TRANSPORT
ISSN 1648-4142 / eISSN 1648-3480
2018 Volume 33 Issue 3: 707–717
https://doi.org/10.3846/transport.2018.1579

MODELLING THE IMPACTS OF UNCERTAIN CARBON TAX POLICY ON MARITIME FLEET MIX STRATEGY AND CARBON MITIGATION

Mo ZHU[1], Michael CHEN[2], Murat KRISTAL[3]

[1]*College of Transportation and Communication, Shanghai Maritime University, China*
[2]*Dept of Mathematics and Statistics, York University, Toronto, Canada*
[3]*Schulich School of Business, York University, Toronto, Canada*

Received 13 September 2015; revised 30 January 2016, 8 March 2016; accepted 4 April 2016

Abstract. The maritime transport industry continues to draw international attention on significant Greenhouse Gas emissions. The introduction of emissions taxes aims to control and reduce emissions. The uncertainty of carbon tax policy affects shipping companies' fleet planning and increases costs. We formulate the fleet planning problem under carbon tax policy uncertainty a multi-stage stochastic integer-programming model for the liner shipping companies. We develop a scenario tree to represent the structure of the carbon tax stochastic dynamics, and seek the optimal planning, which is adaptive to the policy uncertainty. Non-anticipativity constraint is applied to ensure the feasibility of the decisions in the dynamic environment. For the sake of comparison, the Perfect Information (PI) model is introduced as well. Based on a liner shipping application of our model, we find that under the policy uncertainty, companies charter more ships when exposed to high carbon tax risk, and spend more on fleet operation; meanwhile the CO_2 emission volume will be reduced.

Keywords: carbon emission, carbon tax, policy uncertainty, maritime shipping, fleet mix strategy, stochastic programming.

Notations and variables

Sets:

$\mathcal{A}$ – set of container ship types;
$\mathcal{R}$ – set of liner trade routes;
$\mathcal{L}_r$ – set of legs in route r;
$\mathcal{S}$ – set of carbon tax scenarios.

Parameters:

α_i^t – chartering fee of ship type i for whole period t [USD/ship];
ϵ_{ir}^t – variable voyage costs of ship type i in period t on route r (e.g., fuel expenses, port charges, container handling fees) [USD/voyage/ship];
η_{ir}^t – fixed voyage costs of ship type i in period t on route r (e.g., crew salaries, maintenance expenses, ship insurance) [USD/voyage/ship];
ψ_i^t – laying-up costs of ship type i for whole period t [USD/ship];
φ^t – CO_2 emissions tax in period t [USD/ton];
μ – capital discount rate during planning horizon;
κ_i – carrying capacity of ship type i [Twenty foot Equivalent Unit (TEU)/per ship];
E_i^0 – number of ships type i existing in the fleet at the beginning of planning horizon;
ρ_{rl}^t – container demands on leg l of route r in period t [TEU];
γ_r^t – voyage interval required by market on route r in period t [days];
β_{ir} – convention factor for CO_2 emissions of ship type i;
υ_{ir}^t – number of voyages that can be completed per ship type i on route r in period t;
Δt – duration of period t;
ϖ^t – available capital for chartering in period t [USD];
ζ_i^t – capacity available for chartering of ship type i in period t [TEU];
ξ_i^t – available number of ships type i in shipping market in period t.

Variables:

E_i^t – number of available ships type i at the beginning of period t;
W_{ir}^t – number of ships type i assigned to route r in period t;
U_i^t – number of laid-up ships type i in period t;

*Corresponding author. E-mails: *mozhu@shmtu.edu.cn, momozhu2014@163.com*

Q_{irl}^{t} – number of containers transported by ship type i assigned to route r in leg l during period t per ship;

I_{ip}^{t} – number of ships type i chartered-in for duration p at the beginning of period t.

1. Introduction

Around 80% of global goods by volume are carried by ships and handled by ports (UNCTAD 2013). Since the global economic depression began in 2008, maritime shipping companies have faced a more complicated financial market and been concerned more over climate change by international community.

By far, CO_2 is the most abundant Greenhouse Gas (GHG), and also the most problematic from an environmental standpoint. Though shipping is more CO_2 efficient than other transportation modes, emissions from ships do contribute to climate change. In 2007, CO_2 from shipping represented 3.3% of global emissions (IMO 2009). The emissions could grow 1.9…5.2% by 2050 if there is no action taken and the regulatory control is one of these possible actions, but not the only one (Lee *et al.* 2013).

Various market-based measures could mitigate emission levels, including: (1) applying a tax or required contribution against all CO_2 emissions; (2) developing emissions trading systems for ships; and (3) establishing schemes based on a ship's actual efficiency (IMO 2009). With regards to the first measure – regulators could fix tax rates for the industry, and emissions would decrease according to ship operators' responses to their increased tax burden (Franc, Sutto 2014). On the other hand, this would introduce greater financial burden on ship operators.

Yet, environmental concerns must necessarily come into play in fleet management decision-making, as inevitably, profits are affected by regulatory uncertainty – especially uncertainty brought about by climate change activism. One possible solution is *chartering* – a tactic that improves a company's ability to manage uncertain business factors, as risks tied to vessel ownership are transferred to charter-owners (Cariou, Wolff 2013; Mason, Nair 2013).

This paper investigates optimal maritime fleet mix strategy made under carbon tax uncertainty. A multi-period integer Stochastic Programming (SP) is established to model the fleet planning decisions, and a scenario tree is employed to describe carbon taxation and price uncertainty; this is important, because simple predictions cannot reflect the dimensional structure of variable carbon taxes, especially as they relate to future business strategies. A numerical experiment based on a real-world case in liner shipping is designed to analyse the impact of carbon tax uncertainty on fleet mix decisions, costs and CO_2 emissions. In the experiment, several carbon tax risk levels which indicate different chances of getting a high carbon tax are incorporated.

1.1. Literature review

In the last decade, various deterministic models have been developed to investigate fleet strategy (Mason, Nair 2013; Bang *et al.* 2012; Fagerholt *et al.* 2009; Meng *et al.* 2015). However, these models have been unable to fully manage uncertainty factors.

