P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : *https://tci-thaijo.org/index.php/SciTechAsia* Science & Technology Asia
Vol.29 No.3 July - September 2024 Page: [36-56]
Original research article

Dynamic Network for Air Freight Forwarder's Stochastic Capacity Management

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Received 4 January 2024; Received in revised form 29 April 2024
Accepted 13 May 2024; Available online 25 September 2024

ABSTRACT

A freight forwarder, a key player in the air cargo service chain, collects individual packages from shippers and transports consolidated shipments to air carriers, some of which have long-term block space agreements with the forwarder. If, on any day, the total demand from the consolidated shipment exceeds the allotment specified in the block space agreement, the forwarder may need to purchase additional space in the spot market, where the freight rate is often higher. Alternatively, the forwarder may opt to delay some shipments, storing them overnight at a warehouse and incurring inventory holding costs. On the other hand, if the total demand is less than the allotment, the forwarder is required to pay at least the minimum charge. For each destination and each day of the week, demand exhibits significant week-to-week variation, while the capacity supply on each day of the week remains fixed over the contract duration. In the long-term problem, the forwarder must decide on the allotment before knowing the random daily demand. In the short-term problem, it determines how to allocate the realized demand to multiple carriers with different freight rates. The problem is formulated as a two-stage stochastic program, embedding the multi-day network of time-varying demand. The proposed solution is compared to the current approach in a case study, utilizing historical demand data from one of Thailand's largest forwarders. Based on the top four destinations from April 2020 to July 2021, our proposed solution yields significant cost savings.

Keywords: Air freight; Capacity management; Linear programming; Mathematical programming; Stochastic programming

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1. Introduction

The pivotal role of air cargo within the intricate framework of the global logistics network has become increasingly apparent in recent years, driven by the forces of globalization and the exponential growth of e-commerce. As of October 2023, there has been a consistent year-on-year growth in global air cargo tonne-kilometers, marking the third consecutive increase at 3.8% [1]. Air cargo shipments encompass a diverse range of items, including those that are time-sensitive, temperature-sensitive, dangerous goods, live animals, and perishable cargo. Amid the challenges posed by the COVID-19 pandemic, essential medical supplies such as vaccines, oxygen cylinders, and personal protective equipment have been transported via air cargo, underlining the critical role of the sector in delivering life-saving resources during emergencies.

The air cargo service chain constitutes a complex network involving various crucial entities, including shippers (consignors), air freight forwarders, carriers (airlines), and consignees. Air cargo shipments can traverse diverse channels, utilizing dedicated freighters, the cargo holds of passenger planes, or the adaptable passenger decks commonly referred to as "preighters." Within this intricate ecosystem, air freight forwarders play a pivotal role. They engage in consolidating shipments from multiple shippers into larger units and manage the deconsolidation process at the destination airport. Serving as intermediaries between air cargo carriers and shippers, forwarders contribute significantly to the smooth flow of operations. Their responsibilities extend to assisting with customs clearance procedures, ensuring strict adherence to import and export regulations within the dynamic air cargo landscape.

Freight forwarders typically do not own airplanes; instead, they secure long-term cargo space through contracts with carriers. If the acquired long-term capacity is insufficient, forwarders may obtain additional *ad hoc/free sale* space from the spot market. A vital contractual arrangement for securing cargo space is the *allotment* or *block space agreement (BSA)*, established on a long-term basis over a specified period. On high-demand trade lanes, forwarders often secure allotments with multiple flights, known as BSA flights. If daily demand exceeds the allotment after the season starts, forwarders can book extra ad hoc space on various non-BSA flights in the spot market. Negotiated between the forwarder and the carrier, BSA freight rates are generally more favorable than non-BSA rates. However, BSAs come with a minimum usage requirement, often termed *minimum chargeable weight*. If cargo demand falls below the minimum chargeable weight, the forwarder must pay for the unused portion of the allotment. If the total capacity from all BSA and non-BSA flights falls short of demand, some shipments may need to be offloaded, stored overnight at the airport warehouse, incurring inventory holding, storage costs, and potential penalties for late arrivals at the destination. These costs also include intangibles like damage to the forwarder's goodwill and business reputation.

In this article, we investigate the stochastic dynamic capacity management problem faced by the forwarder under demand uncertainty and formulate a two-stage stochastic programming model. In the first stage, the forwarder establishes long-term allotments in the face of uncertain demand. Each BSA comes with a distinct freight rate and a minimum chargeable weight requirement. In the second stage, once the daily demand is realized, the forwarder makes short-term decisions regarding the allocation of cargo between BSA and non-BSA flights. Note that non-BSA flights do not impose the minimum chargeable weight requirement but may have higher freight rates compared to BSA flights. Striking a balance between these considerations is crucial. If the allotment is too conservative, the forwarder might resort to more expensive non-BSA flights or some shipments may be delayed to the next day. Associated with the inventory of shipments kept over night, the holding cost is incurred. Conversely, an excessively generous allotment could lead to underutilization, resulting in the forwarder incurring costs for unused allotments. From a theoretical standpoint, we formulate a unified mathematical programming model that addresses both the forwarder's long-term and short-term challenges. In a practical context, we assess the performance of these solutions in a case study involving a Thai logistics firm. Our findings indicate that our approach has the potential to yield significant cost savings when compared to the firm's existing policy.

An examination of the air cargo industry is presented in [2–4]. Yeung and He [5] and Feng et al. [6] offer a thorough survey of air cargo literature, categorizing research articles based on whether they adopt a forwarder or airline perspective. Our manuscript considers both long- and short-term decision-making from a forwarder's standpoint. Long-term decisions involve the establishment of BSA contracts between multiple carriers and a forwarder before the season commences. Short-term decisions revolve around the allocation of shipments to various BSA and non-BSA flights during the selling season.

In addressing the short-term planning challenge for forwarders, the primary objective is to consolidate individual shipments and assign them to cargo space on both BSA and non-BSA flights, each characterized by varying freight costs. Li et al. [7] proposes a Lagrangian-based heuristic in instances featuring a discount scheme, where the freight rate decreases with an increase in chargeable weight. Li et al. [8] enhances the forwarder's consolidation problem by considering essential factors such as the departure and arrival times of flights, ready times of shipments, and constraints related to weight and volume. For multi-modal networks, [9] introduces heuristics for a deterministic shipment planning problem, while [10] focuses on the air inter-modal freight short-term transportation problem. The ground transportation costs are considered in [11, 12]. The problem with random activity processing times is formulated as a two-stage stochastic program in [13]. These studies typically assume exogenously given capacity, whereas our model uniquely incorporates the forwarder's long-term decision regarding capacity.

