Joint Optimization of Multiple Supply Chains Under Cap-And-Trade Regulation: A Bi-Level Programming Model and Solution Algorithm

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Among the carbon regulation policy schemes, the cap-and-trade has received more attention because of its efficiency and flexibility. Two primary challenges with the cap-and-trade scheme are determining the correct cap and carbon trading price in the carbon market. This paper presents a bi-level model to investigate these two challenges in the cap-and-trade scheme formed between multiple supply chains and the government. At the first level, the government minimizes the cap in such a way that the costs of the supply chains do not rise too much. At the second level, the supply chains minimize their costs according to their cap and trade the dedicated allowances. An exact and a heuristic method are developed to solve the bi-level model. The computational results on a set of randomly generated instances show the effectiveness of the presented heuristic. Sensitivity analysis demonstrates that the government should choose proper amounts of caps to balance costs and environmental benefits.

Keywords: Cap-and-trade; bi-level programming; Stackelberg game; heuristic; carbon price; supply chain management.

1. Introduction

Increasing greenhouse gases (GHG), as a result of industrial modernization, puts the environment in danger rapidly and raises the likelihood of natural disasters and human diseases (Hong *et al.*, 2017). To control emissions, governments have introduced various policies to curb the amount of carbon emissions, including carbon cap, carbon emission tax, carbon offset, and cap-and-trade (Mohammed *et al.*, 2017).

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Supply chain activities like logistical activities, facility location, production, and transportation are significant sources of GHG emissions (Mohammed *et al.*, 2017). For example, 14% of the total emissions around the world are related to the transportation sector (Liu *et al.*, 2020). The studies conducted by Benjaafar *et al.* (2012), Palak *et al.* (2014), and Du *et al.* (2016) show the importance of developing quantitative models and decision support systems that consider issues related to reducing carbon emissions in the supply chain. Most studies in this field indicate that among the existing policies, the cap-and-trade has attracted a lot of attention because of the ease of implementation and flexibility (Tang and Zhou, 2012). The cap-and-trade or emission trading scheme is defined in paper 17 of the Kyoto Protocol. This protocol was passed by 37 industrialized countries and the European Union. They committed to reducing GHG emissions to an average of five percent against 1990 levels (Abdallah *et al.*, 2012). Under the carbon trading scheme, a limited number of tradable emissions allowances, the cap, are allocated to the firms. Firms generating more emissions than the allocated allowances have two ways. One is to purchase emissions allowances off the market from those generating fewer than the allowed emissions, and the other to adopt green technology to reduce the carbon of unit products (Xu *et al.*, 2017).

There are several cap-and-trade schemes in the world. They have been implemented at different levels and scales, including global, international, national, regional, and even corporate levels. They also cover different sectors (Burtraw *et al.*, 2013; Qi *et al.*, 2014; Ruth *et al.*, 2008). For example, China has approved seven cap-and-trade schemes. Their sector coverage range from 4 to 26 sectors (Zhang, 2015). The Rational Greenhouse Gas Initiative (RGGI) cap-and-trade scheme applies to coal-fired, oil-fired, and gas-fired electric generating units (Ruth *et al.*, 2008). At the corporate level, some companies like BP and Royal Dutch Shell have created an internal cap-and-trade scheme (Sandor *et al.*, 2002). In the literature, Cong and Wei (2010) present a cap-and-trade scheme consisting of power plants. Dormady (2014) considers a cap-and-trade scheme for the energy sector. Anger (2010), Pentelow and Scott (2011), and Deja *et al.* (2010) investigate this scheme on the aviation industry, tourism industry, and cement industry, respectively.

The two important factors in developing a cap-and-trade scheme are the cap (emission cap) and carbon trading price (Mohammed *et al.*, 2017; Li and Haasis, 2017). When the cap is too high, supply chains are reluctant to use green technology; therefore, the cap-and-trade scheme does not reduce emissions. On the other hand, when the cap is too low, the supply chains increase the use of green technology to reduce their emission under the cap; therefore, supply chains incur higher costs. Thus, the government must determine an appropriate cap to maintain a balance between carbon emission and economic benefits. For carbon trading price, authors such as Chang *et al.* (2015), Jin *et al.* (2014), and Sabzevar *et al.* (2017) have emphasized the carbon trading price has a significant impact on maximizing firms' profit. Zhang and Xu (2013) have highlighted the carbon trading price can change the supply chain's network design. However, little attention has been paid to how

governments determine the cap and how the carbon trading price has been adjusted. Therefore, we focus on determining the carbon trading price and cap in this paper.

Motivated by the above facts, this paper presents a bi-level model under a cap-and-trade scheme that simultaneously determines the cap and carbon trading price. Given that the carbon cap influences the carbon trading price, the government as the leader allocates emission allowances or the cap to the supply chains at the first level. It tries to minimize the cap while preventing the costs of each supply chain in the cap-and-trade policy exceed a certain percentage higher than their costs when there is no emission reduction policy in action. In the second level, supply chains as the followers determine optimal operational and tactical decisions according to their allowances. In reality, supply chains are the firms that have production facilities and warehouses and deliver manufactured products to customers. They can trade emission allowances among each other to comply with the emission regulation imposed by the government. The free market economy is used to analyze the carbon trading market and determine the carbon trading price according to carbon allowance supply and demand. Since bi-level models are NP-hard (Ben-Ayed and Blair, 1990), a heuristic method is presented based on iterated local search (ILS) and the bisection method to solve large-size instances. To investigate the efficiency of the proposed heuristic method, some numerical examples are conducted and compared their results with those obtained by an exact method based on the bisection method and CPLEX. In summary, the major contributions of this paper include the following: (1) presenting a cap-and-trade scheme consisting of multiple supply chains; (2) utilizing the free-market mechanism to determine the carbon trading price; and (3) developing a heuristic method to deal with the difficulties of the bi-level model.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature to this work and underlines the contributions. The problem definition and bi-level model are presented in Sec. 3. The exact and heuristic method are provided in Sec. 4 to solve the bi-level model. Section 5 includes computational experiments to analyze the efficiency of the heuristic method. Section 6 presents a sensitivity analysis on a numerical example as well as the managerial implication. Finally, Sec. 7 concludes the paper and offers direction for future research.

2. Literature Review

There has been an increasing body of literature that examines the application of the cap-and-trade scheme on different supply chains. For example, (Zakeri *et al.*, 2015) present an analytical supply chain planning model examining the supply chain performance at the tactical/operational planning level under cap-and-scheme. Xu *et al.* (2016) formulate a two-echelon sustainable supply chain under the cap-and-trade policy composed of one supplier and one manufacturer that is a major producer of emissions. Yang *et al.* (2017) present two competitive supply chains, including one manufacturer and one retailer, under the cap-and-trade policy and solve and

compare the equilibrium solutions of supply chains with several different structures. Mohammed *et al.* (2017) propose an optimization model for designing and planning a multi-period, multi-product closed-loop supply chain under demand and returns uncertainties to examine the impact of cap-and-trade and other policies on the supply chain's operational and strategic decisions. Tong *et al.* (2019) investigate the behavior of manufacturers and retailers in a supply chain under a cap and trade policy. Wang *et al.* (2020) consider a two-echelon supply chain with cap-and-trade regulation and analyze its impact on emission abatement, product quantity, and profit of supply chain members. Although these studies have all made significant contributions to the cap-and-trade scheme in the supply chains, they consider the carbon trading price and the cap as parameters.

Definitely, in a real carbon market, the correct values of the carbon price and cap must be determined. A small number of studies determine one or two of these factors. For example, Du *et al.* (2015) present a Stackelberg game-theoretic model. One of the players, as the leader, is a carbon allowance seller, and another, the follower, is a buyer. The leader determines the carbon trading price such that its profit is maximized, and the follower accepts it and tries to maximize its profit. Rezaee *et al.* (2017) propose a stochastic model to design a green supply chain under a cap-and-trade scheme incorporated by uncertainty in carbon trading price and product demand given a fixed cap. They find the supply chain configuration can be highly sensitive to the probability distribution of the carbon trading price. Sabzevar *et al.* (2017) investigate the impact of cap-and-trade policy on two competitive firms producing goods. They determine which firm is a carbon allowance seller or buyer. They also assess the carbon trading price in which trading will occur and what price makes firms benefit equally under a fixed cap. Although researchers determine the carbon trading price value in these studies, they ignore how the government determines the right cap to balance environmental and economic goals. Some studies determine the optimal cap, but they consider the carbon trading price as a parameter. For example, Cao *et al.* (2017) formulate a Stackelberg model where the government is the leader, and the manufacturer is the follower. They assume that the government determines the optimal cap to maximize social welfare under the cap-and-trade policy. Ji *et al.* (2020) present a Stackelberg model in which the government as a leader optimizes the total cap, and the supply chain as a follower determines their optimal operational decisions. The carbon trading price is considered as a parameter.

