A GIS-based green supply chain model for assessing the effects of carbon price uncertainty on plastic recycling

Hongtao Ren[a], Wenji Zhou[b,*], Ying Guo[c], Lizhen Huang[b], Yongping Liu[b], Yadong Yu[a], Liyun Hong[e], Tieju Ma[a,d]

[a] School of Business, East China University of Science and Technology, Meilong Road 130, 200237, Shanghai, China

[b] Department of Manufacturing and Civil Engineering, Norwegian University of Science and Technology (NTNU), Teknologivn 22, 2815 Gjøvik, Norway

[c] School of Energy Science and Engineering, Central South University, Lushan South Road 932, 410083, Changsha, China

[d] International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, A-2361, Laxenburg, Austria

[e] Zhejiang Development and Planning Institute, Hangzhou 310012, Zhejiang, China

∗Corresponding author: Wenji Zhou

Email: wenji.zhou@ntnu.no

A GIS-based green supply chain model for assessing the effects of carbon price uncertainty on plastic recycling

Abstract

Recycling plastic can abate the environmental pollution as well as CO_2 emissions by saving the carbon-intensive feedstock input. The uncertain carbon price places significant effects on the establishment and operation of the whole supply chain. This study develops a green supply chain model combined with geographic information system (GIS) to account for carbon price uncertainty and evaluate its effects on the closed-loop supply chain (CLSC) of plastic recycling. A two-stage stochastic programming model is constructed, in which the stochastic variable, CO_2 price is modeled as a geometric Brownian motion process. Six scenarios are designed with respect to price expectation and volatility. A case study is performed with the GIS information of the plastic supply chain in Zhejiang province, China. The results illustrate that triggering the establishment of reverse logistics requires a carbon price threshold significantly beyond current level. Lower price volatility would facilitate the decision-making of investment into the reverse logistics. Mechanisms to alleviate the market variation shall be introduced. A sound market condition is desired to obtain the optimal balance that encourages the CLSC without creating extra pressure on the firms. The proposed modeling framework can be easily applied to other sectors with similar characteristics.

Keywords

green supply chain; reverse logistics; decision support systems; uncertainty; emissions trading; circular economy;

1. Introduction

Plastic pollution has been drawing increasing attention worldwide. Global plastic increased to as high as 348 million tons in 2017, approximately 30% of which was produced in China, the largest producer, followed by Europe and North America (PlasticsEurope, 2018). A significant portion of plastic waste is mismanaged or inadequately disposed of. Globally, 1.5% to 4% of plastics production ends up in the oceans every year (Jambeck et al., 2015). Moreover, plastics are a major contributor to greenhouse gas (GHG) emissions. Extraction and processing of fossil fuel for plastics feedstocks is carbon-intensive, and incineration of waste plastics releases GHG and many other toxic gases such as dioxins, furans, mercury, and polychlorinated biphenyls into the atmosphere (Verma et al., 2016). Therefore, it is of significant importance to investigate the green supply chain management (GSCM) of plastic, particularly the inclusion of the recycling process, in the concept of circular economy (CE), which aims to alter the current linear economy model by extracting the maximum value from resources while in use and to recover and regenerate products and materials at the end of their service life (Barra and Leonard, 2018). An integration of CE principles with sustainable supply chain management can provide advantages from an environmental perspective (Genovese et al., 2017). Synergies between decarbonization measures and resource efficiency in the CE context have been assessed for some energy-intensive industries such as cement and steel (Zhang et al., 2018; Zhou et al., 2016), yet the measures of recycling have not been explicitly taken into account in these studies.

From the life cycle perspective, recycling can also create significant co-benefits of carbon emissions mitigation through reducing the use of fossil fuels as raw materials. The decision problem regarding the plastic supply chain is distinctively different from other types of problems because the life cycle carbon emissions associated with feedstock supply, such as polyethylene (PE), are significantly higher than in other processes such as manufacturing and transportation etc. Hence the supply chain is more significantly affected by the upstream PE production process in an indirect way when exposed to carbon trading market, which is regarded as an effective mechanism to stimulate low-carbon investment (Zhou et al., 2014). Nonetheless, how the uncertainty of carbon price variation affects the closed-loop supply chain (CLSC) design and operation remains an open question which is far from well-understood. The CLSC models enable modeling of the recycling process of plastic products, reducing consumption of the virgin feedstock and saving the associated cost, which conceptually resemble the advancement of the circular economy paradigm shifting from the conventional linear economy, and management of CLSC is considered a strategic response to the call for corporate sustainability while further expanding the scope of value creation to include product reconstruction (Gaur et al., 2017). This study aims to address this decision-making problem by developing a new analytical framework that integrates modeling carbon price uncertainty with a geographic information system (GIS)-based stochastic CLSC modeling and factors in the life cycle emissions of PE feedstock. The GIS-based modeling provides a visualized platform to observe the alteration of the configurations, the choices of facility locations, and the product flows within the supply chain across scenarios. A geometric Brownian motion (GBM) model is constructed for simulating variation of CO_2 trading prices. Historical data of carbon prices in eight China's pilot carbon trading markets is compiled and employed for estimating the key parameters in the GBM model. Six scenarios are designed regarding different levels of price drift rate and volatility to cover a wide-range of possible carbon market conditions. This modeling of carbon price uncertainty is then incorporated into a two-stage stochastic mixed integer programming (MIP) model for the targeted plastic CLSC. A case study in Zhejiang province, China, is performed to quantitively evaluate these effects.

The remainder of this paper is organized as follows: Section 2 summarizes the literature with regards to accounting for climate policies in green supply chain management. Section 3 elaborates on the problem definition, formulation of the two-stage stochastic model and construction of the GBM model for carbon price. Section 4 introduces the scenario settings regarding carbon price uncertainty and describes the processes of parameter estimation for the GBM model based on historical information. Section 5 presents the results and conducts analysis of the case study, and Section 6 concludes with key policy insights and discussions on further research directions.

2. Literature review

In the past decade, there has been an exponential growth of studies on the integration of environmental concerns into supply chain management practices (Tseng et al., 2019). Models and methodologies that explicitly include a variety of climate policies, for example, carbon tax, cap-and-trade, and carbon offset, have been developed and applied to the GSCM problems (Waltho et al., 2018).

A number of studies assessed the impacts of carbon policies on GSCM, but they varied in the aspects of, for example, supply chain type, regulatory scheme, carbon tax rate/price level, uncertainty factors and the way to treat uncertainty in the model. Table 1 summaries examples of these studies. Among these studies, carbon tax and cap-and-trade are the two most widely adopted mechanisms in climate change regulations that have been incorporated into GSCM. In the way of accounting for carbon price uncertainty, some studies assume carbon price in the trading market as a stochastic variable (Rezaee et al., 2017), and many others use scenario analysis or sensitivity analysis, which simply assumes different levels of carbon price to assess the performance and configuration of the supply chain, particularly for the carbon tax cases (Yang et al., 2016; Zakeri et al., 2015). On top of carbon price, many other factors such as capacities in different echelons, or demand side variation have also been treated as uncertain (Ghelichi et al., 2018; Shaw et al., 2016).

Table 1 Summary of literature review of incorporating climate policies into GSCM

Reference	Supply chain type	Climate policies	Uncertainty factors
Rezaee et al. (2017)	Forward logistics	Carbon trading	Carbon price (stochastic); product demand (stochastic)
Yang et al. (2016)	Forward logistics	Carbon tax	Carbon tax rate (scenario)
Shaw et al. (2016)	Forward logistics	Carbon trading	Capacities of suppliers, plants and warehouses (stochastic), carbon price (scenario)

Guo et al. (2017)	Forward and reverse logistics	Carbon tax	-
Fahimnia et al. (2015)	Forward logistics	Carbon tax	-
Ghelichi et al. (2018)	Forward logistics	-	Biofuel supply and demand (stochastic)
Paksoy and Özceylan (2014)	Forward logistics	Carbon tax	-
Zakeri et al. (2015)	Forward logistics	Carbon tax/ Carbon trading	Carbon price (scenario)
Fahimnia et al. (2013)	Forward and reverse logistics	Carbon tax	Carbon tax rate (scenario)
Peng et al. (2016)	Forward logistics	Carbon tax/ Carbon trading	Carbon price (scenario)
Martí et al. (2015)	Forward logistics	Emissions cap/carbon tax	Product demand (stochastic)
Han et al. (2017)	Forward and reverse logistics	-	Demand, recovery rate, discarding rate etc. (scenario)
Diabat et al. (2013)	Forward and reverse logistics	Carbon trading	Carbon price (scenario)

Some models, although not incorporating uncertainty of carbon price, have been developed in a multi-objective way to assess the impacts from climate policy on the supply chain emissions from the supply chain. Typical example includes bi-objective tactical planning models that integrate economic and carbon emission objectives under a carbon tax policy scheme (Fahimnia et al., 2015; Han et al., 2017).

Comparing the impacts and effectiveness of different policy instruments on the performance of GSCM has also been conducted in these studies. Some conclusions drawn from these study include that a carbon trading mechanism, despite limitations, results in improved supply chain performance in terms of emissions generation, cost, and service levels (Choudhary et al., 2015; Zakeri et al., 2015) , although a carbon tax may be favorable from an uncertainty perspective and the right level of tax can be a priori computed to achieve a given emission reduction (Martí et al., 2015).