Instead, some researchers have proposed dynamic and SP tools that are more effective at modelling problems with uncertainty: Bakkehaug *et al.* (2014) develop a general SP model to handle fleet planning based on variable freight rates and shipping demand. The resulting formulation significantly improves fleet renewal decisions when compared to traditional deterministic programming. Yu (2009) also evaluates fleet planning using mixed-integer SP, where unstable shipping demand is described by a scenario tree and a branch and price framework. Meng and Wang (2010) employ a chance constraint programming model, where variable cargo demand is represented by normal distribution. Meng and Wang (2011) then extend their research using a scenario tree and integer linear programming that solve the dynamic model by a shortest path algorithm. However, Meng and Wang (2011) use pre-determined values for chartering, buying, selling, and keeping in each period, while we treat them as important decision variables of the fleet planning problem.

For the researches focusing on the market-based mechanisms that can promote industries to reduce emission, Kim *et al.* (2013) conclude that carbon taxation is a more effective constraint than emissions for optimizing speed and fleet size according to their case study. Conversely, He *et al.* (2012) claims that there is no winner between carbon tax and emission trading system, as policies show their relative advantages and disadvantages with respect to different criteria. As the emission reduction mechanism has not been determined, which mechanism has better effect on mitigation is still in dispute. However, International Chamber of Shipping (ICS 2009) worries that maritime shipping is expected to be a long-term buyer of carbon allowances or credits, irrespective of whether the market-based instrument adopted is an emission-trading concept or a tax scheme.

Regarding studies on carbon tax uncertainty, Avi-Yonah and Uhlmann (2009) argue that once taxation is in place, it is usually not so hard to raise its rate despite oppositions to tax hikes. Ramseur and Parker (2010) conclude that policymakers could devise a tax program that yields short-term emission fluctuations, and one of the disadvantages of a carbon tax is that it would yield uncertain emissions.

The emission reduction mechanism and its potential impact is affected by many factors, that is why no comprehensive tax policy has been so far used or seriously contemplated widely (Strand 2013). For example, if the centralized agency is fully informed about the emissions and abatement costs of all parties, setting emission price and mitigation levels are a straightforward task. Unfortunately, parties prefer to keep the information private and the costs of emission reductions remain unknown (Ermolieva *et al.* 2010). Another important factor is fuel price, Hammoudeh *et al.* (2014) conclude that an increase in the crude oil price generates a substantial drop in the carbon prices when the latter is very high; in spite of their study focuses on emission trading allowance price, their conclusion may indicate that along with the rising of fuel price, emitters may require fewer allowances as they emit less.

As the potential impact of emission reduction mechanism is sophisticated, it is meaningful to do research on this topic. Our paper suggests an SP model to accommodate multi-period fleet planning under carbon tax uncertainty. Uncertainty is outlined as a scenario tree, which requires uniform decision structure to maintain risk neutrality (King, Wallace 2012). Improving upon models proposed by Bakkehaug *et al.* (2014) and Kim *et al.* (2013), we introduce non-anticipativity constraints in order to achieve uniform the decision steps and carbon tax scenarios, and consider carbon taxation and price uncertainty in terms of implementation time and magnitude. We aim to develop a practical model that can help managers coping with uncertain carbon tax factors when making fleet mix decision first; and further study the impact of carbon tax on fleet mix strategy and carbon mitigation.

1.2. Problem description

Fleet planning involves two important aspects: (1) fleet size and mix problem, which determines the size and number of ships, and requires strategic oversight on ship purchasing, selling, chartering, and scrapping; and (2) fleet deployment, which includes ship routing based on demand (Pantuso *et al.* 2014). As this paper focuses on fleet mix strategy, ships' routing and demand is assumed to be predictable, which is used to support the fleet size. A fleet can increase its capacity by purchasing ships, but this requires large amounts of capital and a view of the company's long-term strategic prospects. By comparison, chartering is a more agile option, because it offers flexible contract periods and lower capital investments than owning a vessel outright.

In order to highlight chartering decisions under carbon tax uncertainty, this paper limits fleet planning to short-term, where increased fleet capacity can be achieved only through chartering. As suggested by Bakkehaug *et al.* (2014), it is more significant to describe near-term uncertainty with fleet planning than in distant periods. There are several business modes in shipping practice, e.g. liner shipping, tramp shipping; each one has different operation characteristics. Here we focus on liner shipping, one of the main modern transportation methods for containerized cargoes. Liner shipping is defined as a fleet that operates according to a published itinerary between fixed ports.

The company makes its fleet-planning decisions at the start of each period, as realizations of carbon taxes are revealed. Only the carbon tax is uncertain in our fleet planning problem, and other operational factors are known or can be predicted. In order to minimize operational costs, the company needs to adjust fleet capacity based on their specific business environment and CO_2 emissions taxation realizations. Note that chartered vessels can only be redelivered or idle when there is temporary overcapacity; subletting and chartering out is not allowed here for the short-term consideration.

1.3. Assumptions

Multi-period fleet planning includes consecutive single plans with t periods, as $t = 1, 2, \ldots, N$. Here we take the length of one year, so the planning horizon includes t years. Vessels can be charted in at the beginning of each period, but returned only at the end of a period to comply with shipping practices. The shortest chartering period is set to one year and the longest time can be the whole planning period.

Types of available containerships are denoted by set $\mathcal{A}$ on $\mathcal{R}$ routes; each route has $\mathcal{L}_r$ legs. Demand for container transportation on each leg is estimated from historic transportation volume.

Ships call ports in a pre-determined order and interval. Thus, duration of a round trip and the total number of voyages completed by a single ship are fixed.

Capital used for the existing fleet is deemed 'sunken', and will not affect decisions in planning periods. In view of time value, all capitals referred are discounted to the beginning of the planning horizon.

1.4. CO_2 emissions tax scenario design

We follow Reinelt and Keith (2007) by modelling a future CO_2 tax with uncertain execution time and magnitude.