Another pivotal short-term decision involves the ongoing evaluation of whether to accept or reject booking requests as they arrive sequentially. This aspect, widely recognized in revenue management theory as the booking control problem. Levina et al. [14], the air cargo booking control problem within a network is cast as a Markov decision process (MDP), and in [15], it is alternatively modeled as a multistage stochastic programming problem. However, solving the MDP optimally often grapples with the inherent curse of dimensionality. To mitigate this, [16] proposes a heuristic by assuming a finite set of demand points. Additionally, [15] develops decomposition algorithms to address the air cargo network problem, considering stochastic capacity. Closely intertwined with the booking control problem is the pricing problem, which entails determining a dynamic price as each booking arrives sequentially. Fu et al. [17] introduces a pricing model tailored for an air cargo carrier. Both the booking control and pricing problems receive extensive scrutiny in revenue management theory, where the capacity is typically fixed and perishable. A comprehensive review of air cargo revenue management is available in [18] and in Section 4.1 of [19]. In contrast to the revenue management problem, where capacity is predetermined, our long-term problem introduces a distinctive element, as the forwarder must ascertain capacity through BSA contracts with multiple carriers.

In the context of the long-term capacity management problem, the establishment of BSA contracts precedes the arrival of spot demand, represented by short-term ad hoc booking requests. Amaruchkul et al. [20] derives an optimal contract parameter designed to maximize the total expected profit within the air cargo service chain. Note that Amaruchkul et al. [21] explores the air cargo service chain with a configuration involving a single carrier and multiple forwarders. In contrast, our study focuses on a single forwarder and multiple carriers. The investigation by Lin et al. [22] centers on a buy-back contract, while Elhedhli et al. [23] examines two discount schemes, namely the system-wide and the double-discount, within the context of multiple flights. In the domain of risk-averse decision-making, Wada et al. [24] formulates a two-stage stochastic programming model to aid a carrier in making optimal allocation decisions between reserved and on-the-spot spaces when dealing with multiple flights. Additionally, Wen et al. [25] explores a scenario where two air cargo carriers engage in price competition, deriving long-run equilibrium prices. It is important to note that these aforementioned studies specifically concentrate on long-term decision-making aspects. In contrast, our study uniquely contributes by addressing both long- and short-term decisions within the framework of air cargo capacity management from the forwarder's viewpoint.

Our approach to combined long- and short-term capacity management addresses securing BSA capacity allotments and daily demand decisions. From the carrier's perspective, Feng et al. [26] introduces a distributionally robust optimization model for selecting a freight forwarder portfolio under disruptions. Moussawi-Haidar [27] explores an airline's long-term allocation agreements and booking control decisions. The Lagragian heuristic for this problem is proposed in [28]. These studies take on the airline's perspective, while our work uniquely addresses the combined problem from the forwarder's viewpoint.

From the forwarder's standpoint, [29] formulates an MDP to minimize the total expected freight cost, considering both long- and short-term capacities. The model accommodates spot prices as random variables, allowing the forwarder flexibility in acquiring capacity from contractual agreements and the spot market. He et al. [30] and Leung et al. [31], forwarders can secure capacities from three sources: carrier allotments, alliance bookings, and subcontracting, using a three-stage stochastic program. Bertazzi et al. [32] integrates tactical and short-term decisions, encompassing production, inventory, and transportation, explicitly incorporating transportation lead time. Similar to these papers, our model accounts for rate differences between long- and short-term capacities. However, uniquely, our approach also considers the minimum chargeable weight specified by the long-term contract.

In our capacity management problem, holding costs are incurred when the total supply from both BSA and non-BSA flights is insufficient to accommodate the entire demand, leading to the need to store some shipments overnight. Holding costs are ubiquitous in many settings, grounded in inventory management theory. Specifically, the dynamic lot sizing model in inventory management aims to minimize the total cost, which encompasses both holding costs of inventory and the fixed ordering costs, for the setting of time-varying demand. Chowdhury et al. [33] develops an algorithm employing list and stack data structure and analyzes its computational complexity. The dynamic lot-sizing problems are reviewed in [34,35]. Fan et al. [36] investigates the dynamic lot sizing with bounded inventory for a perishable product. The model with demand substitution and storage capacity is studied in [37]. The model with stochastic demand is considered in [38]. The cost function in our model differs from that in the lot-sizing model. For the BSA flight, there is a minimum chargeable weight requirement. If the usage falls below this threshold, the forwarder pays for the unused portion of the allotment.

The remainder of the manuscript is organized as follows: Section 2 presen ts a mathematical programming formulation of the forwarder's capacity management problem. The analyses and their results are provided in Section 3, followed by concluding remarks in Section 4.

2. Formulation

Consider an air freight forwarder without dedicated cargo space but adeptly securing it through a combination of long-term BSA contracts with carriers and short-term ad hoc space acquisitions from the dynamic spot market. Let B and B' represent the sets of available BSA flights and non-BSA flights, respectively. For brevity, let $F = B \cup B'$ denote the comprehensive set of all available flights. Define T as the index set representing the days of the week (DoW): $T = \{1, 2, \dots, 7\}$ with Monday as 1, Tuesday as 2, and Sunday as 7. Note that, from a mathematical standpoint, the index set T can commence on any day. Table 1 succinctly outlines the input parameters and decision variables in the model. The unit of demand is kilogram (kg).

The capacity supply comes from two sources: BSA and non-BSA flights. For a given day $t \in T$ and BSA flight $i \in B$, the maximum number of available pallets for allotment is x^u_{ti}, each equipped to carry a maximum weight (pallet capacity) of κ^p_{ti}. Meanwhile, for non-BSA flight $j \in B'$, the maximum weight on the flight (flight capacity) is represented by κ^f_{tj}. Note that not all flights operate every day of the week. If on day $t \in T$, BSA flight i or non-BSA flight j is unavailable, then $x^u_{ti} = 0$ and $\kappa^f_{tj} = 0$ respectively. The set of available BSA flights on a specific day, say Monday ($t = 1$), may be different from the set on another day, such as Tuesday ($t = 2$):

$$\{i \in B : x^u_{1i} > 0\} \neq \{i \in B : x^u_{2i} > 0\}.$$

The allotment on BSA flight i on day t, denoted as x_{ti}, is determined before the season commences, i.e., before daily demands are realized. Let $\mathbb{Z}^n_+$ denote the set of n-dimensional nonnegative integers. For shorthand, $\tau = |T|$ and $b = |B|$. The feasible set of allotment vector is defined in (2.1):

$$\mathcal{X} = \left\{x \in \mathbb{Z}^{\tau b}_+ : x_{ti} \leq x^u_{ti},\ t \in T,\ i \in B\right\}, \quad (2.1)$$

Table 1. Input parameters and decision variables.

