the agent-based approach. (2) All information of the players in the supply chain is open in NSGA-II, i.e., the project manager knows the actual delivery dates and the costs of the material suppliers. Therefore, we can exactly obtain the non-dominated solutions by NSGA-II.

The algorithms are programmed in Microsoft Visual Studio 2015 (C++ language) and run on a single computer (Intel core i7, 2.40 GHz, 4.00 GB RAM operating the Microsoft 7 Desktop Edition). Both algorithms are performed until 5000 solutions are explored and are run 30 times for each test instance. The size of the routine is $H_1 = 200$, and the archive size H_2 is half of H_1. In addition, the probability of mutation is 0.2.

In our experiments, two performance measures for the sets are introduced from the work of Xiao et al. (2016). (1) The Set Coverage (C-metric) indicates the ratio of solutions of one set dominated by solutions of another set. A value of 1 means that all solutions are dominated by the other set; a value of 0 implies that no solution is dominated. (2) The Distance from the Pareto Front (D-metric) represents the arithmetic average of the minimum Euclidean distance of the solutions of a set. The minimum Euclidean distance of a solution is the minimum value of the Euclidean distance between the solution and all solutions of the Pareto Front (PF). In the experiment, the non-dominated solutions admitted by both algorithms are used as the PF. Each objective is normalized before computing the distances to avoid significant differences among the objectives.

Figs. 5–7 present the set coverage between the two algorithms for test sets J30, J60, and J90, respectively. It is obvious that NSGA-II performs better than the mixed algorithm, and its C-metric values are mostly below 0.05. However, the gap between the two algorithms decreases with the test set from J30 to J90, i.e., fewer solutions of the mixed algorithm are dominated by the solutions of NSGA-II as the activities increase. The C-metric value of the mixed algorithm is always below 0.4, even for the J30 set. Figs. 8–10 show the distances from the Pareto Front to the nondominated sets of the two algorithms for J30, J60 and J90. The curves of NSGA-II in the figures are relatively stable and are mainly below 0.01. The curves of the mixed algorithm fluctuate highly but become increasingly close to those of NSGA-II as the activities increase. The D-metric value even exceeds the value of NSGA-II in several instances of J90. Similarly, the D-metric value of the mixed algorithm is not very high (mostly below 0.04) for all instances. In conclusion, the performance of the mixed algorithm is lower than that of NSGA-II, but the gap is very small and even visibly decreases with the growth of the project size. Moreover, Table 5 shows that the mixed algorithm consumes less computation time.

6.2.2. Analysis of different contracts

Four types of contracts—fixed-price contract (**fc**), instalment contract (**ic**), penalty contract (**pc**) and non-financial incentive contract (**nc**)—have different effects on the interests of the project manager and the material suppliers. We present Figs. 11 and 12 to measure the influences on the project-driven supply chain. Because the suppliers are homogeneous, we select supplier l as a representative. The mixed algorithm is also performed until 5000 solutions are explored for only the test set J90. In the figure, the broken line describes the optimal objective value of the project manager or the supplier, and the columns show the relevant backorder cost. For example, the column of the backorder cost under **ic** in Fig. 12 occurs at instance 3. It is the backorder cost of the third instance for the case of the optimal objective of supplier 1 under the instalment contract.

As shown in Fig. 11, **pc** or **nc** generally results in the lowest project cost. Their backorder cost arises less often but remains. By contrast, the highest project costs are always generated under **ic**, and the relevant

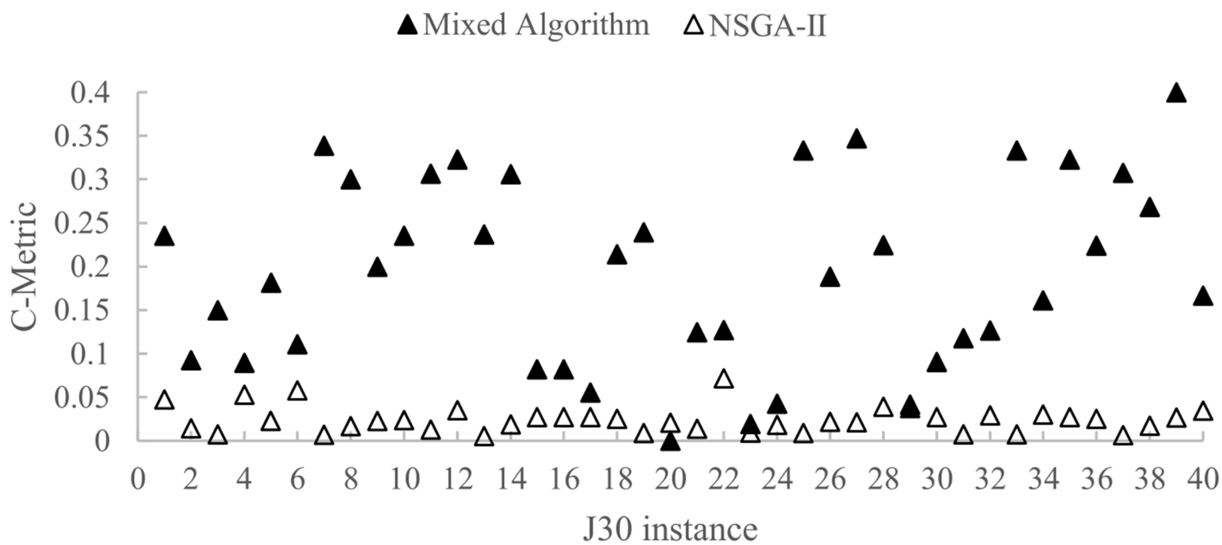

Fig. 5. C-metric between algorithms for J30.