Transportation in supply chains has been drawn much interest from researchers in this field, as in many supply chains, transportation is the most carbon-intensive process (Yang et al., 2016). Optimization models are built to choose optimal routes or transportation modes, such as freight (Liotta et al., 2015) or truck (Allevi et al., 2018). Some studies provide detailed information on the trade-offs between various parameters such as vehicle speed, fuel, time, emissions, noise, and their total cost, and offers managerial insights on economies of environmentally conscious supply chain optimization (Paksoy and Özceylan, Taylor & Francis, 2014).

It is noteworthy that although transportation is the most carbon-intensive process of many supply chains, it is not necessarily true in other cases. For instance, many production processes such as plastic production or fuel production, can emit significantly higher CO_2 compared to the transportation process of these products (Ghelichi et al., 2018). Therefore, modeling those supply chains should place a distinct focus on the life cycle emissions of the upstream sectors (Ren et al., 2019). One typical example is whether to consider the reversed logistics. Recycling some carbon-intensive products, such as plastic, is one of the most effective measures for abating CO_2 emissions, and is also a common practice in the real world. Hence, the closed-loop supply chain model provides a useful means for evaluating the effectiveness of climate policy on this issue. To our knowledge, only a few studies have incorporated the effect of climate policy in designing and planning CLSC. Moreover, the studies have been surprisingly scarce regarding accounting for climate policy in the decision-making problems of the plastics CLSC.

This study attempts to fill the knowledge gap by conducting a deep investigation into how fluctuating carbon price impacts the CLSC network planning and operations for the plastic industry. Considering China is the world's largest plastic producer, and is also launching the world's largest nation-wide carbon market, such an analysis within this background is urgently necessary to inform the involved decision-makers managing these challenges.

3. Problem definition and model formulation

3.1 Problem background

This study considers a decision-making problem, that is, in an environment of an uncertain carbon market, a company that produces, distributes, and sells plastic products decides whether and how it should establish a CLSC by designing recycling-related facilities and integrating them into the existing infrastructure of forward logistics. Fig. 1 represents the network of the proposed supply chain. As the diagram shows, the facilities of the forward supply chain are connected by solid lines, and the dashed lines represent the potential reverse logistics under planning. The feedstocks required for the manufacturing process are provided by the suppliers at certain price levels. The production processes of the feedstocks are carbon-intensive. As a result, the fluctuation of the carbon market leads to the variation of the feedstocks' costs and, consequently, the feedstock prices. In the forward supply chain, the manufacturers produce and sell two types of plastic products, namely, A and B, with different quality grades. Product A is a higher quality grade and made from the virgin feedstocks, whereas product B with is a lower quality grade that can be produced either from the virgin feedstocks or from recycled feedstocks. These two types of products are shipped from the manufacturing plants to the distribution centers (DC) and then delivered to various markets to meet their demands. In a linear forward supply chain without the reverse logistics, the manufacturers can either purchase virgin feedstocks or recycled feedstocks to produce product B. Because using the virgin feedstocks is not cost-efficient in this case, the company can either buy the recycled feedstocks from external suppliers (e.g., plastic waste importers) or establish its own CLSC for supply these feedstocks.

The recycled feedstock market is also subject to the carbon market, indicating that a higher carbon price will increase the price of the recycled feedstock and increase the cost of manufacturing recycled plastic product B. To address this uncertainty, the company may reduce the costs by establishing its own reverse logistics, comprising collection centers (CC), recycling centers (RC), and disposal centers (SC). The CCs gather the waste of plastic products from the markets and separate the waste that can be further processed and treated through waste-sorting, detection, and pre-treatment. The RCs process those wastes to make plastic feedstocks and send them back to the manufacturers. The remaining waste without recycling value is sent to the disposal centers for final treatment.

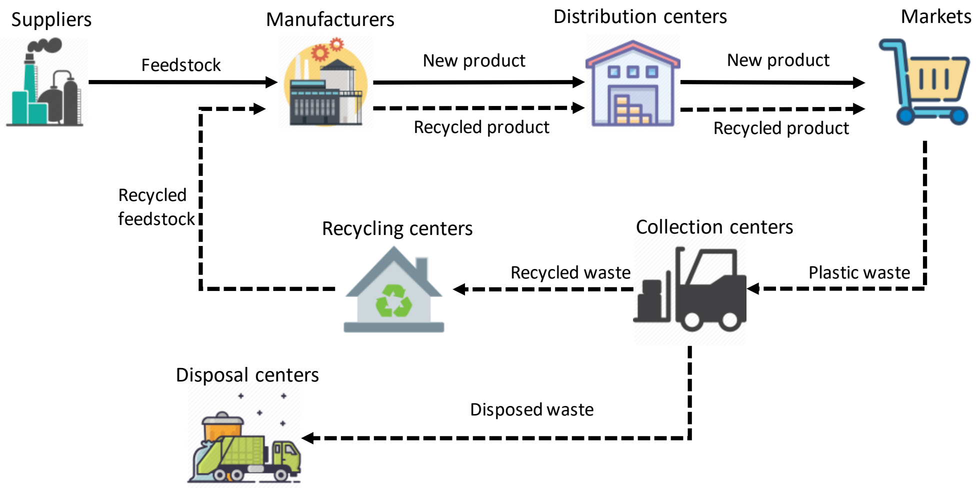

Fig. 1 Diagram of the proposed CLSC network

To illustrate the decision-making process, this study applies a case study of the plastic supply chain in Zhejiang province, China. The main feedstock is low-density polyethylene (LDPE), one of the most widely-used PE raw materials in the plastic market. In China, PE is mostly produced from oil-based route. The CO_2 emissions factor of oil-based PE is approximately 2.50 tons CO_2/ton (China Chemical Industry Information Center, 2016; Liu et al., 2013; Zhu et al., 2010), which is higher than the natural gas route but much lower than the coal-based route (Zhou et al., 2011; Zhu et al., 2010). The company purchase oil-based LDPE to produces two types of plastic packaging materials.

3.2 Model formulation

3.2.1 Deterministic MILP model

The objective of this model is to minimize the total cost, discuss the change in the supply chain structure under a certain carbon price, and discuss the choice of supply and demand and transportation mode in each link. The general form of the mixed-integer linear programming model is as follows:

$$\begin{array}{ll} \min & z = c^T x \\ \mathrm{s.t.} & Ax = b \\ & d_1 \leq x \leq d_2 \end{array} \tag{1}$$

Where *x* represents the variables, *c* is the vector of the cost coefficients, *A* is the matrix of the coefficients in the constraints, *b* denotes the right-hand side column vector of the constraints, and d_1 and d_2 represent the vectors of lower and upper bounds on the variables, respectively. The objective function *z* in Eq. (2) specifies the total SCND cost, which comprises the corresponding cost components associated with each part of the supply chain, namely, the purchasing cost of feedstock (*FDC*), the manufacturing cost (*MFC*), the transportation cost (*TRC*), the distribution cost (*DTC*), the collection cost (*CLC*), the recycling cost (*RCC*), and the disposal cost (*DPC*).

$$min\ z = FDC + MFC + TRC + DTC + CLC + RCC + DPC \tag{2}$$

The complete specification of the implemented model is summarized as follows.

3.2.1.1 Indices

f Index of plants, $f = 1, \dots, F$

d Index of distribution centers, $d = 1, \dots, D$

m Index of markets, $m = 1, \dots, M$

c Index of collection centers, $c = 1, \dots, C$

r Index of recycling centers, $r = 1, \dots, R$

s Index of disposal centers, $s = 1, \dots, S$

p Index of product types, $p = 1, \dots, P$

fd Index of feedstock types, $fd = 1, \dots, FD$

n Index of the types of new products, subset of *p*, $n = 1, \dots, N$

u Index of the types of recycled products, subset of *p*, $u = 1, \dots, U$

fn Index of the types of virgin feedstocks, subset of *fd*, $fn = 1, \dots, FN$

fr Index of the types of recycled feedstocks, subset of *fd*, $fd = 1, \dots, FD$

fa Index of the types of additives, subset of *fd*, $fa = 1, \dots, FA$

3.2.1.2 Parameters

prc carbon price, yuan/ton CO_2

$vartr$ transportation cost for delivering 1 ton of production for 1 km, yuan/km*ton