Sets		
B	=	set of BSA flights
B'	=	set of non-BSA flights
F	=	$B \cup B'$ set of all BSA and non-BSA flights
T	=	set of days in one week
Ω	=	set of scenarios of shipment demand vector
Input parameters		
c_{ti}	=	daily per-pallet upfront cost on BSA flight i on day t (monetary unit/pallet)
r_{tk}	=	freight rate of flight k on day t (monetary unit/kg)
h_t	=	holding cost on day t (monetary unit/day/kg)
x^u_{ti}	=	the maximum number of allotment on BSA flight i on day t (pallet)
ρ_{ti}	=	minimum chargeable weight of a pallet on BSA flight i on day t (kg/pallet)
κ^p_{ti}	=	pallet capacity on BSA flight i on day t (kg)
κ^f_{tj}	=	flight capacity of non-BSA flight j on day t (kg)
$D_t(\omega)$	=	demand on day t in scenario ω (kg)
$\xi(\omega)$	=	$(D_t(\omega) : t \in T)$ demand vector in scenario ω
$s_0(\omega)$	=	initial inventory at the beginning of the week in scenario ω
$G(\xi)$	=	probability distribution of demand vector ξ
Decision variable		
x_{ti}	=	allotment on BSA flight i on day t
$w_{tk}(\omega)$	=	usage on flight k on day t given demand scenario ω
$y_{ti}(\omega)$	=	contract chargeable weight on BSA flight i on day t given demand scenario ω
$s_t(\omega)$	=	inventory on day t given demand scenario ω

where

$$\begin{aligned} x &= (x_{ti} : t \in T, i \in B) \\ &= ((x_{11}, \ldots, x_{1b}), \ldots, (x_{\tau 1}, \ldots, x_{\tau b})), \end{aligned}$$

is the vector of all allotments in all days of week. Note that this article exclusively considers the weight dimension, omitting the volume dimension, as long-term capacity management issues predominantly center around weight capacity for most forwarders.

Assume that shipment demands are stationary across different weeks. For instance, the shipment demand on Monday in the first week has the same distribution as those in the second week, the third week, and so on. Henceforth, we focus on one week with T being the set of days in one week. Let Ω be the set of all demand scenarios. For $\omega \in \Omega$, let $\xi(\omega) = (D_t(\omega) : t \in T)$ where $D_t(\omega)$ is the demand on day t in scenario ω. The demands on different days of week, $D_1(\omega), D_2(\omega), \ldots, D_7(\omega)$, may be correlated. Let $G(\xi)$ denote the multivariate distribution of the demand vector. The forwarder can construct the distribution from historical data. In this article, the 7-day planning horizon is assumed for expositional purpose. This corresponds to a practical situation where the majority of air shipment bookings are received at least on week in advance. Conversely, in an extreme situation where the bulk of bookings arrive within a single day, the planning horizon would be reduced to one day, with the set T containing only one element. Mathematically, the set of planning days T can be any finite set. Specifically, if a significant portion of bookings typically arrives within τ days, the set of planning days would be denoted as $T = \{1, 2, \ldots, \tau\}$.

Once the scenario $\omega \in \Omega$ is revealed, the forwarder proceeds to make short-term allocation decisions. Let $w_{tk}(\omega)$ be the usage on flight $k \in F$ on day $t \in T$. In cases where the available capacity on day t cannot accommodate the entire shipment demand $D_t(\omega)$, any excess demand must be stored overnight at the warehouse, resulting in a delay until the following day. For each day $t \in T$, let $s_t(\omega)$ represent the inventory, indicating the excess demand delayed at the end of that day. For each $t \in T$, the inventory at the end of day t is equal to the inventory from the previous day plus the current daily demand minus the total of today's shipments on all flights:

$$s_t(\omega) = s_{t-1}(\omega) + D_t(\omega) - \sum_{k \in F} w_{tk}(\omega). \tag{2.2}$$

For the initial day, when $t = 1$, the parameter $s_0(\omega)$ in Eq. (2.2) denotes the initial delayed demand at the beginning of the week.

The multi-day problem can be visually presented in Fig. 1. In this network representation, nodes correspond to inventories stored at the warehouse overnight, and arcs correspond to flows of shipments. Given scenario ω on day t, the inflow to node t is the sum of the inventory at the end of the previous day, $s_{t-1}(\omega)$, and the today's demand $D_t(\omega)$. The outflow from node t is the sum of today's shipments on both BSA and non-BSA flights, $(w_{ti}(\omega) : i \in B)$ and $(w_{tj}(\omega) : j \in B')$, respectively, along with the inventory at the end of the day, $s_t(\omega)$. Inventory flows are depicted as horizontal arcs moving from left to right in Fig. 1. Shipment demand flows are represented by vertical arcs originating from the top of the figure and connecting to nodes. Flight usage flows are portrayed as vertical arcs originating from nodes and extending to the bottom of the figure. Constraint (2.2) can be written equivalently as

$$s_{t-1}(\omega) + D_t(\omega) = \sum_{i \in F} w_{tk}(\omega) + s_t(\omega), \tag{2.3}$$

for each $t \in T$. This so-called *balance constraint* in Eq. (2.3) asserts that the inflow (on the left-hand side) must equal the outflow (on the right-hand side) for each node in the network.

The forwarder faces two types of costs: the freight cost and the inventory holding cost. For day $t \in T$ and flight $k \in F$, let r_{tk} be the freight rate. Typically, the freight rate on a BSA flight is lower than that on a non-BSA flight, but the BSA contract stipulates a minimum chargeable weight requirement. For BSA flight $i \in B$, let $\rho_{ti} \in [0, \kappa_{ti}^{p}]$ denote the minimum chargeable weight requirement on day $t \in T$. In scenario $\omega \in \Omega$, the chargeable weight after applying the minimum chargeable weight is

$$y_{ti}(\omega) = \max\{w_{ti}(\omega), \rho_{ti} x_{ti}\}. \tag{2.4}$$

Additionally, there may be an upfront daily payment c_{ti} associated with the allotment x_{ti}. If the costs on flight i are invariant with respect to the DoW, the parameters would be $r_{1i} = \cdots = r_{\tau i}$ and $c_{1i} = \cdots = c_{\tau i}$, aligning with observed practices. Unlike passenger airlines' ticket prices, air cargo prices do not vary with the DoW; instead, they depend on factors such as origin, destination, and shipment types (e.g., general cargo or dangerous goods). The general model is presented for mathematical completeness. The holding cost for delayed shipments at the end of day t is denoted as h_t. To prevent any remaining inventory at the end of the planning horizon, a substantial penalty cost $h_{|T|} \gg \max\{h_t : t = 1, 2, \ldots, |T| - 1\}$ is assumed.

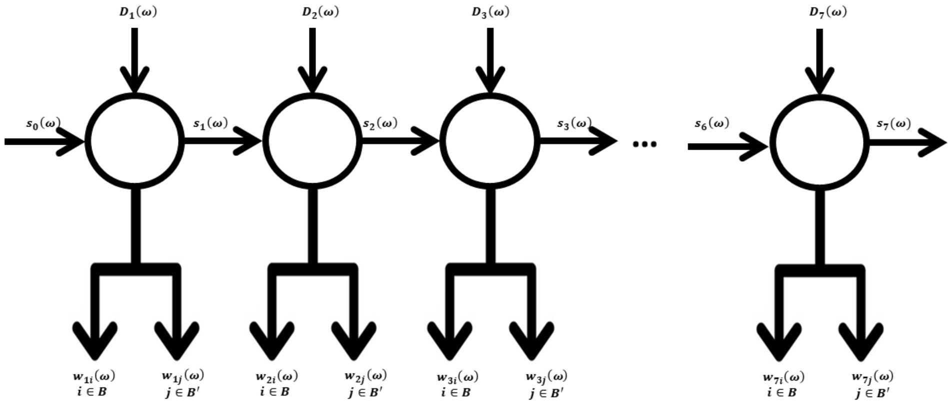

Fig. 1. Network representation.

