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Stochastic green profit-maximizing hub location problem

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Abstract:	This paper proposes a two-stage stochastic profit-maximizing hub location problem (HLP) with uncertain demand. Additionally, the model incorporates several carbon regulations, such as carbon tax policy (CTP), carbon cap-and-trade policy (CCTP), carbon cap policy (CCP), and carbon offset policy (COP). In the proposed models, an enhanced sample average approximation (ESAA) method was used to obtain a suitable number of scenarios. To cluster similar samples, k-means clustering and self-organizing map (SOM) clustering algorithms were embedded in the ESAA. The L-shaped algorithm was employed to solve the model inside the ESAA method more efficiently. The proposed models were analyzed using the well-known Australian Post (AP) data set. Computational experiments showed that all of the carbon regulations could reduce overall carbon emissions. Among carbon policies, CCTP could achieve better economic results for the transportation sector. The results also demonstrated that the SOM clustering algorithm within the ESAA method was superior to both k-means inside ESAA and classical SAA algorithms according to the %gap and standard deviation measures. In addition, the results showed that the L-shaped algorithm performed better than the commercial solver in large-scale instances.

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Response to the Reviewers' Comments on Manuscript TJOR-2022-OP-0098.R2

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We very much appreciate the encouraging, critical, and constructive comments on this revision of the manuscript by the referees, editor, and associate editor. This manuscript has been improved greatly by addressing provided comments. We strongly believe that the comments and suggestions have improved the value of the revised manuscript by many folds. We have taken them fully into account in the revision. The revised manuscript is submitted accompanied by a response to reviewers' comments. Answers are provided in blue and indicate what measures have been taken to address the raised points. Major changes have been highlighted in the revised manuscript using red colored text.

Editor

> We are nearly there and well done. The authors are encouraged to incorporate the minor changes raised by the referees, perform a thorough spell check and consider if possible any recent related papers from this journal and related ones to position your work within the state of the art in this area. Good luck and look forward to receiving your final version.

Response: We would like to thank the editor for giving us the opportunity to revise the manuscript. We have addressed the reviewers' comments. We hope that the revised manuscript will better suit the Journal of the Operational Research Society. In the revised version of the manuscript, we have also reviewed recently published papers, specifically in JORS. The whole revised manuscript was edited by the Authors to fix potential errors.

Moreover, the paper was edited by a native English editor.

Referee #1

> The authors have addressed my comments and I suggest the paper be accepted in its current form.

Response: We are thankful for your positive feedback about our revised manuscript acceptance in the JORS. We believe that your constructive comments in previous stages improved our paper, significantly.

Referee #2

> I appreciate the authors' efforts to further improve their manuscript. They provided responses to all my comments and made the necessary adjustments to their paper. However, I have one minor comment about the first paragraph of Section 2.1. I am not sure about the first sentence of that paragraph. I believe it does not fully reflect what the authors try to explain there. Therefore, it would be better if the authors rewrite that paragraph to point out that how those maximal covering hub location problems are related to profit-maximizing hub location problems. Except for this minor issue, I do not have any further major or minor comments.

Response: We appreciate your careful reading of the paper and providing positive feedback and also constructive comments and guidance to improve the manuscript. Your constructive comments in all three review stages have led to a significant improvement in the manuscript. The mentioned sentence in the revised paper is edited. It is changed to "By considering the hub location studies in the literature, it can be concluded that there are two main categories of such studies, in the first category the main objective is minimizing the cost with the aim of delivering all demand. In the second category, there is no obligation to deliver all demand and instead, partial demand will be delivered only. Some studies in this category aim to maximize profits, while others aim to maximize covered demand. One of the early studies is Campbell (1994) proposing a covering p-hub location problem that maximized the origin-destination demand using the established hub facilities".

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Campbell, J.F., 1994. Integer programming formulations of discrete hub location problems. European Journal of Operational Research 72, 387 – 405. URL: http://www.sciencedirect.com/science/article/pii/0377221794903182, doi:https://doi.org/10.1016/0377-2217(94)90318-2.