$emtr$	carbon intensity of transportation, ton/ton*km
crm_{fd}	conversion rate of feedstock *fd* in the manufacturing process
clr	collection rate
$crr_{n,fr}$	conversion rate of product waste *n* in the recycling process for making recycled feedstock *fr*
$prfd_{fd}$	feedstock price, yuan/ton
$emfd_{fd}$	carbon intensity of feedstock, ton CO_2/ton
$prpd_p$	product price, yuan/ton
$dm_{p,m}$	demand for product *p* of market *m*, ton/yr
$cappl_{f,p}$	capacity of plant *f* for producing product *p*, ton/yr
$fxpl_f$	annualized capital cost of establishing plant *f*, yuan/yr
$varpl_{f,p}$	annual variable cost of producing 1 ton of product *p* at plant *f*, yuan/ton
$empl_{f,p}$	CO_2 emissions for producing 1 ton of product *p* in plant *f*, ton CO_2/ton
$capdc_{d,p}$	capacity of distribution center *d* for storing product *p*, ton/yr
$fxdc_d$	annualized capital cost of establishing distribution center *d*, yuan/yr
$vardc_{d,p}$	annual variable cost of distributing product *p* at distribution center *d,* yuan/ton
$emdc_{d,p}$	CO_2 emissions of distributing 1 ton of product *p* at distribution center *d*, ton CO_2/ton
$capcl_{c,p}$	capacity of collection center *c* for collecting product waste *p*, ton/yr
$fxcl_c$	annualized capital cost of establishing collection center *c*, yuan/yr
$varcl_{c,p}$	annual variable cost of collecting product waste *p* at collection center *c*, yuan/ton
$emcl_{c,p}$	CO_2 emissions when collecting 1 ton of product waste *p* at collecting center *c*, ton CO_2/ton
$caprc_{r,p}$	capacity of recycling center *r* for recycling product waste *p*, ton/yr
$fxrc_r$	annualized capital cost of establishing recycling center *r*, yuan/yr
$varrc_{r,p}$	annual variable cost of recycling 1 ton of product waste *p* at recycling center *r*, yuan/ton
$emrc_{r,p}$	CO_2 emissions of recycling one ton waste at recycling center *c*, ton CO_2/ton
$capdp_{s,p}$	capacity of disposal center *s* for disposing product waste *p*, ton/yr
$fxdp_s$	annualized capital cost of establishing disposal center *s*, yuan/yr
$vardp_{s,p}$	annual variable cost of disposing of 1 ton of product waste *p* at disposal center *s*, yuan/ton
$emdp_{s,p}$	CO_2 emissions of disposing of 1 ton of product waste *p* at disposal center *s*, ton CO_2/ton

$disfd_{f,d}$ distance from plant *f* to distribution center *d*, km

$disdm_{d,m}$ distance from distribution center *d* to market *m*, km

$dismc_{m,c}$ distance from market *m* to collection center *c*, km

$discr_{c,r}$ distance from collection center *c* to recycling center *r*, km

$discs_{c,s}$ distance from collection center *c* to disposal center *s*, km

$disrf_{r,f}$ distance from recycling center *r* to plant *f*, km

3.2.1.3 Decision variables

$VRM_{f,fd} \geq 0$ amount of feedstock *fd* purchased by plant *f*, ton/yr

$VP_{f,p} \geq 0$ output of product *p* from plant *f*, ton/yr

$VFD_{f,d,p} \geq 0$ amount of product *p* shipped from plant *f* to distribution center *d*, ton/yr

$VDM_{d,m,p} \geq 0$ amount of product *p* shipped from distribution center *d* to market *m*, ton/yr

$VMC_{m,c,p} \geq 0$ amount of product waste p shipped from market m to collection center c, ton/yr

$VCR_{c,r,p} \geq 0$ amount of product waste *p* shipped from collection center *c* to recycling center *r*, ton/yr

$VCS_{c,s,p} \geq 0$ amount of product waste *p* shipped from collection center *c* to disposal center *s*, ton/yr

$VRF_{r,f,fr} \geq 0$ amount of recycled feedstock *fr* shipped from recycling center *r* to plant *f*, ton/yr

VCB_c 1 if collection center *c* is established, 0 otherwise

VRB_r 1 if recycling center *r* is established, 0 otherwise

VSB_s 1 if disposal center *s* is established, 0 otherwise

$VRVB$ 1 if the entire reverse flow is established, 0 otherwise

The profit expression is shown in Eq. (3). The total profit is equal to the total revenue from selling all products subtracted by the total cost.

$$profit = \sum_{f,p} \left(prpd_p \cdot VP_{f,p} \right) - z \tag{3}$$

Eqs. (4)–(6) formulate the seven cost components. The purchasing costs (*FDC*) defined in Eq. (5) include the purchasing costs of raw materials in each plant *f* and the additional cost for the CO_2 emissions embodied in the supply of raw materials. Notably, such a cost is included in the feedstock price in the real market, whereas in this study, we separate it from the feedstock price and express it explicitly to better illustrate the impact from the carbon price uncertainty.

$$FDC = \sum_{f,fd} \left(prfd_{fd} \cdot VRM_{f,fd} + prc \cdot emfd_{fd} \cdot VRM_{f,fd} \right) \tag{4}$$

The manufacturing costs (MFC) include the annualized capital costs of each plant f, the variable production costs in the manufacturing processes, and the associated costs for CO_2 emissions, as shown in Eq. (5).

$$MFC = \sum_{f} fxpl_f + \sum_{f,p}\left(varpl_{f,p} \cdot VP_{f,p}\right) + prc \cdot \sum_{f,p} empl_{f,p} \cdot VP_{f,p} \tag{5}$$

In Eq. (6), the TRC include all the shipping costs for delivering products, wastes, and the recycled feedstocks, and the associated cost of CO_2 emissions resulted from fuel use. In this study, we assume there is only one shipping mode, must truck transportation on the road, which is fueled by diesel.

$$TRC = (vartr + prc \cdot emtr) \cdot \{\sum_{f,d,p}\left(disfd_{f,d} \cdot VFD_{f,d,p}\right) + \sum_{d,m,p}\left(disdm_{d,m} \cdot VDM_{d,m,p}\right) + \sum_{m,c,p}\left(dismc_{m,c} \cdot VMC_{m,c,p}\right) + \sum_{c,r,p}\left(discr_{c,r} \cdot VCR_{c,r,p}\right) + \sum_{c,s,p}\left(discs_{c,s} \cdot VCS_{c,s,p}\right) + \sum_{r,f,fr}\left(disrf_{r,f} \cdot VRF_{r,f,fr}\right)\} \tag{6}$$

Eq. (7) represents the distribution costs (*DTC*), which have three parts: the annual fixed costs of establishing all the distribution centers, the variable costs of the distribution processes, and the costs for the corresponding CO_2 emission.

$$DTC = \sum_{d} fxdc_d + \sum_{d,m,p}\left(vardc_{d,\mathrm{p}} \cdot VDM_{d,m,p}\right) + prc \cdot \sum_{d,m,p}\left(emdc_{d,\mathrm{p}} \cdot VDM_{d,m,p}\right) \tag{7}$$

Eq. (8) formulates the collection costs (*CLC*). The relevant cost components include the annual fixed costs of all the CC, the variable costs of the collection processes, and the costs for the associated CO_2 emissions.

$$CLC = \sum_{c}(fxcl_c \cdot VCB_c) + \sum_{m,\mathrm{c},p}\left(varcl_{c,p} \cdot VMC_{\mathrm{m,c,p}}\right) + prc \cdot \sum_{m,c,p}\left(emcl_{c,p} \cdot VMC_{m,c,p}\right) \tag{8}$$

The recycling costs (*RCC*) are shown in Eq. (9). Likewise, these costs comprise the annualized capital costs of CC, the variable costs of the recycling processes, and the costs for the associated CO_2 emissions.

$$RCC = \sum_{r}(fxrc_r \cdot VRB_r) + \sum_{c,r,p}\left(varrc_{r,p} \cdot VCR_{c,r,p}\right) + prc \cdot \sum_{c,r,p}\left(emrc_{r,p} \cdot VCR_{c,r,p}\right) \tag{9}$$

Eq. (10) defines disposal costs (DPC). These costs include the annualized capital costs of establishing all the disposal centers, the variable costs of the disposal processes, and the costs for the associated CO_2 emissions.

$$DPC = \sum_{s}(fxdp_s \cdot VSB_s) + \sum_{c,s,p}\left(vardp_{s,p} \cdot VCS_{c,s,p}\right) + prc \cdot \sum_{c,s,p}\left(emdp_{s,p} \cdot VCS_{c,s,p}\right) \tag{10}$$

3.2.1.4 Model constraints

The constraints on the objective function are explained as follows. Constraints Eqs. (11)–(15) represent capacity constraints. The constraint Eq. (11) ensures that the actual output of product *p* from plant *f* should not exceed the corresponding production capacity. The constraint Eq. (12) ensures that the amount of product *p* shipped from plant *f* to distribution center *d* is within the storage capacity of the distribution center. The constraint Eq. (13) enforces that the amount of collected waste in collection center c should be within its maximum capacity. Likewise, the constraints Eqs. (14) and (15) formulate the capacity limitation for the RC and the distribution centers.

$$VP_{f,p} \leq cappl_{f,p} \quad \forall f \in F, p \in P \tag{11}$$

$$\textstyle\sum_f VFD_{f,d,p} \leq capdc_{d,p} \quad \forall d \in D, p \in P \tag{12}$$

$$\textstyle\sum_m VMC_{m,c,p} \leq capcl_{c,p} \cdot VCB_c \quad \forall c \in C, p \in P \tag{13}$$

$$\textstyle\sum_c VCR_{c,r,p} \leq caprc_{r,p} \cdot VRB_r \quad \forall r \in R, p \in P \tag{14}$$

$$\textstyle\sum_c VCS_{c,s,p} \leq capdp_{s,p} \cdot VSB_s \quad \forall s \in S, p \in P \tag{15}$$