We formulate the forwarder's capacity management challenge as a two-stage stochastic program, addressing both long-term and short-term considerations. In the first stage, the forwarder determines the long-term allotment before the demand scenario is unveiled. Subsequently, in the second stage, the demand vector $\xi(\omega)$ is realized, and the forwarder determines the allocation of shipment demand on each flight and the inventory at the end of each day. The two-stage stochastic program in an implicit form is given in Eqs. (2.5)-(2.12).

$$\min_{x \in \mathcal{X}} \left\{ \sum_{t \in T} \sum_{i \in B} c_{ti} x_{ti} + \int Q(x, \xi) dG(\xi) \right\}, \tag{2.5}$$

where

$$Q(x, \xi(\omega)) = \min \Big\{ \sum_{t \in T} \big[\sum_{i \in B} r_{ti} y_{ti}(\omega) + \sum_{j \in B'} r_{tj} w_{tj}(\omega) + h_t s_t(\omega) \big] \Big\}, \tag{2.6}$$

subject to:

$$\sum_{k \in F} w_{tk}(\omega) + s_t(\omega) = D_t(\omega) + s_{t-1}(\omega), t \in T, \tag{2.7}$$

$$w_{ti}(\omega) \le \kappa_{ti}^{p}, x_{it}, t \in T, i \in B, \tag{2.8}$$

$$w_{tj}(\omega) \le \kappa_{tj}^{f}, t \in T, j \in B', \tag{2.9}$$

$$y_{ti}(\omega) \ge w_{ti}(\omega), t \in T, i \in B, \tag{2.10}$$

$$y_{ti}(\omega) \ge \rho_{ti} x_{ti}, t \in T, i \in B, \tag{2.11}$$

$$w_{tk}(\omega) \ge 0, t \in T, k \in F, s_t(\omega) \ge 0, t \in T. \tag{2.12}$$

The objective function is given in Eq. (2.5): the first term is the upfront allotment cost in the first stage, and the second term is the minimum expected weekly cost in the second stage. The expectation is calculated using the Riemann-Stieltjes integral with respect to the demand distribution G. In the second-stage problem (2.6) given the demand scenario ω, the forwarder observes the weekly demand vector $\xi(\omega)$, and the minimum weekly cost is $Q(x, \xi(\omega))$ given the long-term allotment x from the first stage. In the second stage, the objective function includes the total freight cost on the BSA and non-BSA flights in the first two terms as well as the inventory holding cost in the last term.

The first-stage constraint is the upper bound and the integrality on the allotment vector: $x \in \mathcal{X}$, and the second-stage constraints are Eqs. (2.7)-(2.12). Constraint Eq. (2.7) is the balance constraint previously discussed in Eqs. (2.2)-(2.3). Constraints Eqs. (2.8)-(2.9) pertain to capacity constraints on BSA and non-BSA flights, respectively. The capacity on the BSA flight, $\kappa_{ti}^{p} x_{ti}$, depends on the first-stage decision. The chargeable weight on BSA flight Eq. (2.4) is linearized by introducing an auxiliary variable $y_{ti}(\omega)$ in Eqs. (2.10)-(2.11). Finally, Eq. (2.12) is the non-negativity constraint on the allocation usage $w_{tk}(\omega)$ and the inventory level $s_t(\omega)$. The non-negative inventory implies that the daily usages on all flights are at most the effective demand; i.e.,

$$\sum_{k \in F} w_{tk}(\omega) \leq D_t(\omega) + s_{t-1}(\omega),$$

followed from the definition of the inventory level Eq. (2.2).

3. Results

3.1 Theoretical results

In a similar manner to x in Eq. (2.1), let $c = (c_{ti} : t \in T, i \in B)$. Let

$$\mathcal{Q}(x) = \int Q(x, \xi) dG(\xi),$$

be the value function or the recourse function. The model (2.5)–(2.12) can be concisely expressed as

$$\min_{x \in \mathcal{X}} \{c^{\top} x + \mathcal{Q}(x)\}, \tag{3.1}$$

Our model (3.1) is the two-stage stochastic program with fixed recourse. The first-stage variable is the long-term allotment x_{ti}, and the second-stage variables are $w_{tk}(\omega), y_{ti}(\omega), s_t(\omega)$. The coefficients of the first-stage variable are the pallet capacity κ_{ti}^{p} in Eq. (2.8) and the minimum chargeable weight ρ_{ti} in Eq. (2.11); they are fixed and do not depend on the scenario, making the recourse fixed. In stochastic programs with random recourse, challenges in characterizing the feasibility region may arise.

Theorem 3.1. *Assume that demand vector ξ has finite second moments and that the warehouse supply capacity is infinite. The program (3.1) attains a finite optimal cost.*

Proof. From the assumption of infinite warehouse capacity, no realized demand $\xi(\omega)$ can lead to infeasibility in the second stage. The inventory level (excess demand) can be as large as needed. The two-stage stochastic program has complete recourse. It follows from Theorem 6 in [39] that and the value function in the second stage $\mathcal{Q}(x)$ is finite. Recall from Eq. (2.1) that $0 \leq x_{ti} \leq x_{ti}^{u}$. The constraint set in the first stage $\mathcal{X}$ is bounded for $x \in \mathcal{X}$. Hence, in the two-stage stochastic program $\inf_{x \in \mathcal{X}} \{c^{\top} x + \mathcal{Q}(x)\} = \min_{x \in \mathcal{X}} \{c^{\top} x + \mathcal{Q}(x)\} < \infty$; the minimum cost is attainable. Without the assumption of the infinite warehouse capacity, if the realized demand is extremely large, the problem in the second stage may become infeasible, and the value function would not be finite $\mathcal{Q}(x) = +\infty$. □

Theorem 3.1 ensures that the problem is well-defined. The two assumptions concerning shipment demand and warehouse capacity supply are commonly applicable in practical scenarios, and they can be addressed analytically. For instance, consider probability distributions without finite second moments such as Cauchy and Pareto distributions. Truncating or censoring them from above results in finite second moments. A discrete distribution G with a finite support Ω also has a finite moment.

In the case of finite warehouse capacity, $\kappa_e^s < \infty$. The model would incorporate the warehouse capacity constraint $s_t(\omega) \leq \kappa_e^s$ for each $t \in T$ and $\omega \in \Omega$. To maintain feasibility in the second-stage problem $Q(x, \xi(\omega))$ in Eqs. (2.6)-(2.12), we would introduce a dummy flight with infinite capacity and a significantly large freight cost. Let e represent the dummy flight with an associated extremely high cost $r_e \gg \max\{r_k : k \in F\}$. Define $B'_e = B \cup \{e\}$ and $F_e = B \cup B'_e$. The model would then be modified by replacing the set of non-BSA flights B' with B'_e and the set of all flights F with F_e.