Let φ^t indicate the carbon tax rate in period t with probability denoted by q^t for $t = 1, 2, \ldots, N$. The distribution of tax execution time is uniform during planning periods; the tax rate remains constant once imposed. Let u^t denote the execution probability of a carbon tax at the beginning of period t. If the tax is not executed in any period, the execution probability in the following period will be:

$$u\left(t' \mid \text{not executed in period } t < t'\right) = \frac{u^{t'}}{\sum_{t=t'}^{N} u^t}. \qquad (1)$$

Thus, a scenario structure is introduced to describe carbon tax uncertainty. Several proper realizations occur in each period, and every realization is a branch in one period. Carbon tax realizations are only available until the beginning of each period. Let s represent a carbon tax scenario which belongs to set $\mathcal{S}$, namely $s \in \mathcal{S}$. For each scenario s, a carbon tax development path is described by φ^{ts} and p^s for $t = 1, 2, \ldots, N$, where φ^{ts} denotes the tax rate in period t under scenario s, realization probability of scenario s is indicated by p^s, satisfying $\sum_{s \in \mathcal{S}} p^s = 1$.

The remainder of our paper is structured as follows. Section 2 develops a multi-stage stochastic integer program and an extended SP model. Section 3 details the numerical study and results. Conclusions and future work are discussed in the last section.

2. Mathematical model

This section describes our method for establishing a mathematical model for chartering decisions analysis. Deterministic formulation, parameters, and variables are developed first for an explicit SP model base. The deterministic model can be extended to a SP model by considering more than one carbon tax scenarios.

Deterministic objective function:

$$\text{Min } cost\ Z = \sum_{t=1}^{N}\left(1+\mu\right)^{t-1}\cdot\sum_{i\in\mathcal{A}}\left(\sum_{r\in\mathcal{R}}\left(\int_{ir}^{t}+\eta_{ir}^{t}\right)\cdot W_{ir}^{t}\cdot\upsilon_{ir}^{t}+ U_{i}^{t}\cdot\psi_{i}^{t}+\sum_{p=1}^{N-t+1}\alpha_{i}^{t}\cdot I_{ip}^{t}\cdot p+\varphi^{t}\cdot\sum_{r\in\mathcal{R}}\left(\sum_{l\in\mathcal{L}_{r}}Q_{irl}^{t}\right)\cdot\beta_{ir}\right). \quad (2)$$

In Eq. (2), all parameters are assumed to be predictable and known, and it is assumed that there are three different types of ships i (e.g. ship type 1, 2 and 3). Note that all the ships in the same category are the same (e.g. all the ships categorized in ship type 1 are the same type of ship). As mentioned above, tax realization is described as scenarios. Decisions must have the identical structure within the scenario tree in order to focus on and cope with uncertainty. Scenario dependent decision variables are further indexed by s.

The objective function becomes:

$$\text{Min } ECost=\sum_{s\in\mathcal{S}}p^{s}\cdot f_{s}\left(E_{i}^{ts},W_{ir}^{ts},U_{i}^{ts},Q_{irl}^{ts},I_{ip}^{ts}\right), \quad (3)$$

where: E_i^{ts} is an intermediate variable explained by relative constraint.

Subject to the following constraints:

$$E_{i}^{ts}=E_{i}^{0}+\sum_{z=1}^{t}\sum_{p=t-z+1}^{N-z+1}I_{ip}^{zs},$$
$$\forall i\in\mathcal{A},\ t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (4)$$

$$\sum_{i\in\mathcal{A}}\sum_{p=1}^{N-t+1}\left(\alpha_{i}^{t}\cdot I_{ip}^{ts}\cdot p\right)\leq\varpi_{t},$$
$$\forall t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (5)$$

$$\sum_{p=1}^{N-t+1}I_{ip}^{ts}\leq\xi_{i}^{t},$$
$$\forall i\in\mathcal{A},\ t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (6)$$

$$\sum_{r\in\mathcal{R}}W_{ir}^{ts}+U_{i}^{ts}=E_{i}^{ts},$$
$$\forall i\in\mathcal{A},\ t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (7)$$

$$\sum_{i\in\mathcal{A}}W_{ir}^{ts}\cdot\upsilon_{ir}^{t}\geq\frac{\Delta t}{\gamma_{r}^{t}},$$
$$\forall r\in\mathcal{R},\ t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (8)$$

$$\sum_{i\in\mathcal{A}}Q_{irl}^{ts}\geq\rho_{rl}^{t},$$
$$\forall l\in\mathcal{L}_{r},\ r\in\mathcal{R},\ t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (9)$$

$$W_{ir}^{ts}\cdot\upsilon_{ir}^{t}\cdot\kappa_{i}\geq Q_{irl}^{ts},$$
$$\forall l\in\mathcal{L}_{r},\ r\in\mathcal{R},\ t=1,2,\ldots,N,\ s\in\mathcal{S}; \quad (10)$$

$$Y_{t}^{s}=Y_{t}^{s'},$$
$$\forall s,\ s'\in S_{s_{1},\ldots,s_{t-1}}^{t},\ t=1,2,\ldots,N; \quad (11)$$

$$E_{i}^{ts},W_{ir}^{ts},U_{i}^{ts},Q_{irl}^{ts},I_{ip}^{ts}\in\mathbb{Z}^{+}\cup\{0\},$$
$$\forall i\in\mathcal{A},\ l\in\mathcal{L}_{r},\ r\in\mathcal{R},\ t=1,2,\ldots,N. \quad (12)$$

Eq. (3) denotes the minimization of discounted fleet costs for the whole planning horizon under different tax scenarios, includes chartering fees, fixed operating costs, variable voyage costs, laying-up costs, and carbon taxes. The left-hand side of Constraint (4) is an intermediate variable indicating the number of available ships of type i at the beginning of period t. Constraint (5) ensures that capital used for chartering will not exceed the company's available budget. Eq. (6) safeguards that chartered capacity will not outweigh market supply. The left-hand side of Eq. (7) indicates that available ships of type i can be assigned to routes or laid up given overcapacity. Constraint (8) confirms that voyages completed by ships on each route can satisfy market requirements for sailing frequency. Eq. (9) requires that containers carried by vessels on each shipping leg should at least meet market demands; this implies that the company will keep its market share under different situations. Constraint (10) indicates that the total carrying capacity assigned to each route should be equal to or greater than accomplished container volume on each leg. Eq. (11) is a non-anticipativity constraint, which requires decision variables with the same ancestor nodes and developed paths to be identical. Constraint (12) requires all decision variables to be non-negative integers.

Figure 1 shows the relationship between decision variables bounded by non-anticipativity.