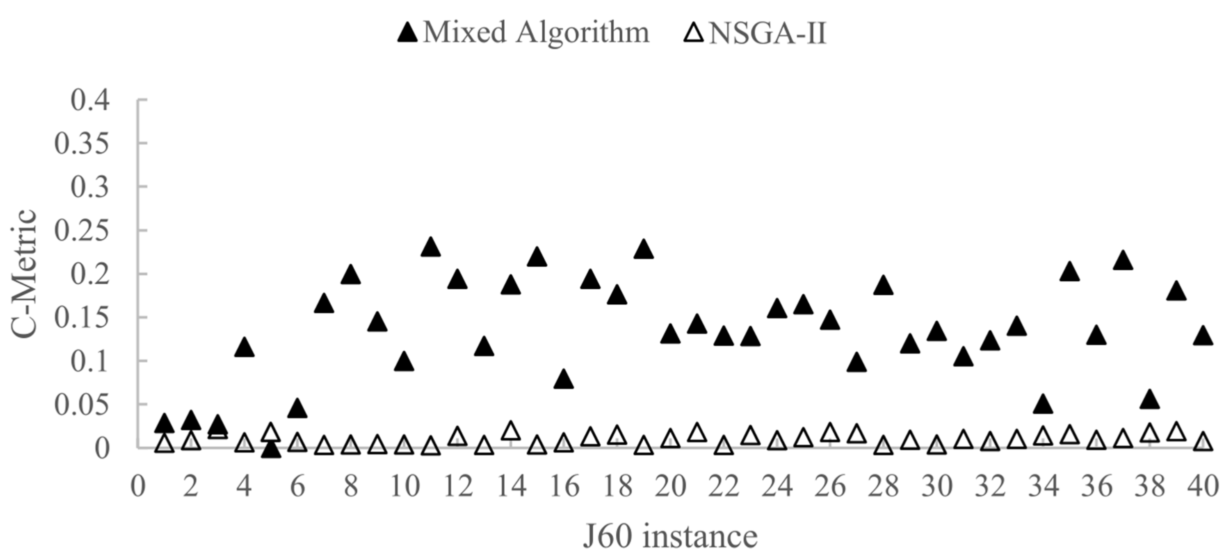

Fig. 6. C-metric between algorithms for J60.

backorder costs frequently occur. This means that the delayed delivery cannot be avoided completely by investing more costs in the project, such as an advanced payment. The values of the project cost under **fc** mostly perform mediocre, but sometimes better than under **nc**. Thus, the penalty contract and the non-financial incentive contract are mainly beneficial to the project manager, closely followed by the fixed price contract.

Fig. 12 shows that **ic** always improves the supplier's profits to the maximum extent, closely followed by **fc** or **nc**. The supplier's profits under **pc** are generally at the worst level. Comparatively, the backorder cost under **pc** is the least frequently gained, and its value is much less. Thus, the supplier prefers the instalment contract, and the supplier under **pc** barely brings the project a backorder cost. The performance of the non-financial incentive contract and fixed-price contract is essentially the same and is very close to that of the instalment contract. In conclusion, the non-financial incentive contract is profitable for both the project manager and the suppliers, and the penalty contract is effective in reducing the delayed delivery of the suppliers.

Roughly, we may think that the project manager prefers the **pc**, and the suppliers are inclined to the **ic**. The overall results can support this intuition. However, from Figs. 11 and 12, **nc** and **fc** perform well or even better than **pc** (**ic**) from the perspective of the project manager (suppliers). Moreover, we may also think that **nc** is better than **fc** in reducing late delivery. Compared to **nc**, **fc** obtains a better result for some cases, such as instances 10, 23 and 39 in Fig. 11. Note that there is no order cost under both contracts at these instances. The preference set for the non-financial incentive contract may impede a better selection of the suppliers to reduce the project cost, in case of no late delivery.

7. Conclusion

We study the project-driven supply chain under information asymmetry, assuming that the project manager cannot estimate the delivery date of the suppliers accurately and does not know the information about the suppliers' costs. The project manager has to use incentive contracts to promote on-time deliveries and to share risks. In the paper, four types of incentive contracts are considered: fixed-price contract, instalment contract, penalty contract and non-financial incentive contract. The instalment contract and the penalty contract are financial incentive contracts, while the non-financial incentive contract takes a follow-up transaction as an incentive. Moreover, the incentive parameter is a decision variable in the model, i.e., the project manger can

