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Decision Support

Optimal configuration of a green product supply chain with guaranteed service time and emission constraints

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ABSTRACT

This paper studies a supply chain configuration (SCC) problem for a green product family in consideration of guaranteed service time and emission constraints. Several alternative options can be employed to implement the functions of each stage and safety inventory is adopted to satisfy stochastic demands. An SCC model is formulated to optimize the service time and option selection decisions to minimize the overall cost of the supply chain. The structural properties of the model are addressed and the problem is decomposed into two subproblems, namely, the service time decision problem and option selection problem. For the service time decision problem, the structural properties of the supply chain network is carefully studied, based on which a spanning tree-based algorithm (STA) is presented to solve the problem optimally. For the option selection problem that is proven to be NP-hard, a particle swarm optimization algorithm (PSO) is adopted to efficiently solve the problem. Consequently, a hybrid algorithm (STA+PSO) is developed to solve the SCC model. The numerical results show that the hybrid algorithm can efficiently and effectively solve the SCC model. The emission constraints on green products have significant effects on the supply chain cost and the emissions of the products; while the guaranteed service time also remarkably influences the supply chain configuration.

1. Introduction

Supply chain management faces new challenges in the context of sustainable development and Internet economy. The challenge of sustainable development is to provide environmentally friendly products to consumers with the increasing environmental consciousness of society. In a global survey administered by Accenture, more than 80% of the interviewees pay attention to the greenness of products when purchasing them.[1] Governments also play an important role in sustainable production. In 2006, the European Union set an emission limit for electronics and electrical equipments to control hazardous industrial emissions (Dangelico & Pujari, 2010), while some subsidy policies are applied to promote sustainable production (Wang, Chang, Chen, Zhong, & Fan, 2014; Zhang, Xu, & He, 2012). The challenge of the Internet economy is to manufacture and deliver goods faster, cheaper, and better at minimal cost. Internet-based e-commerce significantly affects business models and human lives (Mahadevan, 2000). Recently, Alibaba has surpassed Wal-Mart as the largest retailer with a GMV of 476 billion dollars in 2016.[2] A supply chain plays an important role in pushing the rapid development of the Internet economy. The development of the Internet economy also requires a supply chain for the continuous improvement of customer service by providing diversified goods and increasing on-time deliveries at minimal costs.

This study focuses on a supply chain configuration (SCC) problem to investigate how a supply chain makes production and operation decisions facing guaranteed service time and environmental concerns. Supply chain configuration is to optimize option selection and inventory management from a supply-chain perspective to achieve improved coordination across the supply chain (Graves & Willems, 2005). In this study, a supply chain manufactures a family of green products through a network composed by a number of stages ranging from the supply of raw materials,

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[1] http://newsroom.accenture.com/article_display.cfm?article_id=4801 (accessed on 25 Feb 2009).

[2] http://www.ibtimes.com/alibaba-baba-overtakes-walmart-wmt-largest-retailer-gross-volume-2349025 (6 Apr 2015).

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0377-2217/

manufacturing of individual parts, and assembly of components and final products (Qu, Huang, Cung, & Mangione, 2010). The network structure is common in the real-world supply chain in which multiple pathes are available to connect a starting stage to an ending stage. That is, a downstream stage could directly connect to more than one upstream stages. For example, in a PC supply chain, some stages, like the stages producing PC parts (e.g., motherboard, CPU, hard disk and so on) are in charge of the PC platform products. These stages forms a supply chain network. Each stage in the supply chain network has several alternative options to implement its functions, and each stage is a potential stock-point for inventory (Huang, Zhang, & Liang, 2005). The options at each stage are distinguished from one another in terms of processing lead time, cost, and emissions. Emissions are generated from the processing stages throughout the supply chain. The total emissions from a final product are assumed to be regulated by a subsidy policy where the emissions of the final product are limited by an emission cap, and subsidies can be obtained when the emissions are lower than the control standard. A supply chain is constrained by the guaranteed service time offered to satisfy customer demand (Graves & Willems, 2000; 2005). In this work, we configure the supply chain to minimize overall supply chain cost when dealing with guaranteed service time and emission constraints. This study investigates the following questions: (1) What are the optimal supply chain configurations? (2) What are the effects of environmental limitations on supply chain management? and (3) What are the effects of guaranteed service time on supply chain management?

To answer these questions, the problem is formulated as an SCC model in which guaranteed service time and emission constraints are considered. We analyze the structural properties of the model, based on which the problem is decomposed into two subproblems, namely, service time decision problem and option selection problem. We develop a hybrid algorithm to solve the problem. In the hybrid algorithm, a spanning tree-based algorithm (STA) is developed to optimally solve the service time problem. A particle swarm optimization (PSO) algorithm is adopted to solve the option selection problem. The numerical results show that our hybrid algorithm (STA+PSO) can solve the model efficiently and effectively. In particular, it obtains the optimal solutions for an 18-stage supply chain network, while PSO (only ues POS) takes more than 1 minute to obtain the near-optimal solutions. The analysis shows that the subsidy policy and guaranteed service time have significant effects on the supply chain configuration.

The rest of this paper is organized as follows. The related research work is reviewed in Section 2. In Section 3, we mathematically formulate the problem and analyze the complexity of the model. Section 4 analyzes the properties of the model and develops a hybrid algorithm to solve the problem. In Section 5, we conduct numerical studies to illustrate the applications of our model and algorithm as well as to explore some interesting managerial insights. Section 6 concludes the study and offers directions for future research.

2. Literature review

Two streams of research are closely related to our work. On the one hand, we review the work on *supply chain configuration*. On the other hand, our work is related to *sustainable operation management*. In what follows, we review studies relevant to each stream and highlight the differences between our work and the existing research.

2.1. Supply chain configuration

A supply chain is configured to pursue minimal inventory and production costs by optimizing the operational/production processes involved at each stage in the supply chain network. Graves and Willems (2000) present an SCC model to minimize the overall cost of multi-product supply chain by determining the service time and option selection.

Researchers have investigated various SCC problems and attempted to develop a series of algorithms to solve the related models. Graves and Willems (2005) use a dynamic programming (DP) algorithm to solve the SCC model; in their algorithm, the decision variables are the option selection and service time for each stage. Our study differs from the existing studies in that the supply chain network in our work is not a tree, and the guaranteed service time impact the supply chain configuration in different ways when considering a network structure. The network structure is common in the real-world supply chain. For example, in a PC supply chain, some stages, like the stages producing PC parts (e.g., motherboard, CPU, hard disk and so on) are in charge of the PC platform products. These stages forms a supply chain network. Huang et al. (2005) formulate an SCC model for a supply chain of a platform product and adopt a genetic algorithm (GA) to solve the problem. GA can identify the best solutions, but it easily jumps into local optima as will be shown in our numerical experiments. Qu et al. (2010) focus on an SCC problem for an assembly supply chain and apply an analytical target cascading approach to solve their model. Li and Womer (2012) study an SCC problem for a made-to-order supply chain; the model of their supply chain is NP-complete. They develop a hybrid Benders decomposition algorithm to solve the model. Unlike the previous studies discussed, our study develops a hybrid algorithm to solve the model efficiently and effectively, where the service time decision problem is solved optimally and the option selection problem is solved by an intelligent heuristic algorithm.

Problems in supply chain configuration are extended in many areas. Francas and Minner (2009) investigate a network design problem for a manufacturing system producing new and remanufactured products. They examine the capacity decisions and expected performance of two alternative configurations for a manufacturing network when demand and return flows are uncertain. Svanberg and Halldórsson (2013) develop a configuration framework for a torrefaction supply chain to satisfy the demands of various types of customers; they find that various SCCs perform differently in terms of product quality, durability, and energy density. Amin and Zhang (2013) propose an SCC model for a closed-loop supply chain involving remanufacturing subcontractors and refurbishing sites. Amini and Li (2015) investigate an SCC problem where a new product supply chain serves two markets. Considering ecological objective of a supply chain, Brandenburg (2015) presents a goal programming model to explore ways to improve ecological benefits through the SCC without damaging economic utilities.

The environmental attributes of supply-chain products and environmental regulations are largely ignored in the existing literature. In this study, we investigate how the SCC can help a supply chain overcome environmental regulations at a minimal supply chain cost. We also consider guaranteed service time, which helps a supply chain fulfill the marketing demands within guaranteed service that is an increasingly important aspect of the Internet economy.

2.2. Sustainable operation management

The literature on sustainable operation management involves operational decision problems that involve environmental issues. The literature on *operations management within environmental regulations* and *green supply chain design* are specifically related to our study.

The operations management involving environmental regulations focuses on the production systems involved in environmental issues and aims to optimize costs or profits for firms by considering production cost, inventory cost, environmental cost, emission constraints, and capacity limitation (Benjaafar, Li, & Daskin, 2013; Hong, Chu, Zhang, & Yu, 2017; Kleindorfer, Singhal, & Wassenhove, 2005; Tang & Zhou, 2012). Hua, Cheng, and Wang (2011) use an EOQ model to investigate the effects of emission constraints in inventory management and to analyze how the trading scheme of carbon emission affects the firm's order decisions and total cost. Extending the work of Hua et al. (2011), Bouchery, Ghaffari, Jemai, and Dallery (2012) introduce the sustainable development criteria into the EOQ model and formulate a multi-objective inventory decision model. Their findings show that operational adjustment can effectively reduce the impacts of environmental regulations. Our study considers emission constraint, which affects option selection and further affects inventory management at each stage of the supply chain.

The other large body of literature is devoted to investigating the effects of emissions constraint in production systems. Benjaafar et al. (2013) propose a series of lot-sizing models to investigate the effects of emission regulations on manufacturers' production decisions. Their findings, similar to those of Bouchery et al. (2012), emphasize that environmental improvement can be achieved by optimizing the production/operation strategy at a low price of economic benefits. Zhang and Xu (2013) propose a profit-maximizing model to study a problem in multi-item production planning under the carbon cap-and-trade scheme. Multiple products are generated to satisfy independent stochastic demands. Absi, Dauzère-Pérès, Kedad-Sidhoum, Penz, and Rapine (2013) and Absi, DauzéPés, Kedad-Sidhoum, Penz, and Rapine (2016) investigate production systems with multiple production modes and emission constraints using lot-sizing models. Considering periodic emission constraints, Hong, Chu, and Yu (2016) formulate a dual-mode production planning model and develop a polynomial dynamic algorithm to solve the problem optimally. Different from the existing studies on production planning, we investigate a supply chain production system with multiple alternative options and stages, where the options at each stage contain emission information. The emissions generated from the production throughout the supply chain are limited by a subsidy scheme. The problem is NP-hard as the emission constraint involved in the model.