In the above papers, researchers examine the effect of cap-and-trade on a single or two decision makers. While in reality, multiple participants are involved in the cap-and-trade scheme. Several researchers investigate the cap-and-trade scheme in the presence of multiple decision makers. For example, Hong *et al.* (2017) propose a Stackelberg game model under a cap-and-trade scheme to examine a local government's decision as a leader aiming to maximize social welfare and firms in its official region as followers seeking to maximize their profits. Their work is limited to production decisions, while other decisions like transportation and facility location

affect costs and emissions. Zhao *et al.* (2018) propose carbon allowance allocation under cap and trade consisting of the regional authority and the building materials suppliers. Although several decision makers compete in this research, they do not investigate how the carbon trading price is formed.

There are a regulator and some participants such as a government and some supply chains in the cap-and-trade scheme. Each of them has its individual objectives, and they are not on the same level in terms of decision-making power. The government is a leader in the first level, and the supply chains are followers in the second level. Bi-level programming can model the conflict between two levels that have been widely used in various fields, including carbon regulations. For example, Almutairi and Elhedhli (2014) design a carbon tax scheme based on emission factors using bi-level programming. He *et al.* (2011) use bi-level programming to manage municipal solid waste and minimize greenhouse gas emissions. Sun *et al.* (2021) develop a bi-level programming approach to model a carbon allowance allocation scheme. At the upper level, the government determines the carbon allowance according to economic and environmental targets, and power plants try to maximize their profits at the lower level. In this model, only the optimal value of the cap is determined, and the carbon trading price is not discussed. Given the successful application of bi-level models in various fields, we intend to use this approach in the proposed cap-and-trade scheme.

To summarize, there is small existing literature on the determination of the carbon trading price, and also the determination of the carbon trading price and the carbon cap simultaneously, and these issues are practically ignored. To the best of our knowledge, a study that focuses on determining the carbon trading price and the carbon cap simultaneously in a carbon trading system consisting of multiple supply chains is non-existent. This paper tries to fill up this research gap by presenting a bi-level model to investigate the decisions of government and supply chains, aiming to minimize the initial allowances and minimize the costs of each supply chain. The free-market economy approach is considered in the carbon trading market, and the carbon price is discovered based on the supply and demand of the permits in this market. To tackle the difficulties of the bi-level model, a heuristic method is also developed.

3. Problem Definition and Mathematical Model

The emission trading system considered in this paper involves the government and multiple supply chains, which is formulated as a bi-level model according to Eq. (1). The leader in the model is the government and minimizes the total cap allocated to supply chains ($TCap$) at the first level. The government's objective function is subject to one constraint that prevents the costs of supply chains exceeds above a certain percentage (Eq. (3)). On the lower level, each supply chain s, as the follower, minimizes its operational and tactical cost (Cost_EC_s) according to the cap imposed by the government. It is assumed that all supply chains are in the same

industry. Each supply chain is subject to constraints such as raw material, inventory, transportation capacity restriction, etc. (Eqs. (6)–(22)). Furthermore, they trade their allowance and compete with others in the carbon trading market. The carbon trading price is the equilibrium price formed based on the demand and supply in the carbon market. Figure 1 illustrates the general framework of the model.

At the first level, the government:

$$\text{minimize TCap,}$$
$$\text{subject to government's constraint,}$$

(1)

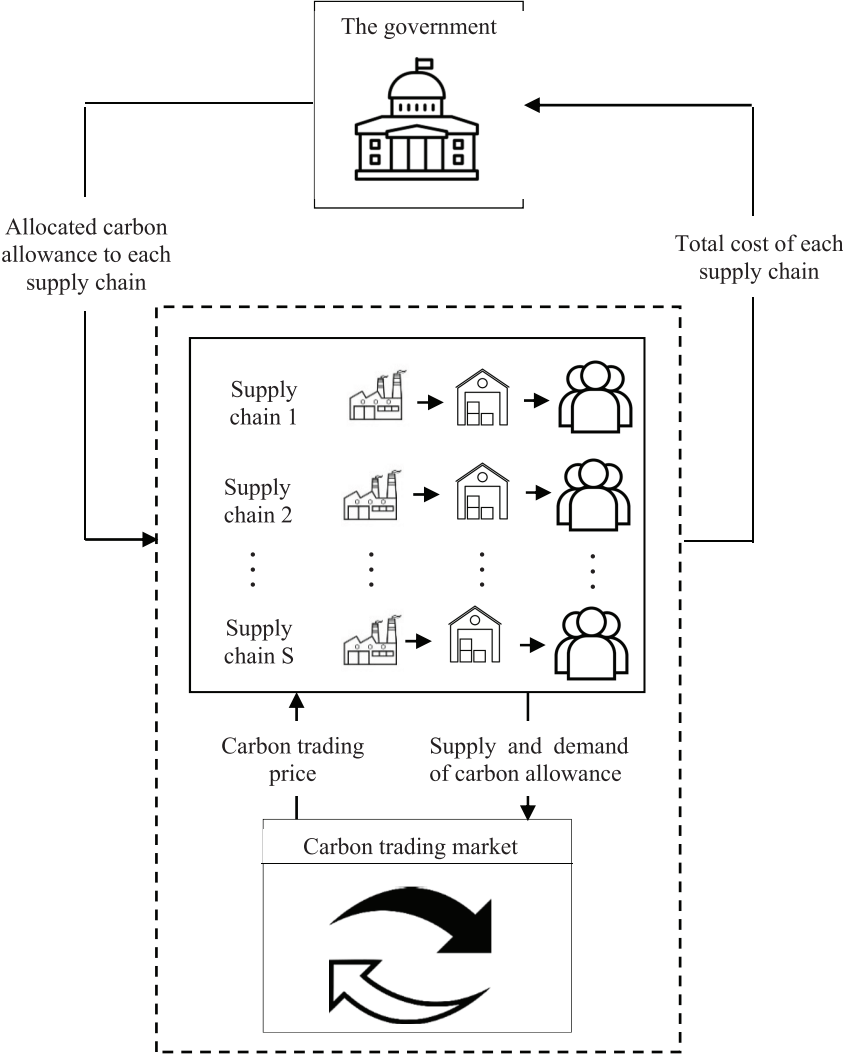Fig. 1. The general framework of the proposed cap-and-trade scheme.

while at the second level, each supply chain s:

$$\text{minimize Cost\_}EC_s,$$

$$\text{subject to supply chain}'\text{s constraints.}$$

In the following, the government decision is first investigated, then the mixed integer programming problem related to each supply chain is analyzed based on a given carbon trading price. Then how to calculate carbon trading price is described.

3.1. *Government's decision problem*

As discussed above, the government is the leader and tries to minimize the total carbon allowances allocated to supply chains and thus reduce the emissions generated by the supply chains. Without cap-and-trade regulation in place, the emissions generated by each supply chain and its optimal cost are equal to HEC_s and Cost_HEC_s respectively. Therefore, the total carbon allowance required by supply chains is equal to $\sum_s \text{HEC}_s$. The government uses a reduction coefficient $\phi(0 < \phi < 1)$ to force the supply chains to reduce their emissions and use green technology. Therefore government minimizes the total initial caps dedicated to the supply chains, i.e., $TCap$ through Eq. (2).

$$\text{Min } TCap = \phi \sum_s \text{HEC}_s. \tag{2}$$

By using an emission reduction coefficient, the costs of each supply chain in the cap-and-trade scheme, i.e., $\text{Cost\_}EC_s$ may increase due to requirements for buying extra allowances from the carbon market or using green technology. To ensure that ϕ does not incur a significant reduction in the profitability of the supply chains, the following constraint is considered for the leader.

$$\text{Cost}_{EC_s} \leq \lambda \times \text{Cost\_HEC}_s, \quad \forall s, \tag{3}$$

where λ $(\lambda \geq 1)$ shows the maximum allowed increase in supply chain costs. Constraint (3) ensures that the costs of each supply chain in the carbon trading scheme do not exceed a given coefficient of the costs when there is no carbon regulation in place.

3.2. *Supply chain's decision problem*

In each supply chain, multiple product types (i) are produced in different manufacturing plants (m) on a set of machines (j). There are two types of machines, namely green and regular. The machines with green technology produce fewer emissions, but they cost more than regular ones. The final products are sent to the warehouses (w) and then to the customer zones (c). Likewise the machines, there are two types of transportation modes (v) in which green transportation yields fewer emissions, but its unit transportation cost is more than the regular one. Each supply chain tries

to balance its costs and emissions by applying the right technology for production and transportation over a specified planning horizon consisting of T periods.