Material flow equilibriums are expressed by constraints Eqs. (16)–(24). Constraints Eqs. (16) and (17) formulate the mass balances of the conversion processes, making product *p* from feedstock *fd* and additive fa, respectively. Eq. (18) shows the same process for the recycled product u, which can be made from the recycled feedstock *fr*. There are two approaches to obtain *fr*, which can be either directly purchased from the market or collected from the reverse logistics. The constraint Eq. (19) enforces that the outflow of product *p* from plant f equals the total inflow of the same product to all the distribution centers. The constraint Eq. (20) ensures that the demand for product *p* in market *m* should be satisfied by the total amount of this product delivered from all the distribution centers to the market. The constraint Eq. (21) balances the flow quantities of product *p* flowing in and out of any distribution center *d*. The constraint Eq. (22) enforces the mass balance of product waste *n* for each collection center *c*, that is, the inflow of *n* collected from all the markets to collection center *c* should be equal to the total outflows from this collection center either to recycling or disposal. The constraint Eq. (23) balances the material quantities in the conversion process of product waste *n* to recycled feedstock *fr* at recycling center *r*. The constraint Eq. (24) defines the overall flow equilibrium of the whole reverse logistics, that is, the total quantities of product waste *n* collected from all the markets (as a portion of total demand) should be equal to the total amount of *n* flowing into all the CC.

$$crm_{fn} \cdot VRM_{f,fn} = VP_{f,n} \quad \forall f,n,fn \tag{16}$$

$$crm_{fa} \cdot VRM_{f,fa} = \textstyle\sum_{p} VP_{f,p} \quad \forall f,fa \tag{17}$$

$$crm_{fr} \cdot VRM_{f,fa} + crm_{fr} \cdot \textstyle\sum_{r} VRF_{r,f,fr} = VP_{f,u} \quad \forall f,u,fa \tag{18}$$

$$VP_{f,p} = \textstyle\sum_{d} VFD_{f,d,p} \quad \forall f,p \tag{19}$$

$$dm_{m,p} = \textstyle\sum_{d} VDM_{d,m,p} \quad \forall m,p \tag{20}$$

$$\textstyle\sum_{f} VFD_{f,d,p} = \sum_{m} VDM_{d,m,p} \quad \forall d,p \tag{21}$$

$$\textstyle\sum_{m} VMC_{m,c,n} = \sum_{r} VCR_{c,r,n} + \sum_{s} VCS_{c,s,n} \quad \forall c,n \tag{22}$$

$$crr_{n,fr} \cdot \textstyle\sum_{c} VCR_{c,r,n} = \sum_{f} VRF_{r,f,fr} \quad \forall r,n,fr \tag{23}$$

$$clr \cdot \textstyle\sum_{m} dm_{m,n} \cdot VRVB = \sum_{m,c} VMC_{m,c,n} \quad \forall n \tag{24}$$

3.2.1.5 Outcome variables

Eqs. (25)–(33) express the calculation of CO_2 emissions (TE) and the associated costs (TEC) for different echelons, namely, feedstock purchase (FDE), manufacturing (MFE), distribution (DTE), transportation (TRE), waste collection (CLE), recycling (RCE), and disposal (DPE).

$$TEC = prc \cdot TE \tag{25}$$

$$TE = FDE + MFE + DTE + TRE + CLE + RCE + DPE \tag{26}$$

$$FDE = \textstyle\sum_{f,fd} emfd_{fd} \cdot VRM_{f,fd} \tag{27}$$

$$MFE = \textstyle\sum_{f,p} empl_{f,p} \cdot VP_{f,p} \tag{28}$$

$$DTE = \textstyle\sum_{d,m,p} emdc_{d,p} \cdot VDM_{d,m,p} \tag{29}$$

$$TRE = emtr \cdot \{\textstyle\sum_{f,d,p}(disfd_{f,d} \cdot VFD_{f,d,p}) + \sum_{d,m,p}(disdm_{d,m} \cdot VDM_{d,m,p}) + \sum_{m,c,p}(dismc_{m,c} \cdot VMC_{m,c,p}) + \sum_{c,r,p}(discr_{c,r} \cdot VCR_{c,r,p}) + \sum_{c,s,p}(discs_{c,s} \cdot VCS_{c,s,p}) + \sum_{r,f}(disrf_{r,f} \cdot VRF_{r,f})\} \tag{30}$$

$$CLE = \textstyle\sum_{m,c,p}(emcl_{c,p} \cdot VMC_{m,c,p} \cdot VCB_{c}) \tag{31}$$

$$RCE = \textstyle\sum_{c,r,p}(emrc_{r,p} \cdot VCR_{c,r,p} \cdot VRB_{r}) \tag{32}$$

$$DPE = \textstyle\sum_{c,s,p}(emdp_{s,p} \cdot VCS_{c,s,p} \cdot VSB_{s}) \tag{33}$$

3.2.2 Two-stage stochastic programming model

Incorporating the random variable of carbon price increases the computation complexity compared to the determinist model. Transforming the stochastic programming model into a two-stage version therefore offers a more efficient approach. As carbon price is the only stochastic variable in this proposed model, we separate the objective function into two parts according to whether the cost terms (CT) contain the variable of CO_2 price (prc), i.e., CT_{nprc} and CT_{prc}. As a result, the first-stage programming problem is dealing with the decision-making when CO_2 price is absent, hence it becomes a deterministic model of the forward logistics in our case. The second stage then decides the investment and operation strategy pertaining to variables affected by CO_2 price uncertainty. Compared to the first-stage deterministic model, the second-stage stochastic programming model assigns a number of samples of prc. Denote the k^{th} ($k \in K$) sample of the stochastic variable prc of as prc_k, the related cost terms become $CT_{prc,k}$, therefore the total cost *z* of the k^{th} sample can be reformulated as:

$$z_k = CT_{nprc} + CT_{prc,k} \tag{34}$$

Decision variables of the second-stage model include $VRM_{f,fd,k}$, $VP_{f,p,k}$, $VFD_{f,d,p,k}$, $VDM_{m,c,p,k}$, $VMC_{d,m,p,k}$, $VCR_{c,r,p,k}$, $VCS_{c,s,p,k}$, $VRF_{r,f,fr,k}$, $VCB_{c,k}$, $VRB_{r,k}$, $VSB_{s,k}$, and $VRVB_k$. The expected total cost $E_{k\in K}(\mathrm{z}_k)$ is equivalent to the sum of the first-stage cost and the expectation of second stage costs of all the samples.

$$min \quad E_{k\in K}(z_k) = CT_{nprc} + \sum_{k\in K}\left(\pi_k \cdot CT_{prc,k}\right) \tag{35}$$

where π_k represents the probability of the k^{th} carbon price sample.

3.3 Modeling CO_2 price uncertainty

We use the time-dependent geometric Brownian motion (GBM) to incorporate CO_2 price fluctuation into the stochastic supply chain model. GBM has been widely used for modeling stochastic price movement, including carbon market prices (Zhou et al., 2014). According to the standard GBM formulation, carbon price variation can be calculated as Eq. (36):

$$dP_t = \mu P_t dt + \sigma P_t dW_t \tag{36}$$

where P_t is the CO_2 price at time t, coefficients μ and σ are both constant in this model which represent the drift and volatility respectively. W_t is a Wiener process (Brownian Motion), and $\mathrm{d}W_t$ is normally distributed with variance $\mathrm{d}t$:

$$dW_t = \varepsilon\sqrt{dt} \tag{37}$$

where ε is a standard normal random number, so Eq. (1) can be reformulated as:

$$dP_t/P_t = \mu dt + \sigma\varepsilon\sqrt{dt} \quad (38)$$

According to the method of Euler-Maruyama Approximation, a discretized form for calculating P_t is given in Eq. (39):

$$P_t = P_0 + \mu P_0 dt + \sigma P_0 \varepsilon\sqrt{dt} \quad (39)$$

To simulate the price movement numerically, some important parameters need to be obtained, including the initial price level P_0, the drift μ and the volatility σ. We use the real historical data of carbon price in the eight carbon trading markets in China (China carbon trading, 2019) to estimate the parameters. Based on the historical information, we set different levels of these parameters to perform scenario analysis with regards to carbon price uncertainty. The scenario settings and parameter estimation are described in detail in Section 4.

3.4 Data collection and parameter assumptions

The supply chain background of this decision-making problem is in Zhejiang province, China. This province comprises 11 prefectural-level municipalities with different population sizes, economic development levels, and plastic demands. The forward logistics include three plants, five distribution centers, and 11 prefectural-level markets. The assumptions on capacity and establishment costs for the plants and the distribution centers are made according to the plastic industry data in Zhejiang (China Plastic Processing Industry Association, 2018). Table 2 and Table 3 present these assumptions for the forward and reverse logistics respectively.