The green supply chain design is to redefine the structure of the traditional supply chain by embedding environmental concerns in it (Beamon, 1999). In previous studies, researchers mainly focus on economic objectives and optimize the supply chain costs or profits by making trade-offs between the environmental impact and the operation cost. Chen (2001) examine the coordination between traditional and environmental attributes when developing green products. The results show that environmental improvement does not require stricter environmental standards. Wang, Lai, and Shi (2011) investigate a design problem in a supply chain network; they consider environmental investments and propose a multi-objective model to achieve the best trade-off between the supply chain cost and environmental impact.

Some studies have also considered environmental objectives. Elhedhli and Merrick (2012) incorporate environmental cost into the supply chain cost; they propose a design model for a green supply chain to optimally determine warehousing location in the distribution network. Paksoy, Pehlivan, and Özceylan (2012) propose a fuzzy, multi-objective model in designing a closed-loop supply chain network. Their optimization model considers the economic costs of transportation and reverse logistics as well as the environmental objectives of recyclable materials. In the existing literature, most formulations on green supply chain design are deterministic, while stochastic scenarios largely ignored (Brandenburg, 2015). Different from the existing work, our study considers a subsidy scheme for green products, the emissions of which generated throughout the supply chain are limited.

In summary, this study tries to fill the research gap in SCC literature. We consider the environmental attributes and emission regulations of a supply chain product to investigate a sustainable SCC problem. Guaranteed service time is also considered in our model to satisfy the promised service of a supply chain product. Methodologically, we develop a hybrid algorithm to solve our model.

3. Mathematical formulation

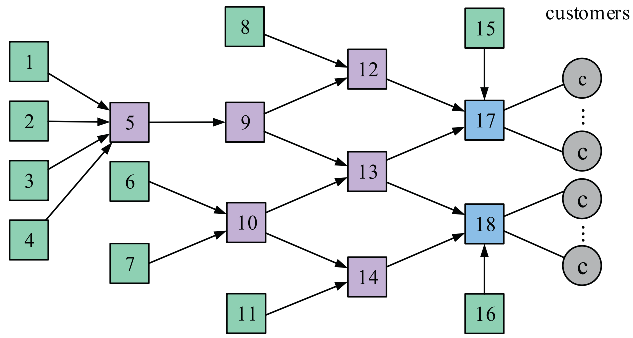
The supply chain involved in this study serves consumers with a product family of green products, which undergoes a sequence of processing stages, ranging from supply of raw materials, manufacturing of individual parts, and assembly of components and final products. Alternative processing options can be employed at each stage, which are distinguished in terms of processing lead time, cost, and emissions. Customers require guaranteed service time for each final product, i.e., the products should be available at a promised service time. The emissions generated from the production of a final product throughout the supply chain are constrained by a subsidy regulation scheme. We investigate a supply chain configuration problem that optimally chooses alternative options and assigns service time for each stage, aiming to minimize the overall supply chain cost. In what follow, we introduce the research setting and mathematically formulate the problem.

3.1. Supply chain network

A product family of green products are manufactured through a supply chain to satisfy a mass-customized demand. The supply chain is represented as a network. As shown in Fig. 1, a supply chain is a multi-stage network $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{P})$, where the nodes (defined by $\boldsymbol{V}$) represent the stages in the supply chain, and arcs (defined by $(i, j) \in \boldsymbol{P}$) are the precedence constraints of the conjoint stages which imply that an upstream stage supplies a downstream stage, and the stages are indexed by $1, \ldots, i, \ldots, j, \ldots, N$.

A stage represents a major processing operation in the supply chain, such as supply of raw materials, manufacturing of individual parts, sub-assembly of sub-products, and assembly of final products. For convenience, we classify stages in the supply chain into three sets. The first set (namely $\boldsymbol{R}$) consists of all raw-material *procurement stages*; the second set (namely $\boldsymbol{F}$) consists of all *processing stages* which manufactures parts of components or assembles components; the third set (namely $\boldsymbol{A}$) consists of all *demand stages*, where final products is assembled. Note that, we have $\boldsymbol{V} = \{\boldsymbol{R}, \boldsymbol{F}, \boldsymbol{A}\}$. For convenience, a raw material, component or product that is supplied, manufactured or assembled at stage j is called an item if $j \in \boldsymbol{R} \cap \boldsymbol{F}$, and a final product if $j \in \boldsymbol{A}$. Note that a stage j $(j \in \boldsymbol{R} \cap \boldsymbol{F})$ may serve the production and operations of two or more final products, such as stage 13 in the supply chain as shown in Fig. 1. The supply chain with network structure is common in the real-world supply chain. For example, many stages (parts), like motherboard, CPU, hard disk, etc., are shared for the PC platform products. These stages construct a supply chain network.

The supply chain network considered in this study is extended from a specific application case adopted by Graves and Willems (2005), which involves an SCC problem for two notebook computers sold in the United States and European markets. However, as shown in Fig. 1, the supply chain network considered in this study is different from that of Graves and Willems (2005) in which the supply chain in their paper is a tree that is an undirected graph in which any two vertices are connected by exactly one path (Sedgewick & Wayne, 2016). By contrast, the supply chain in our study is a multi-path network, i.e., multiple pathes are available



$\boldsymbol{R} = \{1, 2, 3, 4, 6, 7, 8, 11, 15, 16\}$, $\boldsymbol{F} = \{5, 9, 10, 12, 13, 14\}$, and $\boldsymbol{A} = \{17, 18\}$.

Fig. 1. The network of a multi-stage supply chain.

to connect a starting stage to an ending stage. That is, the service time of a downstream stage could directly impact more than one upstream stages in our network setting, whilst only one upstream stage is directly connected by a downstream stage in a supply chain with a tree structure. Consequently, the guaranteed service time plays different impacts on the supply chain configuration as will be discussed in the coming section.

3.2. Product demand and emission constraints

The supply chain provides consumers with a product family that includes multiple green products (e.g., Products 1 and 2 in Fig. 1), which is driven by mass-customized demand. The stochastic demand of each final product j ($j \in \boldsymbol{A}$) is identically and independently distributed following a normal distribution with mean μ_j and standard deviation σ_j. The demand correlation between two final products i and j ($i, j \in \boldsymbol{A}$) is defined by ρ_{ij}. Let $\boldsymbol{A}(j)$ be a set of final products requiring item j ($j \in \boldsymbol{R} \cap \boldsymbol{F}$), and ϕ_{ij} be the production coefficient that indicates the number of item i ($i \in \boldsymbol{R} \cap \boldsymbol{F}$) that is necessary to produce one unit of final product j ($j \in \boldsymbol{A}$). Consequently, the demand of item j ($j \in \boldsymbol{R} \cap \boldsymbol{F}$) is normally distributed with mean

$$\mu_j = \sum_{k \in \boldsymbol{A}(j)} \phi_{jk} \mu_k, \tag{1}$$

and deviation

$$\sigma_j^2 = \sum_{k \in \boldsymbol{A}(j)} \sum_{l \in \boldsymbol{A}(j)} \rho_{kl} \phi_{jk} \phi_{jl} \sigma_k \sigma_l. \tag{2}$$

At each stage, multiple options (or modes) are alternative for operation. Let m ($m = 1, \ldots, M$) be the index of the option. These options at each stage differ in terms of production cost (defined by c_{jm}), lead time (defined by t_{jm}) and emissions (defined by e_{jm}). Let X_{jm} be a binary variable, $X_{jm} = 1$, if option m is selected at stage j; otherwise $X_{jm} = 0$. The emissions generated from producing final product j are calculated by

$$e_j = \sum_{j \in \boldsymbol{A}(i)} \sum_{m=1}^{M} \phi_{ij} e_{im} X_{im}. \tag{3}$$

The emissions of each production are regulated by the government with a subsidy policy. In the scheme, the emissions of each product are limited by an emission cap E_0, which indicates the highest controlled emission level of a green product. Subsidies can be obtained according to the product emission level. The subsidy for a product is calculated by

$$\theta_j = \begin{cases} 0, & E_h < e_j \le E_0, \\ \theta_L, & E_l \le e_j \le E_h, \\ \theta_H, & e_j < E_l, \end{cases} \tag{4}$$

where E_h and E_l represent the high and low emission levels of the product, respectively. θ_H and θ_L represent the high- and low-level subsidies paid to the products with different emission levels.

3.3. Service time and inventory management

Customers require a guaranteed service time, which means that the products must be available to customers at a promised time. Facing the stochastic demand, a periodic review base-stock policy is used to control the inventory at each stage (Magee & Boodman, 1967). Under this policy, safety inventory is permitted to ensure smooth operation and the safe inventory level depends on service time, processing lead time, and inventory reviewing time (Inderfurth & Minner, 1998). Different the existing literature on supply chain configuration (Graves & Willems, 2005; Huang et al., 2005; Qu et al., 2010), the service time (S_j) is relaxed to a real number in our research setting. Examples with real-number service time are commonly faced by a real-world supply chain. In an e-commerce business, orders from consumers are instantaneously. These orders are responded or fulfilled by the supply chain in real time in which the service time of the supply chain is real number.