The extensive form of the problem (3.1) is a large mixed integer linear program (MILP). The first-stage variable x_{ti} is an integer, whereas the second-stage variables $w_{tk}(\omega), y_{ti}(\omega), s_t(\omega)$ are continuous. In the first stage, the number of variables is $|T||B|$. In the second stage given the demand scenario of $\omega \in \Omega$, the number of variables is $|T||\Omega|(|F| + |B| + 1)$. Thus, the extensive form of our two-stage stochastic program has the total variables of

$$|T|\big(|B| + |\Omega|(|F| + |B| + 1)\big). \qquad (3.2)$$

The integer program is NP-complete. The initial proposal of the L-shaped method for stochastic integer programs with complete recourse can be traced back to [40], while additional heuristic algorithms are documented in [41–43].

3.2 Numerical results

The dataset, obtained from one of Thailand's largest air freight forwarders, spans from April 1, 2020, to March 31, 2021, covering a total of 53 weeks. It focuses on the export of general cargo originating from BKK airport. When ranking yearly demands, the top four destinations are NRT, HKG, PVG and MNL, respectively. Let $A = \{\text{NRT}, \text{HKG}, \text{PVG}, \text{MNL}\}$. Fig. 2 shows the yearly demand and the total supply, which is the sum of the yearly BSA and non-BSA capacities. The daily demand displays significant variation, characterized by large coefficient of variation (cv) and positive skewness, as shown in the upper section of Table 2. From Fig. 2, the yearly supply surpasses the total demand by a considerable margin. For all destinations, the non-BSA capacity exceeds the BSA capacity. Despite this excess capacity, the non-BSA freight rate is, on average, higher than the BSA rate. All monetary values are presented in Thai Baht (THB).

The sets of BSA and non-BSA flights, along with their details on each DoW, are given in Tables 3-6. The set of planning horizon is $T = \{1, 2, \ldots, 6, 7\}$. On these lanes, all BSA carriers do not impose upfront costs for their allotments; i.e., $c_{ti} = 0$ for $t \in T$ and $i \in B$. Except the last day of week (Sunday), the holding cost is $h_t = 17.5$ THB/kg/day for $t \in \{1, 2, \ldots, 6\}$. This is derived from the handling and storage charges at a warehouse at the BKK airport, along with the estimated goodwill loss. For the last day of the planning horizon, the holding cost is notably higher at $h_7 = 1017.5$ THB/kg/day, aligning with the assumption of no initial inventory $s_0(\omega) = 0$. As stated in Theorem 3.1, assume that the warehouse capacity is infinite. This is observed in practice, as there are numerous warehouses near BKK airport.

3.2.1 Algorithm evaluation scheme

We aim to assess the applicability of our proposed model for the top four lanes. The forward-chaining cross-validation for time series serves as our chosen evaluation technique. In forecasting literature, this ap-

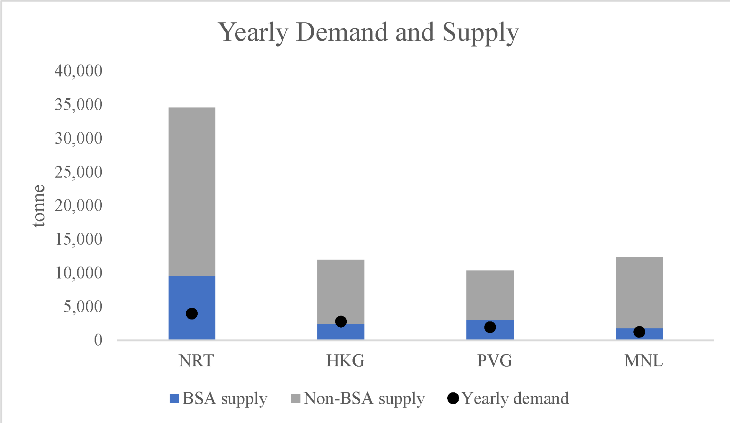

Fig. 2. Yearly demand and supply.

Table 2. Top four trade lanes.

Destination	NRT	HKG	PVG	MNL
Daily demand				
Mean, Stdev. (kg)	10739, 7557	7478, 7091	5217, 6533	3417, 4743
cv, Skewness	0.70, 0.45	0.95, 1.11	1.25, 2.38	1.39, 3.50
Average rate (THB/kg)	121.05	37.62	31.33	116.06
BSA $\bar{r}_B$	100.33	25.00	18.50	78.67
Non-BSA $\bar{r}_S$	130.62	39.91	35.00	124.69
%Diff. $(\bar{r}_S - \bar{r}_B)/\bar{r}_S$	23.19	37.36	47.14	36.91

Table 3. PVG flight details.

Dest.	No. (k)		Rate	DoW (t) M	Tu	W	Th	F	Sa	Su	ρ_{tk}	κ^p_{tk}	κ^f_{tk}
PVG	1	B	18	0^1	2	0	0	0	0	0	1500	2500	
PVG	2	B	19	0	2	2	2	2	2	2	2200	4500	
PVG	3	B'	12	1^2	0	1	0	0	1	0			2500
PVG	4	B'	12	0	1	0	1	1	0	0			5000
PVG	5	B'	40	1	1	1	1	1	1	1			5000
PVG	6	B'	43	0	0	1	0	0	0	0			2500
PVG	7	B'	43	0	1	0	1	0	0	0			5000
PVG	8	B'	45	0	1	1	1	1	1	1			10000
PVG	9	B'	50	0	1	0	0	0	0	0			10000

Notes: 1 On BSA flight, this is the maximum number of allotment; and 0 if there is no allotment available on this DoW.
2 On non-BSA flight, this is an indicator of 1 if the flight operates on this DoW; and 0 otherwise.

proach is also referred to as "evaluation on a rolling forecasting origin" [44]. Under this time series cross-validation method, we initiate with a training set of eight weeks ($n_0 = 8$) and incrementally extend the size of successive training sets by a set size of one week; see Fig. 3. Over the span of one year ($n_T = 53$ weeks), each destination un-

Table 4. HKG flight details.

Dest.	No.		Rate	DoW (t)							ρ_{tk}	κ^p_{tk}	κ^f_{tk}
	(k)			M	Tu	W	Th	F	Sa	Su			
HKG	1	B	12	2	0	2	0	0	0	0	1650	2500	
HKG	2	B	38	0	0	0	5	0	5	5	1650	2500	
HKG	3	B'	30	0	0	1	0	0	0	0			5000
HKG	4	B'	30	1	0	0	0	0	0	0			10000
HKG	5	B'	32	0	0	0	0	0	1	1			2500
HKG	6	B'	32	0	1	0	0	0	0	0			5000
HKG	7	B'	39	0	1	1	0	1	1	1			2500
HKG	8	B'	39	1	0	0	0	0	0	0			5000
HKG	9	B'	45	0	0	0	1	0	1	1			10000
HKG	10	B'	48	0	0	0	0	1	0	0			5000
HKG	11	B'	48	0	1	1	1	0	1	1			10000
HKG	12	B'	48	0	0	0	0	1	0	0			5000
HKG	13	B'	48	0	1	1	1	0	1	1			10000

Table 5. NRT flight details.