Each supply chain determines production and transportation planning through its facilities at different levels to minimize its total costs and exchange carbon allowance among each other to follow the government emission regulation.

The following assumptions are considered for each supply chain's mathematical model:

- The number, location, and capacity of manufacturing centers and warehouses are known.
- The number, location, and demand of each customer zone are known.
- The demand for each product should be satisfied during each period.
- The capacity hours of each machine, the capacity of total raw material, the inventory holding capacity of warehouses and manufacturing centers, and transportation capacities are known.
- The carbon emission is considered for production, transportation, and inventory holding.
- A unit of raw material is required to produce a unit of the final product.

The sets include the following:

S	Set of supply chains	W	Set of warehouses
I	Set of products	C	Set of customer zones
J	Set of machines	V	Set of transportation modes
M	Set of manufacturing centers	T	Planning horizon

The input parameters include the following:

d_{sict} Forecasted demand for product i in customer zone c in period t in supply chain s

fm_{sm} Fixed costs for manufacturing center m to operate in each period in supply chain s

fw_{sw} Fixed costs for warehouse w to operate in each period in supply chain s

hcm_{sim} Unit holding cost per period for product i in manufacturing center m in supply chain s

hcw_{siw} Unit holding cost per period for product i in warehouse w in supply chain s

Icm_{sm} Holding capacity in manufacturing center m in each period in supply chain s

Icw_{sw} Holding capacity in warehouse w in each period in supply chain s

Vo_i The volume of product i

pt_{sij} Processing time (h) to produce a unit of product i on machine j in supply chain s

lc_{sij}	Labor/hour cost to produce a unit of product i on machine j in supply chain s
cr_{si}	Cost of raw material for producing a unit of product i in supply chain s
vc_{sim}	Variable overhead cost for producing a unit of product i in manufacturing center m in supply chain s
mr_{sjm}	Capacity hours for the production in manufacturing center m on machine j in each period in supply chain s
cur_{sim}	Capacity units of raw material supply for product i in manufacturing center m in each period in supply chain s
tmw_{simwv}	Unit transportation cost of product i from manufacturing center m to warehouse w through mode v in supply chain s
twc_{siwcv}	Unit transportation cost of product i from warehouse w to customer zone c through mode v in supply chain s
$t_{1\ max\atop smwv}$	Maximum transportation capacity from manufacturing center m to warehouse w through mode v in each period in supply chain s
$t_{2\,max\atop swcv}$	Maximum transportation capacity from warehouse w to customer zone c through mode v in each period in supply chain s
$Ip_{1_{sim}}$	Inventory level of product i in manufacturing center m at the start of the planning horizon
$Ip'_{1_{sim}}$	Inventory level of product i in manufacturing center m at the end of the planning horizon
$Ip_{2_{siw}}$	Inventory level of product i in warehouse w at the start of the planning horizon
$Ip'_{2_{siw}}$	Inventory level of product i in warehouse w at the end of the planning horizon
ep_{sij}	Carbon emissions to produce a unit of product i on machine j in supply chain s per unit time
et_{simwv}	Carbon emissions for the shipment a unit of product i from manufacturing center m to warehouse w through mode v in supply chain s
et'_{siwcv}	Carbon emissions for the shipment a unit of product i from warehouse w to customer zone c through mode v in supply chain s
eh_{sim}	Carbon emissions for holding a unit of product i in manufacturing center m in each period in supply chain s
eh'_{siw}	Carbon emissions for holding a unit of product i in warehouse w in each period in supply chain s
λ	Maximum allowed increasing percentage in supply chain costs
G	A large number

The decision variables include the following:

AP_{sijmt} — Quantity of product i produced in manufacturing center m on machine j at period t in supply chain s

Qt_{simwvt} — Quantity of product i shipped from manufacturing center m to warehouse w through mode v at period t in supply chain s

Qt'_{siwcvt} — Quantity of product i shipped from warehouse w to customer zone c through mode v at period t in supply chain s

Im_{simt} — Inventory level of product i in manufacturing center m at the end of period t in the supply chain s

Iw_{siwt} — Inventory level of product i in warehouse w at the end of period t in the supply chain s

$Zm_{smt} = \begin{cases} 1, \\ 0, \end{cases}$ — If manufacturing center m operates in period t in supply chain s

Otherwise

$Zw_{smt} = \begin{cases} 1, \\ 0, \end{cases}$ — If warehouse w operates in period t in supply chain s

Otherwise

$\text{Cost\_}ECs$ — Total costs of supply chain s in the cap-and-trade system

EC_s — Total carbon emission produced in supply chain s

TEC — Total carbon emission produced in all supply chains

Cap_s — Maximum allowed carbon emissions (carbon cap) for supply chain s

$TCap$ — Total allowed carbon emissions for all supply chains

π — Carbon trading price

ϕ — Emission reduction coefficient

According to the above-mentioned parameters and variables, the objective function for each supply chain can be formulated using mixed-integer linear programming based on a given carbon trading price. The objective function presented in Eq. (4) represents total costs for each supply chain.

$$\text{Cost\_}EC_s = \text{Min} \sum_{m}\sum_{t} fm_{sm}Zm_{smt} + \sum_{w}\sum_{t} fw_{sw}Zw_{swt}$$

$$+ \sum_{i}\sum_{j}\sum_{m}\sum_{t} AP_{sijmt}(pt_{sij}lc_{sij} + cr_{si} + vc_{sim})$$

$$+ \sum_{i}\sum_{m}\sum_{t} hcm_{sim}Im_{simt} + \sum_{i}\sum_{w}\sum_{t} hcw_{siw}Iw_{siwt}$$

$$+ \sum_{i}\sum_{m}\sum_{w}\sum_{v}\sum_{t} tmw_{simwv}Qt_{simwvt}$$

$$+ \sum_i \sum_w \sum_c \sum_v \sum_t twc_{siwcv} Qt'_{siwcvt}$$

$$+ \pi(EC_s - Cap_s), \quad \forall s. \tag{4}$$

Objective function Cost$\_EC_s$ consists of eight components. The first two components represent fixed costs for operating and opening manufacturing centers, and warehouses, respectively. Component 3 shows production costs. Components 4 and 5 express inventory holding costs in manufacturing centers, and warehouses, respectively. Transportation costs for the shipment of products from manufacturing centers to warehouses and from warehouses to customer zones are calculated in components 6 and 7, respectively. Component 8 shows the revenue (cost) of selling (buying) carbon allowances. Total carbon emissions generated by supply chain s (EC_s) is formulated in Eq. (5).

$$EC_s = \sum_i \sum_j \sum_m \sum_t pt_{sij} ep_{sij} AP_{sijmt} + \sum_i \sum_m \sum_w \sum_v \sum_t et_{simwvt} Qt_{simwvt}$$

$$+ \sum_i \sum_w \sum_c \sum_v \sum_t et'_{siwcvt} Qt'_{siwcvt} + \sum_i \sum_m \sum_t eh_{sim} Im_{simt}$$

$$+ \sum_i \sum_w \sum_t eh'_{siw} Iw_{siwt}, \quad \forall s. \tag{5}$$

Equation (5) consists of 5 components. Component 1 represents the generated carbon emission in manufacturing. Components 2 and 3 express the emission generated for the shipment of products from manufacturing centers to warehouses and from warehouses to customer zones, respectively. Components 4 and 5 formulate inventory holding emissions in manufacturing centers and warehouses, respectively.