At a certain stage, the time within which successors receive their orders is guaranteed by service time S_j and service level ζ_j. The service level indicates the percentage of time that the demand is satisfied at time S_j. A final product at stage j ($j \in \boldsymbol{A}$) should be available with guaranteed service time ss_j, i.e., $S_j \le ss_j$. Note that, an optimal solution achieves at $S_j = ss_j$ to ensure the minimal inventory cost. Each stage is guaranteed by an input service time IS_j, which depends on its immediate predecessors. In particular, the input service time for stage $j \in \boldsymbol{R}$ is assumed to be zero, i.e., $IS_j = 0$ for any $j \in \boldsymbol{R}$. The input service time is equal to the maximum service time of all its predecessors and is given by

$$IS_j = \max\{S_i\}, \ i \in \boldsymbol{V}, \ j \in \boldsymbol{F} \cap \boldsymbol{A}, \ (i, j) \in \boldsymbol{P}. \tag{5}$$

Safety inventory is placed to guarantee that orders will be delivered within the promised service time. In other words, the safety inventory should cover demand over the net replenishment time at each stage. Let r_j be the periodic review time and T_j be the lead time of stage j ($j \in \boldsymbol{A}$), where $T_j = \sum_{m=1} t_{jm} X_{jm}$. The net replenishment time at stage j is the replenishment time minus the service time. Therefore, the expected safety inventory level

(Inderfurth & Minner, 1998) at stage j is

$$E[I_j] = \begin{cases} \zeta_j\sigma_j\sqrt{r_j + T_j - S_j}, & j \in \boldsymbol{R}, \\ \zeta_j\sigma_j\sqrt{r_j + IS_j + T_j - S_j}, & j \in \boldsymbol{F} \cap \boldsymbol{A}. \end{cases} \quad (6)$$

The expected pipeline inventory level is

$$E[PI_j] = \begin{cases} 0, & j \in \boldsymbol{R}, \\ \mu_j T_j, & j \in \boldsymbol{F} \cap \boldsymbol{A}. \end{cases} \quad (7)$$

3.4. The model and complexity analysis

A supply chain configuration problem is to minimize the overall supply chain cost, which is achieved by optimally determining the service time and choosing options for all stages that serve all the platform products. Let TC be the total cost of the supply chain and h_j be the inventory holding cost rate of stage j. Then, the problem is formulated as an SCC model, namely Model SCC, as follows:

Model SCC

$$\min_{S_j, X_{jm}} \quad TC = \sum_{j\in \boldsymbol{R}} h_j\zeta_j\sigma_j\sqrt{r_j + T_j - S_j} + \sum_{j\in \boldsymbol{F}\cap\boldsymbol{A}} (h_j\zeta_j\sigma_j\sqrt{r_j + IS_j + T_j - S_j} + h_j\mu_j T_j) + \sum_{j\in \boldsymbol{V}}\sum_{m=1}^{M} \mu_j c_{jm} X_{jm} - \sum_{j\in\boldsymbol{A}} \theta_j\mu_j, \quad (8)$$

$$\text{s.t.} \quad e_j(X_{jm}) \le E_0, \ \forall j \in \boldsymbol{V} \ and \ m = 1, \ldots, M, \quad (9)$$

$$\sum_{m=1}^{M} X_{jm} = 1, \ \forall j \in \boldsymbol{V}, \quad (10)$$

$$r_j + T_j - S_j \ge 0, \ \forall j \in \boldsymbol{R}, \quad (11)$$

$$r_j + IS_j + T_j - S_j \ge 0, \ \forall j \in \boldsymbol{F} \cap \boldsymbol{A}, \quad (12)$$

$$S_j \ge 0, \ \forall j \in \boldsymbol{V}, \quad (13)$$

$$S_j \le ss_j, \ \forall j \in \boldsymbol{A}, \quad (14)$$

$$X_{jm} = \{0, 1\}, \ \forall j \in \boldsymbol{V} \ and \ m = 1, \ldots, M, \quad (15)$$

where the objective function (8) consists of four terms. The first term is the safety inventory cost of all procurement stages; the second term is the safety inventory and pipeline inventory costs of the procurement and demand stages; the third term is the production cost of all stages in the network; the fourth term is the subsidy from the government. Constraint (9) limits the emissions of a green product. Constraint (10) ensures that exact one option is adopted by each stage. Constraints (11) and (12) ensure that the service time is not longer than the operation time. Constraints (13) and (14) provide the bound of decision variable and ensures that the product is ready for consumers within the guaranteed service time. Constraint (15) shows that an option can be adopted by each stage or not.

We then analyze the complexity of Model SCC from two aspects: determining the service time when options are given, and determining the option choice when the service time is fixed. First, we investigate the complexity of the service time decision problem with given operation options. As discussed in Section 3.1, the structure of the supply chain network considered in this study differs from that of the previous work (Graves & Willems, 2005). The constraint of guaranteed service time brings aftereffects on the service time and option selection decisions to a supply chain. That is, the input service time at a stage may be determined by its predecessors or by its successors in the supply chain.

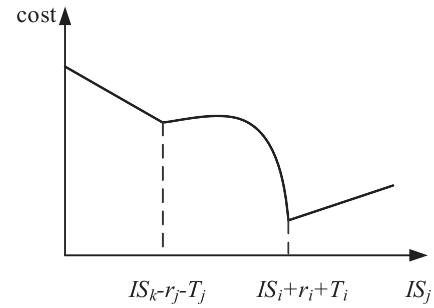


Fig. 2. Optimal solution for a three-stage example.

Let us consider a simple example where stage j has only one processor i and one successor k, i.e., $(i, j) \in \boldsymbol{P}$ and $(j, k) \in \boldsymbol{P}$. We optimally determine service time to minimize the overall inventory cost of the three stages. Given that S_j is one-to-one with IS_i, we take IS_i as the decision variable. As shown in Fig. 2, the optimal solution of IS_i may be determined by stage i, i.e., $IS_j = IS_i + r_i + T_i$, or by stage k, i.e., $IS_j = IS_k - r_j - T_j$. That means the objective function is piecewise differential with respect to IS_i. The problem may have several local solutions because of the square root characteristic, which causes difficulty in finding the global optimal solution. Nevertheless, as discussed in the network structure, the input service time of a stage may be obtained from more than one predecessor or successor. This further complicates the problem.

We then analyze the option selection problem with fixed service time at each stage. The following property shows the complexity of this problem. The problem can be easily degenerated into a knapsack problem that is proven to be NP-hard (Garey & Johnson, 1979). We thus omit the proof here.

Proposition 1. *For any given S_i, optimally solving X_{jm} is NP-hard.*

The NP-hardness of the problem indicates that it is difficult to optimally solve the problem in polynomial time. When changing the option of a certain stage, optimal service time decisions vary as well, thereby further complicating the problem. Moreover, some pseudo-polynomial algorithms, such as the dynamic programming algorithm, are incapable of dealing with this problem. This finding indicates that it is difficult to solve the option selection problem optimally and numerical algorithms may be considered in solving the problem.

4. Structural properties and a hybrid algorithm

In this section, we develop a hybrid algorithm to efficiently solve the model. In the algorithm, a spanning-tree based algorithm is developed to solve the variable S_j and an intelligent algorithm is adopted to solve the variable X_{jm}. The algorithm is developed based on the structural properties of the problem, where the original problem is decomposed into two subproblems.

4.1. Problem decomposition

In Model SCC, S_j appears only in the first two terms of the objective function and in constraints (11)–(14). In an optimal solution, for any given X_{jm}, the value of S_j must be such that the sum of the first two terms of the objective function is minimized and constraints (11)–(14) are satisfied. Consequently, a proposition indicating the structural property of the problem is directly addressed in the following proposition.

Proposition 2. *The problem can be decomposed into two subproblems:*

(i) The first subproblem is to compute the optimal value of S_j for any given X_{jm}, such that the sum of the first two terms of the objective function is minimized while satisfying constraints (11)–(14).

(ii) The second subproblem is to compute the optimal value of X_{jm}.

The first subproblem is the service time decision problem that determines S_j when X_{jm} is given, while the second subproblem is the operational option selection problem that determines X_{jm}. When both problems are solved, we obtain the solutions of the model.

For the service time decision problem, the objective is to minimize the overall inventory cost, including the safety inventory cost and pipeline inventory cost, by optimally determining the service time at each stage. For analytical convenience, we take IS_i as the adjusted decision variables, which always hold since the one-to-one relationship between S_j and IS_i, as shown in Eq. (5). The constraint of the decision variable is then reduced by only one, i.e., $ISj \geq 0$. In particular, $IS_i = 0, \text{ if } j \in \boldsymbol{R}$.

Let $f(IS_j)$ be the inventory cost with given X_{jm}. Then, the decision problem is formulated as Model SCC-S as follows:

Model SCC-S

$$\begin{aligned} \min_{IS_j} \ f(IS_j) = & \sum_{j \in \boldsymbol{R}} h_j \zeta_j \sigma_j \sqrt{r_j + T_j - S_j} \\ & + \sum_{j \in \boldsymbol{F} \cap \boldsymbol{A}} (h_j \zeta_j \sigma_j \sqrt{r_j + IS_j + T_j - S_j} + h_j \mu_j T_j), \\ & \text{s.t.} \quad \textit{Constraints } (11)\text{–}(14). \end{aligned} \tag{16}$$

For the operational option selection problem, the aim is to minimize the total cost, including the overall inventory cost, production cost, and benefit from government subsidy by optimally determining the operation option of each stage. Then, the problem can be formulated as the following Model SCC-M:

Model SCC-M

$$\min_{X_{jm}} \quad TC(X_{jm}) = f(IS_j) + \sum_{j \in \boldsymbol{V}} \sum_{m=1}^{M} \mu_j c_{jm} X_{jm} - \sum_{j \in \boldsymbol{A}} \theta_j \mu_j, \tag{17}$$

$$\text{s.t.} \quad \textit{Constraints } (9) \textit{ and } (10).$$

4.2. Service time decision problem

As discussed in the complexity of Model SCC, the objective function is piecewise differential even though the operation options are given. In other words, obtaining analytical solutions of Model SCC-S is difficult. Several researchers suggest using intelligent algorithms to obtain near-optimal solutions, such as genetic algorithm (GA) (Huang et al., 2005). However, in this study, we try to develop an exact algorithm to optimally solve the model.

4.2.1. Properties of a branch in the network

As shown in Fig. 1, a supply chain network is composed of many branches consisting of nodes and arcs. The nonstructural properties of the network depend on the properties of branches in the network. Let $A_j = h_j \zeta_j \sigma_j$, $B_j = r_j + T_j$, and $C = \sum_{j \in \boldsymbol{F} \cup \boldsymbol{A}} h_j \mu_j T_j$. The decision problem can be rewritten as

$$\min_{IS_j} \quad f(IS_j) = \sum_{j \in \boldsymbol{V}} A_j \sqrt{B_j + IS_j - S_j} + C, \tag{18}$$

$$\text{s.t.} \quad \textit{Constraints } (11)\text{–}(14),$$

where $S_j = \min_{IS_j} \{r_i + IS_i + T_i | j : (i, j) \in \boldsymbol{P}\}$.

As shown in the function above, $f(IS_j)$ achieves its minimum either at the extreme point, where its first-order derivative equals zero, or at the mutation point, where the derivative fails to exist.

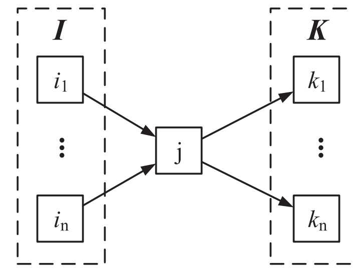


Fig. 3. A branch in a supply chain network.