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ABSTRACT
This paper proposes a two-stage stochastic profit-maximizing hub location problem (HLP) with uncertain demand. Additionally, the model incorporates several carbon regulations, such as carbon tax policy (CTP), carbon cap-and-trade policy (CCTP), carbon cap policy (CCP), and carbon offset policy (COP). In the proposed models, an enhanced sample average approximation (ESAA) method was used to obtain a suitable number of scenarios. To cluster similar samples, k-means clustering and self-organizing map (SOM) clustering algorithms were embedded in the ESAA. The L-shaped algorithm was employed to solve the model inside the ESAA method more efficiently. The proposed models were analyzed using the well-known Australian Post (AP) data set. Computational experiments showed that all of the carbon regulations could reduce overall carbon emissions. Among carbon policies, CCTP could achieve better economic results for the transportation sector. The results also demonstrated that the SOM clustering algorithm within the ESAA method was superior to both k-means inside ESAA and classical SAA algorithms according to the %gap and standard deviation measures. In addition, the results showed that the L-shaped algorithm performed better than the commercial solver in large-scale instances.

KEYWORDS
Location; Stochastic Programming; Sustainability; Transport; Integer Programming.

1. Introduction

As strategic and operational decisions, the assignment of proper hubs and routing paths is determined in the hub location problems (HLPs). Flows with the same destination are collected in hubs from each origin and then transferred to their destinations to gain the benefits of economies of scale. This reduces overall system costs compared to classical transportation networks, in which vehicles that transport flows from origins to destinations may not be fully loaded (e.g., less than truckloads). O'Kelly (1986) shed light on many areas of research on HLPs that have received significant attention in recent decades. The important applications of hub networks include freight and passenger transportation, telecommunications, postal delivery, cargo delivery systems, and express shipment (Campbell and O'Kelly 2012; Contreras 2015; Azizi and Salhi 2022). Many companies, especially online shops, use express shipments. The Laura Ashley company locates its warehouses near FedEx hubs to improve responsiveness to customers Thus, transportation costs are reduced, and delivery times for customers are shortened (Song et al. 2000). Amazon, DHL, and FedEx are just a few examples of companies using

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hub networks to reduce costs and take advantage of them (O'Kelly 2014; Bowen 2012). Transport costs make up a significant portion of products' prices, and hub networks can reduce the prime cost of products. The initial research on HLPs was done on the assumption that flows should be routed through one or two hubs that are fully interconnected, entirely demand-satisfying, and without point-to-point connections between nodes. Nevertheless, these assumptions can be relaxed, and demand can be satisfied directly between origin-destination nodes without using hubs, or more than two hubs can be served to satisfy demand (Taherkhani and Alumur 2019).

Hub facilities can serve as production centers, where flows of materials from any origin are assembled in hub facilities, and commodities are transferred to destinations (Ghodratnama et al. 2012). A number of material handling activities are conducted in hubs to manage and sort flows. Therefore, some machinery (e.g., forklifts, industrial machinery, etc.) is needed at hub facilities, which can cause environmental pollution. Thus, in addition to economic development decisions, environmental concerns should also be considered. Creating hub facilities is a strategic decision that will have a long-term effect, and an appropriate decision should be made about their location. Climate change has been caused by certain human activities, including industrialization, deforestation, and the emission of greenhouse gases. The sea level rises as a result of climate change. The expansion of the transportation infrastructure for people and commodities is necessary for economic development. However, this transportation causes environmental problems such as carbon emissions. Governments have imposed regulations on transportation companies to control carbon emissions, which is currently a global concern. In the transportation sector, the highest carbon emissions are produced by vehicles that use fossil fuels (e.g., gasoline and diesel), including planes, trucks, trains, and ships. Accordingly, hub facilities and pathways are essential for designing green hub networks, which should be carefully chosen to achieve the desired environmental objectives.