Dest.	No.		Rate	DoW (t)							ρ_{tk}	κ^p_{tk}	κ^f_{tk}
	(k)			M	Tu	W	Th	F	Sa	Su			
NRT	1	B	90	0	0	2	3	2	0	0	1500	2500	
NRT	2	B	90	0	0	1	0	0	0	0	1500	2500	
NRT	3	B	90	0	1	0	0	0	0	0	1500	2500	
NRT	4	B	90	0	2	0	0	0	0	2	1500	5000	
NRT	5	B	106	0	9	9	9	9	0	9	1650	2500	
NRT	6	B	136	0	2	0	0	2	0	2	1650	5000	
NRT	7	B'	74	1	1	1	1	1	1	1			5000
NRT	8	B'	105	1	1	1	1	1	1	1			5000
NRT	9	B'	101	1	1	1	1	1	1	1			5000
NRT	10	B'	95	1	1	1	1	1	1	1			5000
NRT	11	B'	115	1	1	1	1	1	1	1			5000
NRT	12	B'	130	1	0	0	0	0	0	0			5000
NRT	13	B'	130	0	1	1	1	1	1	1			10000
NRT	14	B'	145	1	1	1	1	1	1	1			5000
NRT	15	B'	137	1	1	1	1	1	1	1			5000
NRT	16	B'	130	1	1	1	1	1	1	1			5000
NRT	17	B'	172	1	1	1	1	1	1	1			10000
NRT	18	B'	182	1	0	0	0	0	0	0			5000
NRT	19	B'	182	0	1	1	1	1	1	1			10000

dergoes $n_T - n_0 = 53 - 8 = 45$ trials, resulting in a total of $45 \times 4 = 180$ problem instances for all four destinations.

Specifically, in week w at destination a, let $d_t^{(a)}(w)$ denote the daily demand on DoW t where $a \in A$ and let $d^{(a)}(w) = (d_1^{(a)}(w), ..., d_7^{(a)}(w))$ denote the weekly demand vector. For the wth resample where $w = 1, 2, ..., n_T - n_0$, the week index set of the training data is

$$S(w) = \{w, w+1, \ldots, w + n_0 - 1\},$$

the training set of demands is $(d^{(a)}(\ell) : \ell \in$

Table 6. MNL flight details.

Dest.	No. (k)		Rate	M	Tu	W	Th	F	Sa	Su	ρ_{tk}	κ^p_{tk}	κ^f_{tk}
MNL	1	B	75	0	2	0	3	0	3	0	1500	2500	
MNL	2	B	76	0	0	0	2	0	2	0	1500	2500	
MNL	3	B	85	0	0	0	0	0	2	0	1500	2500	
MNL	4	B'	94	1	0	0	0	0	0	0			2500
MNL	5	B'	94	0	1	0	1	1	1	1			5000
MNL	6	B'	95	1	1	1	1	1	1	1			2500
MNL	7	B'	120	0	0	0	1	0	0	0			5000
MNL	8	B'	120	1	0	0	0	0	0	0			2500
MNL	9	B'	120	0	1	1	1	1	1	0			5000
MNL	10	B'	120	0	1	1	1	0	1	0			5000
MNL	11	B'	125	0	1	1	1	1	1	1			5000
MNL	12	B'	130	1	0	0	0	0	0	0			2500
MNL	13	B'	130	0	0	1	0	1	1	1			5000
MNL	14	B'	135	1	0	0	0	0	0	0			2500
MNL	15	B'	135	0	1	1	1	0	1	0			5000
MNL	16	B'	203	0	1	1	1	1	1	1			5000

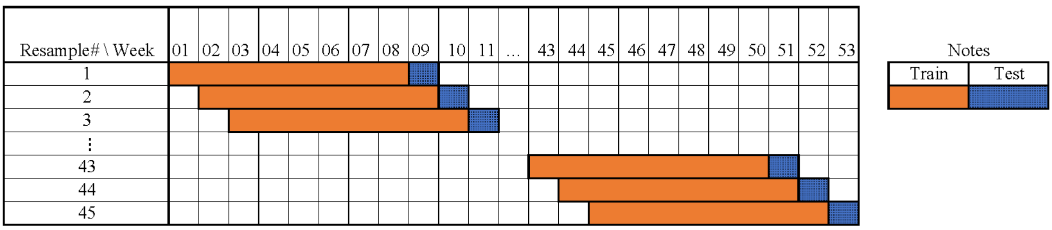

Fig. 3. Time series cross validation scheme.

$S(w)$) and the testing demand is $d^{(a)}(w+n_0)$.

To assess the effectiveness of our proposed strategy (denoted as H), we compare it against two distinct policies: the ideal (perfect) policy (denoted as P) and the existing (current) approach (denoted as C). Denote the set of three models as $M = \{C, H, P\}$. In the context of the perfect solution, we assume complete knowledge of random demands in the test set for making both long-term allotment and short-term allocation decisions. The weekly cost from ours would be compared to the benchmark from the perfect policy.

As for the current operational practices at the case study, the procedure involves reserving the maximum number of allotments as long-term capacity. For short-term decisions, team members manually allocate shipments to familiar flights, with each staff member overseeing multiple trade lanes. However, the current policy is accompanied by several drawbacks. The long-term maximum allotment capacity is consistently too large for the majority of daily shipments, leading to underutilization of the allotment. As a consequence, the minimum chargeable weight stipulated by the BSA contract is frequently not met, resulting in the forwarder having to pay for the unused portion of the allotment. In addressing the short-term allocation challenge, staff members often allocate numerous shipments to a single BSA flight boasting the largest allotment, neglecting other flights with lower freight rates. Staff may demonstrate reluctance in breaking up shipments and may lack clarity on how to divide them into different master air waybills. These drawbacks of the current policy could be alleviated by using our model.

The long-term allocation in our model is derived from the training set, whereas the perfect model relies on the test set. To establish the long-term allotment for these two policies, we employ the two-stage stochastic program introduced in Section 2. Within the stochastic program, we utilize the empirical distribution for generating demand scenarios. Consider the destination airport a. Let $x_{ti}^{(a,m)}(w)$ denote the allotment on flight i on DoW t if model m is used. For the wth resample, the set of scenarios is $S(w)$, and each scenario is equally likely to occur with probability $1/n_0$ where $n_0 = |S(w)|$. At destination a, the probability distribution G in Eq. (2.5) of random demand vector $\xi^{(a)}(w)$ is given as

$$\Pr\left(\xi^{(a)}(w) = d^{(a)}(\ell)\right) = \frac{1}{n_0}, \qquad (3.3)$$

for each $\ell \in S(w)$. That is,

$$\begin{aligned} &\Pr\left(\xi^{(a)}(w) = d^{(a)}(w)\right),\\ &\quad = \Pr\left(\xi^{(a)}(w) = d^{(a)}(w+1)\right),\\ &\quad \vdots\\ &\quad = \Pr\left(\xi^{(a)}(w) = d^{(a)}(w+n_0-1)\right),\\ &\quad = \frac{1}{n_0}. \end{aligned}$$