In order to investigate the properties of the optimal solutions, we first consider a simple branch of the supply chain network, where a stage j has only one processor i and one successor k, i.e., $(i, j) \in \boldsymbol{P}$ and $(j, k) \in \boldsymbol{P}$. Then, we have the minimal value of the objective function as follows:

$$\begin{aligned} f(IS_j) = & A_i \sqrt{B_i + IS_i - S_i} + A_j \sqrt{B_j + IS_j - S_j} \\ & + A_k \sqrt{B_k + IS_k - S_k} + C', \end{aligned} \tag{19}$$

where $C' = \sum_{l \in \{i,j,k\}} h_l \mu_l T_l$. The three-stage branch has the following property that provides an approach to calculate the minimal inventory cost. The proof is shown in Appendix A.

Lemma 1. *Function (19) achieves its minimum at $B_i + IS_i$ at stage i or $IS_k - B_j$ at stage k.*

Based on the property of the simple example, we can directly obtain the similar property of a branch of the supply chain network. In the branch as shown in Fig. 3, define $\boldsymbol{I}$ as the set of *direct* processor stages of stage j and $\boldsymbol{K}$ as the set of *direct* successor stages of stage j. Let stage i be a stage of set $\boldsymbol{I}$ and k be a stage of set $\boldsymbol{K}$. The minimal cost of all stages in the branch is then formulated as follows:

$$\begin{aligned} f(IS_j) = & \sum_{i \in \boldsymbol{I}} A_i \sqrt{B_i + IS_i - S_i} + A_j \sqrt{B_j + IS_j - S_j} \\ & + \sum_{k \in \boldsymbol{K}} A_k \sqrt{B_k + IS_k - S_k} + C'. \end{aligned} \tag{20}$$

The property of function (20) is given in the following proposition, which can be proven directly by an induction approach. We omit the proof here.

Proposition 3. *In a branch defined by (20), the minimal overall inventory cost of the branch achieves at the value of IS_j that is equal to $B_i + IS_i$ at stage i or $IS_k - B_j$ at stage k.*

Proposition 3 is a critical property to calculate the optimal input service time of each stage in a network.

4.2.2. Structural properties of the network

For convenience, we reformulate the supply chain network by adding several dummy stages to indicate the relationships between stages; their lead time is zero. Taking the supply chain network in Fig. 1, we add two dummy stages to the network for example, i.e., dummy stage 19 as the direct successor of stage 17 and dummy stage 20 as the direct successor of stage 18. The new network within dummy stages is shown in Fig. 4. We have $IS_{19} = ss_{17}$ and $IS_{20} = ss_{18}$, which imply that the service time of the upstream stages is constrained by the input service time of stages 19 and 20. We further let $\boldsymbol{F}' = \boldsymbol{F} \cup \boldsymbol{A}$ be the new set of process stages and $\boldsymbol{A}'$ be the set of ending stages. That is, $\boldsymbol{A}' = \{19, 20\}$ in the example.

Based on the properties of a branch, we go to investigate the network properties. For analysis convenience, we initially provide the following two critical definitions to investigate the network properties.

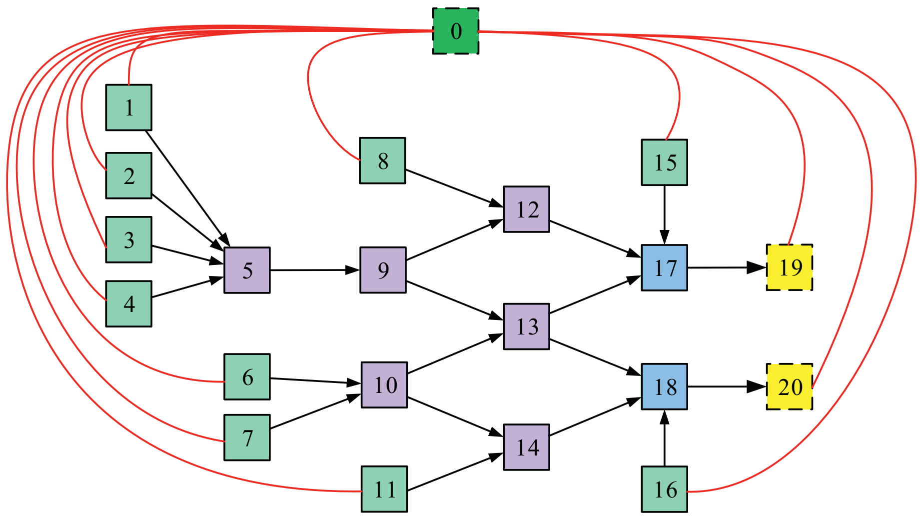


Fig. 4. The supply chain network for generating spanning trees.

Definition 1. (Direct connection) *Stage i directly connects stage j* ($i, j \in \boldsymbol{V}$)*, namely,* $i \sim j$*, if*

$$\begin{cases} IS_j = IS_i + B_i, & \text{for any } (i,j) \in \boldsymbol{P}, \\ IS_j = IS_i - B_j, & \text{for any } (j,i) \in \boldsymbol{P}. \end{cases} \tag{21}$$

Definition 2. (Connection) *Stage i connects stage k* ($i, k \in \boldsymbol{V}$)*, if* $i \sim j_1 \sim j_2 \sim ... \sim k$ *is true.*

Note that the definition of connection is used to calculate the optimal IS_j. Using the definition of the network connection, we obtain the following property of the network. The proof is shown in Appendix B.

Proposition 4. *In an optimal solution, the following statements of the network are true:*

(i) there exists at most one connection that makes i connect k ($i, k \in \boldsymbol{V}$)*;*

(ii) any stage i ($i \in \boldsymbol{F}'$) *connects at least one stage k* ($k \in \boldsymbol{R} \cup \boldsymbol{A}'$)*;*

(iii) any two stages i and k ($i, k \in \boldsymbol{R} \cup \boldsymbol{A}'$) *do not connect to each other.*

Proposition 4 indicates that the network in an optimal solution can be restructured as a spanning tree, based on which we develop an exact algorithm to optimally solve the service time decision problem.

4.2.3. An exact algorithm for the service time decision problem

We first introduce another dummy stage as shown in Fig. 4, namely stage 0, to construct a spanning tree, where stage 0 connects to stage j ($j \in \boldsymbol{R} \cup \boldsymbol{A}'$) in the network. According to Proposition 4, in an optimal solution, the original supply chain network that is a connected graph can be reconstructed a spanning tree, where the direct connection is an edge and each stage is a vertex. Consequently, we develop an exact algorithm, namely *spanning-tree based algorithm* (STA), to optimally solve the problem.

In the algorithm, we first generate all feasible spanning trees and calculate the minimal values of the objective function of each tree, according to Proposition 3 and the definition of the direct connection. Consequently, we obtain the optimal solutions corresponding to the spanning tree with the minimal value of $f(IS_j)$. All feasible spanning trees are generated according to a fundamental cut set approach (Cheng, 2013; Wang, 2003). The procedure of the algorithm is listed below.

Step 1 Generate all feasible spanning trees.

Step 1.1 Label the edge of the nodes i and j as e_{ij} ($i, j \in \boldsymbol{V}$),
Step 1.2 Select edges e'_{0i}s (the number of the edges is $N_1 = |\boldsymbol{R} \cup \boldsymbol{A}'|$) and edges e'_{jk}s ($j \neq k$,
the number of the edges is $N_2 = |\boldsymbol{V}| - N_1 - 1$), which could form a spanning tree labeled as S.
Step 1.3 Label edges e_{0i}'s as e^1_m ($m = 1, 2, \ldots, N_1$), and let $\boldsymbol{L}^1_m = \{e^1_m\}$.
Label edges e_{jk}'s as e^2_n ($n = 1, 2, \ldots, N_2$), and let $\boldsymbol{L}^2_n = \{e_{ij} | S - e^2_n + e_{ij}$ is a
spanning tree$\}$.
Step 1.4 Take the Cartesian product of the sets $\boldsymbol{L}^1_m$ and $\boldsymbol{L}^2_n$, and plus all homologous
elements to obtain a polynomial equation L.
Step 1.5 Obtain all feasible spanning trees. For any edge α in a term of L, let $\alpha \cdot \alpha = 0$.
For any term β of L, let $\beta + \beta = 0$. Then, each remaining term in L construct a feasible spanning tree.

Step 2 Calculate the value of $f(IS_j)$ of each spanning tree.

Step 2.1 Calculate the value of IS_j of each spanning tree.
Step 2.1 Calculate the value of $f(IS_j)$ of each spanning tree.

Step 3 Output the optimal solutions.
Step 3.1 Select the spanning tree with minimal value of $f(IS_j)$.
Step 3.2 Output the optimal solutions IS^*_j and the minimal cost $f^*(IS_j)$.

The computational time complexity is $\mathcal{O}(N^{\chi})$ in which χ is the average number of arcs that a vertex (stage) connects in the supply chain network, and N is the number of stages of the supply chain. Note that the structure is commonly steady and fixed for a real-world supply chain, and thus the feasible spanning trees just needs to be computed and generated once and are stored for the computation of operational optimization. That is, the computation on generating the feasible spanning trees does not take computation time in the operational optimization of supply chain configuration.

4.3. Operational option selection problem

The option selection problem is difficult to optimally solve since its NP-hardness as discussed in Section 5.3. We thus develop an intelligent algorithm called PSO to overcome the difficulties. However, we can also use the enumerating approach to obtain the optimal solutions as the benchmark for evaluating the performance of our algorithm.

PSO can efficiently solve the problem, benefiting from the advantages of its capacity to deal with the non-concavity of objective functions and efficiency to find a globally near optimum (Kennedy, 2011). Apparently, other intelligent algorithms, like GA, also provide similar features. For example, Huang et al. (2005) adopt GA to solve the overall SSC problem.

We introduce our PSO algorithm based on the standard PSO procedure (Poli, Kennedy, & Blackwell, 2007). In a D-dimensional searching space, K particles are initialized with random positions and velocities. Specifically, the particle i locates at $\boldsymbol{Z}_i = (z_{i1}, z_{i2}, \ldots, z_{iD})$ $(i = 1, 2, \ldots, K)$ in the space, where location $\boldsymbol{Z}_i$ contains the option information of all stages. The location of each particle corresponds to a fitness value of the objective function Eq. (8). Apparently, a real number is transferred into an integer X_{jm} $(j = 1, 2, \ldots, N$ and $m = 1, 2, \ldots, M)$ when calculating the fitness value. The higher the fitness value, the better the position that particle i locates.