Governments deployed various carbon regulations to control carbon emissions, such as carbon tax policy (CTP), carbon cap policy (CCP), carbon cap-and-trade policy (CCTP), and carbon offset policy (COP). In terms of CTP, a carbon tax is charged on each ton of carbon emitted into the atmosphere, and there is no limit on carbon emissions. Nevertheless, companies should pay for their emissions. Due to the revenue and tax paid for carbon emissions, companies can decide whether to satisfy demand. Carbon emissions are not taxed in CCP, but there is a limit on the amount of pollution, and emissions cannot exceed a specified range. In CCTP, carbon can be sold or purchased. Accordingly, much like the CCP, a restriction is placed on the amount of carbon, while carbon can be sold or bought on carbon markets. COP is similar to CCTP; however, only carbon purchases are permitted (Sherafati et al. 2020). It is worth mentioning that carbon pricing and carbon trade policies were implemented in 64 countries globally in 2021 (WORLD BANK GROUP. n.d.).

Carbon regulations have been widely used in various problems (e.g., transportation, facility location, and supply chain problems). From the transportation sector decision-maker perspective, carbon regulations increase the costs of systems. Therefore private companies are less interested in implementing carbon policies through their transportation networks. So some economic incentives should be provided by governments. Decision-makers and firms can use the proposed mathematical models to predict their revenue by considering different carbon regulations. Decision-makers can choose the ap-

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propriate carbon policy depending on net profit and overall carbon emission reduction goals. In classical HLPs, the objective function consists of transportation and hub establishment costs, and decisions are related to locations and allocations. Therefore, hub establishment costs, as well as transportation costs, can affect decisions. Introducing carbon policies in these problems resulted in more established hubs without significant reductions in emissions, since the HLP model should satisfy all demand (Dukkanci et al. 2019). Interestingly, even for CCP, the model may become infeasible. In other words, the model is forced to meet all demand, while emissions are capped at a specific value. In this case, overall emissions cannot be appropriately reduced, resulting in an infeasible solution, while CCTP and COP models are forced to buy more carbon on the market. Therefore, overall carbon emissions were not reduced to achieve the desired environmental levels. Profit-maximizing HLPs, on the other hand, are not obligated to satisfy demand. As a result, several flows may not be met to reduce carbon emissions.

CTP was implemented with a price of \$23 in Australia from 2012 to 2013 and \$24.15 from 2013 to 2014. Although CTP reduced overall emissions in Australia from 2012 to 2014 (on average %1.4), it faced significant challenges from the public and opponents. It increased energy prices for industries and households and was rescinded in 2014. Since 2016, Australia has used an emission trading system covering around half of its greenhouse gas emissions. Several countries, such as Canada and Mexico, have implemented or are scheduled to implement CTP and CCTP. CCTP is heavily reliant on the price of carbon in the market and the maximum amount of carbon emitted, and is more flexible than the other carbon cap policies. Decision-makers can earn money by selling surplus carbon to the carbon market. Despite the excess amount of carbon allowance, this policy encourages firms to emit less carbon. In COP, however, firms are not encouraged if they emit less than a predetermined carbon allowance. The main challenge of cap-based policies is to determine the maximum amount of carbon emitted (Australian Government. n.d.).

Given the information on uncertain parameters, there are several ways to deal with model uncertainty, including robust optimization, fuzzy programming, and stochastic programming. In the stochastic programming approach, the uncertain parameters are known with a probability distribution. Nonetheless, the main challenge in using this approach involves the modeling problem related to the probability distribution of uncertain parameters. To handle these uncertainties, chance-constrained and scenario-based stochastic programming are employed in this approach (Birge and Louveaux 2011; Zhen et al. 2021). The information on uncertain parameters in fuzzy programming is ambiguous, while in classic robust optimization, the information about uncertain parameters belongs to uncertainty sets (Soyster 1973; Ben-Tal et al. 2009; Chu et al. 2019).