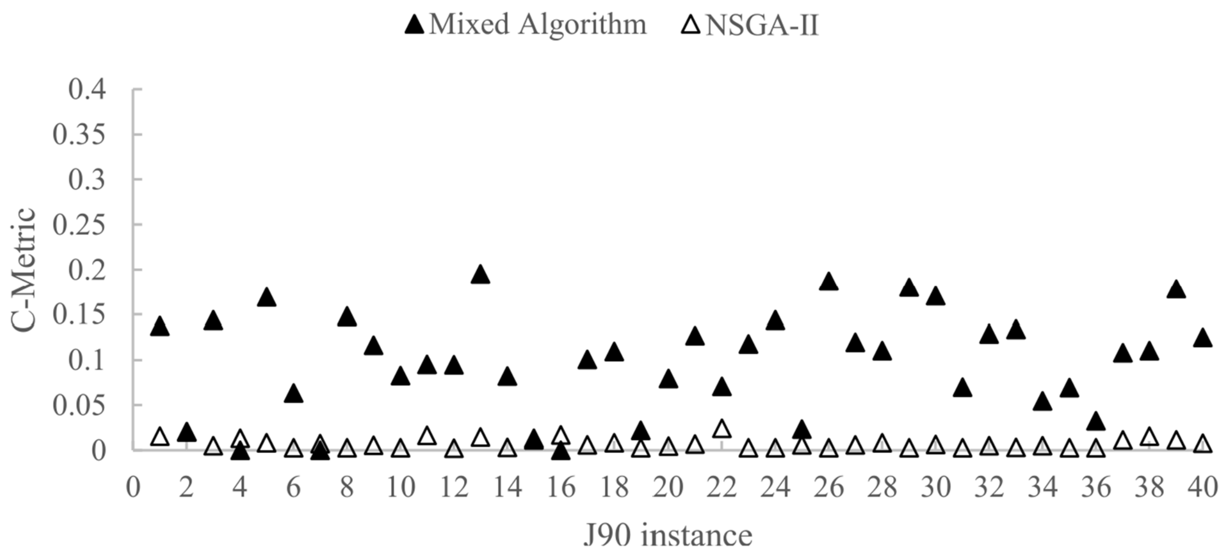

Fig. 7. C-metric between algorithms for J90.

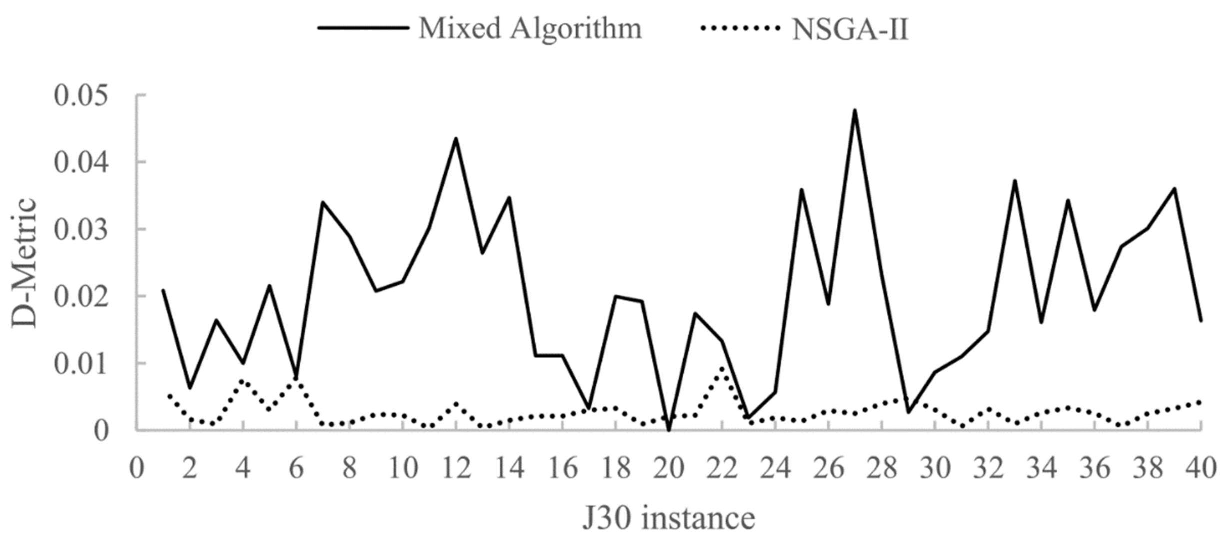

Fig. 8. D-metrics of algorithms for J30.

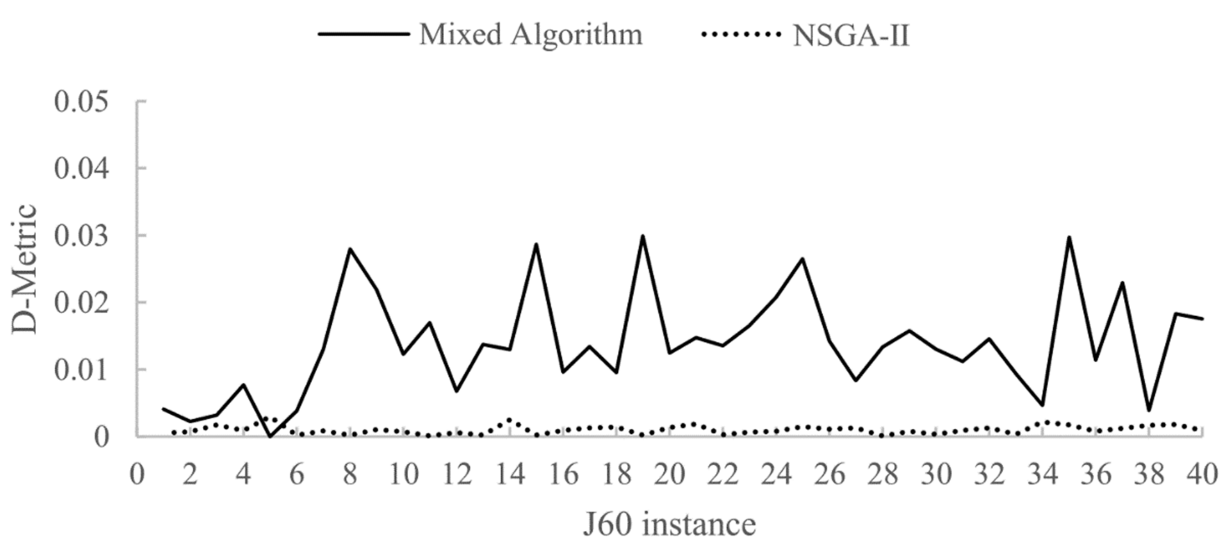

Fig. 9. D-metrics of algorithms for J60.