Let the velocity of particle i be $\boldsymbol{V}_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ $(i = 1, 2, \ldots, K)$ and the previous best position be $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ with a fitness value of $pbset_i$. Let the previous best position of all particles be $P_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$, where it achieves by particle g with a fitness value of $gbset_g$. Then, the position and velocity of particle i are updated using the following equations:

$$\begin{cases} \boldsymbol{V}_i(l+1) = \boldsymbol{V}_i(l) + c_1 r_1 (P_i - \boldsymbol{X}_i(l)) + c_2 r_2 (P_g - \boldsymbol{X}_i(l)), \\ \boldsymbol{X}_i(l+1) = \boldsymbol{X}_i(l) + \boldsymbol{V}_i(l+1). \end{cases} \tag{22}$$

where l is the iterative number, c_1 and c_2 are learning rates, and r_1 and r_2 are random numbers. The optimal global solutions are those with the best fitness value.

4.4. Summary of hybrid algorithm

Recall that the service time decision problem is solved by STA, and the option selection problem is solved by PSO. We summarize the hybrid algorithm, namely STA+ PSO, and present its procedure as follows:

Step 1 Initialize X_{jm} by PSO (see Section 4.3).
/**Obtaining the global optima**/
Step 2 *While the termination condition of PSO is not satisfied*

a) Update X_{jm} by PSO. /**Obtaining the local optima with the given* X_{jm}*/
b) Optimize IS_j by STA and calculate $f(IS_j)$ (see Section 4.2).
c) Calculate $TC(IS_j, X_{jm})$

Step 3 End while
Step 4 Output the optimal solutions IS_j^* (i.e., S_j^*) and the minimal cost TC^*.

As shown in the procedure, the hybrid algorithm is composed of STA and PSO, where STA is used to obtain the optimal IS_j with any given X_{jm} generated by PSO, while PSO is responsible for the output loop to find the global optima of X_{jm}.

5. Numerical experiment

5.1. The base example

We extend a specific application case adopted by Graves and Willems (2005), based on which the network is modified and the related data are added according to our research setting. The supply chain network is shown in Fig. 1 and the parameters are given in Table 1. Other parameter are introduced as follows.

Table 1
Parameters of the stages.

Stage	Option	Lead time	Cost	Emissions
1	1	40	130.00	5.0
	2	20	133.25	8.0
	3	10	134.94	9.0
	4	0	136.59	5.0
2	1	20	200.00	10.0
	2	10	202.50	10.0
	3	0	205.03	9.0
3	1	10	155.00	4.0
	2	0	156.93	8.0
4	1	0	200.00	6.0
5	1	20	120.00	4.0
	2	5	150.00	8.0
6	1	60	300.00	10.0
	2	5	350.00	18.0
7	1	30	200.00	4.0
8	1	70	225.00	4.0
	2	30	240.00	9.0
9	1	10	100.00	1.0
10	1	5	120.00	6.0
	2	2	132.00	4.0
11	1	40	30.00	4.0
	2	5	35.00	6.0
12	1	1	30.00	2.0
13	1	40	15.00	3.0
	2	5	16.50	2.0
14	1	3	30.00	1.0
15	1	5	12.00	2.0
	2	1	20.00	3.0
16	1	15	15.00	7.0
	2	2	30.00	3.0
17	1	5	12.00	1.0
	2	1	20.00	1.0
18	1	5	15.00	2.0
	2	2	20.00	2.0

Table 2
Parameters of product demand and subsidy policy.

Parameters	μ	σ	ρ	ss	E_0	E_h	E_l	θ_L	θ_H
Product 1	200	120	0	3	80	70	62	80	100
Product 2	125	80							

The supply chain is constrained by the guaranteed service time at the demand stages (i.e., stages 17 and 18). The required service time at the demand stage consists of three days, i.e., $ss_{17} = ss_{18} = 3$. The demand information of the two products and the subsidy policy are given in Table 2. In inventory management, the periodic review time at each stage is five days, i.e., $r_j = 5$ $(j \in \boldsymbol{V})$. The service level is set at 98% at each stage, i.e., $\zeta_j =$ 98% $(j \in \boldsymbol{V})$. The production coefficient of the two final products are: $\phi_{17j} = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0]$ and $\phi_{18j} = [1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1]$ $(j \in \boldsymbol{V})$. The holding costs of the stages are $h = \{1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2, 4, 2, 1, 1, 5, 5\}$, where the cost at the demand stage is the highest. Note that, the unit time is one day, the monetary unit is US dollar, and the emissions are measured by one unit (e.g., 1 kilogram per unit). For simplicity, we omit the unit in the table and figures hereafter.

To examine the efficiency of the hybrid algorithm (STA+PSO), we compare it with the exact algorithm STA+Enumerating (hereafter, STA+ENU) that obtains the optimal solutions and the intelligent algorithm that only PSO is used to solve the problem. The numerical experiments are performed in Matlab with a Core i7 2.7 GHz CPU and 24G RAM PC. Note that the parameters of PSO in the

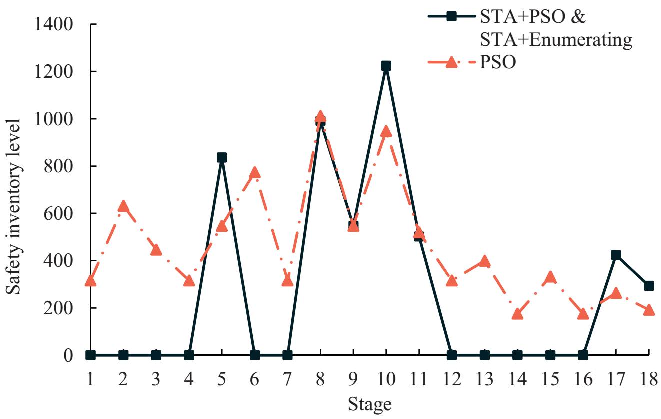


Fig. 5. The safety inventory level of each stage.

Table 3
Configuration costs and computation time of three algorithms.

Parameters	STA+PSO	STA+ENU[a]	PSO
Inventory cost	27,635	27,635	31,688
Production cost	556,388	556,388	556,388
Subsidy income	26,000	26,000	26,000
Total cost	558,022	558,022	562,075
Computation time	**17 seconds**	**7 minutes 33 seconds**	**41 seconds**

[a] *Note:* Indicates the optimal solutions are obtained by the algorithm STA+ENU.

Table 4
Configuration options and service time of three algorithms.

Stage	STA+PSO		STA+ENU[a]		PSO	
	Option	Service time	Option	Service time	Option	Service time
1	1	5	1	5	1	0
2	1	25	1	25	1	5
3	1	15	1	15	1	5
4	1	5	1	5	1	0
5	2	0	2	0	2	0
6	1	65	1	65	1	35
7	1	35	1	35	1	30
8	1	4	1	4	1	1
9	1	0	1	0	1	0
10	1	0	1	0	1	0
11	1	4	1	4	1	1
12	1	10	1	10	1	2
13	2	10	2	10	2	2
14	1	10	1	10	1	2
15	1	10	1	10	1	2
16	1	10	1	10	2	2
17	1	10	1	10	2	3
18	1	10	1	10	2	3

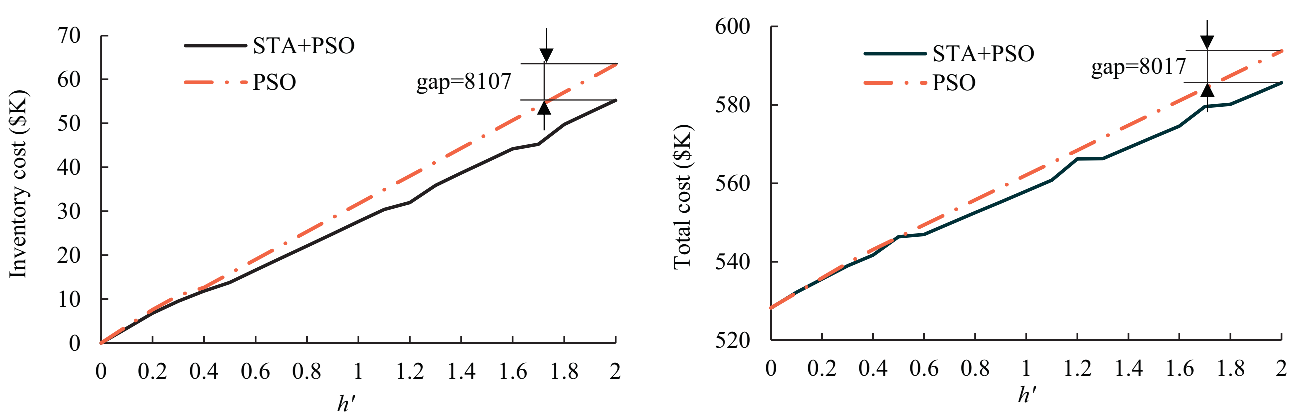
[a] *Note:* Indicates the optimal solutions are obtained by the algorithm STA+ENU.

hybrid algorithm are: $c_1 = 1.2$ and $c_2 = 1.0$; the parameters of the pure PSO are: $c_1 = 1.2$ and $c_2 = 0.23$. A trial and error method is used to set these parameters to improve the efficiency of the algorithm.

The results are presented in Tables 3 and 4 and Fig. 5. Note that we test the numerical example by the hybrid algorithm 30 times, the results will be addressed and analyzed in the next section. In the 30 sets of results, 22 tests obtain the objective values that are same to this obtained by the exact algorithm STA+ENU. We here present and analyze one group of results of the base example. The results show that our hybrid algorithm STA+PSO can solve the problem efficiently and effectively. As shown in Tables 3 and 4, STA+PSO obtains the optimal solutions that are the same to those of STA + Enumerating. STA+PSO requires only 17 seconds to obtain the optimal solutions, whereas STA+ENU requires more than 7 minutes. Note that the time to generate spanning trees is not added to the computational time because the structure of a supply chain is normally fixed when operational decisions are made. As shown in the fifth and sixth rows in Table 3, STA+PSO receives a lower cost than that of PSO, whereas taking less computing time than PSO.

The results reveal certain insights. The efficiency and effectiveness of STA+PSO benefit from the exact algorithm STA to solve the service time decision problem. As shown in the second row of Table 3, the production cost and subsidy income obtained in the three algorithms are the same, but the inventory cost obtained by STA+PSO is less than that obtained by PSO. This finding means that both STA+PSO and PSO obtain the optimal solutions for the option selection, but STA+PSO obtain the optimal service time, and PSO fails. In this case study, the inventory cost accounts for only a small proportion of the total cost, i.e., $27635/558022 \times 100\% = 4.95\%$. As will be shown in Fig. 6, our hybrid algorithm STA+PSO possesses much more advantages and potential in solving the problem where the inventory cost accounts for a large proportion of the total cost.

From a managerial perspective, we find that the safety inventory should be assigned at the stages with lower inventory holding cost rate. As shown in Fig. 5, among the stages within nonzero safety inventory (except for demand stages 17 and 18 that must hold a safety inventory to cover the stochastic demand (since $r = 5 > ss = 3$), only stage 9 has a holding cost rate more than 1.