The objective function in Eq. (4) is subject to the following constraints:

$$\sum_j AP_{sijmt} \leq cur_{sim}, \quad \forall s, i, m, t, \tag{6}$$

$$\sum_i AP_{sijmt} pt_{sij} \leq mr_{sjm}, \quad \forall s, j, m, t, \tag{7}$$

$$\sum_i Vo_i Im_{simt} \leq Icm_{sm}, \quad \forall s, m, t, \tag{8}$$

$$\sum_i Vo_i Iw_{siwt} \leq Icw_{sw}, \quad \forall s, w, t, \tag{9}$$

$$\sum_i (Vo_i Qt_{simwvt}) \leq t_{1 \max_{swcv}}, \quad \forall s, m, w, v, t, \tag{10}$$

$$\sum_{i} (Vo_i Qt'_{siwcvt}) \leq t_{2\,max}, \quad \forall s, w, c, v, t, \tag{11}$$

$$Im_{simt} - Im_{sim(t-1)} = \sum_{j} AP_{sijmt} - \sum_{w} \sum_{v} Qt_{simwvt}, \quad \forall s, i, m, t, \tag{12}$$

$$Iw_{siwt} - Iw_{siw(t-1)} = \sum_{m} \sum_{v} Qt_{simwvt}$$

$$- \sum_{c} \sum_{v} Qt'_{siwcvt}, \quad \forall s, i, w, t, \tag{13}$$

$$\sum_{j} \sum_{m} \sum_{t} AP_{sijmt} = \sum_{c} \sum_{t} d_{sict} + \sum_{m} Ip'_{1_{sim}} - \sum_{m} Ip_{1_{sim}}$$

$$+ \sum_{w} Ip'_{2_{siw}} - \sum_{w} Ip_{2_{siw}}, \quad \forall s, i, \tag{14}$$

$$\sum_{w} \sum_{v} Qt'_{siwcvt} = d_{sict}, \quad \forall s, i, c, t, \tag{15}$$

$$Im_{sim0} = Ip_{1_{sim}} \quad \& \quad Im_{simT} = Ip'_{1_{sim}}, \quad \forall s, i, m, \tag{16}$$

$$Iw_{siw0} = Ip_{2_{siw}} \quad \& \quad Im_{siwT} = Ip'_{2_{siw}}, \quad \forall s, i, w, \tag{17}$$

$$0 \leq AP_{sijmt} \leq GZm_{smt}, \forall s, i, m, t, \tag{18}$$

$$0 \leq Qt_{simwvt} \leq GZm_{smt} \quad \& \quad 0 \leq Qt_{simwvt} \leq GZw_{swt}, \quad \forall i, m, w, v, t, \tag{19}$$

$$0 \leq Qt'_{siwcvt} \leq GZw_{swt}, \quad \forall s, i, w, c, v, t, \tag{20}$$

$$0 \leq Im_{simt}, \quad \forall s, i, m, t, \tag{21}$$

$$0 \leq Iw_{siwt}, \quad \forall s, i, w, t. \tag{22}$$

Constraint set (6) formulate the limitation on raw material supply. Constraint set (7) represents a restriction on the total available working hours for each machine. Constraints (8) and (9) express storage capacity restrictions in manufacturing centers and warehouses, respectively. Constraints (10) and (11) present limitations on transportation capacity for the shipment of products from the manufacturing centers to the warehouses and the warehouses to the customer zones. Constraints (12)–(14) enforce the inventory balance in manufacturing centers, warehouses, and customer zones, respectively. Constraint (15) ensures that total demand should be satisfied in each period. Constraints (16) and (17) represent inventory levels in manufacturing centers and warehouses at the start and end of the planning horizon. Constraints (18)–(22) enforce restrictions on decision variables.

3.3. *Determining carbon trading price in a free market mechanism*

A free market is a system in which the prices of goods and services are determined by the forces of supply and demand and without the intervention of the government. In such a market, the prices are allowed to reach the point of equilibrium.

The supply chains can trade their dedicated allowances. This constitutes a carbon market. If a supply chain has surplus allowances, it can sell them; otherwise, the supply chain should buy them in the carbon market (Lou and Ma, 2018). The carbon trading price and production and transportation decisions of supply chains can affect each other. If supply chains use green technology for production and transportation, the surplus carbon allowances increase, and consequently, the carbon trading price decreases. With a reduction in the carbon trading price, the profitability of the supply chains with green technology decreases. As a result, they reduce their usage of green technology; consequently, the surplus carbon allowances drop along with rising in the carbon trading price. This process continues until the carbon trading price reaches the equilibrium point. The supply chains are the free market participants. The equilibrium price is achieved in this market when supply and demand are equal (Greaves, 1982). Therefore in the presented problem, when the total cap is equal to total emissions, the equilibrium carbon trading price is obtained, i.e., $Tcap = TEC$.

4. Solution Methodology

The bi-level programming with multiple followers can be divided into two groups. In the first group, followers are independent. In other words, there are no sharing variables between followers, and each follower's performance is not dependent on the performance of other followers. They are also called uncooperative (Calvete and Galé, 2007; Shi *et al.*, 2005). Several approaches are extended to solve this kind of problem. For example, Shi *et al.* (2005) develop the Kth-best approach. Calvete and Galé (2007) reformulate the problem to have a single follower. Lu *et al.* (2006) extend the Kuhn-Tucker approach for finding the optimal solution.

In the second group, the followers are dependent, which means they share some common variables. This kind of problem is more challenging than the first group (Lu *et al.*, 2006). Because the optimal decision of each follower depends on the leader's decision as well as the decisions of other followers, some heuristic approaches are developed for this group. For example, Liu (1998) design a genetic algorithm to solve this kind of problem. Angelo and Barbosa (2015) propose a differential evolution method. They test the algorithm performance employing several test problems. Islam *et al.* (2016) present a memetic algorithm to solve problems with multiple followers.

Our model falls into the second group because the carbon trading price is a common variable in all follower problems. The carbon trading price affects the decisions of supply chains and vice versa. Therefore a heuristic algorithm is provided based on ILS. In the following, an exact method is first presented to examine the performance

of the proposed algorithm. This method is not efficient for big problems, and this case shows the necessity of providing a heuristic method.

4.1. *Exact method* (*Bisection* + *CPLEX*)

In the exact method, the bisection method is used to find the optimum value for ϕ and π, and for each value of π, CPLEX is used to obtain the optimal decisions for each supply chain. Therefore, at first, we would explain how to obtain the optimal decisions of the supply chains and the optimal value of π in the follower problem. Then we discuss how to find the best value for ϕ at the leader's problem.

4.1.1. *Determining the optimal carbon trading price and supply chain decisions*

The optimal decisions of supply chains are obtained using CPLEX for a known value of π The carbon trading price (π) is a continuous variable. Since green technology has more cost than the regular one, it is obvious that in an optimal plan, actual emissions of a supply chain are nondecreasing with the decrease in carbon trading price. Therefore, the bisection method is used to deal with this variable and obtain an ε-approximate optimal solution. The procedure is illustrated in Fig. 2. It has six steps as follows:

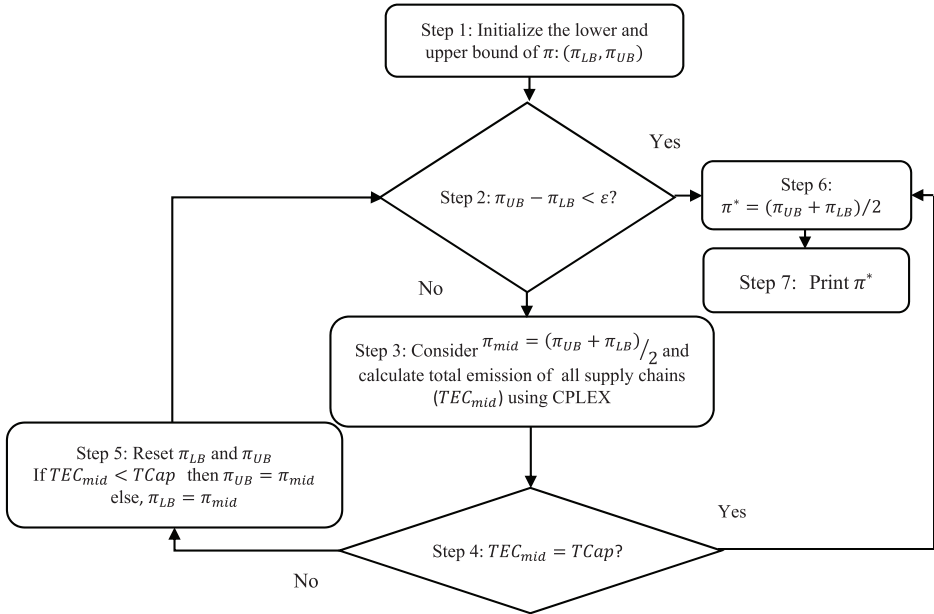**Step 1:** The lower and upper bounds of $\pi : (\pi_{LB}, \pi_{UB})$ are initialized.

Fig. 2. Procedure for solving the follower's problem.

Step 2: The gap between the lower and upper bound is calculated and compared with ε, a given small value. The gap less than ε indicates that the interval containing the optimal carbon trading price is small. Therefore, if this termination condition is satisfied, go to step 6.

Step 3: The mean value of the interval (π_{LB}, π_{UB}), π_{mid}, is calculated, Then the emission of each supply chain (EC_s) is obtained based on π_{mid} by optimizing each supply chain using CPLEX. According to EC_s, the total carbon emission produced by all supply chains (TEC) is obtained.

Step 4: TEC is compared to the total initial allowances $(Tcap)$. If they are equal, the second condition termination is satisfied, then go to step 6; otherwise, go to step 5.