Non-anticipativity constraints prevent using future information in the decision; in other words, if two scenario paths share same history so far, then all historical decisions should be identical. Unrevealed information cannot be used (King, Wallace 2012). Thus, companies could remain neutral about risk and avoid loss caused by replacing uncertain factors with average or extreme values.

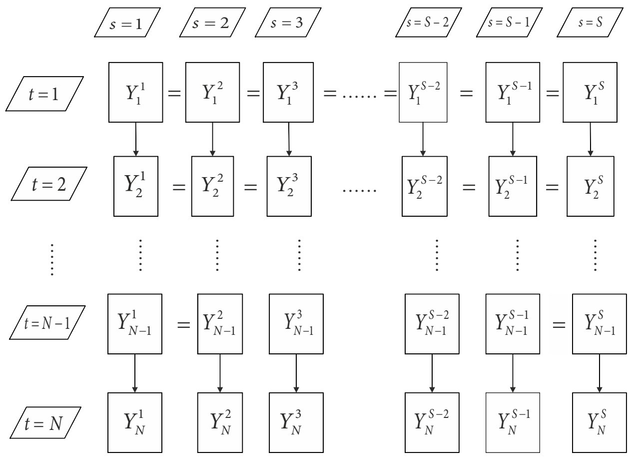

Figure 1. Decision steps with non-anticipativity constraints

3. Numerical study

This section outlines the design, computes the numerical case from our model, and delivers resulting decisions of liner company. Most of the data has been collected from international company reports based in China in order to expose the capabilities of our model and not to discuss the case-results per se.

3.1. Case design

Consider Company *X* that intends to build a three-year fleet plan for transport between East Asian and European ports. For simplicity, we assume two legs on one typical route (i.e., Shanghai, China to Hamburg, Germany, and back). Clarkson Research Services Ltd (2014) forecasted basic container volume demand on East Asian-European routes in 2014 at 7.2 million TEUs eastbound and 14.9 million TEUs westbound. This company must complete at least 10% of container demands to maintain market share. Container shipping demand increases by 3% annually.

Table 1. Fleet composition at the beginning of planning period

	Ship type		
	1	2	3
Capacity [TEU]	8000	13000	16000
Technical condition	old	old	new
Self-owned number	10	5	0
CO_2 emission convention factor [ton/TEU]	0.98	0.81	0.64
Available [days/year]	360	355	350
Sailing [days/round trip]	61	64	67

Note: ship type 1 – old type with low emission efficiency; ship type 2 – old type with median emission efficiency; ship type 3 – new type with high emission efficiency.

Per Table 1, at the beginning of the planning horizon, Company *X* only owns ships of types 1 and 2; we assume that ships of type 3 will be available besides ships of types 1 and 2 in the next three years. Based on IMO (2009) estimation, we adopt a CO_2 emission conversion coefficient of 0.98 for ships of type 1 containerships (combining the distance between Shanghai and Hamburg). For ships of types 2 and 3, 17% and 35% conversion discounts are taken, respectively, based on better carbon-efficiency.

To our knowledge, no public records exist charter fixtures for containerships over 13000 TEU. Thus, we use a one-year chartering fee for an 8000 TEU containership (Seaspan Corporation 2013). We adopt 5 and 10% discounts for two- and three-year chartering fees, respectively, to conform to chartering practices. We then estimate a 3% increase in chartering fees per year to cover inflation (Table 2).

Per Table 3, variable, fixed, and laying-up costs cover one round trip per ship. In our model, capital and ships are abundant enough to meet chartering requirements, including a rising annual rate of USD$100000 for inflation.

3.2. Carbon tax scenario tree assumptions

As discussed in Section 1.2, CO_2 taxation is modelled with uncertain execution time and magnitude. Following Lee *et al.* (2013), we adopt the low tax rate of $\$30/tCO_2$, and a more stringent high rate of $\$300/tCO_2$.

For the first planning year, tax is set to 0 because no carbon tax is levied on shipping. For year 2, suppose even probabilities for levying tax, which means 50% probability to impose and 50% probability for no tax. Thus, if taxation is adopted, the probability for the low or the high rate is also equal. Once applied, taxation remains unchanged until the end of the planning horizon. Upon year 3, there is 50% probability to levy either the low or high tax rate. Accordingly, in Table 4, four scenarios are created (*s*1, *s*2, *s*3, *s*4).

Table 2. Charter fee by ship type

Charter fee [M$USD]		Ship type				Ship type				Ship type		
		1	2	3		1	2	3		1	2	3
1-year	t = 1	12	20.5	27.5	t = 2	12.36	21.1	28.32	t = 3	12.73	21.75	29.17
2-year		22.8	38.95	52.25		23.28	40.11	53.81				
3-year		32.4	55.35	74.25								

Note: ship type 1 – old type with low emission efficiency; ship type 2 – old type with median emission efficiency; ship type 3 – new type with high emission efficiency.

Table 3. Operational and laying-up costs by ship type

		Ship type				Ship type				Ship type		
		1	2	3		1	2	3		1	2	3
Variable cost [M$USD/round trip]	t = 1	5.1	8.1	9.3	t = 2	5.3	8.3	9.6	t = 3	5.4	8.6	9.9
Fixed cost [M$USD/round trip]		3.7	6	7.7		3.8	6.2	7.9		3.9	6.4	8.1
Laying-up expense [M$USD/year]		4.4	5.6	6.7		4.5	5.8	6.9		4.7	6	7.1

Note: ship type 1 – old type with low emission efficiency; ship type 2 – old type with median emission efficiency; ship type 3 – new type with high emission efficiency.

Table 4. Carbon tax scenario paths and probabilities

t = 1	t = 2	t = 3	Path
tax = 0	tax = 0, 50%	tax = 30, 25%	$s1$
		tax = 300, 25%	$s2$
	tax = 30, 25%	tax = 30, 25%	$s3$
	tax = 300, 25%	tax = 300, 25%	$s4$

3.3. Numerical results

A solver developed by *Frontline Solvers* that can be added-in *MS Excel* is used to do the calculations in this case.

Table 5 summarizes decision variable values, and Table 6 provides results with basic assumptions set in Section 3.1 and 3.2, where realization probabilities of carbon tax scenarios are equal.