Table 2 Assumptions on capacities and establishment costs of plants and distribution centers

	Capacity (ton/yr)		Establishment cost (yuan)
	Product A	Product B	
Plant 1	20,000	6,000	30,000,000
Plant 2	30,000	10,000	40,000,000
Plant 3	15,000	5,000	28,000,000
Distribution center 1	15,000		4,500,000
Distribution center 2	25,000		6,700,000
Distribution center 3	25,000		6,700,000
Distribution center 4	35,000		8,200,000
Distribution center 5	15,000		4,500,000

Table 3 Assumptions on capacities and establishment costs for the reverse logistics

	Capacity (ton/yr)	Establishment cost (ton)

Collection center 1	5,500	7,500,000
Collection center 2	5,500	7,500,000
Collection center 3	5,000	7,000,000
Collection center 4	5,000	7,000,000
Collection center 5	4,500	6,500,000
Collection center 6	4,500	6,500,000
Collection center 7	4,500	6,500,000
Recycling center 1	6,000	12,000,000
Recycling center 2	6,000	12,000,000
Recycling center 3	5,000	11,000,000
Recycling center 4	4,000	10,000,000
Recycling center 5	4,000	10,000,000
Disposal center 1	12,000	21,000,000
Disposal center 2	10,000	19,000,000

The assumptions on the prices of feedstocks and products are made by estimation on averaged plastic price levels through the last five years (Wind Data Service, 2019). The price of the virgin feedstock is relatively higher than that of the recycled feedstock. As a result, product A made from the virgin feedstock also has higher costs than the recycled product B. Regarding CO_2 price, a detailed explanation of setting scenarios to reflect the price uncertainty in the model is presented in Section 4, hence is not discussed here.

Table 4 Price assumptions for feedstocks, products and CO_2 emissions allowances

	Price (yuan/ton)
Virgin feedstock	8,500
Recycled feedstock	6,000
Additive	13,000
Product A	12,000
Product B	8,000

The potential locations of all the facilities in the forward logistics (the red shapes) and the potential locations of the CC, RC, and disposal centers in the reverse logistics (the blue shapes) were obtained by communication with local industry experts (Fig. 2). The purpose of the whole supply chain is to provide PE products for the 11 prefecture markets. We use Geocoder API and Direction API from Baidu Maps to obtain the road distance data and the latitude and longitude data for each facility in the geographic coordinate system of Zhejiang province.

As the purchasing costs of feedstocks are influenced by the carbon price uncertainty, the strategic problem regarding whether the reverse logistics should be established is determined by the proposed model. Moreover, the model determines the optimum number and locations of the collection, recycling, and disposal centers, and the flow between each facility. The obstacle in modeling such a decision-making problem is representing carbon price uncertainty in the model. To overcome this problem, a scenario-based model is developed considering seven scenarios of carbon price levels (Table 4). Scenario 1 is zero carbon price and represents the cases of the absence of such a carbon market or the exemption of the LDPE production from attending the carbon market. Scenarios 2–7 reflect the market conditions with ascending price levels.

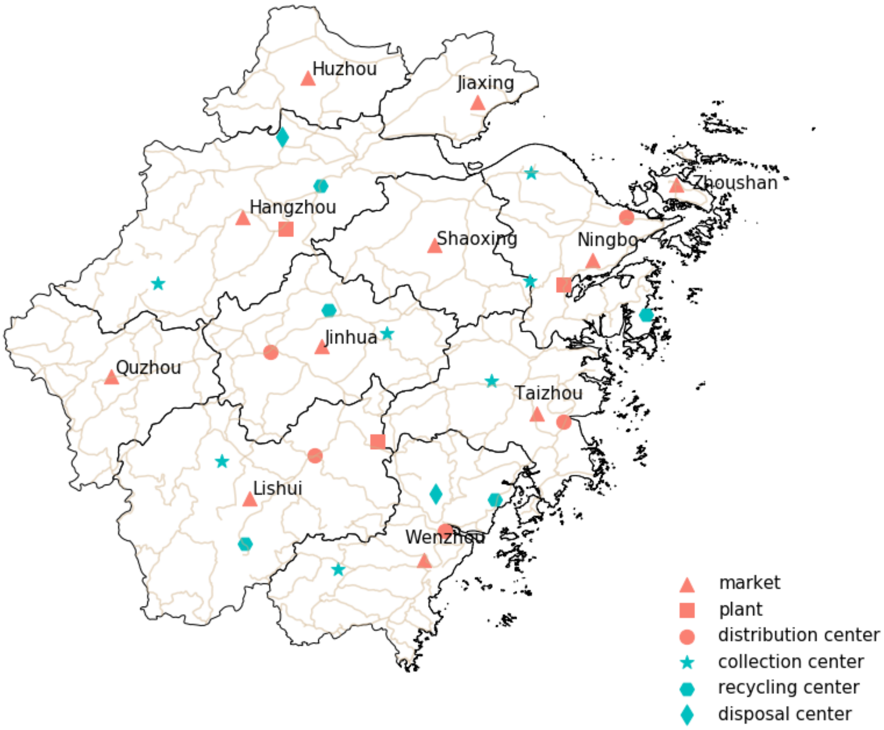

Fig. 2 Locations of the facilities in the whole supply chain.

4. Scenario settings for carbon price uncertainty

4.1 Carbon prices in the pilot markets

For investigating carbon price uncertainty, we complied historical data of carbon prices from the eight pilot markets, namely, Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Hubei, Chongqing and Fujian, shown in Fig.3. The data source is from the online database of (China carbon trading, 2019). Zhejiang, where our case study is located, has no such market pilot. Nevertheless, the major carbon-intensive industries in Zhejiang, and in other provinces as well, are expected to be subject to the nation-wide carbon market gradually in years.

Note that as each market started at different time, timespan of the data is not the same across these markets. Shenzhen is the first market pilot in China dating back to June, 2013, therefore it has relatively complete price data. Fujian, on the contrary, established in December of 2016, has the shortest history and the smallest number of the time-series data. For some months, the data is not available for some markets, thus each market may not necessarily have the fully continuous historical data. Panel B of Fig. 3 displays the statistics of these data as boxplots, presenting information of minimum, median, maximum, interquartile range (IQR) from the 25th (Q1) to the 75th percentile (Q3), and outliers (Q1-1.5·IQR, and Q3+1.5·IQR). From these statistics, it is observed that the eight markets show remarkably different patterns of price movement. Beijing and Chongqing have the highest and the lowest levels of carbon price, respectively.

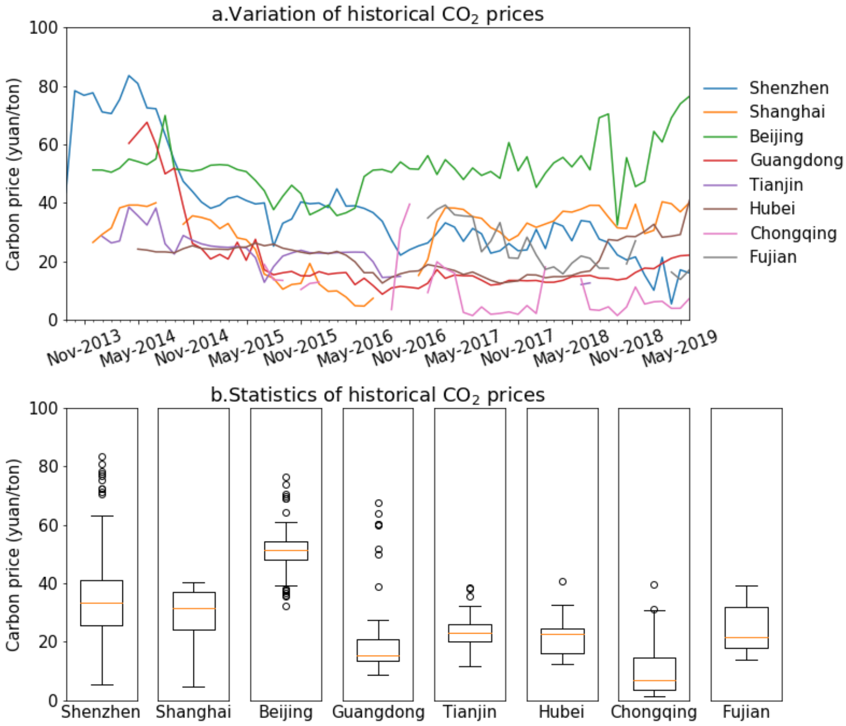

Fig. 3 Historical variation and statistics of CO_2 prices in the eight pilot markets.

4.2 Scenario settings and parameter estimation

We estimated the key parameters for the GBM model of CO_2 prices from historical data. To reflect a full picture of CO_2 price movement in the future, we combined GBM simulations with scenario analysis. This part of work was conducted in the following steps:

Step 1: Estimate the parameters for carbon prices in each market, from which we obtained eight sets of the drift parameter μ and the volatility parameter σ. Unsurprisingly, these resulted parameters vary significantly among the eight markets.

Step 2: Simulate future price movement for each market by the GBM model with the estimated μ and σ. The number of time steps is 50 months, or approximately 4 years, and the number of simulations is 1000 times.

Step 3: Calculate the parameters of the price distribution obtained by simulations for each market, which include the expectation and standard deviation.

Step 4: Design six scenarios by identifying three levels of expectation (low, medium, high) and two levels of standard deviation (small and large). The different levels of price expectation and standard deviation reflect different speed rates of how fast the price increases and different magnitudes of the price volatility, respectively. A detailed description of these scenarios and the associated parameters are provided in Table 5.

Step 5: The average price in the last entry of the historical data in the eight markets, which is 31.8 yuan/ton, was taken as the uniform starting price level for our simulation of future price movement in the expected nation-wide carbon market. As such the distribution of prices in each scenario was obtained, shown in Fig. 4.