Step 5: The lower and upper bounds of $\pi : (\pi_{LB}, \pi_{UB})$ are updated. If $TEC_{\text{mid}} < TCap$ then $\pi_{UB} = \pi_{\text{mid}}$ else, $\pi_{LB} = \pi_{\text{mid}}$. Then, go back to step 2 and iterate the algorithm until one of the termination conditions is satisfied.

Step 6: The optimal carbon trading price $\pi^* = (\pi_{UB} + \pi_{LB})/2$ is calculated.

### 4.1.2. *Determining the optimal value of ϕ*

The government, as the leader, seeks to decrease total carbon emissions. This goal could be achieved by decreasing the total initial allowances granted to the supply chains, i.e., the value of ϕ. By reducing the value of ϕ, the supply chains are forced to decrease their emissions by using green technology for production and transportation to satisfy the environmental regulation imposed by the government. Therefore, their costs may increase. The government wants to apply the environmental regulation that was economically viable for the supply chains. So λ is defined to restrict the possible economic losses of the supply chains.

The value of ϕ can be obtained by using the bisection method, like the procedure for π. The procedure is illustrated in Fig. 3. The details of the procedure are as follows:

Step 1: The lower and upper bounds of $\phi : (\phi_{LB}, \phi_{UB})$ are initialized.

Step 2: The gap between the lower and upper bound is calculated and compared with ε, a given small value. The gap less than ε indicates that the interval containing the optimal emission reduction coefficient is small. Therefore, if this termination condition is satisfied, go to step 4.

Step 3: The mean value of the interval (ϕ_{LB}, ϕ_{UB}), ϕ_{mid}, is calculated. Then the costs of each supply chain $(\text{Cost\_}EC_s)$ are obtained based on π_{mid} by solving the follower problem. Then the constraint in Eq. (3) is checked for all supply chains. If this constraint is satisfied, we set $\phi_{UB} = \phi_{\text{mid}}$ to examine if ϕ can be decreased further. If the constraint is not satisfied, it shows that ϕ is low, and should be increased, so we set $\phi_{LB} = \phi_{\text{mid}}$.
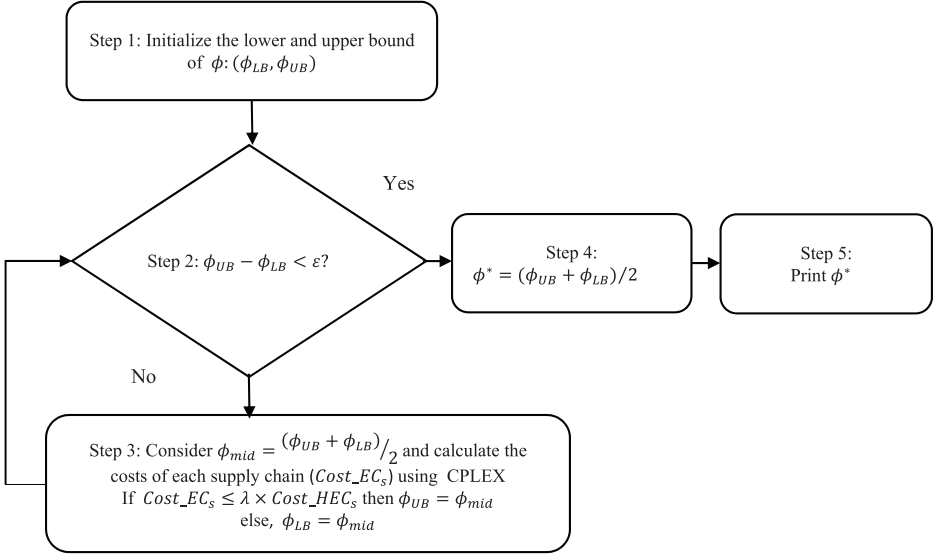
Fig. 3. Procedure to find ϕ.

4.2. *Heuristic method* ($\boldsymbol{Bisection + ILS}$)

The exact method is unable to find the optimal solution for large-size instances in a reasonable time. Most of the time is related to finding the optimal decisions for the supply chains for a given value of the carbon price in the follower problem. Therefore, an algorithm based on ILS is proposed to obtain the optimal decisions of supply chains. This algorithm is repeated for each carbon trading price π. We continue to use of bisection method for ϕ and π to solve the bi-level model in this heuristic.

In each iteration of the heuristic algorithm, the binary variables related to the manufacturing centers and warehouses (Zm_{smt} and Zw_{swt}) are fixed, and then the remained linear model is solved by CPLEX for each supply chain. The general scheme of the proposed algorithm is shown in Fig. 4. For each carbon trading price and each supply chain, the following steps are executed. First, using the initialization procedure, a feasible and initial solution (S_{ini}) is obtained. Then, the initial solution is improved as much as possible by using the local search approach. The best solution in this step is named S_{imp}. The local search approach involves six types of neighborhoods. Two types of these neighborhoods are related to binary variables of manufacturing center locations, and four types of them are related to warehouse location binary variables. These neighborhoods will be described in the next sections.

The main drawback of the local search approach is that it gets trapped in local optima. Perturbation is applied to escape from local optima. The perturbation is executed on manufacturing center location variables in such a way that it accepts

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Input: problem data
Output: best solution (S_{best})
$S_{best} = \emptyset$
$S_{ini} = Initialization();$
$S_{imp} = local\ search(S_{ini});$
$S_{cur} = S_{imp}$
$Iter = 0;$
While ($Iter < Not\_imp$) **do**
    $Iter = Iter + 1;$
    $S_p = perturbation(S_{cur});$
    If ($\text{cost}(S_p) < \text{cost}(S_{cur})$) **Then**
      $S_{cur} = S_p$
    End
    Else
      $S_{cur} = S_{cur}$
    End
End
$S_{best} = S_{cur}$
Return S_{best}

Fig. 4. The general scheme of the ILS.

swapping open manufacturing centers to closed manufacturing centers that produce a worse solution than the local optima. Suppose the number of these swaps is equal to Not_imp, so the number of iterations of the perturbation procedure will be Not_imp. If the solution obtained in each iteration (S_p) is better than local optimum (S_{imp}), the best solution (S_{best}) is set to S_p. Otherwise, this solution is ignored, and the next iteration of perturbation is executed on S_{imp}.

4.2.1. *Initialization procedure*

To generate an initial feasible solution for each supply chain's decision problem, the following steps are done.

Step1: For each manufacturing center, compute the average distance between that center and the warehouses (priority_m) and sort them in descending order.

Step 2: Relax the binary variables corresponding to the manufacturing centers (Zm_{smt}) and the warehouses (Zw_{swt}) and solve the model using CPLEX. Then If Zm_{smt} and Zw_{swt} are greater than 0, fix it to 1.

Step 3: For each period, close the opened manufacturing centers according to priority_m, i.e., the manufacturing center with the highest priority is closed. If the objective function is improved, repeat step 3 until the number of infeasible or worse solutions is equal to the number of periods.

Step 4: For each warehouse, calculate the average distance between that warehouse and the opened manufacturing centers and customer zones (priority_w) and sort them in ascending order.

Step 5: All binary variables related to warehouses' locations are set to zero.

Step 6: For each period, open the warehouse with higher priority (priority$_w$) until getting a feasible solution. Repeat the procedure until the number of worse solutions is equal to the number of periods.

4.2.2. *The local search procedure*

The MC-swap (Neigh1): This procedure is executed for each period and each opened manufacturing center. This neighborhood closes an open manufacturing center and opens a closed one. If the objective function is improved, the new solution is accepted.

The POM-exchange (Neigh2): This procedure is executed on those manufacturing centers where the number of periods they are opened is greater than zero and less than T (planning horizon). Suppose manufacturing center m is open in period t and it is close in period t'. For doing this procedure, m is closed in t and opened in t'. If the objective function is improved, the new solution is accepted. Then the procedure is iterated for m in other periods.

The W-drop (Neigh3): In each period, this procedure closes an open warehouse center. If the solution is feasible and the objective function is improved, this neighborhood is accepted.

The W-swap (Neigh4): This procedure is similar to MC-swap. The only difference between them is that in this procedure, swapping open warehouse w and closed warehouse w' occurs when priority$_{w'}$ − priority$_w < \alpha$.

The POW-exchange (Neigh5): This procedure is applied to the warehouses the same as the POM-exchange.

The W-swap/POW-exchange (Neigh6): This procedure is executed for each period and each open warehouse. Suppose warehouse w is open and warehouse w' is close in period t. w' is opened and w is closed in t and opened in period t' in which $Zw_{swt'}$ is equal to zero. If the objective function is improved, this solution is accepted. Otherwise, this operator is checked for other periods.

The neighborhoods explained in this subsection are used in the scheme represented in Fig. 5.