Table 5. Decision variables and objective function under different scenarios

Scenario	Period	Ship type	W_{ir}^{ts}	U_i^{ts}	Q_{irl}^{ts}, east	Q_{irl}^{ts}, west	I_{ip}^t, p = 1	I_{ip}^t, p = 2	I_{ip}^t, p = 3	E_i^t
$s1$	t = 1	1	24	0	359454	1133114	13	1	0	24
		2	5	0	360546	356886	0	0	0	5
		3	0	0	0	0	0	0	0	0
	t = 2	1	25	0	381054	1174154	7	7		25
		2	5	0	360546	360546	0	0		5
		3	0	0	0	0	0	0		0
	t = 3	1	17	0	0	802285	0			17
		2	5	0	345938	360546	0			5
		3	5	0	417910	417910	5			5
$s2$	t = 1	1	24	0	359454	1133114	13	1	0	24
		2	5	0	360546	356886	0	0	0	5
		3	0	0	0	0	0	0	0	0
	t = 2	1	11	0	0	505498	0	0		11
		2	5	0	72944	360546	0	0		5
		3	8	0	668656	668656	1	7		8
	t = 3	1	10	0	0	467957	0			10
		2	5	0	11610	360546	0			5
		3	9	0	752238	752238	2			9
$s3$	t = 1	1	24	0	359454	1133114	13	1	0	24
		2	5	0	360546	356886	0	0	0	5
		3	0	0	0	0	0	0	0	0
	t = 2	1	25	0	381054	1174154	14	0		25
		2	5	0	360546	360546	0	0		5
		3	0	0	0	0	0	0		0
	t = 3	1	26	0	403302	1220195	16			26
		2	5	0	360546	360546	0			5
		3	0	0	0	0	0			0
$s4$	t = 1	1	24	0	359454	1133114	13	1	0	24
		2	5	0	360546	356886	0	0	0	5
		3	0	0	0	0	0	0	0	0
	t = 2	1	25	0	381054	1174154	14	0		25
		2	5	0	360546	360546	0	0		5
		3	0	0	0	0	0	0		0
	t = 3	1	10	0	0	467957	0			10
		2	5	0	11610	360546	0			5
		3	9	0	752238	752238	9			9

Table 6. Part of computing results

Minimum cost [USD]	5797820203
Total CO_2 emission [ton]	5929163
Container volume [TEU]	6830889

The non-anticipativity constraint requires decisions in period 1 under each tax scenario to be identical. Because managers are not able to determine which scenario they are in, unrevealed information cannot be used. The requirement for decisions in period 2 of scenarios 3 and 4 is the same: Managers only know that there is a 50% probability of no tax at the beginning of period 2 for these two scenarios, but they still do not know which tax scenario will realize for period 3.

Generally, results show that ships of type 1 are most popular. They represent the oldest and smallest ships; have the highest carbon emission factor, unit voyage and operating costs, but the lowest chartering fees. Ships of type 3 ships are ranked second – they are most carbon-efficient, have the lowest unit voyage and operating costs, but the highest chartering fees. More ships of type 3 are chartered under high carbon tax scenarios (*s*2 and *s*4). In terms of periods, no ships are chartered with three-year contracts, because this relatively long period is not flexible enough to deal with uncertain tax scenarios. Values in Table 5 are weighted by combining tax scenario probabilities and relevant parameters. These will be used as indicators for comparison of decisions under different situations.

3.4. Comparison with decisions under perfect information

We can find that the implementation timing and magnitude of carbon taxation is still uncertain by using the same distribution and probabilities from the scenario tree in Section 3.2. However, with the application of Perfect Information (PI) (Birge, Louveaux 2011), we can obtain more precise information that can apply to decision-making prior to carbon tax realization timelines.

In this section, we investigate chartering decisions based on SP versus PI planning to gain insights into fleet strategies that deal with carbon tax uncertainty.

We now introduce different carbon tax scenario probabilities to represent risk levels.

3.4.1. Even carbon tax scenario probabilities

Eq. (2) with relative constraints developed in Section 2 can solve decisions with PI. Let $X^s\left(\varphi_t^s\right)$ denote the optimal solution of Model (1) with carbon tax realization φ_t^s, define:

$$PI^s = \min \mathcal{Z}\left(X^s\left(\varphi^{ts}\right)\right), \tag{13}$$

where: PI^s is the value of objective minimum costs with carbon tax φ^{ts}. Then the expected value of the objective function with PI can be written as $EPI = \sum_{s \in S} p^s \cdot PI^s$, where p^s is the occurrence probability of the carbon tax scenario defined in Section 1.2. $EX = \sum_{s \in S} p^s \cdot X^s\left(\varphi^{ts}\right)$ can be calculated, where *EX* indicates each variable's expected value, including chartering.

All data required to compute *EX* and *EPI* follow assumptions from Section 3.1, here the carbon tax scenario probabilities for *s*1, *s*2, *s*3, *s*4, are even (1/4, 1/4, 1/4, 1/4), denoted by *M*, to represent medium chances of high carbon taxes.

For simplicity, Table 7 and Figure 2 summarizes only the results that contribute to chartering capacity comparison. Chartering capacity is a product of ship numbers, periods, and container capacities. 'Total CO_2 emission' and 'Number of containers (being carried)' take into account the sum for the whole fleet in the planning horizon. 'Minimum cost' is the value of the objective function.

Company *X* charters more capacity to complete the same container volume with SP than through PI-based decisions (Table 7, Figure 2). Among ship types, SP charters more ships of type 3 but fewer ships of type 1. These results in lower fleet CO_2 emissions, which relates to carbon tax costs directly, but leads to higher overall costs.