The literature on HLPs includes few studies on carbon emissions and even fewer studies that use carbon policies in their problems. Additionally, that research has only considered transportation as an emission source, while hub facilities connect transport chains and produce emissions. Logistic sites are any hubs that connect origin-destination pairs or form the beginning or end of transportation chains. Therefore, in this study, both transportation and hub facilities are considered sources of carbon emissions. Furthermore, most of the studies on sustainable HLPs have used a deterministic approach, leading to unrealistic decisions. In contrast, this study applies two-stage stochastic programming and Monte Carlo simulation to deal with uncertain demand. Finally, all of the

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research in the sustainable HLP literature has used commercial solvers or meta-heuristic algorithms to solve their problems. In contrast, this study uses an exact algorithm (L-shaped algorithm) to solve the problem more efficiently.

The main contributions of this study are summarized as follows: 1) Modeling a profit-maximizing HLP through different carbon policies, such as carbon tax, carbon cap-and-trade, carbon cap, and carbon offset, to achieve economic and environmental objectives. Carbon emissions will cause many environmental hazards, so the proposed model will maximize profit by transferring flows from origins to destinations while, at the same time, addressing environmental concerns. Each country can use different policies to reduce carbon emissions, so this study analyzes all of those policies. 2) Using a two-stage stochastic programming approach to address uncertain demand in the proposed models. 3) Applying an enhanced sample average approximation (ESAA) method to achieve the proper number of scenarios. Based on the probability distribution of the uncertain parameters, a large number of possible scenarios can be generated, and clustering methods (such as k-means and self-organizing map [SOM] clustering algorithms) can be used to reduce the number of possible scenarios. 4) Using an L-shaped algorithm and several variable fixing strategies to solve the proposed models more efficiently.

The rest of the paper is organized as follows: The review of literature on profit-maximizing HLPs, uncertainty, the Benders decomposition algorithm, and sustainability are discussed in Section 2. Section 3 provides the mathematical models of stochastic sustainable profit-maximizing HLPs under different carbon policies according to the SAA method. Section 4 introduces several methods that can be used to enhance the capabilities of the SAA method. Section 5 presents the L-shaped algorithm for solving models within the ESAA method; several ways of variable fixing are also provided for improving the algorithm's performance. In Section 6, the performance of different carbon policies, algorithms, and scenario generation methods are analyzed for solving the proposed models. Finally, the last section provides the conclusion and recommendations for future works.

2. Literature review

The concept of HLP was presented by Goldman (1969). O'Kelly (1986) proposed the application of air transportation in HLP. O'Kelly (1987) introduced HLP in which the flows are transferred through only one hub. In other words, there is only one stop in hubs throughout the hub network. Later, a mathematical model was introduced by Campbell (1994) by considering hub establishment and transportation costs. Farahani et al. (2013) presented a review of solution methods, problems, and applications of HLPs from 2007 to 2012. They studied several applications of HLPs and presented different variants of mathematical models and solution algorithms, which are widely used in the literature. Furthermore, several real cases are briefly introduced. Alumur et al. (2020) specified several research gaps in HLPs, which can be helpful in the field. In addition to incorporating economies of scale in HLPs, they recommended using economies of density and economies of spatial scope in the concept of HLPs.

An overview of four classes of studies on HLPs is provided in this section, including research on profit-maximizing hub location problems, HLPs under uncertainty, the

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Benders decomposition algorithm for HLPs, and sustainable HLPs.

2.1. *Profit-maximizing hub location problems*

By considering the hub location studies in the literature, it can be concluded that there are two main categories of such studies, in the first category the main objective is minimizing the cost with the aim of delivering all demand. In the second category, there is no obligation to deliver all demand and instead, partial demand will be delivered only. Some studies in this category aim to maximize profits, while others aim to maximize covered demand. One of the early studies is Campbell (1994) proposing a covering p-hub location problem that maximized the origin-destination demand using the established hub facilities. Hwang and Lee (2012) presented an uncapacitated p-hub maximal covering model with a single assignment strategy. Peker and Kara (2015) introduced a partial coverage p-hub maximal covering problem with multiple and single assignment strategies.