4.2.3. *Perturbation procedure*

The perturbation tries to escape from local optima and investigate new areas of solution space. Before executing this procedure, the value of the parameter different$_{mm't}$ should be calculated in Neigh1. This parameter is computed for those swaps that don't improve the objective function. It means that if S'_{imp} is the objective function of swapping manufacturing center m and manufacturing center m' in period t, the

Input: S_{ini}
Output: S_{imp}
$cost(S_{imp}) = M$(a large number);
Permission1=True;
While (Permission1) **do**
    Permission2=True;
    While (permission2) **do**
        S_{ini}=Neigh1(S_{ini});
        S_{ini}=Neigh3(S_{ini});
        S_{ini}=Neigh2(S_{ini});
        If $(cost(S_{ini}) < cost(S_{imp}))$ **then**
          $S_{imp} = S_{ini}$;
        End
        Else
          Permission2=False;
        End
    End
    S_{ini}=Neigh4(S_{ini});
    S_{ini}=Neigh5(S_{ini});
    S_{ini}=Neigh6(S_{ini});
    If $(cost(S_{ini}) < cost (S_{imp}))$ **then**
      $S_{imp} = S_{ini}$;
    End
    Else
      Permission1=False;
    End

End
Return S_{imp}

Fig. 5. The scheme of the local search procedure.

Input: $S_{imp}, Pert , Not\_imp, different_{mm't}, S_{cur}$
Output: S_{cur}
$S_{cur} = S_{imp}$;
While $(Iter < Not\_imp)$ **do**
    $Iter = Iter + 1$;
    in S_{cur}, put $Zm_{smt} = 0$ and $Zm_{sm't} = 1$; $Pe_{iter} = (m, m', t) \epsilon Pert$
    Solve the model;
    If (the solution is feasible) **Then**
      $S_{p=}solution$;
      $S_{p=}neigh3(S_p)$;
      $S_{p=}neigh4(S_p)$;
      $S_{p=}neigh5(S_p)$;
      $S_{p=}neigh6(S_p)$;
      If $(cost(S_p) < cost(S_{cur}))$ **Then**
        $S_{cur} = S_p$
      End
      Else
        $S_{cur} = S_{cur}$
      End
    End
End

Fig. 6. The scheme of the perturbation procedure.

value of this parameter is calculated according to the following equation:

$$\text{different}_{mm't} = (S'_{\text{imp}} - S_{\text{imp}})/S_{\text{imp}}. \tag{23}$$

Those swaps in which the value of $\text{different}_{mm't}$ is smaller than β are considered for perturbation. These swaps are shown by $\text{Pert} = \{Pe_i\}$ that Pe_i is a triple vector (m, m', t). If the number of members in this set is equal to Not_imp, the scheme of the perturbation procedure will be as Fig. 6.

5. Computational Experiments

In this section, some instances are presented to test the performance of the proposed heuristic algorithm. All the algorithms are coded in C++, and the exact solutions are obtained by using ILOG CPLEX 12.3. All experiments have been done on a 64-bit computer benefits from Intel Core i7 3.60 GHz processor and 16 GB of RAM.

5.1. *Data generation*

As shown in Table 1, four sets of problems are generated to represent the different supply chain networks. Each of these sets contains ten instances that are randomly created. The number of supply chains and products is considered 4 and 3, respectively, for all instances. The manufacturing centers, warehouses, and customer zones are generated randomly in a square area with a size 10×10 unit of distance. Euclidean distance is considered between the two centers. This distance is used for the initial solution and for parameters whose values are dependent on the distance. These parameters are generated by the following formulas (the brackets are used to indicate the generation of a random number from a uniform distribution in the interval inside the brackets):

$$tmw_{simwv} = Vo_i[2, 4] * \text{dis}_{mw} * ts_v, \tag{24}$$

$$twc_{siwcv} = Vo_i[2, 4] * \text{dis}_{wc} * ts_v, \tag{25}$$

$$et_{simwv} = Vo_i[2, 4] * \text{dis}_{mw} * cts_v, \tag{26}$$

$$et'_{siwcv} = Vo_i[2, 4] * \text{dis}_{wc} * cts_v, \tag{27}$$

Table 1. Specifications of the problem sets.

Problem set	Number of production centers	Number of warehouses	Number of customer zones	Number of periods
s1	2	3	4	6
s2	2	4	5	6
s3	2	4	5	12
s4	3	5	6	12

where dis_{mw} and dis_{wc} are the distance between manufacturing center m and warehouse w and between warehouse w and customer zone c, respectively. The parameter ts_v indicates the cost of transportation for one unit of product per unit of distance through transportation mode v. parameters ts_1 and ts_2 are generated from uniform distributions in the intervals $[1,2]$ and $[2,3]$, respectively. In the same way, cts_v indicates carbon emissions for shipping a unit of product in a unit of distance through mode v. cts_1 and cts_2 are determined according to the uniform distributions in the interval $[16*10^{-3}, 20*10^{-3}]$ and $[12*10^{-3}, 16*10^{-3}]$, respectively. For calculating Cost_HEC_s, we run the follower model for each supply chain without the cap-and-trade scheme. The demand (d_{sict}) is drawn from a uniform distribution between 30 and 200. Also, the fixed cost to operate a manufacturing center and a

Table 2. Parameters tuning.

Parameters	Different tested values	Selected value
α	$\{1.2, 1.5\}$	$\{1.5\}$
β	$\{0.003, 0.005, 0.009\}$	$\{0.009\}$

Table 3. The results of ILS for small size problems.

Problem set	Instances	Average objective Function		Average time		Average gap (%)
		CPLEX	ILS	CPLEX	ILS	
s_1	1	1540859	1542784	1.0	5.3	0.12
	2	1901398	1902080	2.8	5.0	0.04
	3	1827495	1832661	3.2	7.5	0.28
	4	1766290	1769030	1.8	7.3	0.16
	5	1843191	1856096	1.5	5.7	0.70
	6	1699995	1701956	0.6	3.5	0.12
	7	1652451	1654689	1.0	4.1	0.14
	8	1877119	1877119	1.7	8.4	0.00
	9	1678311	1688507	1.3	6.5	0.61
	10	1702254	1704798	2.3	7.2	0.15
Average				1.7	6.0	0.23
s_2	1	2310769	2322749	15.4	19.0	0.52
	2	2356243	2365956	7.6	12.4	0.41
	3	2256906	2261907	9.8	13.4	0.22
	4	2285738	2288682	30.8	19.6	0.13
	5	2323289	2331080	8.1	12.9	0.34
	6	2390670	2391795	18.3	12.4	0.05
	7	2437636	2454944	25.1	27.5	0.71
	8	2350522	2362622	18.5	13.3	0.51
	9	2452085	2459414	25.7	15.4	0.30
	10	2365330	2375082	18.5	14.4	0.41
Average				17.8	16	0.36
Average				9.7	11.0	0.30

warehouse vary from 40,000 to 60,000 and 30,000 to 40,000 of cost unit, respectively. The inventory level for all products at the start and the end of the planning horizon in the manufacturing centers and warehouse are zero. The lower and upper bounds of the ϕ and π are considered $[0.5, 1]$ and $[100, 800]$, respectively. The other parameters are generated randomly.

Before comparing the exact and the heuristic method for the bi-level model in all generated instances, it is necessary to assess the performance of the ILS algorithm for the follower problem. For this purpose, we generate ten instances for each problem set. Given that the performance and run time may vary for different carbon trading prices, we run each instance for three carbon trading prices, including $\{121, 343, 622\}$ that randomly selected from the interval $[100, 800]$. The proposed ILS algorithm has two important parameters that influence the solution quality and computing time. These parameters, different tested values, and selected values are illustrated in Table 2. All 18 possible combinations are solved by CPLEX and the ILS on a subset of the generated instances to select the proper parameters. Then the resulting gaps are analyzed by the use of the non-parametric Friedman test at a significance level of 0.05. The results demonstrate that there is a meaningful difference between the performances of the parameter combinations. So, we select the combination with the minimum average gap over the instances as in Table 2.

Table 4. The results of ILS for large-size problems.