Table 7. Optimization results

	PI	*SP*
Minimum cost [USD]	5778966192	5797820203
Total CO_2 emission [ton]	5989384	5929163
Container volume [TEU]	6830889	6830889

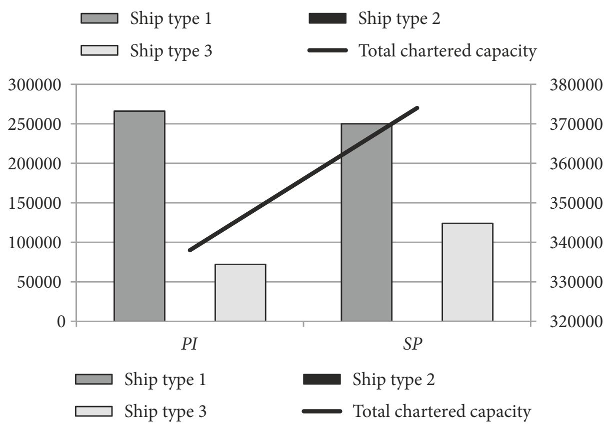

Figure 2. Chartering capacity comparison

3.4.2. Uneven probabilities of carbon tax scenarios

First, we change the carbon tax scenario probabilities to (1/6, 1/3, 1/6, 1/3) for *s*1, *s*2, *s*3, *s*4, denoted by *H*, to represent greater chances of high carbon taxes. We apply the same method to optimize fleet planning with SP and PI models. Next, we assign probabilities of (1/3, 1/6, 1/3, 1/6) to *s*1, *s*2, *s*3, *s*4, denoted by *L*, to represent greater chances of low carbon taxes. Besides scenario probabilities, other data remains unchanged.

H: probabilities of (1/6, 1/3, 1/6, 1/3) for *s*1, *s*2, *s*3, *s*4;

L: probabilities of (1/3, 1/6, 1/3, 1/6) for *s*1, *s*2, *s*3, *s*4.

With greater probability of high carbon taxes, Company *X* still charters more capacity under SP, with increased usage of ships of types 2 and 3, but fewer ships of type 1 (Table 8, Figure 3).

Compared to decisions under probability *H*, Company *X* makes similar chartering strategies under *L* (Table 9, Figure 4). Generally, similar results are found under different carbon tax probabilities. For instance, ships of type 1 may be most useful when dealing with carbon tax uncertainty due to their low chartering fees, even if they have relatively high voyage and operating costs and unit carbon emissions levels. Ships of type 3 are not as highly preferred by SP compared to PI, likely due to their higher chartering fees.

In addition, all results demonstrate that different carbon tax scenario probabilities will not change chartering trends. The uptrend is stable, so as long as carbon tax uncertainty exists, rational liner companies who are risk-neutral will charter more ships to cope with that uncertainty.

3.5. Chartering trend under different risk levels

The aforementioned scenario trees *L*, *M*, *H* share the same two structures: (1) equal probabilities of carbon tax realization in planning years 2 and 3, and (2) two outcomes of carbon tax rate – \$30/tCO_2 or \$300/tCO_2. Hence, the ordering of risk for *L*, *M*, *H* is equivalent to the order of the carbon tax itself. For *L*, conditional probability of high carbon tax is 1/3; conditional probability of low carbon tax is 2/3. Accordingly, the conditional carbon tax risk of *L* is lower than *M*, for which the conditional probability of both high and low carbon tax is 1/2. Similarly, the conditional carbon tax risk of *M* is lower than *H*, for which conditional probability of high carbon tax is 2/3, and conditional probability of low carbon tax is 1/3. We can conclude that in a business setting, for *H*, the chance of getting a higher carbon tax is high. As a result, the company would be exposed to high risk. In the same way, the company would be at medium risk for *M*, and low risk for *L*.

The above intuitive explanation of why *H* is riskier than *M*, which is riskier than *L*, can be rigorously proven using stochastic dominance theory: *H*, *M*, *L* exhibits first-order stochastic dominance (Dentcheva, Ruszczynski 2003):

$$H >_{(1)} M >_{(1)} L. \tag{14}$$

A proof is in the Appendix.

Figure 5 represents the chartering capacity balance between SP and PI decisions under various risk levels. Results show that Company *X* would charter more ship capacity to cope with increased carbon tax risk. It can then be deduced that a greater degree of tax risk will result in increased containership chartering demand.

3.6. Fleet costs and CO_2 emissions under different risk levels

Figure 6 summarizes the solution from SP model under three carbon tax risk levels. With increasing risk levels, Company *X* spends more on running the fleet for the same container volume (6830889 TEUs); however, CO_2 emission does go down. We conclude that higher carbon tax would give more pressure to liner companies, and they are inclined to discharge less CO_2. Some similar discussions can be found from Psaraftis (2012) and Fagerholt *et al.* (2015), which in turn echoes our opinions from other perspectives. However, this causes financial burden to liner companies. As our case study results show, when

Table 8. Optimization results – under *H*

	PI	*SP*
Minimum cost [USD]	5888447219	5915953943
Total CO_2 emission [ton]	5876695	5874083
Container volume [TEU]	6830889	6830889

Table 9. Optimization results – under *L*

	PI	*SP*
Minimum cost [USD]	5669485165	5689326000
Total CO_2 emission [ton]	6102073	5981730
Container volume [TEU]	6830889	6830889