Table 5 Scenario description and parameters

Scenario	Description	Expectation	Standard deviation
LS-SV	Low speed of price increase, small volatility	35.07	7.22
LS-LV	Low speed of price increase, large volatility	35.74	18.99
MS-SV	Medium speed of price increase, small volatility	134.09	29.12
MS-LV	Medium speed of price increase, large volatility	129.51	68.08
HS-SV	High speed of price increase, small volatility	328.80	68.53
HS-LV	High speed of price increase, large volatility	322.06	173.79

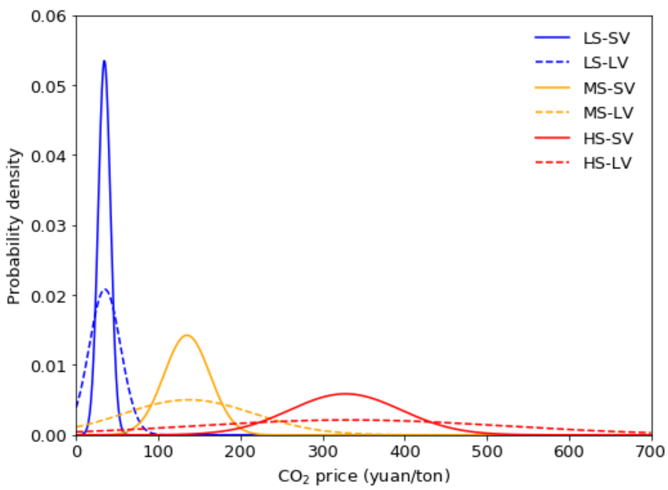

Fig. 4 Simulations of CO_2 prices in the six scenarios

5. Results and analysis

5.1 Comparison of outcome variable distribution across scenarios

We selected four metrics from the outcome variables of the stochastic programing model, namely, total cost, profit, total emissions of CO_2 and total cost of CO_2 emissions, to make comparison across the six scenarios (see Fig. 5). In these violin graphs, the short lines on the top and bottom represent the extreme values at the two ends, and the short lines in the middle show the mean values, or the expectation values of the metrics. The results illustrate that higher expected carbon price increases the total cost and the cost of CO_2 emissions alike, which in turn, reduces the profit of the supply chain. For all the three metrics other than CO_2 emissions, the expected value is equal in the two paired scenarios with the same expected value of CO_2 price (e.g. LS-SV and LS-LV), but the variation (indicated by standard derivation) is much more significant in the scenarios with larger carbon price volatility (the '-LV' group scenarios).

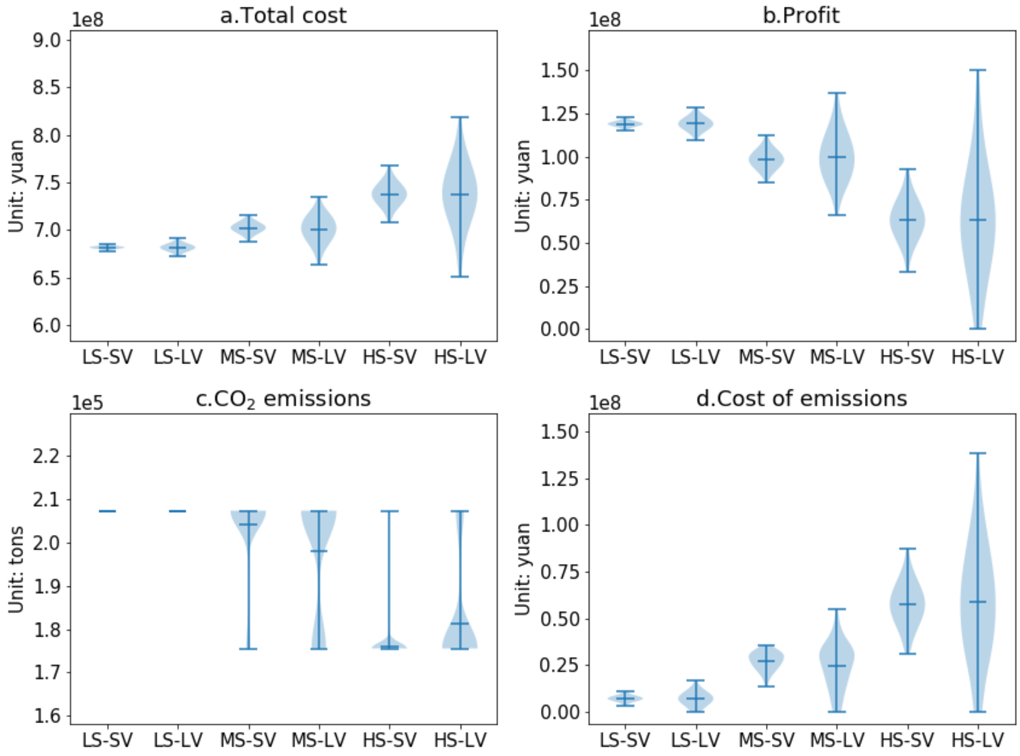

Fig. 5 Distributions of selected outcome variables across the six scenarios.

These scenarios display interesting results of CO_2 emissions. CO_2 emissions are the highest in LS-SV and LS-LV, the two scenarios with the lowest carbon price expectation, as the expected prices are too low to trigger installation of the reverse logistics, regardless of the price volatility. However, in the other four scenarios where the carbon price reaches a relatively high level, there are divergent possibilities of the reverse logistics installation, depending on the price distribution. The probability varies greatly across these four scenarios (see Table 6). We draw an interesting finding here that, scenarios with smaller carbon price volatility (i.e. MS-SV and HS-SV) have higher certainty regarding the decision-making of whether to build the reverse logistics. That is, the reverse supply chain is more likely to be built in HS-SV than in HS-LV. Likewise, there is higher possibility to not build the reverse logistics in MS-SV than in MS-LV. This also explains the difference of the expected CO_2 emissions in the paired scenarios shown in Panel (c) of Fig.5. Speculation in financial market can increase liquidity to some degree, but excessive speculation somehow causes hesitation of long-term investments in the market. This is especially true in the carbon market. Our results illustrate that lowering uncertainty of CO_2 price would facilitate the decision-making of low-carbon investment by delivering clearer message to industrial stakeholders. Thus, managing market expectation and maintaining a relatively lower volatility is essential to the operations of industrial stakeholders, who are mainly the long-term players in carbon markets.

Table 6 Probability of establishing the reversed logistics across the six scenarios

Scenario	Probability
LS-SV	0
LS-LV	0
MS-SV	0.10
MS-LV	0.29
HS-SV	0.99
HS-LV	0.82

5.2 Impacts on the CLSC establishment

Our results demonstrate the direct impacts of the carbon price variation on the decision-making of the CLSC. Figs. 6 and 7 present the results of the two scenarios with low and high carbon price, respectively. The reverse logistics are ruled out in the low price scenario (LS-SV), as shown in Fig. 6. The demands of the four markets in the west, that is, Huzhou, Hangzhou, Quzhou, and Jinhua, can be satisfied solely by Plant1 and DC2. The other seven markets are covered by the remaining DCs with the supply from Plants 2 and 3. Jiaxing, the northernmost market, receives products from DC4 rather than DC1, which is much closer because the capacity of DC1 can satisfy the demands of only two neighboring markets, Ningbo and Zhoushan.

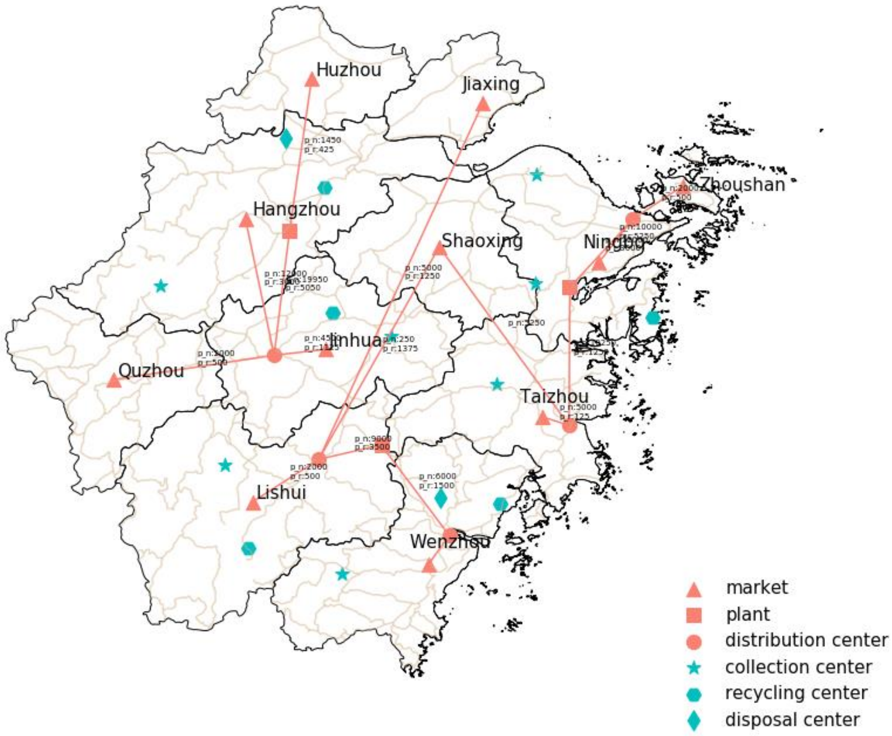

Fig. 6 Configuration and product flows of the supply chain in LS-SV.