Clearly, the empirical demand distribution Eq. (3.3) has finite second moments, ensuring the existence of an optimal solution for the problem (see Theorem 3.1). For our approach in the wth resample, the two-stage stochastic programming model with the empirical distribution given in Eq. (3.3) is solved, and the allotment $x_{ti}^{(a,H)}(w)$ is obtained. For the perfect policy in the wth resample, the two-stage stochastic programming model with the empirical distribution from the test demand:

$$\Pr\left(\xi^{(a)}(w) = d^{(a)}(w+n_0)\right) = 1. \qquad (3.4)$$

Distribution Eq. (3.4) is a degenerate distribution with the support of a single demand vector $d^{(a)}(w+n_0) = ((d_t^{(a)}(w+n_0) : t \in T)$ from the test set. Let $x_{ti}^{(a,P)}(w)$ denote the allotment from the perfect policy in the wth resample. In contrast to policies $\{H, P\}$, the current policy adopts a straightforward approach, using the maximum allotment from Tables 3-6, without engaging in solving any mathematical programs in the first stage. From the current policy, the allotment is $x_{ti}^{(a,C)}(w) = x_{ti}^{u}$. Denote the allotment vector for each policy $m \in M$ as $x^{(a,m)} = (x_{ti}^{(a,m)} : t \in T)$. Note that unlike the allotment from ours and the perfect policy, the allotment from the current policy does not depend on the wth resample data, but we write $x^{(a,C)}(w)$ simply to have a consistent notation with the other policies $\{H, P\}$.

In the second stage, following the determination of the initial allotment in the first stage, each policy establishes the daily allocation based on the realization of shipment demands in the test set. In the wth resample, the second-stage problem Eqs. (2.6)-(2.12) with the test demand $d^{(a)}(w+n_0) = (d_t^{(a)}(w+n_0) : t \in T)$ materializes, and the allocation among the BSA and non-BSA flights as well as the warehouse storage is determined. For each policy $m \in M$, the minimum weekly cost (excluding the upfront allotment cost) in Eq. (2.6) becomes $Q(x^{(a,m)}(w), d^{(a)}(w+n_0))$.

The calculations of the allotment before demands materialize and the cost after demands materialize are summarized in Table 7.

Table 8 summarizes the performance of the three policies. The weekly average allotted weight for policy m (aggregated across all destinations and resample trials) is calculated as

$$\sum_{t\in T}\sum_{i\in B}\Big(\frac{1}{45\times 4}\sum_{w=9}^{53}\sum_{a\in A}x_{ti}^{(a,m)}(w)\Big), \tag{3.5}$$

and the weekly average cost is given as

$$\sum_{t\in T}\sum_{i\in B}\Big(\frac{1}{45\times 4}\sum_{w=9}^{53}\sum_{a\in A}\tilde{Q}^{(a,m)}(w)\Big), \tag{3.6}$$

where $\tilde{Q}^{(a,m)}(w) = Q(x^{(a,m)}(w), d^{(a)}(w+n_0))$. In the first stage, in comparison to the current allotments, the allotments from our proposed model closely align with those from the perfect model; the difference from the perfect model is only 5.5%. The allotted weight from the current policy is more than 200% of the perfect allotted weight. Our proposed model results in significant cost savings compared to the current policy. Moreover, the cost difference between ours and the perfect model is less than 5%.

3.2.2 Discussions and insights

Across all four destinations, the allotment weights from the current policies are the largest, compared to those from the perfect policies and ours. Fig. 4 shows the weekly average allotted weight for policy m over all resample trials for each destination $a \in A$:

$$\sum_{t\in T}\sum_{i\in B}\Big(\frac{1}{45}\sum_{w=9}^{53}x_{ti}^{(a,m)}(w)\Big). \tag{3.7}$$

Ours and the perfect allotments do not differ significantly. However, for the current policy, the differences between the current allotment and the perfect allotment are much larger at all destinations, with the largest difference at NRT airport. Recall from Fig. 2 at NRT airport, the yearly BSA capacity supply is much larger than the yearly demand. NRT has the largest difference between the yearly BSA capacity and the yearly demand. The current policy uses the entire BSA capacity. This leads to the poorest performance of the current policy at NRT airport.

Our problem shares similarities with the so-called newsvendor problem in stochastic inventory theory. In ours, the allotment is determined before the cargo demand during the season materializes. In the newsvendor problem, the stocking (order) quantity is determined before the single-period demand materializes. The optimal order quantity that minimizes the expected total cost is $F^{-1}(c_u/(c_u + c_o))$ where F is the demand distribution, c_u is the unit underage cost and c_o is the unit overage cost. If p is the unit selling price and v is the unit cost, then the critical ratio is

$$\frac{c_u}{c_u + c_o} = \frac{p - v}{p} = 1 - \frac{v}{p}.$$

In ours, suppose that the average BSA rate is $\bar{r}_B$ and the average non-BSA rate is $\bar{r}_S$. The underage cost is the incremental cost of $\bar{r}_S - \bar{r}_B$ if the allotment is less than the realized demand. The overage cost is the BSA freight rate if the allotment is larger than the realized demand, and the forwarder pays for the unused allotment at the rate of $\bar{r}_B$. The critical ratio for our air cargo problem becomes

$$\frac{c_u}{c_u + c_o} = \frac{\bar{r}_S - \bar{r}_B}{\bar{r}_S} = 1 - \frac{\bar{r}_B}{\bar{r}_S}.$$

Table 7. Allotment and cost of three policies at destination a in the wth resample.

Approach	Allotment before knowing demand	Cost after knowing demand
Current	$x^{(a,C)}$ from x^u_{ti}	$Q(x^{(a,C)}(w), d^{(a)}(w+n_0))$
Ours	$x^{(a,H)}(w)$ from solving (2.5) with (3.3)	$Q(x^{(a,H)}(w), d^{(a)}(w+n_0))$
Perfect	$x^{(a,P)}(w)$ from solving (2.5) with (3.4)	$Q(x^{(a,P)}(w), d^{(a)}(w+n_0))$

Table 8. Policy evaluation.

Weekly	Current	Proposed	Perfect
Avg Allotted Weight (kg) in (3.5)	326,500	99,589	105,400
% Diff. from Perfect	209.8	-5.5	
Avg Cost (THB) in (3.6)	4,369,813	2,960,956	2,836,810
% Diff. from Perfect	54.0	4.4	

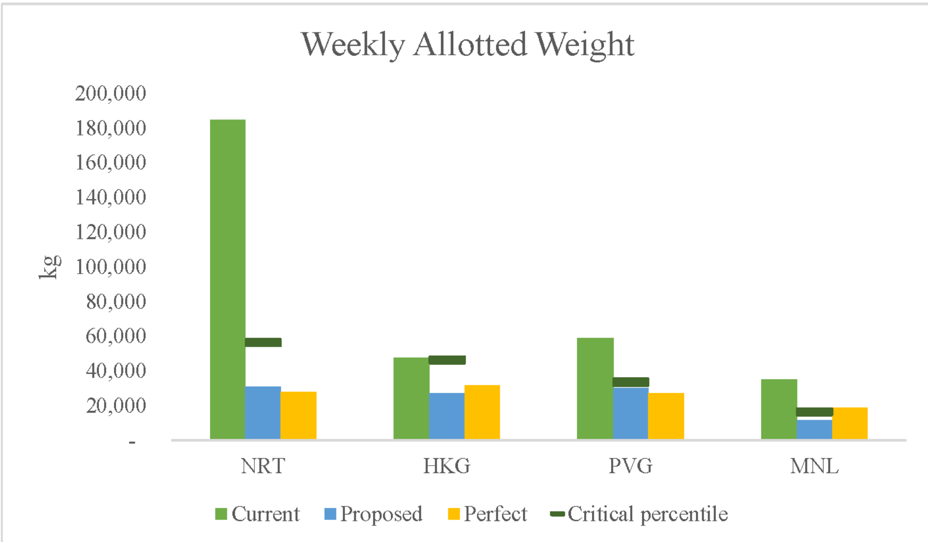

Fig. 4. Allotted weight in (3.7) for each destination.