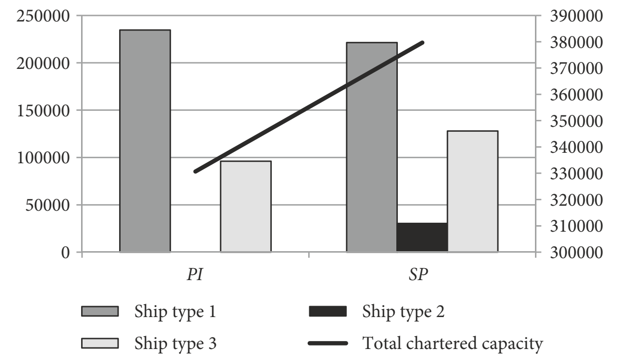

Figure 3. Chartering capacity comparison – under *H*

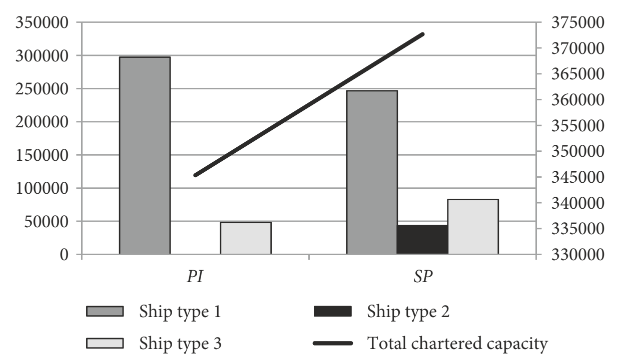

Figure 4. Chartering capacity comparison – under *L*

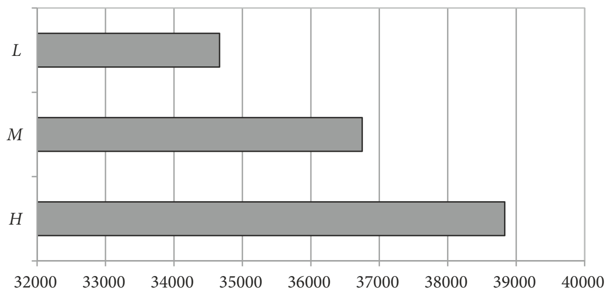

Figure 5. Increased chartering capacity

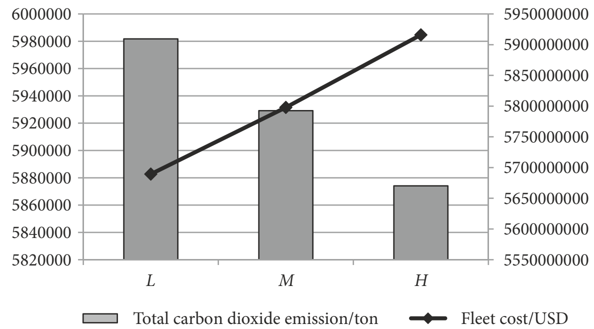

Figure 6. Optimization results from SP model

companies face high carbon tax risk, they charter more ships of type 3, which stands for new type with high emission efficiency to undertake the same cargo volume, compared with lower tax risks situations; but the chartering of ships of type 3 leads to higher fleet cost as they require more capital cost (variable, fixed cost per voyage as well as chartering fee per period) although the energy consumption of ships of type 3 is lower relatively.

Conclusions

This paper investigates the fleet mix strategy under carbon emissions tax uncertainty through comparing planning decisions using SP and PI programming, non-anticipativity constraints are applied to ensure that the formulated decisions maintain alignment with uncertainty factors. Results demonstrate the feasibility of the SP model and recourse decisions in different planning periods and scenarios. Upon investigating decisions from real-world case, we find that the uncertain carbon tax policy and its risk levels do have an impact on fleet planning strategies. More ships are chartered when company does not have PI about future carbon emissions taxation; company tends to charter more capacity when it is exposed to high carbon tax risk.

While new ships with better energy and carbon efficiency seems not preferred by the company compared with older ones due to their higher capital costs, which may indicate that shipping companies care more about minimizing costs than CO_2 emissions. In terms of tax policy impact, higher carbon tax risks make company reduce CO_2 emissions, but it costs more to manage the fleet. Therefore, high taxation risk does motivate carbon mitigation with causing more costs to companies; policy makers should embark on setting out a reasonable tax rate and the way to make use of potential revenue.

Further, market based instruments will have different impact on emission reduction with different fuel price levels. Shipping companies may reduce ship's speed to save costs when the fuel price rises, which may lead to emission reduction per ship. However, more ships capacity will be required if the cargo transportation keeps the same volume while ships reduce speed, it is hard to say whether total emission was reduced or not of the whole industry.

In view of the complicated impact of taxation on carbon emission, it will be interesting to do further investigation on this topic, which in turn shows how important the study on uncertain carbon reduction instrument is. This study can be extended in several ways. First, we assume the impact of carbon emissions regulations by way of a carbon tax. However, other regulations (such as emissions trading systems) could provide a counterpoint to market-based measures. Second, other uncertain factors, such as fuel price, ship speed, and freight rates could be introduced under SP to arrive at a more comprehensive and realistic business perspective.

Acknowledgements

The authors appreciate the editor's valuable comments. This work was supported by the Discovery Grant from the Natural Sciences and Engineering Research Council of Canada under Research Grant No 386474–2012; and the Graduate Student's Innovation Fund from Shanghai Maritime University, China, under Grant No 2013ycx056.

Funding

This work was supported by the Discovery Grant from the Natural Sciences and Engineering Research Council of Canada under Research Grant No 386474–2012; and the Graduate Student's Innovation Fund from Shanghai Maritime University, China, under Grant No 2013ycx056.

Disclosure statement

The authors declare that there is no conflict of interests regarding the publication of this paper.

References

Avi-Yonah, R. S.; Uhlmann, D. M. 2009. Combating global climate change: why a carbon tax is a better response to global warming than cap and trade, *Stanford Environmental Law Journal* 28(3): 3–50.

Bakkehaug, R.; Eidem, E. S.; Fagerholt, K.; Hvattum, L. M. 2014. A stochastic programming formulation for strategic fleet renewal in shipping, *Transportation Research Part E: Logistics and Transportation Review* 72: 60–76. https://doi.org/10.1016/j.tre.2014.09.010

Bang, H.-S.; Kang, H.-W.; Martin, J.; Woo, S.-H. 2012. The impact of operational and strategic management on liner shipping efficiency: a two-stage DEA approach, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 39(7): 653–672. https://doi.org/10.1080/03088839.2012.740165

Birge, J. R.; Louveaux. 2011. *Introduction to Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. Springer. 485 p. https://doi.org/10.1007/978-1-4614-0237-4

Cariou, P.; Wolff, P.-C. 2013. Chartering practices in liner shipping, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 40(4): 323–338. https://doi.org/10.1080/03088839.2013.781280

Clarkson Research Services Ltd. 2014. *Container Intelligence Quarterly: Second Quarter 2014*. Available from Internet: http://www.crsl.com

Dentcheva, D.; Ruszczynski, A. 2003. Optimization with stochastic dominance constraints, *SIAM Journal on Optimization* 14(2): 548–566. https://doi.org/10.1137/S1052623402420528

Ermolieva, T.; Ermoliev, Y.; Fischer, G.; Jonas, M.; Makowski, M.; Wagner, F. 2010. Carbon emission trading and carbon taxes under uncertainties, in M. Jonas, Z. Nahorski, S. Nilsson, T. Whiter (Eds.). *Greenhouse Gas Inventories*. Springer, 277–289. https://doi.org/10.1007/978-94-007-1670-4_16