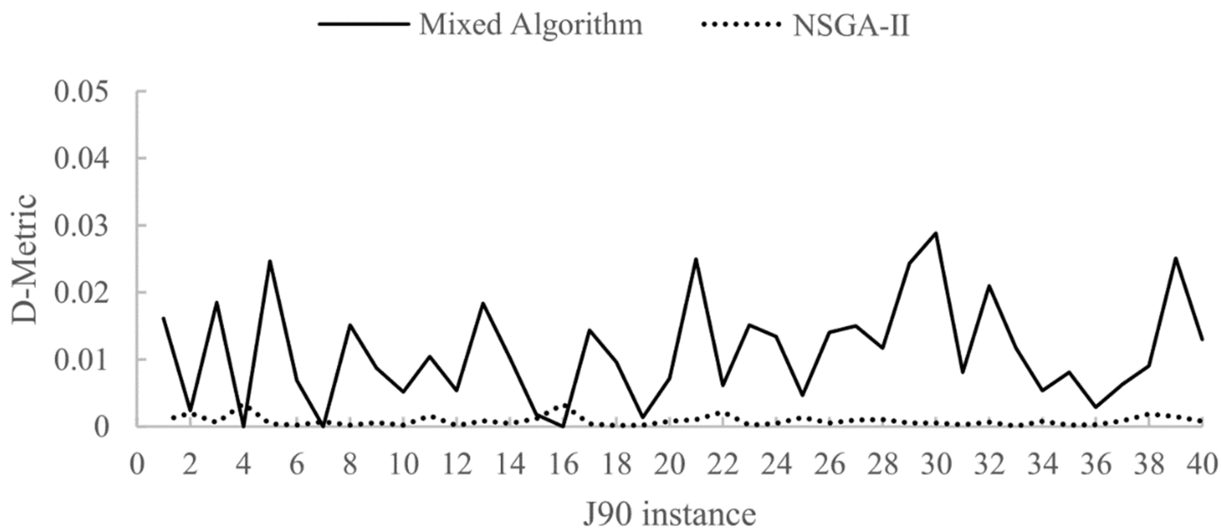

Fig. 10. D-metrics of algorithms for J90.

Table 5
Average computation time of algorithms.

Item	J30 (s)	J60 (s)	J90 (s)
Mixed algorithm	108.94	244.00	460.97
NSGA-II	498.22	667.08	946.59

adjust the incentive strength according to the project status and the potential suppliers. We present a mixed algorithm that combines an agent-based approach with an evolutionary algorithm to simulate the decentralized decision-making process. The agent-based approach ensures the solution procedure under information asymmetry, while the evolutionary algorithm improves the solution globally. The agents can negotiate with each other and evaluate the solutions collectively. In this process, if a supplier denies the contract, the project manager will change the incentive parameter or select the other suppliers; if the project's requirement is not satisfied, the project manager will adjust the schedule and change the due date of delivery.

The experimental results show that the gap between the mixed algorithm and NSGA-II is very small and visibly decreases with the growth of the project size. The analysis of the effect of the contracts shows that the non-financial incentive contract is beneficial to the project manager and does not harm the suppliers' interest. The penalty contract is the most useful to eliminate late delivery by the suppliers. Therefore, we suggest that the project managers use the non-financial incentive contract in case of normal risks to achieve double wins, but replace it with the penalty contract in the event of a very tight deadline.

Existing commercial softwares can be used for project-driven supply chain management. For example, the *Oracle Project-driven Supply Chain* can help the project manager maintain the project-specific inventory and keep track of the implementation of the orders; it also enables the suppliers to compartmentalize manufacturing operations to serve multiple projects. This software can explicitly show the material flow and the fund flow with respect to each project, but it cannot autonomously make any decision on behalf of these players in the supply chain. In this paper, the proposed approach can help the players reach an agreement via a decentralized decision-making process by means of human–computer interactions.

The model in this paper can be further extended. First, we only consider three types of incentive contracts. Problems with diverse and combinatorial incentive measures can be studied in the future. Second, we consider only one type of material in the model. A variety of