Problem set	Instances	Average objective Function		Average time		Average gap (%)
		CPLEX	ILS	CPLEX	ILS	
s_3	1	4084576	4087038	30.7	38.2	0.06
	2	4249858	4254014	309.1	56.0	0.10
	3	4060242	4080727	280.5	36.9	0.50
	4	4255996	4280876	134.9	71.3	0.58
	5	4238135	4239530	141.8	44.8	0.03
	6	4244289	4307949	32.4	45.1	1.50
	7	4244054	4249166	115.6	47.2	0.12
	8	4182170	4199704	318.0	69.3	0.42
	9	4272298	4292509	16.8	41.9	0.47
	10	4202861	4227193	277.9	92.7	0.58
Average				165.8	54.4	0.44
s_4	1	4922915	4976676	3757.7	246.3	1.09
	2	4946559	4966456	3731.5	281.6	0.40
	3	4740989	4754811	1943.1	177.4	0.29
	4	4242976	4276430	1984.9	122.9	0.79
	5	4515100	4571299	6339.1	266.1	1.24
	6	4594552	4674047	4134.4	305.8	1.73
	7	4631205	4659432	3789.6	238.3	0.61
	8	4494748	4502081	4072.9	184.1	0.16
	9	4791888	4813733	3657.4	242.2	0.46
	10	4649342	4706722	2907.9	456.8	1.23
Average				3631.8	252.2	0.80
Average				1898.8	153.3	0.62

5.2. *Computational experiments for ILS*

The results of the proposed ILS heuristic for the follower problem are presented in Tables 3 and 4. In these tables, columns 1 and 2 present the label of problem sets and their instances. Columns 3 and 4 show the average objective function of CPLEX and ILS over three carbon trading prices, respectively. The next two columns indicate the average computing time for these two methods. Finally, the last column presents the average gap between the results obtained by CPLEX and ILS. The gap is calculated as:

$$\text{gap}(\%) = \frac{Z_{ILS} - Z_{CPLEX}}{Z_{CPLEX}} \times 100,$$

where Z_{ILS} and Z_{CPLEX} show the best solutions obtained by the ILS heuristic and CPLEX, respectively.

As shown in Table 3, CPLEX outperforms the ILS heuristic with regard to computing time for instances of $s1$. But for five instances of $s2$, ILS finds the best solution faster than CPLEX. Furthermore, ILS provides reasonable results with small gaps in the objective functions. The average gap varies from 0 to 0.71% for the two problem sets.

Table 5. The results of the heuristic algorithm for small size problems.

Problem set	Instances	Leader's obj function		Time		Carbon trading price		Gap (%)
		Exact	Heuristic	Exact	Heuristic	Exact	Heuristic	
s_1	1	11353	11353	109.8	325.4	101	101	0
	2	9487	9814	187.2	369.4	101	101	3.45
	3	11720	11720	320.7	507.5	101	101	0
	4	8794	8794	391.3	702.4	155	161	0
	5	9166	9166	182.5	664.7	130	130	0
	6	11711	11711	35.5	174.9	101	101	0
	7	7327	7327	161.3	480.3	150	150	0
	8	13312	13312	146.7	536.6	101	101	0
	9	6800	6800	127.1	464.1	138	168	0
	10	8940	8940	252.7	416.5	136	133	0
	Average			191.5	464.2	121.4	124.7	0.34
s_2	1	13531	13531	2672.0	2683.0	101	101	0
	2	13935	13935	659.4	1103.4	193	193	0
	3	13573	13573	1631.5	838.1	101	101	0
	4	13936	13936	2940.4	2405.3	101	101	0
	5	14731	14731	1956.2	785.8	101	101	0
	6	13125	13125	3032.8	1493.2	101	101	0
	7	9670	9670	2350.5	1022.1	216	216	0
	8	12321	12321	1106.2	1329.5	101	101	0
	9	15003	15003	521.0	1034.6	153	154	0
	10	15002	15002	436.5	705.7	101	101	0
	Average			1730.7	1340.1	126.9	127	0
Average				961.1	902.1	124.15	125.85	0.17

Regarding Table 4, as the size of the instances increases (s3, s4), the ILS reaches the best solution faster than CPLEX. On average, the ILS decreases computing time by 68% for $s3$ and 91.9% for $s4$ compared to CPLEX with a low average gap. The average gap varies from 0.03% to 1.73%. Since in the bilevel model, each supply chain has to be solved multiple times for each carbon trading price, so using the heuristic is reasonable to save computational time.

5.3. *Computational result of the heuristic algorithm*

In this section, the results of the exact and heuristic algorithm are compared for all problem sets. Given that the computing time for problem set s4 is too large in the exact algorithm, a time limit of 1,200s is set in each iteration of CPLEX. The results are given in Tables 5 and 6. Columns 1 and 2 show the problem sets and their instances, respectively. The next two columns present the leader's objective function for the exact and the heuristic, respectively. Similarly, every two adjacent columns demonstrate the time and carbon trading price for each algorithm. The last column illustrates the gap between the results obtained by the exact and the

Table 6. The results of the heuristic algorithm for large-size problems.

Problem set	Instances	Leader's obj function		Time		Carbon trading price		Gap (%)
		Exact	Heuristic	Exact	Heuristic	Exact	Heuristic	
s_3	1	19988	19988	3694.8	5625.1	232	232	0
	2	14121	14121	1195.2	1359.0	799	799	0
	3	20979	20979	729.4	4737.1	799	799	0
	4	21066	21066	15672.1	3990.6	376	376	0
	5	19682	19682	21006.1	10314.3	446	358	0
	6	16990	16990	1652.5	2464.1	502	502	0
	7	19085	19085	1431.1	6364.5	317	254	0
	8	17366	17366	5694.4	3749.3	308	292	0
	9	20962	20962	1612.9	5624.5	361	361	0
	10	22384	22384	41501.4	10622.3	604	604	0
Average				9419.0	5485.1	474.4	457.7	0
s_4	1	19427	16778	26230.2	12762.0	799	795	−13.64
	2	20178	17546	18890.7	21329.2	306	799	−13.04
	3	23847	20595	32992.0	15188.2	366	799	−13.64
	4	17286	16326	43798.8	14857.4	278	799	−5.56
	5	22583	15996	69656.5	8625.0	259	303	−29.17
	6	16200	13114	48540.4	18571.4	799	650	−19.05
	7	18450	16693	54494.9	18542.9	274	799	−9.52
	8	15224	13049	72557.6	4720.8	544	799	−14.29
	9	22743	20676	8748.0	4290.7	344	799	−9.09
	10	24137	22038	49042.2	35667.0	432	689	−8.70
Average				42495.1	15455.5	440.10	723.10	−13.57
Average				25957.1	10470.3	457.25	590.40	−6.78

heuristic. The relative gap is calculated as:

$$\text{gap}(\%) = \frac{Z_{\text{Heuristic}} - Z_{\text{Exact}}}{Z_{\text{Exact}}} \times 100,$$

where $Z_{\text{heuristic}}$ and Z_{Exact} show the best solution by the heuristic and the exact algorithm, respectively.

As is evident from the last column of Table 5, the heuristic present the same results of the exact method for s_1 but computing time is higher than the exact. However, it decreases the computing time by 23%, with 0.0% of the average gap for s_2. The carbon trading prices obtained in the two methods are the same for 16 out of 20 instances, and the average gap is 1.3%.

As shown in Table 6, with an increase in the size of the instances, the computing time for the heuristic reduces significantly compared to the exact method with time limitation for CPLEX. For instances of s_3, the gap is 0%, and the solutions found by the heuristic are equal to the one obtained by the exact. The carbon trading prices obtained in the two methods are the same for 7 out of 10 instances in s_3. There are 10 instances in s_4 in which the gap is negative. i.e., for these instances, the heuristic finds better solutions than the exact method. It seems that the heuristic is efficient on relatively large-size problems, and it delivers even negative gaps regarding the exact method with time limitation.

6. Sensitivity Analysis and Discussion

The parameter λ, the maximum percentage increase in supply chain costs, is important and effective in the proposed cap-and-trade scheme and has a significant role in determining the proper cap in such a way that it does not jeopardize the profitability of the supply chains. Therefore, the effect of different values of λ is examined on the system. In the same way, the impact of the ratio of green technology costs to regular one is evaluated for both manufacturing and transportation (for simplicity, it is named γ from now on) with the sensitivity analysis. For this purpose, an instance from set s_1 is generated, in which there are two manufacturing centers, three warehouses, four customer zones, and six periods. The other parameter values are fixed during the analysis and generated according to Sec. 5.1.