(a) Effects on the inventory cost (b) Effects on the total cost

Fig. 6. Effects of the holding cost rate.

Table 5
Performance of three algorithms on solve SCCP with different number of stages.

Stage-product	Algorithms	Total cost			Computation time		
		Min	Max	**Aver**	Min	Max	**Aver**
	STA+PSO	292,872	292,872	292,872	0.50 seconds	0.65 seconds	0.59 seconds
10-2[a]	PSO	293,870	293,870	293,870	17 seconds	20 seconds	18 seconds
	STA+ENU	–[b]	–	292,872	–	–	0.6 seconds
	STA+PSO	558,022	561,429	558,611	17 seconds	20 seconds	18 seconds
18-2	PSO	562,075	562,075	562,075	34 seconds	43 seconds	36 seconds
	STA+ENU	–	–	558,022	–	–	7 minutes 33 seconds
	STA+PSO	877,992	880,914	878,524	1 minute 12 seconds	1 minute 30 seconds	1 minute 21 seconds
25-2	PSO	884,127	884,194	884,159	2 minutes 13 seconds	3 minutes 58 seconds	2 minutes 29 seconds
	STA+ENU	–	–	877,992	–	–	13 minutes 10 seconds
	STA+PSO	316,118	316,691	316,142	4 minutes 3 seconds	6 minutes 8 seconds	5 minutes 2 seconds
25-4	PSO	321,806	322,134	321,978	5 minutes 23 seconds	5 minutes 40 seconds	5 minutes 32 seconds
	STA+ENU	–	–	316,118	–	–	68 minutes 38 seconds
	STA+PSO	443,096	450,612	445,525	11 minutes 4 seconds	11 minutes 29 seconds	11 minutes 21 seconds
30-4	PSO	457,451	458,065	457,752	14 minutes 22 seconds	16 minutes 16 seconds	15 minutes 10 seconds
	STA+ENU	–	–	~[c]	–	–	~

[a] *Note:* Indicates the supply chain has 10 stages and 2 final products, which is similar for other examples.
[b] Indicates the algorithm STA+ENU just executes once.
[c] Indicates the algorithm STA+ENU cannot run anymore.

This condition can help the supply chain save inventory cost by taking advantage of the configuration from a supply chain perspective.

5.2. Performance of the hybrid algorithm

To examine the performance of the proposed hybrid algorithm, we test different supply chain networks with different number of stages. We here analyze three supply chain networks with 10, 18, 25, and 30 stages, respectively. Note that we test the 25-stage network in two different network structures to examine the network structure' effects on the computation. The related parameters of the supply chain networks are given in Appendix C. Note that the number of stages normally is not with a large scale in real world. Even facing the supply chain network with a relatively large scale, some related stages could be combined into an analytic unit as a new stage that constructs a new supply chain network with smaller scale. The similar approaches can be also used to deal with the cases that the supply chain network structures are complicated.

We test each example 30 times for the algorithms STA+PSO and PSO, and once for STA+ENU that obtains the optimal solutions as the benchmarks. Note that the algorithm STA+ENU cannot run anymore and the Matlab is "out of memory" when the supply chain is with a 30-stage network. The computation results with mean, maximum and minimum values are presented in Table 5.

The results in Table 5 show that the proposed hybrid algorithm (STA+PSO) can efficiently and effectively solve the SCC model, compared to the exact algorithm (STA+ENU) and pure intelligent algorithm (PSO). For the 10-2 example, STA+PSO always achieves the objective values that are equivalent to this obtained by STA+ENU in the 30 tests. That is, STA+PSO obtains the optimal solutions in all 30 tests. The numbers of times that obtain the same values as STA+ENU are 22, 25 and 21 in the 18-2, 25-2 and 25-4 examples, respectively. However, STA+ENU always takes more time, especially when the scale of the problem goes larger. The pure PSO takes more time on searching the solutions and achieves worse objective values than STA+PSO. PSO cannot jump out the local optimum, while STA+PSO can improve or even jump out the local optimal solutions and achieve the better objective value.

Both the scale and network structure of the supply chain have significant impacts on the computation. As shown the results given in Table 5, the computation time increases with the increase of the number of stages. In particular, when the number of stages increases by 30, the algorithm STA+ENU cannot run anymore in our test. The computation time of STA+PSO also increases dramatically. Furthermore, as shown by the results of 25-2 and 25-4 examples, the computation time dramatically increases when the supply chain structure becomes complicated even though the number of the stages is the same. The number of options in each stage also has the similar impacts on the computation. This is because the solution space explodes when the scale gets larger or the network structure becomes complicated.

Table 6
Configuration options under different holding cost rates.

Stage	h'										
	0	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
1	1	1	1	1	1	1	1	1	1	1	1
2	1	2	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1
5	2	2	2	2	2	2	2	2	2	2	2
6	1	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	2	1	1	1	1
11	1	1	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	1	1	1
13	2	2	2	2	2	2	2	2	2	2	2
14	1	1	1	1	1	1	1	1	1	1	1
15	1	1	1	1	1	1	1	1	1	1	1
16	2	2	2	2	2	2	2	2	2	2	2
17	1	1	2	2	2	2	2	2	2	2	2
18	1	1	1	2	2	2	2	2	2	2	2

5.3. The effects of the holding cost rate

The holding cost rate is an important strategy parameter in supply chain configuration. To investigate the effects of the holding cost rate, we define a new holding cost rate based on the holding cost rate set in the base example, where and ranges from 0 to 2 in the sensitivity analysis. Note that, the hybrid algorithm (STA+PSO) is adopted to execute the numerical analysis in Sections 5.2 and 5.3.

The effects of the holding cost rate on the total cost and inventory cost are shown in Fig. 6. As shown in Fig. 6, the inventory cost rate has significant effects on the total cost and inventory cost.

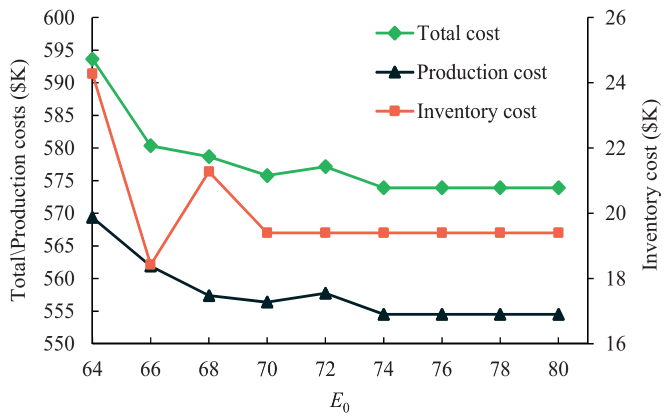


Fig. 7. The effects of the emission cap.

However, Fig. 6 (a) and (b) indicates that the increasing total cost is mainly from the increase in the inventory cost. Different from the findings of Graves and Willems (2005) and Huang et al. (2005), the holding cost rate fails to have obvious effects on option selection in our model. As shown in Table 6, adopting an option at each stage varies slightly with the increase in the holding cost rate. This is due to the emission constraint that makes the supply chain choose options not only according to the trade-off between lead time and cost but also the trade-off between the emissions of the green products and subsidy income.

The results presented in Fig. 6 further show the advantage of the hybrid algorithm STA+PSO in solving the problem. As shown in Fig. 6 (a) and (b), STA+PSO can obtain solutions with lower total cost and inventory cost than that of PSO, especially when the holding cost rate increases. When h' reaches 2, STA+PSO saves a cost of $8107 or nearly 20% of the inventory cost.

5.4. The effects of the emission constraints

As discussed in Section 5.2, apart from the holding cost rate, the emission constraints and subsidy also have effects on the option selection decisions and further affects the production cost and inventory cost of the supply chain. To investigate the effects of emission constraints and subsidy, respectively, we consider the following two scenarios: (*i*) changing E_0 when no subsidy is considered; and (*ii*) changing θ_L and θ_H when fixing E_0, E_l and E_h.

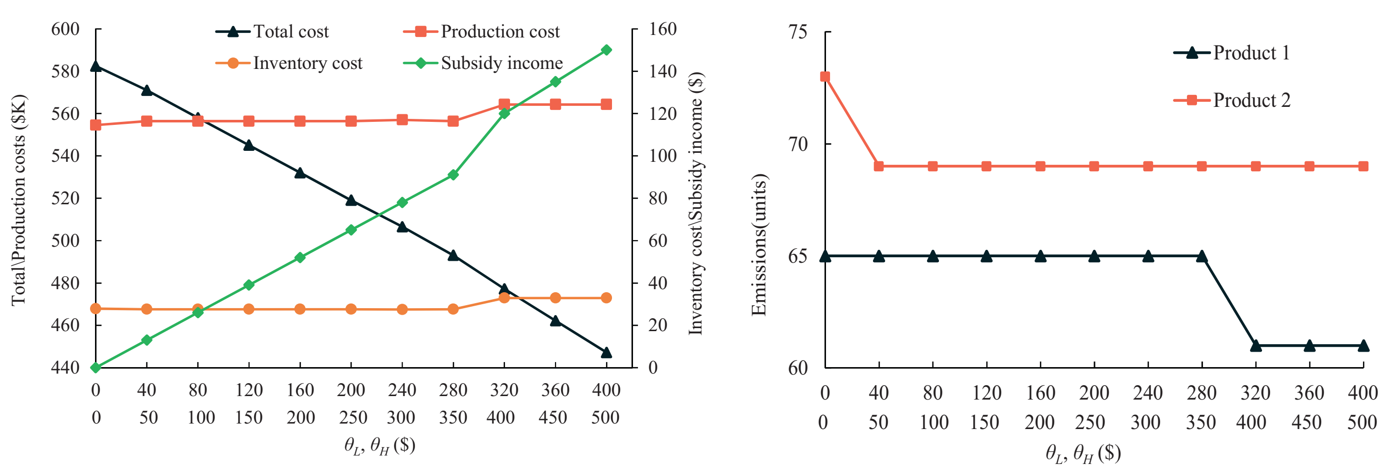
Table 7
Configuration options under different emission caps.