As the same hub maximal covering problems, in profit-maximizing HLPs, all demand nodes are not forced to be satisfied. There is also no given budget for locating hub facilities, and profit is maximized rather than covering demand. Furthermore, the covering hub location works did not take the total transportation costs into account. Alibeyg et al. (2016) proposed a hub network design problem with multiple assignments by maximizing the net profit objective, including transportation costs, hub establishment costs, and total revenue. In order to design a hub network, they considered many factors, such as the location of hub facilities, activation of edges, and specification of flow pathways for transporting commodities. In addition, Alibeyg et al. (2018) presented a Lagrangian relaxation framework augmented with the branch and bound algorithm to obtain bounds at each branching of a node for their previous research work (Alibeyg et al. 2016). Lin and Lee (2018) presented hub network configurations based on cost minimization and profit maximization. In their study, a hub location design with inelastic demand and minimization objective was extended to a hub location design with elastic demand and maximization objective. Taherkhani and Alumur (2019) proposed profit-maximizing HLPs that considered a single assignment, r-allocation, and multiple assignment strategies. Their objective function consisted of total revenue minus transportation and hub establishment costs. Any node can be assigned to any, precisely one, and r number of hub facilities, respectively, in multiple, single, and r-allocation strategies. In addition, they modeled a profit-maximizing HLP by allowing direct connections between demand nodes. As a result, flows could be transferred directly between origin-destination nodes without hubs. Taherkhani et al. (2020) modeled a two-stage stochastic profit-maximizing HLP with uncertain demand by considering multiple classes of commodities. They used an L-shaped algorithm to solve the models inside the SAA method. Taherkhani et al. (2021) presented robust stochastic profit-maximizing HLP with min-max regret criteria. In addition, revenue and demand are considered to be uncertain. They applied the Benders decomposition algorithm to solve the proposed model. Oliveira et al. (2022) presented multiple allocation hub networks with a profit maximization objective in an incomplete network. Their proposed model seeks to determine the location of hub facilities, allocations, the topology of the network, and origin-destination routing.

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Furthermore, the Benders decomposition algorithm was employed to solve the problem.

2.2. *Hub location under uncertainty*

In the literature on HLPs, several uncertainty approaches (such as robust optimization and stochastic programming) are used to address uncertainties. Contreras et al. (2011b) proposed a two-stage stochastic HLP with uncertain demand and transportation costs. Taking into account uncertain dependent transportation costs or demand, the stochastic solutions resembled the expected value problem (EVP). The independent transportation costs, on the other hand, were not equal to EVP. Taherkhani et al. (2020) modeled a profit-maximizing HLP, in which the capacity of hubs was considered limited and should not exceed a predetermined amount of flow. As a result, the stochastic solution considering uncertainty in demand is not necessarily equivalent to EVP. Hult et al. (2014) proposed stochastic programming for an uncapacitated p-hub center problem with a single assignment strategy and uncertain travel times. Adibi and Razmi (2015) modeled a stochastic p-hub median problem with uncertain transportation costs and demand. Sadeghi et al. (2015) proposed a stochastic hub covering location problem taking into account road disruptions, i.e., the road capacity was uncertain. Furthermore, the differential evolution algorithm (DEA) and genetic algorithm (GA) were employed to solve the model more efficiently and obtain near-optimal solutions in a reasonable computation time. Correia et al. (2018) proposed a multi-period HLP with uncertainty. A stochastic programming approach was used to deal with demand uncertainty. In addition, several valid inequalities were introduced to solve large-scale instances.