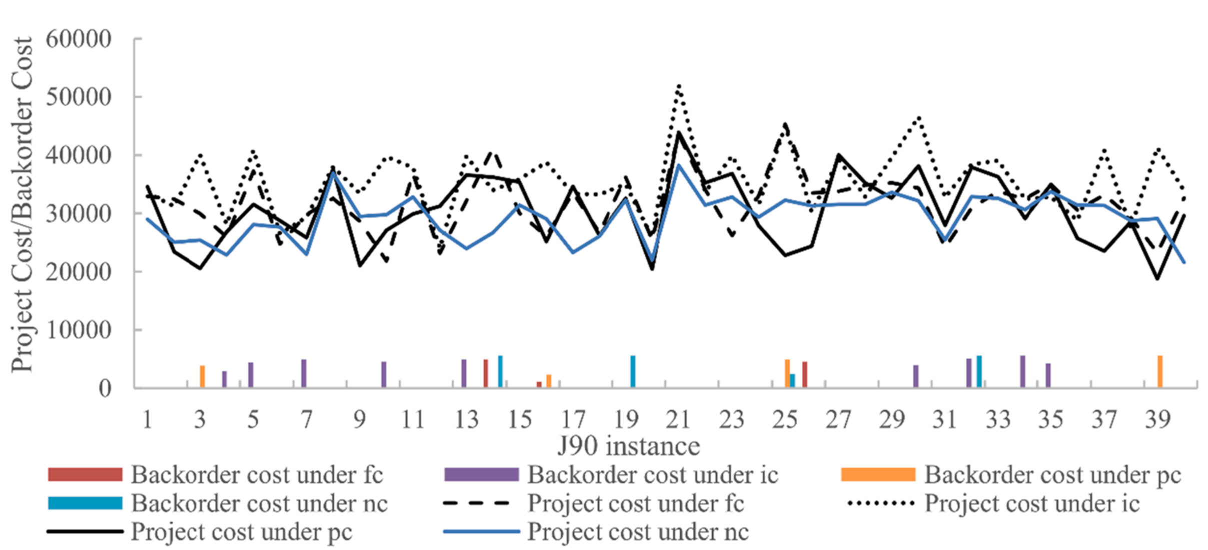

Fig. 11. Objective value and backorder cost under different contracts for project.

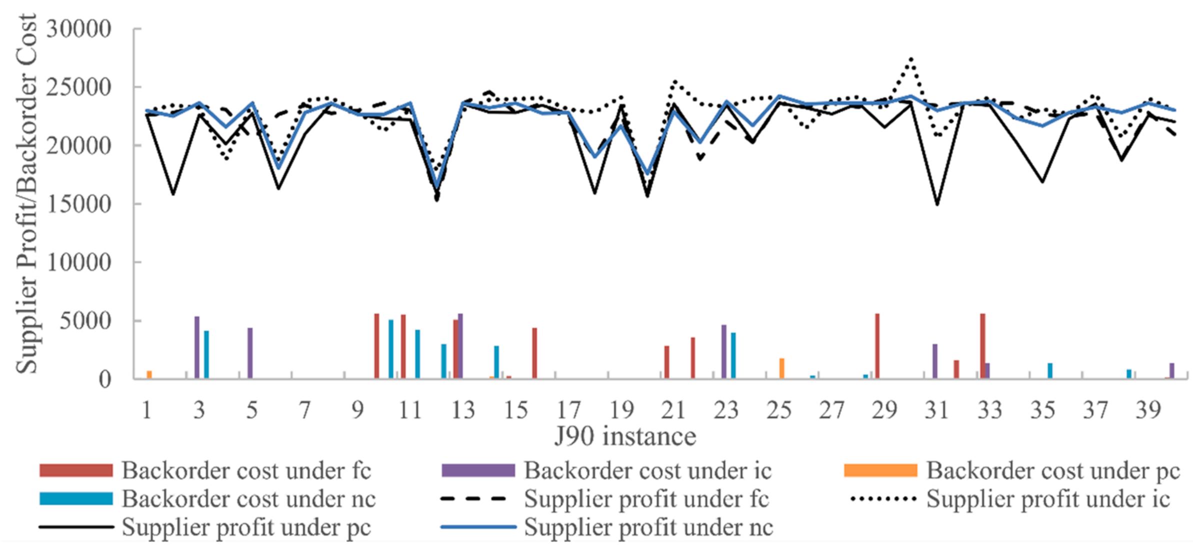

Fig. 12. Objective value and backorder cost under different contracts for supplier.

materials will make this problem more challenging. Wide scope remains for further exploration.

Funding

This work was supported by the National Natural Science Foundation of China [grant numbers 71801224, 72071210].

CRediT authorship contribution statement

Fang Fu: Conceptualization, Methodology, Software, Writing - original draft. **Wei Xing:** Writing - review & editing.

Appendix A. Proof of Proposition 1

For a supplier l under the fixed-price contract (**fc**), the behaviour of suppliers for the current contract are dependent of the future opportunities, so we can analyse the mode selection separately.

First, if $O_g + ld_{l,m} \le D_g$ holds for all the modes, $AD_{g,l} = D_g$. Due to $MC_{g,l} = MP_l \times q_{g,l}$ and $DC_{g,l} = SC_{l,m} q_{g,l}(1+\alpha)^{-(AD_{g,l}+O_g)/2}$ for a given mode m, $SP^{\mathbf{fc}}_{g,l} = \left[MP_l(1+\alpha)^{-D_g} - SC_{l,m}(1+\alpha)^{-(D_g+O_g)/2}\right] \times q_{g,l}$. Only the variable $SC_{l,m}$ depends on the mode m, so $m^* = \underset{m}{\operatorname{argmin}} SC_{l,m}$. The cost $SC_{l,m}$ is sorted in ascending order, so $m^* = 1$.

Second, if $O_g + ld_{l,m} \ge D_g$ holds for all the modes, $AD_{g,l} = O_g + ld_{l,m}$. $SP^{\mathbf{fc}}_{g,l} = \left[MP_l(1+\alpha)^{-(O_g+ld_{l,m})} - SC_{l,m}(1+\alpha)^{-(ld_{l,m}/2+O_g)}\right] \times q_{g,l} = \left[MP_l(1+\alpha)^{-ld_{l,m}/2} - SC_{l,m}\right] \times q_{g,l} \times (1+\alpha)^{-O_g - ld_{l,m}/2}$. Let $\eta = (1+\alpha)^{-ld_{l,m}/2}$, $m^* = \underset{m}{\operatorname{argmax}}\{\eta(\eta MP_l - SC_{l,m})\}$ for the given contract.