The configuration and product flows are completely changed in HS-SV with its high carbon price, shown in Fig. 7. This scenario, in which the expected carbon price reaches above 320 yuan/ton, features established reserves logistics, represented by the green shapes and lines in the figure. Among the facilities in the reverse flow, CC1, 3, 5, 6, and 7 are selected out of the seven potential collection center sites, and RC1, 2, 4, and 5 are determined from the five options as the recycling centers by the model. The displayed landscape indicates that by and large the more central the centers are located, the more likely they can be selected. This is because of the reduced transportation costs from shorter distances between these centers, plants and markets. By contrast, remote sites tend to be neglected by the model, such as CC4 and RC3, or selected only for waste disposal, such as CC7. The flows in the forward chains of the high carbon price scenario are also remarkably different from those in LS-SV. For example, the two markets in the north, Jiaxing and Huzhou, are enabled to diversify their supply from different distribution centers.

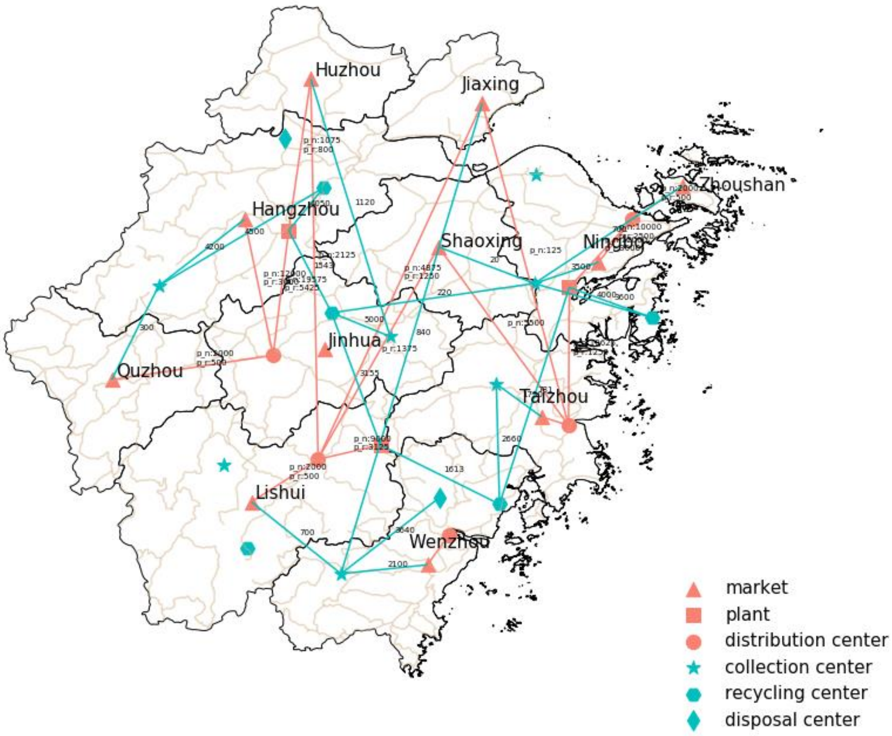

Fig. 7 Configuration and product flows of the CLSC in HS-SV.

5.3 Impacts on emissions and costs

The results indicate that carbon price variation places significant impacts on the costs and CO_2 emissions of the supply chain. Fig. 8 shows how the relation of the supply chain cost and CO_2 emissions change across the seven scenarios, in which the blue lines represent the total and the orange lines represent the costs and emissions associated with feedstock purchase. Notably, the total emissions in this calculation consist of two components, that is, the life cycle emissions of feedstock, and the emissions from manufacturing, distribution, and transportation of the products. Therefore, the gap between the total emissions and the life cycle emissions of feedstock in each scenario denote the emissions associated with the processes of manufacturing, distribution, and transportation in the whole supply chain.

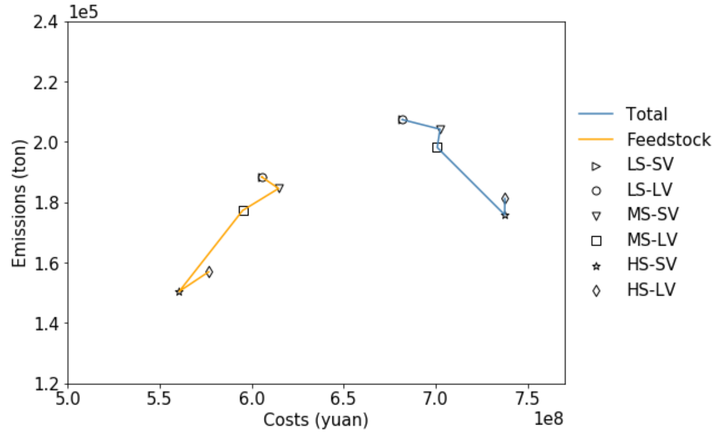

Fig. 8 Expected costs and CO_2 emissions across the six scenarios.

Note that the scenario LS-SV overlaps with LS-LV as these two scenarios have very close expected costs and emissions. These remain nearly unchanged because the establishment of reverse logistics is not triggered when the carbon price is too low; and the increased price volatility exerts no effect. The threshold of carbon price enabling the reverse supply chain is between 150 and 200 yuan/ton, observed from the simulation results of MS-SV and MS-LV.

With the possibility of closing the loop increased, the total emissions decline by approximately 15% from 207.4 thousand tons (kt) in LS-SV to 175.9 kt in HS-SV, and rise again to 181.2 kt in HS-LV. The life cycle emissions from PE feedstock production decrease from 188.4 kt in LS-SV to 150.5 kt in HS-SV, with a higher reduction rate of approximately 20%. The establishment of reverse logistics saves the feedstock associated emissions by reducing the purchased feedstock amount, which also decreases the purchase costs of feedstock remarkably. However, this cost reduction is offset by the establishment cost of the reverse supply chain, leading to a slight increase in the total cost.

The breakdown of the total cost provides details regarding the contributions from each cost component to the overall change across these scenarios (Fig. 9). In the waterfall graph, the total costs of the whole supply chain are divided into four components, namely, feedstock purchase, production and distribution, transportation, and the costs associated with reverse logistics establishment. The increase in the total cost from LS-SV to MS-SV is mainly caused by the change in feedstock purchase cost, accounting for approximately 90% of the total increase, whereas the contributions from production and distribution are much smaller, and those from transportation are almost negligible. In the established closed-loop case, however, the TRCs increase because of the extra shipment incurred by the collection, recycling, and disposal processes of the reverse logistics. The most notable change, however, is the reduced costs of feedstock purchase, which largely offset the extra costs for the establishment and operation of the reverse supply chain.

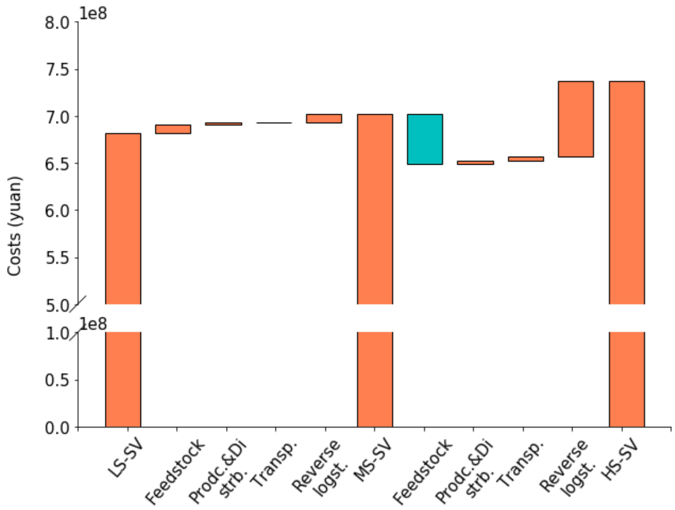

Fig. 9 Contributions of cost components in the change of total costs between scenarios.

6. Conclusions and discussion

This study deals with the important decision-making problem regarding how the carbon price uncertainty affects establishment of the reverse logistics, the costs, emissions, choices of facility locations and the landscape of product flows in the targeted plastic supply chain. To do so, a two-stage stochastic mixed integer programming model is constructed and coupled with a geometric Brownian motion model for simulating carbon price variation. A case study of the PE plastic supply chain in Zhejiang province is performed by integrating scenario analysis into this GIS-based CLSC modeling framework. Key findings from this study are listed as follows:

- Installation of reverse supply chain can be triggered in the scenarios with carbon price above approximately a level at 150-200 yuan/ton. In the scenarios with high CO_2 price expectation, large price volatility tends to lower the probability of reverse logistics establishment, thus increases the expected emissions. At the same carbon price expectation, it is easier to decide whether or not to build the reverse logistics when the market volatility is low, which facilitates the decision-making of low-carbon investment by delivering clearer message to stakeholders.
- The impacts of the carbon market on the PE plastic supply chain are mainly conveyed through an indirect manner, for example, the direct emissions from the manufacturing, distribution, and transportation process in the supply chain are significantly lower than those life cycle emissions in the PE feedstock production process. Thus, the change of feedstock cost caused by carbon price variation takes effect on the decisions of the supply chain design of the downstream sectors.
- The establishment of the CLSC completely changes the configuration and flows of the entire supply chain. Regarding choices of the facility locations in the reverse logistics, the more central

the centers' location, the more likely they can be selected. This phenomenon occurs because of the reduced transportation costs attributed to shorter distances from these centers to plants and markets.