Fagerholt, K.; Gausel, N. T.; Rakke, J. G.; Psaraftis, H. N. 2015. Maritime routing and speed optimization with emission control areas, *Transportation Research Part C: Emerging Technologies* 52: 57–73. https://doi.org/10.1016/j.trc.2014.12.010

Fagerholt, K.; Johnsen, T. A. V.; Lindstad, H. 2009. Fleet deployment in liner shipping: a case study, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 36(5): 397–409. https://doi.org/10.1080/03088830903187143

Franc, P.; Sutto, L. 2014. Impact analysis on shipping lines and European ports of a cap- and-trade system on CO_2 emissions in maritime transport, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 41(1): 61–78. https://doi.org/10.1080/03088839.2013.782440

Hammoudeh, S.; Nguyen, D. K.; Sousa, R. M. 2014. Energy prices and CO_2 emission allowance prices: a quantile regression approach, *Energy Policy* 70: 201–206. https://doi.org/10.1016/j.enpol.2014.03.026

He, Y.; Wang, L.; Wang, J. 2012. Cap-and-trade vs. carbon taxes: a quantitative comparison from a generation expansion planning perspective, *Computers & Industrial Engineering* 63(3): 708–716. https://doi.org/10.1016/j.cie.2011.10.005

ICS. 2009. *Greenhouse Gas Emissions and Market Based Instruments: MBI Analysis Report*. International Chamber of Shipping (ICS). Available from Internet: http://www.ics-shipping.org

IMO. 2009. *Second IMO GHG Study 2009*. International Maritime Organization (IMO). 240 p. Available from Internet: http://www.imo.org/en/OurWork/Environment/Pollution-Prevention/AirPollution/Documents/SecondIMOGHGStudy2009.pdf

Kim, J.-G.; Kim, H.-J.; Lee, P. T.-W. 2013. Optimising containership speed and fleet size under a carbon tax and an emission trading scheme, *International Journal of Shipping and Transport Logistics* 5(6): 571–590. https://doi.org/10.1504/IJSTL.2013.056835

King, A. J.; Wallace, S. W. 2012. *Modeling with Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. Springer. 173 p. https://doi.org/10.1007/978-0-387-87817-1

Lee, T.-C.; Chang, Y.-T.; Lee, P. T. W. 2013. Economy-wide impact analysis of a carbon tax on international container shipping, *Transportation Research Part A: Policy and Practice* 58: 87–102. https://doi.org/10.1016/j.tra.2013.10.002

Mason, R.; Nair, R. 2013. Strategic flexibility capabilities in the container liner shipping sector, *Production Planning & Control: the Management of Operations* 24(7): 640–651. https://doi.org/10.1080/09537287.2012.659873

Meng, Q.; Wang, T.; Wang, S. 2015. Multi-period liner ship fleet planning with dependent uncertain container shipment demand, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 42(1): 43–67. https://doi.org/10.1080/03088839.2013.865848

Meng, Q.; Wang, T. 2011. A scenario-based dynamic programming model for multi-period liner ship fleet planning, *Transportation Research Part E: Logistics and Transportation Review* 47(4): 401–13. https://doi.org/10.1016/j.tre.2010.12.005

Meng, Q.; Wang, T. 2010. A chance constrained programming model for short-term liner ship fleet planning problems, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 37(4): 329–346. https://doi.org/10.1080/03088839.2010.486635

Pantuso, G.; Fagerholt, K.; Hvattum, L. M. 2014. A survey on maritime fleet size and mix problems, *European Journal of Operational Research* 235(2): 341–349. https://doi.org/10.1016/j.ejor.2013.04.058

Psaraftis, H. N. 2012. Market-based measures for greenhouse gas emissions from ships: a review, *WMU Journal of Maritime Affairs* 11(2): 211–232. https://doi.org/10.1007/s13437-012-0030-5

Ramseur, J. L.; Parker, L. 2010. *Carbon Tax and Greenhouse Gas Control: Options and Considerations for Congress*. BiblioGov. 60 p.

Reinelt, P. S.; Keith, D. W. 2007. Carbon capture retrofits and the cost of regulatory uncertainty, *The Energy Journal* 28(4):101–127. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No4-5

Seaspan Corporation. 2013. *FORM 20-F: Annual and Transition Report (Foreign Private Issuer)*. 295 p. Available from Internet: http://www.seaspancorp.com/wp-content/uploads/2014/10/SSW_2013_Annual_Report_20-F.pdf

Strand, J. 2013. Strategic climate policy with offsets and incomplete abatement: carbon taxes versus cap-and-trade, *Journal of Environmental Economics and Management* 66(2): 202–218. http://doi.org/10.1016/j.jeem.2013.03.002

UNCTAD. 2013. *Review of Maritime Transport 2013*. United Nations Conference on Trade and Development (UNCTAD). 204 p. Available from internet: http://unctad.org/en/PublicationsLibrary/rmt2013_en.pdf

Yu, Y. 2009. *Stochastic Ship Fleet Routing with Inventory Limits*. PhD Dissertation. University of Edinburgh, UK 130 p. Available from Internet: https://www.era.lib.ed.ac.uk/handle/1842/4640

APPENDIX

Definition:

A real valued *r.v.* A has first-order stochastic dominance over a real valued *r.v.* B, or $A >_{(1)} B$, $P(A \geq x) \geq P(b \geq x)$, $\forall x \in R$
and for some x, $P(A \geq x) > P(b \geq x)$, $\forall x \in R$.

Theorem:

$H >_{(1)} M >_{(1)} L$.

Proof:

For $x \in [0, 30]$:

$P(L \geq x) = 1 = P(M \geq x) = P(H \geq x)$.

For $x \in (30, 300]$:

$P(L \geq x) = \frac{1}{3} \leq P(M \geq x) = \frac{1}{2} \leq P(H \geq x) = \frac{2}{3}$.

For $x \in (300, +\infty)$:

$P(L \geq x) = P(M \geq x) = P(H \geq x) = 0$.

Note, that policy implementation time is also random, but is independent to the tax rate, and is identical for L, M, H.

For each possible policy implementation, the tax rates of L, M, H exhibit the first-order stochastic dominance relationship. Hence, the conclusion follows.