Lastly, there are several modes to satisfy $O_g + ld_{l,m} \le D_g$ and the others for $O_g + ld_{l,m} > D_g$. We compare the mode $m_1 = \underset{O_g+ld_{l,m}\le D_g}{\operatorname{argmax}} SP^{\mathbf{fc}}_{g,l}$ and the mode $m_2 = \underset{O_g+ld_{l,m}>D_g}{\operatorname{argmax}} SP^{\mathbf{fc}}_{g,l}$. The optimal mode corresponds to $\underset{m}{\max} SP^{\mathbf{fc}}_{g,l}$. $\left(\underset{O_g+ld_{l,m}\le D_g}{\max} SP^{\mathbf{fc}}_{g,l} - \underset{O_g+ld_{l,m}>D_g}{\max} SP^{\mathbf{fc}}_{g,l}\right) \Big/ q_{g,l} = MP_l(1+\alpha)^{-D_g} - SC_{l,m_1}(1+\alpha)^{-(D_g+O_g)/2} - MP_l(1+\alpha)^{-(O_g+ld_{l,m_2})} + SC_{l,m_2}(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} = MP_l\left[(1+\alpha)^{-D_g} - (1+\alpha)^{-(O_g+ld_{l,m_2})}\right] + (SC_{l,m_2} - SC_{l,m_1})(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} + SC_{l,m_1}\left[(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} - (1+\alpha)^{-(D_g+O_g)/2}\right]$. Let $\vartheta = (1+\alpha)^{-(ld_{l,m_2}+O_g)/2}$, $\rho_1 = SC_{l,m_1}(1+\alpha)^{-O_g/2}$ and $\rho_2 = SC_{l,m_2}(1+\alpha)^{-O_g/2}$, and it follows the proposition 1. Note that only if the objective value related to m^* is more than zero, the supplier will accept the contract. So, when the objective value of m_1 or m_2 is less than zero, the comparison is useless.

Appendix B. Proof of Proposition 2

For a supplier l under the instalment contract (**ic**), we also analyse the mode selection at an order separately.

First, if $O_g + ld_{lm} \le D_g$ holds for all the modes, $AD_{gl} = D_g$. $SP^{\mathbf{ic}}_{g,l} = f_{g,l} MP_l \times q_{g,l}(1+\alpha)^{-O_g} + \left(1 - f_{g,l}\right) MP_l \times q_{g,l}(1+\alpha)^{-D_g} - SC_{l,m} \times q_{g,l}(1+\alpha)^{-(D_g+O_g)/2}$. Only the variable SC_{lm} depends on the mode m, so $m^* = \underset{m}{\operatorname{argmin}} SC_{l,m} = 1$.

Second, if $O_g + ld_{l,m} \geq D_g$ holds for all the modes, $AD_{g,l} = O_g + ld_{l,m}$. $SP^{\mathbf{ic}}_{g,l} = \left[f_{g,l}MP_l(1+\alpha)^{-O_g} + \left(1-f_{g,l}\right)MP_l(1+\alpha)^{-(O_g+ld_{l,m})} - SC_{l,m}(1+\alpha)^{-(ld_{l,m}/2+O_g)}\right] \times q_{g,l} = f_{g,l}MP_l(1+\alpha)^{-O_g} + \left[\left(1-f_{g,l}\right)MP_l(1+\alpha)^{-ld_{l,m}/2} - SC_{l,m}\right] \times q_{g,l} \times (1+\alpha)^{-O_g-ld_{l,m}/2}$. Let $\eta = (1+\alpha)^{-ld_{l,m}/2}$, $m^* = \underset{m}{\operatorname{argmax}}\left\{\eta\left[\eta\left(1-f_{g,l}\right)MP_l - SC_{l,m}\right]\right\}$ for the given contract.

Lastly, there are several modes to satisfy $O_g + ld_{l,m} \leq D_g$ and the others for $O_g + ld_{l,m} > D_g$. We compare the mode $m_1 = \underset{O_g+ld_{l,m}\leq D_g}{\operatorname{argmax}} SP^{\mathbf{ic}}_{g,l}$ and the mode $m_2 = \underset{O_g+ld_{l,m}>D_g}{\operatorname{argmax}} SP^{\mathbf{ic}}_{g,l}$. The optimal mode corresponds to $\underset{m}{\max}SP^{\mathbf{ic}}_{g,l}$. $\left(\underset{O_g+ld_{l,m}\leq D_g}{\max} SP^{\mathbf{ic}}_{g,l} - \underset{O_g+ld_{l,m}>D_g}{\max} SP^{\mathbf{ic}}_{g,l}\right)\Big/q_{g,l} = f_{g,l}MP_l(1+\alpha)^{-O_g} + \left(1-f_{g,l}\right)MP_l(1+\alpha)^{-D_g} - SC_{l,m_1}(1+\alpha)^{-(D_g+O_g)/2} - f_{g,l}MP_l(1+\alpha)^{-O_g} - \left(1-f_{g,l}\right)MP_l(1+\alpha)^{-(O_g+ld_{l,m_2})} + SC_{l,m_2}(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} = \left(1-f_{g,l}\right)MP_l\left[(1+\alpha)^{-D_g} - (1+\alpha)^{-(O_g+ld_{l,m_2})}\right] + \left(SC_{l,m_2} - SC_{l,m_1}\right)(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} + SC_{l,m_1}\left[(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} - (1+\alpha)^{-(D_g+O_g)/2}\right]$. Let $\vartheta = (1+\alpha)^{-(ld_{l,m_2}+O_g)/2}$, $\rho_1 = SC_{l,m_1}(1+\alpha)^{-O_g/2}$ and $\rho_2 = SC_{l,m_2}(1+\alpha)^{-O_g/2}$, and it follows the proposition 2. Also, when the objective value of m_1 or m_2 is less than zero, the comparison is useless.