	E_0								
Stage	64	66	68	70	72	74	76	78	80
1	1	1	1	1	1	1	1	1	1
2	3	3	3	1	3	1	1	1	1
3	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1
5	1	2	2	2	2	2	2	2	2
6	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1
10	1	2	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	1
13	2	2	2	2	2	2	2	2	2
14	1	1	1	1	1	1	1	1	1
15	2	1	1	1	2	1	1	1	1
16	2	2	2	2	1	1	1	1	1
17	2	2	2	2	2	2	2	2	2
18	2	2	1	2	2	2	2	2	2

We initially vary emission constraint E_0 ranging from 64 to 80. Note that, no feasible solution exists when E_0 is less than 64, while the emission constraint is removed when E_0 is over 74. As shown in Fig. 7, the total cost decreases with the increase in E_0, which benefits from the decrease in the inventory cost and production cost. When the emission constraint is loosened, the supply chain configuration owns extra space to optimize the service time and option selection decisions for each stage, thereby reducing the inventory and production costs. Thus, the supply chain configuration reaches its best condition. Furthermore, the total cost does not decrease anymore when E_0 is over 74, where the emission constraint fails to work.

The emission constraint further takes effect on the option selection of the supply chain. As shown in Table 7, fewer green options are adopted when the emission constraint is loosened. This finding further explains why the production cost decreases when the emission constraint increases. As shown in Table 7, at the stages where option selection varies, the times of adopting green options decrease with the increase in E_0.

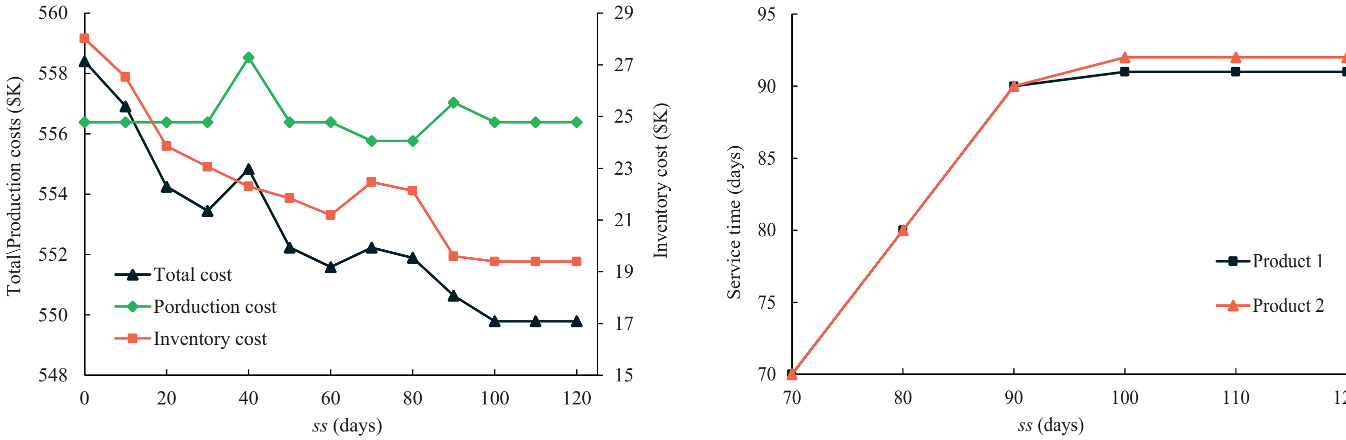
The subsidy to the green products further affects the supply chain configuration. As shown in Fig. 8(a), the total cost decreases, benefiting from the increase in the subsidy to the product. The production cost increases because the green options are adopted



(a) The effects on the costs and subsidy income

(b) The effects on the production emission

Fig. 8. The effects of the subsidy to the products.



(a) The effects on the costs (b) The effects on the demand stages' service time

Fig. 9. The effects of the subsidy to the products.

to obtain extra subsidy income. Furthermore, adopting the green option induces emission reduction from production. As shown in Fig. 8(b), emissions generated from the production of both products are reduced when the subsidy to the products increases.

5.5. The effects of the guaranteed service time

The guaranteed service time constrains the delivery time at the demand stage and affects the supply chain configuration. As shown in Fig. 9(a), the guaranteed service time significantly affects the inventory cost. A looser guaranteed service time provides opportunities to reduce the safety inventory level. Consequently, the inventory cost decreases as the guaranteed service time increases. In this case study, the inventory cost no longer decreases when the guaranteed service time is beyond 100 days. This finding suggests that the constraint from the guaranteed service time is removed when it is beyond 100 days. As shown in Fig. 9(b), the service time at the demand stages becomes constant with $S_{17} = 91$ and $S_{18} = 92$, respectively.

The production cost varies slightly with the changes in the guaranteed service time, as shown in Fig. 9(a). The inventory cost accounts for a small proportion of the total supply chain cost, such that pursuing inventory cost reduction by adopting certain costly options to shorten the lead time is not worthwhile.

6. Conclusions

This study addressed the challenges of supply chain management in the context of sustainable development and the Internet economy. We investigated how a green product supply chain can meet these challenges through supply chain configuration. In the configuration, multiple alternative options can be used to process a stage, and safety inventory can smooth out the stochastic demands at each stage. Specifically, options at each stage are distinguished in terms of lead time, cost, and emissions. The emissions from making a product are limited by a subsidy policy, where the highest emission level cannot exceed an emission cap, and subsidies can be obtained if the emissions are lower than the control level. Furthermore, guaranteed service time is promised to customers at the demand stages. We focused on the SCC problem and aimed to minimize the overall supply chain cost.

The problem was formulated as an SCC model that was proven to be NP-hard. An efficient and effective hybrid algorithm was developed to solve the problem. The structural property of the problem was addressed, and the problem was consequently decomposed into two subproblems, namely, service time decision problem and option selection problem. A spanning tree-based algorithm (STA) was developed to optimally solve the service time decision problem; and a PSO algorithm was adopted to solve the option selection problem. Accordingly, a hybrid algorithm (STA+PSO) combining STA and PSO was developed to solve the original problem. Although the hybrid algorithm cannot ensure the optimality of the solutions, the optimal solutions were obtained in the numerical computation for an 18-stage supply chain network in 22 seconds. If only using the intelligent algorithm PSO to solve the problem, it takes 44 seconds to solve the problem, and the solutions are inferior to those of the proposed hybrid algorithm. The numerical analysis also show that the subsidy policy on green products has significant effects on the supply chain cost and product emissions, whereas the guaranteed service time further influences the supply chain configuration and its related costs.

There are several limitations of this study, and sufficient room is available to extend this research in the future. There still exists some room to develop more efficient algorithms for SCC problems with large scale and complicated supply chain network. The production capacity and inventory limitation are not involved in our current model, which is an interesting direction for further work. Furthermore, from the perspective of sustainable operation management, some other environmental regulation policies, such as emission trading schemes, can be considered in the SCC model.

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Appendix A. Proof of Lemma 1

Proof. In Eq. (17), define $a = A_i\sqrt{B_i + IS_i - S_i}$ and $b = A_j\sqrt{B_j + IS_j - S_j}$. According to $IS_j = \max\{S_i | j : (i, j) \in \boldsymbol{P}\}$, we have

$$a = \begin{cases} 0, & IS_j \geq B_i + IS_i, \\ A_i\sqrt{B_i + IS_i - S_j}, & IS_j < B_i + IS_i. \end{cases}$$

$$b = \begin{cases} 0, & IS_j \le IS_k - B_j, \\ A_j\sqrt{B_j + IS_j - S_j}, & IS_j > IS_k - B_j. \end{cases}$$

The aforementioned functions implies $f(IS_j) = A_i\sqrt{B_i + IS_i - S_i} + A_j\sqrt{B_j + IS_j - S_j} + A_k\sqrt{B_k + IS_k - S_k} + C'$ reaches its minimum at a value of $B_i + IS_i$ or a value of $IS_k - B_j$. □

Appendix B. Proof of Proposition 4

Proof. We prove these properties by contradiction.

(i) We first assume that two ways exist to connect i to k. We define them by $i \sim j_{11} \sim j_{12} \sim \ldots \sim j_{1n} - k$ and $i \sim j_{21} \sim j_{22} \sim \ldots \sim j_{2n} - k$, respectively. According to the definition of the connection, we can obtain IS_{j11} by IS_i, and obtain IS_{j12} by IS_{j11}. Finally, we obtain IS_k by IS_{j1n}. For the second way, we can similarly obtain IS_{j21} by IS_i, as well as IS_{j22} by IS_{j21}. Finally, we obtain IS'_k by IS_{j2n}. If $IS_k \ne IS'_k$, it contradicts the property of the optimal solution. If $IS_k = IS'_k$ we add an infinitely small time to the value of B_{2m} of any stage j_{2m} in the second way. The new problem is equivalent to the original one, but we have $IS_k \ne IS'_k$ which is in contradiction.

(ii) Let $\boldsymbol{I}$ be the set of stages to which stage i ($i \in \boldsymbol{F}'$) is connected. We assume that no stage in $\boldsymbol{I}$ connects to any stages in $\boldsymbol{R} \cup \boldsymbol{A}'$, i.e., $\boldsymbol{I} \cap \boldsymbol{R} \cup \boldsymbol{A}' = \phi$. We consider a special case in which all stages in $\boldsymbol{I}$ are combined into one stage i. Owing to $\boldsymbol{I} \cap \boldsymbol{R} \cup \boldsymbol{A}' = \phi$, some stages in $\boldsymbol{V} - \boldsymbol{I}$ must connect to i in the optimal solution, which contradicts the assumption.

(iii) Let k be a stage in set $\boldsymbol{R} \cup \boldsymbol{A}'$. Then, in an optimal solution, IS_k is fixed. If $k \in \boldsymbol{R}$, $IS_k = 0$. If $k \in \boldsymbol{A}'$, $IS_k = ss_l$, where ss_l is the service time required by consumers. Similar to the proof of (ii), we assume a way connects i to k, which is defined by $i \sim j_1 \sim j_2 \sim \ldots \sim j_n - k$. According to the definition of the connection, we can obtain IS_{j1} by IS_i, and obtain IS_{j2} by IS_{j1}. Finally, we obtain IS_k by IS_{jn}. If $IS_k \ne IS'_k$, the property of the optimal solution is contradicted. If $IS_k = IS'_k$, we add an infinitely small time to the value of B_m at any stage j_m in the second method. The new problem is equivalent to the original one, but we have $IS_k \ne IS'_k$, which is in contradiction.