· In the scenarios where the reverse chain is absent, the increase in carbon price leads to a rigid increase of the total costs, mainly contributed by the additional costs for CO_2 emissions embedded in a feedstock purchase. However, with the CLSC established, the reduced cost of feedstock purchase offsets to a large extent the extra costs incurred by the establishment and operation of the reverse logistics. In aggregation, the total costs increase modestly, but the total emissions decline significantly.

Closing the loop of the plastic supply chain results in additional investments and extra operation costs for the reverse logistics. Without external financial stimulus, these increased costs may create barriers for the investors to conduct decarbonization strategies (Zhou et al., 2019). The carbon market provides the necessary stimulus that may prompt the investors to construct the CLSC. However, a sound market condition is desired to reach the optimal balance that can provide strong price signal but avoid excessive speculation.

Our results show that maintaining a relatively lower volatility of carbon market is essential to the investment decision-making of industrial stakeholders, the main long-term participants in carbon markets, into low-carbon supply chains. Although many measures are currently available to manage the absolute level of carbon price, such as auctioning or floor price, the measures for stabilizing the price fluctuation shall also be emphasized. Lessons should be learnt from other carbon trading markets. For instance, market stability reserve (MSR) began operating in January 2019 in the European Union Emissions Trading Scheme (EU ETS). The reserve addresses the current surplus of allowances and improves the system's resilience to major shocks by adjusting the supply of allowances to be auctioned. The national carbon market being established in China is therefore recommended to introduce this kind of mechanisms as well.

By developing this analytical framework, our study offers decision support for incorporating carbon price uncertainty into the CLSC design and management problems. The framework can be easily applied to other sectors with similar characteristics and is therefore useful for industrial stakeholders and policymakers. Additionally, other crucial elements could be further considered, for example, some critical factors, such as uncertainty on the demand side, the stochastic variation of product market, as well as the interactions between carbon market and feedstock market could be investigated in future research.

Acknowledgements

The authors thank the financial support from the National Natural Science Foundation of China (71961137012, 71571069, 71704055 ,71874055), the National Social Science Fund of China (19BGL273) and the Scientific Project of Hunan Province of China (2013RS4051).

References

Allevi, E., Gnudi, A., Konnov, I. and Oggioni, G. (2018). Evaluating the effects of environmental regulations on a closed-loop supply chain network: A variational inequality approach. *Annals of Operations Research* 261(1-2): 1-43.
Barra, R. and Leonard, S. A. (2018). Plastics and the Circular Economy - a STAP document.
China carbon trading. (2019). "Market data of carbon trading in China." from http://www.tanpaifang.com/.
China Chemical Industry Information Center (2016). China Chemical Industry Yearbook.
China Plastic Processing Industry Association2018. China Plastic Industry Yearbook.
Choudhary, A., Sarkar, S., Settur, S. and Tiwari, M. K. (2015). A carbon market sensitive optimization model for integrated forward–reverse logistics. *International Journal of Production Economics* 164: 433-444.
Diabat, A., Abdallah, T., Al-Refaie, A., Svetinovic, D. and Govindan, K. (2013). Strategic Closed-Loop Facility Location Problem With Carbon Market Trading. *IEEE Transactions on Engineering Management* 60(2): 398-408.
Fahimnia, B., Sarkis, J., Choudhary, A. and Eshragh, A. (2015). Tactical supply chain planning under a carbon tax policy scheme: A case study. *International Journal of Production Economics* 164: 206-215.
Fahimnia, B., Sarkis, J., Dehghanian, F., Banihashemi, N. and Rahman, S. (2013). The impact of carbon pricing on a closed-loop supply chain: an Australian case study. *Journal of Cleaner Production* 59: 210-225.
Gaur, J., Amini, M. and Rao, A. (2017). Closed-loop supply chain configuration for new and reconditioned products: An integrated optimization model. *Omega* 66: 212-223.
Genovese, A., Acquaye, A. A., Figueroa, A. and Koh, S. L. (2017). Sustainable supply chain management and the transition towards a circular economy: Evidence and some applications. *Omega* 66: 344-357.
Ghelichi, Z., Saidi-Mehrabad, M. and Pishvaee, M. S. (2018). A stochastic programming approach toward optimal design and planning of an integrated green biodiesel supply chain network under uncertainty: A case study. *Energy* 156: 661-687.
Guo, J., Wang, X., Fan, S. and Gen, M. (2017). Forward and reverse logistics network and route planning under the environment of low-carbon emissions: A case study of Shanghai fresh food E-commerce enterprises. *Computers & Industrial Engineering* 106: 351-360.
Han, S., Jiang, Y., Zhao, L., Leung, S. C. and Luo, Z. (2017). Weight reduction technology and supply chain network design under carbon emission restriction. *Annals of Operations Research*: 1-24.
Jambeck, J. R., Geyer, R., Wilcox, C., Siegler, T. R., Perryman, M., Andrady, A., Narayan, R. and Law, K. L. (2015). Plastic waste inputs from land into the ocean. *Science* 347(6223): 768-771.
Liotta, G., Stecca, G. and Kaihara, T. (2015). Optimisation of freight flows and sourcing in sustainable production and transportation networks. *International Journal of Production Economics* 164: 351-365.
Liu, X., Chen, D., Zhang, W., Qin, W., Zhou, W., Qiu, T. and Zhu, B. (2013). An assessment of the energy-saving potential in China's petroleum refining industry from a technical perspective. *Energy* 59: 38-49.
Martí, J. M. C., Tancrez, J.-S. and Seifert, R. W. (2015). Carbon footprint and responsiveness trade-offs in supply chain network design. *International Journal of Production Economics* 166: 129-142.

Paksoy, T. and Özceylan, E. (2014). Environmentally conscious optimization of supply chain networks. *Journal of the Operational Research Society* 65(6): 855-872.
Peng, Y., Ablanedo-Rosas, J. H. and Fu, P. (2016). A multiperiod supply chain network design considering carbon emissions. *Mathematical Problems in Engineering* 2016.
PlasticsEurope (2018). Plastics – The facts 2018. An analysis of European plastics production, demand and waste data. .
Ren, H., Zhou, W., Makowski, M., Yan, H., Yu, Y. and Ma, T. (2019). Incorporation of life cycle emissions and carbon price uncertainty into the supply chain network management of PVC production. *Annals of Operations Research*.
Rezaee, A., Dehghanian, F., Fahimnia, B. and Beamon, B. (2017). Green supply chain network design with stochastic demand and carbon price. *Annals of Operations Research* 250(2): 463-485.
Shaw, K., Irfan, M., Shankar, R. and Yadav, S. S. (2016). Low carbon chance constrained supply chain network design problem: a Benders decomposition based approach. *Computers & Industrial Engineering* 98: 483-497.
Tseng, M.-L., Islam, M. S., Karia, N., Fauzi, F. A. and Afrin, S. (2019). A literature review on green supply chain management: Trends and future challenges. *Resources, Conservation and Recycling* 141: 145-162.
Verma, R., Vinoda, K. S., Papireddy, M. and Gowda, A. N. S. (2016). Toxic Pollutants from Plastic Waste- A Review. *Procedia Environmental Sciences* 35: 701-708.
Waltho, C., Elhedhli, S. and Gzara, F. (2018). Green supply chain network design: A review focused on policy adoption and emission quantification. *International Journal of Production Economics*.
Wind Data Service (2019). Wind Database.
Yang, J., Guo, J. and Ma, S. (2016). Low-carbon city logistics distribution network design with resource deployment. *Journal of Cleaner Production* 119: 223-228.
Zakeri, A., Dehghanian, F., Fahimnia, B. and Sarkis, J. (2015). Carbon pricing versus emissions trading: A supply chain planning perspective. *International Journal of Production Economics* 164: 197-205.
Zhang, S., Ren, H., Zhou, W., Yu, Y. and Chen, C. (2018). Assessing air pollution abatement co-benefits of energy efficiency improvement in cement industry: A city level analysis. *Journal of Cleaner Production* 185: 761-771.
Zhou, W., Jiang, D., Chen, D., Griffy-Brown, C., Jin, Y. and Zhu, B. (2016). Capturing CO_2 from cement plants: A priority for reducing CO_2 emissions in China. *Energy* 106: 464-474.
Zhou, W., McCollum, D., Fricko, O., Gidden, M., Huppmann, D., Krey, V. and Riahi, K. J. E. R. L. (2019). A comparison of low carbon investment needs between China and Europe in stringent climate policy scenarios.
Zhou, W., Zhu, B., Chen, D., Zhao, F. and Fei, W. (2011). Technoeconomic assessment of China's indirect coal liquefaction projects with different CO_2 capture alternatives. *Energy* 36(11): 6559-6566.
Zhou, W., Zhu, B., Chen, D., Zhao, F. and Fei, W. (2014). How policy choice affects investment in low-carbon technology: The case of CO_2 capture in indirect coal liquefaction in China. *Energy* 73: 670-679.
Zhu, B., Zhou, W., Hu, S., Li, Q., Griffy-Brown, C. and Jin, Y. (2010). CO_2 emissions and reduction potential in China's chemical industry. *Energy* 35(12): 4663-4670.