Appendix C. Proof of Proposition 3

For a supplier l under the penalty contract (**pc**), we also analyse the mode selection at an order separately.

First, if $O_g + ld_{l,m} \leq D_g$ holds for all the modes, $AD_{g,l} = D_g$. $SP^{\mathbf{pc}}_{g,l} = \left[MP_l(1+\alpha)^{-D_g} - SC_{l,m}(1+\alpha)^{-(D_g+O_g)/2}\right] \times q_{g,l}$. Only the variable SC_{lm} depends on the mode m, so $m^* = \underset{m}{argmin}SC_{l,m} = 1$.

Second, if $O_g + ld_{l,m} \geq D_g$ holds for all the modes, $AD_{g,l} = O_g + ld_{l,m}$. $SP^{\mathbf{pc}}_{g,l} = \left[MP_l(1+\alpha)^{-(O_g+ld_{l,m})} - pn_{g,l}MP_l\left(O_g + ld_{l,m} - D_g\right)^+(1+\alpha)^{-(O_g+ld_{l,m})} - SC_{l,m}(1+\alpha)^{-ld_{l,m}/2-O_g}\right] \times q_{g,l} = \left[MP_l(1+\alpha)^{-ld_{l,m}/2} - pn_{g,l}MP_l\left(O_g + ld_{l,m} - D_g\right)^+ (1+\alpha)^{-ld_{l,m}/2} - SC_{l,m}\right] \times q_{g,l} \times (1+\alpha)^{-O_g-ld_{l,m}/2}$. Let $\eta = (1+\alpha)^{-ld_{l,m}/2}$ and $\pi(m) = \left(O_g + ld_{l,m} - D_g\right)^+$, $m^* = \underset{m}{\operatorname{argmax}}\left\{\eta^2 MP_l\left[1 - pn_{g,l} \times \pi(m)\right] - \eta SC_{l,m}\right\}$ for the given contract.

Lastly, there are several modes to satisfy $O_g + ld_{l,m} \leq D_g$ and the others for $O_g + ld_{l,m} > D_g$. We compare the mode $m_1 = \underset{O_g+ld_{l,m}\leq D_g}{\operatorname{argmax}} SP^{\mathbf{pc}}_{g,l}$ and the mode $m_2 = \underset{O_g+ld_{l,m}>D_g}{\operatorname{argmax}} SP^{\mathbf{pc}}_{g,l}$. The optimal mode corresponds to $\underset{m}{\max}SP^{\mathbf{pc}}_{g,l}$. $\left(\underset{O_g+ld_{l,m}\leq D_g}{\max} SP^{\mathbf{pc}}_{g,l} - \underset{O_g+ld_{l,m}>D_g}{\max} SP^{\mathbf{pc}}_{g,l}\right)\Big/q_{g,l} = MP_l(1+\alpha)^{-D_g} - SC_{l,m_1}(1+\alpha)^{-(D_g+O_g)/2} - MP_l(1+\alpha)^{-(O_g+ld_{l,m_2})} + pn_{g,l}MP_l\left(O_g + ld_{l,m_2} - D_g\right)^+(1+\alpha)^{-(O_g+ld_{l,m_2})} + SC_{l,m_2}(1+\alpha)^{-ld_{l,m_2}/2-O_g} = MP_l\left[(1+\alpha)^{-D_g} - (1+\alpha)^{-(O_g+ld_{l,m_2})}\right] + \left(SC_{l,m_2} - SC_{l,m_1}\right)(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} + SC_{l,m_1}\left[(1+\alpha)^{-(ld_{l,m_2}/2+O_g)} - (1+\alpha)^{-(D_g+O_g)/2}\right] + pn_{g,l}MP_l\left(O_g + ld_{l,m_2} - D_g\right)^+(1+\alpha)^{-(O_g+ld_{l,m_2})}$. Let $\vartheta = (1+\alpha)^{-(ld_{l,m_2}+O_g)/2}$, $\rho_1 = SC_{l,m_1}(1+\alpha)^{-O_g/2}$, $\rho_2 = SC_{l,m_2}(1+\alpha)^{-O_g/2}$ and $\pi(m_2) = \left(O_g + ld_{l,m_2} - D_g\right)^+$, and it follows the proposition 3. When the objective value of m_1 or m_2 is less than zero, the comparison is useless.

Appendix D. Proof of Proposition 4

For a supplier l under the non-financial contract (**nc**), the selected mode will impact the business opportunity at the next ordering. But at the last ordering which has no impact, the optimal mode is determined as proposition 1 shown. We only analyse the scenarios with $g < G$ as follows.

First, if $O_g + ld_{l,m} \leq D_g$ or $O_g + ld_{l,m} \geq D_g$ holds for all the modes, all the modes lead to the same effect on the next cooperation with the project manager. So, the optimal mode under these scenarios is also determined as proposition 1 shown.