As a reference, the critical percentile of the weekly demand records is denoted in a thick black line in Fig. 4. If the current allotment is much larger than the critical percentile, then the current policy is likely to perform poorly, and our approach would potentially offer significant cost savings.

The weekly cost Eq. (3.6), including the inventory holding cost, the BSA freight cost, and the non-BSA freight cost, is presented in Fig. 5. Clearly, our approach outperforms the current policy, while the current policy performs the worst. Specifically, the current policy has the largest BSA freight cost portion. However, for both the perfect policy and ours, the BSA and non-BSA cost portions are not significantly different. Additionally, for all policies, the inventory holding cost accounts for the smallest portion.

The advantages and disadvantages of our approach are as follows: Among key

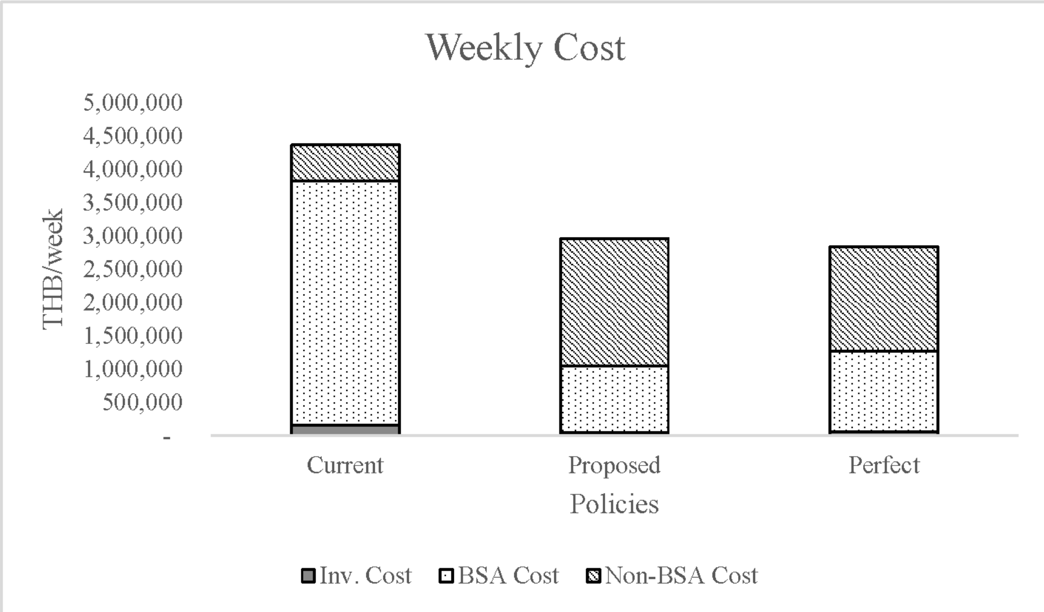

Fig. 5. Weekly cost and its components.

advantages are the cost effectiveness and the applicability of our model. Our approach yields significant cost savings compared to the current policy. The allotment from our approach does not differ notably from the perfect allotment. Moreover, our model is easy to solve, since the problem size is relatively small. Specifically, in the numerical example, the number of scenarios in the two-stage stochastic program is equal to the number of records in the training set; i.e., $|\Omega| = n_0 = 8$. The number of variables, given in Eq. (3.2), for NRT, HKG, PVG and MNL are 1498, 910, 686 and 1141, respectively. As an example, for NRT, according to Table 5 that the number of BSA flights is $|B| = 6$, and the total number of flights is $|F| = 19$: The number of first-stage variables is $|T||B| = (7)(6) = 42$, and the number in the second stage is $|T||\Omega|(|F| + |B| + 1) = (7)(8)(19 + 6 + 1) = 1456$. The extensive form of our two-stage stochastic programming model is written using Python's `PuLP`, and the MILP is solved by the `CBC` (COIN-OR Branch-and-Cut) solver. The computations were performed on a laptop equipped with an 11th Generation Intel Core i7 processor with a reported speed of 1.69 GHz. Across all resample trials, the computational times remained within one second. This means that the weekly allotment for each destination can be computed almost instantaneously. Unlike the current policy, which relies on maximum allotments, our approach provides an efficient allotment strategy.

The obvious practical disadvantage is that our model requires solving a mathematical programming model; this skill is not common among staff at the freight forwarder company. The firm may need to provide users with a decision support system (DSS) that simplifies the process of determining allotments and allocating shipments among BSA and non-BSA flights, without requiring expertise in technical details. A spreadsheet-based DSS could be suitable, as most staff members are familiar with spreadsheet platforms such as Excel or Google Sheet. Additionally, flight details Tables 3-6 need to be entered once at the beginning of the season, and demand scenarios are constructed from historical records from the company's database. At the front end, users input the initial inventory at the beginning of each week, and at the back end, the allocation plan for the entire planning horizon (one week) is reported to the user. The rolling horizon may be used, if a mid-week update is needed. Technical limitations of our model include the one dimensionality of demand, the risk neutrality of the decision maker, the uncertainty source being demand only, and the use of empirical distribution. Some of these limitations are further discussed in the extension in Section 4.

4. Conclusion

In summary, we formulate a two-stage stochastic programming model for the forwarder's capacity management problem. In the first stage, the allotment for the entire season is determined without knowledge of actual demand values. Subsequently, in the second stage, once the demand materializes, the forwarder optimally allocates resources among BSA and non-BSA flights, each having distinct freight rates and minimum chargeable weight requirements. Within this multi-day setting, excess demand from one day is stored overnight and incorporated into the next day's demand, resulting in a dynamic network with time-varying demand. In the case study, we compare our solution to the current policy at one of Thailand's largest freight forwarders. Significant cost savings are obtained from our solution approach.

A few extensions are as follows: Firstly, alternative scenario generation methods can be investigated, supplementing the empirical distribution employed in the case study. Secondly, considering that flights may have different travel times—direct flights potentially having higher freight rates but shorter travel durations—the total cost should encompass both freight and time costs, given the time-sensitive nature of air cargo shipments. Lastly, a contract design problem between a forwarder and a carrier could be examined. Both entities seek to maximize their respective expected profits, leading to a game-theoretic equilibrium characterization. We hope to pursue these topics in the future.

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