The proof is completed. □

Appendix C. Parameters of the supply chain networks with different structures

C.1. The supply chain networks

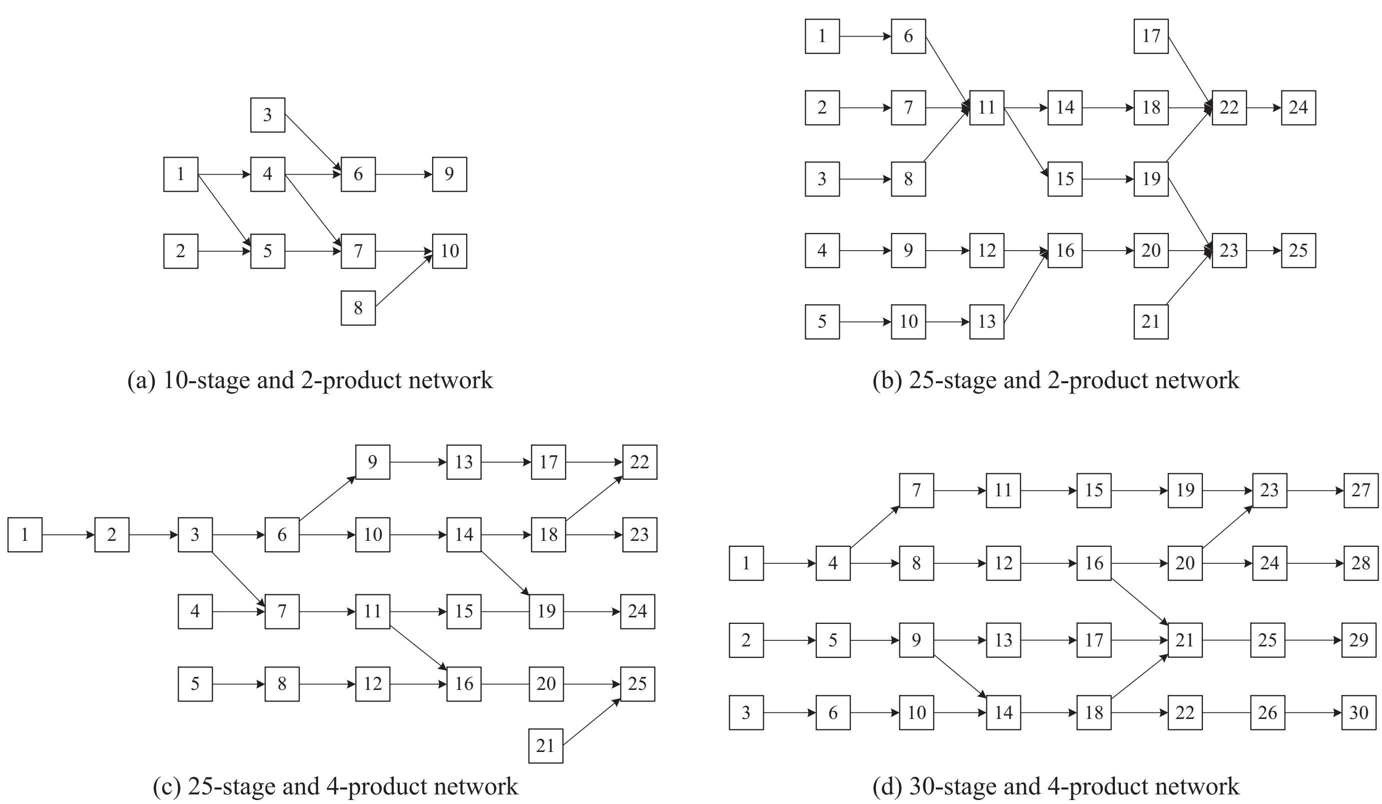
The supply chain networks with 10, 25, and 30 stages are addressed in Fig. C.1.

In what follows, we simplify "*the 10-stage and 2-product supply chain network*" as "*10-2 supply chain*". The similar logograms are used for the other examples.

C.2. Parameters of the 10-2 supply chain

In the 10-stage supply chain, the periodic review time at each stage is: $r_j = 5$ ($j \in \boldsymbol{V}$). The service level is: $\zeta_j = 98\%$ ($j \in \boldsymbol{V}$). Note that r_j and ζ_j are set by the same value in all examples. The production coefficient of the two final products are: $\phi_{9j} = [1, 1, 0, 1, 0, 1, 0, 0, 1, 0]$ and $\phi_{10j} = [1, 1, 0, 1, 1, 0, 1, 0, 0, 1]$ ($j \in \boldsymbol{V}$). The holding costs of the stages are $h = \{1, 1, 1, 1, 2, 2, 1, 1, 4, 5\}$. Note that, the unit time is one day, the monetary unit is US dollar, and the emissions are measured by one unit (e.g., 1 kilogram per unit). For simplicity, we omit the unit in the table and figures hereafter.

The demand information of the two products and the subsidy policy are given in Table C.1. The parameters of options of each stage are given in Table C.2.



(a) 10-stage and 2-product network (b) 25-stage and 2-product network

(c) 25-stage and 4-product network (d) 30-stage and 4-product network

Fig. C.1. The supply chain networks with 10, 25 and 30 stages.

Table C.1
Parameters of demand and subsidy policy of the 10-2 supply chain.

Parameters	μ	σ	ρ	ss	E_0	E_h	E_l	θ_L	θ_H
Product 1	200	120	0	3	65	60	55	80	100
Product 2	125	80							

Table C.2
Parameters of the stages of the 10-2 supply chain.

Stage	Option	Lead time	Cost	Emissions
1	1	40	100	5
	2	30	110	8
	3	10	125	9
2	1	30	120	4
	2	20	120	7
	3	10	130	8
	4	0	140	4
3	1	0	160	5
4	1	10	145	4
	2	0	140	8
5	1	20	90	4
	2	5	60	8
6	1	50	405	10
	2	20	460	12
7	1	5	120	6
	2	2	132	4
8	1	70	225	4
	2	30	240	9
9	1	12	120	2
10	1	30	200	4

Table C.3
Parameters of demand and subsidy policy of the 25-2 supply chain.

Parameters	μ	σ	ρ	ss	E_0	E_h	E_l	θ_L	θ_H
Product 1	150	120	0	3	135	150	125	80	100
Product 2	210	80							

C.3. Parameters of the 25-2 supply chain

In the 25-stage and 2-product supply chain, the production coefficient of the two final products are: $\phi_{24j} = [1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0]$ and $\phi_{25j} = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1]$ ($j \in \boldsymbol{V}$). The holding costs of the stages are $h = \{1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 4, 4\}$.

The demand information of the two products and the subsidy policy are given in Table C.3. The parameters of options of each stage are give in Table C.4.

Table C.4
Parameters of the stages of the 25-2 supply chain.

Stage	Option	Lead time	Cost	Emissions
1	1	10	60	9
	2	0	70	5
2	1	20	200	10
	2	0	205	9
3	1	10	155	4
4	1	0	200	6
5	1	20	90	4
	2	5	60	8
6	1	60	300	4
	2	5	350	7
7	1	30	200	4
8	1	70	225	4
	2	0	240	9
9	1	10	100	1
10	1	5	120	4
11	1	40	30	4
12	1	1	30	2
13	1	40	15	3
	2	5	16.5	2
14	1	1	30	2
15	1	5	12	2
	2	1	20	3
16	1	15	15	7
17	1	5	12	1
	2	0	20	1
18	1	5	15	2
19	1	30	215	5
	2	25	250	7
20	1	15	230	10
	2	0	250	9
21	1	8	122	3
22	1	0	120	5
23	1	20	110	4
24	1	20	200	10
	2	5	210	18
25	1	20	120	4

Table C.5
Parameters of demand and subsidy policy of the 25-4 supply chain.

Parameters	μ	σ	ρ	ss	E_0	E_h	E_l	θ_L	θ_H
Product 1	150	120	0	3	135	150	125	80	100
Product 2	170	80							
Product 3	190	90							
Product 4	210	110							

Table C.6
Parameters of demand and subsidy policy of the 30-4 supply chain.

Parameters	μ	σ	ρ	ss	E_0	E_h	E_l	θ_L	θ_H
Product 1	150	120	0	3	125	140	115	80	100
Product 2	170	80							
Product 3	190	90							
Product 4	210	110							

C.4. Parameters of the 25-4 supply chain

In the 25-stage and 4-product supply chain, the production coefficient of the two final products are: $\phi_{22j} = [1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0]$, $\phi_{23j} = 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0]$, $\phi_{24j} = 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]$, and $\phi_{25j} = 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1]$. The holding costs of the stages are $h = \{1, 1, 1, 2, 1, 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 2, 1, 3, 3, 3, 3\}$.

The demand information of the two products and the subsidy policy are given in Table C.5. The parameters of options of each stage are the same to the 25-2 supply chain, which is shown in Table C.4.

C.5. Parameters of the 30-4 supply chain

In the 30-stage and 4-product supply chain, the production coefficient of the two final products are: $\phi_{27j} = [1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0]$, $\phi_{28j} = [1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0]$, $\phi_{29j} = [1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0]$, and $\phi_{30j} = [0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1]$. The holding costs of the stages are $h = \{2, 2, 2, 2, 2, 2, 2, 2, 4, 2, 2, 4, 2, 4, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 6, 6, 8, 8\}$.

The demand information of the two products and the subsidy policy are given in Table C.6. The parameters of options of each stage are given in Table C.7.

Table C.7
Parameters of the stages of the 30-4 supply chain.

Stage	Option	Lead time	Cost	Emissions
1	1	1	30	2
	2	0.5	40	2
	3	0	55	1
2	1	6	50	8
	2	4	60	9
	3	3	40	15
	4	0	50	12
3	1	6	8	1
	2	2	11	1
4	1	6	200	4
5	1	40	13	3
	2	30	17	2
	3	20	20	3
	4	10	30	1
6	1	1	20	3
7	1	45	260	12
	2	5	280	21
8	1	70	225	4
	2	30	240	9
9	1	10	60	1
10	1	5	120	6
	2	6	180	1
	3	2	190	1
	1	30	150	5
	2	25	120	7
	3	20	130	5
	4	12	170	2
12	1	1	30	2
	2	0.5	40	2
13	1	12	45	4
	2	8	50	4
	3	5	60	3
14	1	1	30	2
15	1	5	12	2
	2	1	20	3
16	1	16	20	1
17	1	10	8	2
	2	10	12	1
	3	5	14	1
	4	1	20	1
18	1	5	15	2
19	1	15	200	11
	2	0	220	9
20	1	25	120	7
21	1	1	20	3
22	1	10	120	5
	2	6	120	6
	3	6	125	4
	4	2	130	2.5
23	1	15	120	4
24	1	20	200	10
	2	5	210	18
25	1	21	130	4
	2	12	145	3
	3	10	145	3
26	1	12	120	5
27	1	12	80	1
28	1	3	80	6
	2	2	100	3
29	1	5	30	1
	2	8	30	1.5
30	1	4	35	1.5
	2	3	35	2

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