6.1. *Sensitivity analysis with respect to λ*

The value of λ is increased from 1 to 1.5 and is reported its effect on ϕ, carbon trading price, the total costs of supply chains, the total cap, and total emissions. The results are shown in Fig. 7. As shown in this figure, when λ is greater than 1.03, it has a considerable effect on the system. When λ less than 1.03, the carbon market is not formed. This is because, when λ is very low, the government has to increase the cap so that the supply chains do not need to buy allowances from the market. Note the results are stable when λ is higher than 1.5.
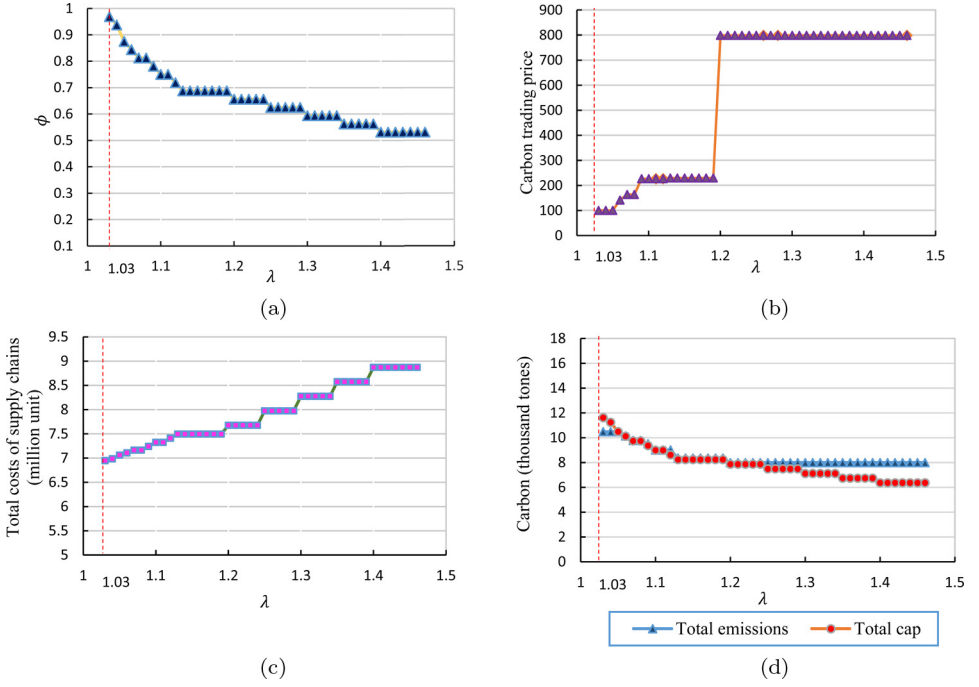
Fig. 7. The effect of λ on (a)ϕ, (b) carbon trading price, (c) total costs of supply chains, and (d) total emissions and total cap.

As shown in Fig. 7(a), the emission reduction coefficient (ϕ) decreases with the increase in λ. This is because, as λ goes up, the government's support to the supply chains to avoid reducing their profitability decreases; therefore, the government lowers ϕ as much as possible to reduce total emissions. Figure 7(b) illustrates that λ has a significant effect on the carbon trading price, and it increases for λ smaller than or equal to 1.2. The reason for this is that the rising λ leads to ϕ reduces. Therefore, the supply of tradable allowances is not enough in the carbon market, and the carbon trading price increases. The price gets its upper limit, i.e., 799 units per ton when λ is greater than or equal to 1.2. So it seems that λ between 1.03 and 1.2 is more reasonable in this case.

As shown in Fig. 7(c), with the increase in λ, the costs of supply chains go up. When λ increases, ϕ decreases (see Fig. 7(a)), and the carbon trading price increases (Fig. 7(b)). With the decrease in ϕ and the increase in the carbon trading price, supply chains have to use green technology more. The more use of green technology has more costs for supply chains.

As shown in Fig. 7(d), the total cap and total emissions decrease as λ increases. Because when λ rises, ϕ decreases (Fig. 7(a)); consequently, the cap reduces. With a decrease in the cap, supply chains have to use green technologies more. Therefore, the total emissions decrease. Note, when λ is greater than or equal to 1.25, the total

emission is greater than the total cap. That is because, for these values of λ, the supply chains are not able to decrease total emissions to the total cap. So, λ value should be adjusted properly to create a balance between costs and environmental benefits.

6.2. *Sensitivity analysis with respect to γ*

The value of γ is changed from 1 to 1.2 and investigated its influence on ϕ, carbon trading price, the total costs of supply chains, the total cap, and total emissions. According to Fig. 8(a), as γ increases, ϕ will rise accordingly. Because, with the increase in the value of γ, the cost of using green technology rises up with respect to regular technology. Given the value of λ remains constant, the government has to raise the cap to support supply chains.

As shown in Fig. 8(b), the carbon trading price decreases when γ increases. Because with the increase in γ, ϕ increases (see Fig. 8(a)). Therefore, supply chains have enough or surplus allowances for their activities. So, tradable allowances in the carbon market increase along with decreasing in carbon trading price.
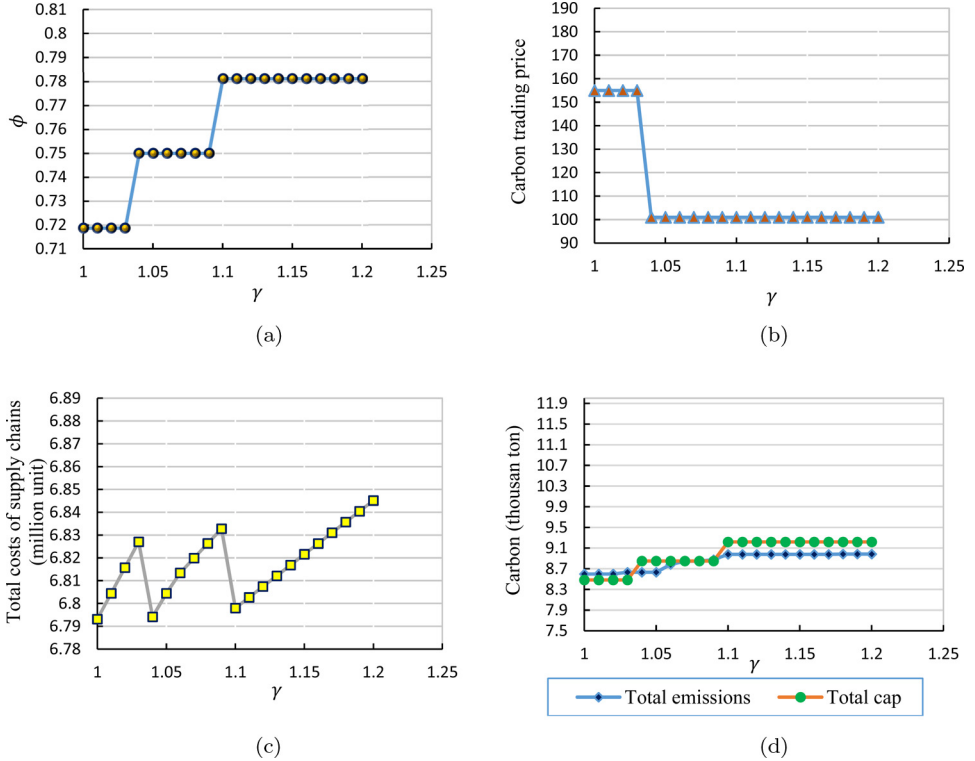

Fig. 8. The effect of γ on (a) ϕ, (b) carbon trading price, (c) total costs of supply chains, and (d) total emissions and total cap.

As demonstrated in Fig. 8(c), the parameter γ has a significant effect on the total costs of supply chains. The total costs increase with increasing γ for the intervals in which the value of ϕ is fixed. This is because, with the growth in the value of γ, the cost of adopting green technology rises. Similarly, with the increase of γ, the total cap and total emissions increase (see Fig. 8(d)). Because it incurs an increase in ϕ (see Fig. 8(a)) that will increase the total cap and consequently total emissions, so, when the cost of using green technology is high, the government will have to give the supply chains more caps to support them, which will lead to increased total emissions.

7. Conclusions

In this paper, a bi-level model is developed for designing a carbon trading scheme. At the first level, the government as the leader determines the emission reduction coefficient and allocates initial allowances to supply chains. This regulation may increase the costs of supply chains. Therefore the government uses a constraint to prevent the decrease in profitability of supply chains. The supply chains are followers and determine optimal operational and tactical decisions and trade allowances among each other to adapt to the regulation imposed by the government. The allowances are traded in the carbon market, and the carbon trading price is discovered based on supply and demand.

Given the complexity of the bi-level model, a heuristic method is presented based on ILS and the bisection method. In particular, the bisection method was applied to obtain the optimal carbon trading price and emission reduction coefficient; the ILS was used to calculate the decisions of supply chains. The algorithm was tested on four randomly generated problem sets. The results demonstrated that the presented algorithm performed well in terms of computing time and solution quality, mainly in large-size problems.

Finally, the effect of the parameters λ and γ is investigated on the cap, carbon trading price, total emissions, and costs in the sensitivity analysis. The result showed that the desired parameters had a significant influence on these issues. Therefore, in designing a cap-and-trade scheme, the government should investigate these parameters carefully to create a good balance between the environmental and economic effects of carbon regulation policy.

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