Second, if there are several modes to satisfy $O_g + ld_{l,m} \leq D_g$ and the others for $O_g + ld_{l,m} > D_g$, we compare the mode $m_1 = \underset{O_g+ld_{l,m}\leq D_g}{\operatorname{argmax}} SP^{\mathbf{nc}}_{g,l}$ and the mode $m_2 = \underset{O_g+ld_{l,m}>D_g}{\operatorname{argmax}} SP^{\mathbf{nc}}_{g,l}$. If $\underset{O_g+ld_{l,m}\leq D_g}{\max} SP^{\mathbf{nc}}_{g,l} > \underset{O_g+ld_{l,m}>D_g}{\max} SP^{\mathbf{nc}}_{g,l}$, the supplier absolutely regard the mode m_1 as the optimal mode; otherwise, it is difficult to compare $\underset{O_g+ld_{l,m}\leq D_g}{\max} SP^{\mathbf{nc}}_{g,l} + \underset{m}{\max}SP^{\mathbf{fc}}_{g+1,l}$ and $\underset{O_g+ld_{l,m}>D_g}{\max} SP^{\mathbf{nc}}_{g,l}$ at the progress of the agent negotiation. During the negotiation, the order date, the due date and the order quantity at the $g+1$ ordering may be changed. Assumed that the supplier is conservative, the worst case of the next ordering is considered for $\underset{m}{\max}SP^{\mathbf{fc}}_{g+1,l}$. The worst value of the $\underset{m}{\max}SP^{\mathbf{fc}}_{g+1,l}$ is zero, because the supplier denies the contract due to no profits. So, we also compare the $\underset{O_g+ld_{l,m}\leq D_g}{\max} SP^{\mathbf{nc}}_{g,l}$ and $\underset{O_g+ld_{l,m}>D_g}{\max} SP^{\mathbf{nc}}_{g,l}$. In conclusion, the optimal mode is selected as proposition 1 shown.

Appendix E. Pseudocodes of coding

Initialization: SS is the set of scheduled activities, $0 \in SS$; $j = 1$; $\pi R_{k,t}$ is the available renewable resource of type k at time t; LS_i, ST_i and FT_i, represents the latest start time, start time and finish time of activity i, respectively.

While $j \leq |DS|$ **Do**

Update DS;

Select i^* from DS with minimal priority

$t = \max\{FT_h|(i,h) \in \mathcal{G}\}$;

$SS = SS \cup \{i^*\}$;

While $t \leq LS_{i^*}$ **Do**

//Delay the activity for lack of renewable resource

If $\exists\ \pi R_{k,t} - r_{i^*,k} < 0$ for $[t, t + d_{i^*})$ **then** $t = t + 1$;

//Delay the activity for lack of materials

Else if $I_t - n_{i^*} < 0$ && $t < LS_{i^*}$ **then** $t = t + 1$;

//Repair due to the deadline

Else if $I_t - n_{i^*} < 0$ && $t = LS_{i^*}$ **then** Repair the solution

Else break;

Endwhile

//Determine start time and finish time

$ST_{i^*} = t$; $FT_{i^*} = ST_{i^*} + d_{i^*}$;

Update I_t for $[t, T]$ and Update $\pi R_{k,t}$ for $[t, t + d_{i^*})$;

$j = j + 1$;

Endwhile

Initialization: the quantity to be ordered $rm = \sum_{t\in[T]}\sum_{i\in[N-1]} n_i x_{i,t}$; $q_{g,l} = 0$ for $\forall g, l$; LS_i is the latest start time of activity i.

//step 1: generate part 1

For $(i = 1; i \le N; i++)$

Priority of the non-dummy activity i is initialized as $LS_i/\sum_{i\in[N-2]} LS_i$.

Endfor

//step 2: generate part 2

For $(g = 1; g \le G; g++)$

If $g = 1$ **then** $O_1 = 0$ and D_1 is generated randomly in range of $\left(ld^{\min}, ld^{\max}\right]$.

Else O_g is generated randomly in range of $\left(D_{g-1}, T-(G-g+1)ld^{\max}\right)$, and D_g in range of $\left(O_g + ld^{\min}, O_g + ld^{\max}\right]$.

Endfor

//step 3: generate the first matrix of part 3

For $(g = 1; g \le G; g++)$

Generate sa_g in range of $[1, L]$;

Endfor

$rm = rm - \sum_{j\in[G]} sa_j + 1$;

For $(g = 1; g \le G; g++)$

For $(i = 1; \left(i < sa_g\right) \vee \left(g < G \wedge i = sa_g\right); i++)$

Select a supplier l^* randomly;

(continued on next page)

Appendix F. . Pseudocodes of decoding

(*continued*)

Generate a quantity new randomly in range of $\left(0,\ \min\left(MQ_{l^*} - \sum_{j\in[g]:AD_{j,l}>O_g} q_{j,l^*},\ rm\right)\right]$ and $q_{g,l^*} = q_{g,l^*} + new$;

$rm = rm - q_{g,l^*} + 1$;

Endfor

Endfor

Select supplier l^* randomly;

$q_{G,l^*} = q_{G,l^*} + \min\left(MQ_{l^*} - \sum_{j\in[G]:AD_{j,l}>O_G} q_{j,l^*},\ rm\right)$;

$rm = rm - q_{G,l^*}$;

While $rm > 0$ **Do**

Select supplier l^* randomly from the suppliers with $q_{g,l} > 0$;

$q_{g,l^*} = q_{g,l^*} + \min\left(MQ_{l^*} - \sum_{j\in[g]:AD_{j,l}>O_g} q_{j,l^*},\ rm\right)$;

$rm = rm - q_{g,l^*}$;

Endwhile

//step 4: generate the second and third matrix of part 3

For $(g = 1;\ g \le G;\ g++)$

For $(l = 1;\ l \le L;\ l++)$

If $q_{g,l} > 0$ **then**

Generate a mode m randomly to make $z_{l,g,m} = 1$;

Generate incentive parameter $pn_{g,l}$ or $f_{g,l}$ randomly in case of **ic** or **pc**;

Endfor

Endfor

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