Shang et al. (2021) modeled a two-stage stochastic multi-modal HLP with a direct shipment strategy and uncertain demand. Rostami et al. (2021) modeled a two-stage stochastic single allocation HLP with uncertain demand. The multiplication of several binary decision variables led to a nonlinear structure in their proposed model. Notably, linearization of binary variable multiplication has an easy way, but it increases the total number of variables and constraints in the model. In order to solve the model more effectively, they suggested a branch-and-cut framework instead of linearizing the model. Momayezi et al. (2021) presented a reliable stochastic capacitated modular single allocation HLP and employed an adaptive large neighborhood search algorithm (ALNS) to solve their proposed model. Taherkhani et al. (2021) presented a robust stochastic approach for a profit-maximizing HLP with uncertain revenue and demand. They also employed the Benders decomposition algorithm for solving the model. Hu et al. (2021) modeled a stochastic single allocation HLP with joint chance constraints. In the stochastic model, demand is considered as an uncertain random parameter with a normal probability distribution. Ghaffarinasab (2022) proposed a two-stage stochastic single and multiple allocation HLP with Bernoulli demand. They also used the Benders decomposition algorithm and Lagrangian relaxation method to solve the problem. Zhang et al. (2022) modeled a two-stage stochastic incomplete multimodal HLP with multiple assignment strategy and uncertain demand. They also applied a restriction on delivery time in their proposed model.

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2.3. *Benders decomposition algorithm for the HLPs*

Contreras et al. (2011a) used the Benders decomposition algorithm in an uncapacitated HLP. Furthermore, they proposed several variable fixing strategies that can be applied in the Benders decomposition algorithm to solve HLP more efficiently. Contreras et al. (2011b) applied the Benders decomposition and L-shaped algorithms in a stochastic uncapacitated HLP with uncertain demand. de Sá et al. (2018) developed robust HLP with uncertain hub establishment costs and demand. In addition, hybrid heuristic approaches (as well as the Benders decomposition algorithm) were used to solve the problem. Lozkins et al. (2019) presented a robust HLP with uncertain demand. To solve the proposed model more efficiently, they used the classical and accelerated Benders decomposition algorithms. Rahmati and Neghabi (2021) proposed a balanced HLP and employed an adjustable robust optimization to handle the uncertain transportation costs. According to the sensitivity of flows in hubs, the amount of flows entering each hub facility is balanced. They used the classical and accelerated Benders decomposition algorithms (Pareto-optimal cut) and demonstrated the superiority of the accelerated one. Taherkhani et al. (2020) used the Benders decomposition, and L-shaped algorithms were used for a two-stage stochastic HLP with multiple demand classes. Rahmati et al. (2021) presented a two-stage robust HLP and utilized the classical and Pareto-optimal cut Benders decomposition algorithm to solve the problem. The Pareto-optimal cut Benders decomposition algorithm performed superior to the classical one. Ghaffarinasab and Kara (2022) presented a risk-averse stochastic median, maximal covering, and center HLP with uncertain demand. The authors applied the Benders decomposition algorithm to solve large-scale instances. Taherkhani et al. (2021) modeled robust stochastic profit-maximizing HLP and applied the Benders decomposition algorithm to solve the problem. Ghaffarinasab (2022) employed the Benders decomposition algorithm to solve a stochastic HLP. Zhang et al. (2022) used the Benders decomposition algorithm for solving a stochastic incomplete multimodal HLP. Also the Benders algorithm was implemented successfully in other problems (Tanksale and Jha 2020; Pearce and Forbes 2019; Çalık et al. 2021).

2.4. *Research on sustainable hub location problems*

Mohammadi et al. (2014) addressed noise and pollution as objective functions of HLP in order to consider sustainability. They used a mixed possibilistic–stochastic programming approach to address uncertainty in the model. The authors also used the imperialist competitive algorithm (ICA) and the simulated annealing algorithm (SA) to solve large-scale instances; the results were compared with a lower bound. Niknamfar and Niaki (2016) modeled a hub-and-spoke network for a p-hub location problem. They considered two objective functions to achieve economic and environmental targets. Zhalechian et al. (2017) proposed a multi-objective multi-modal HLP with uncertainty. They used a possibilistic-stochastic programming approach to address uncertainty in their proposed model. In the presented model, the objective functions minimized transportation and traffic noise pollution, as well as the maximum transportation time. Moreover, they applied a hybrid DE and hybrid ICA to solve the model. Musavi and Bozorgi-Amiri (2017) presented a sustainable hub location-vehicle scheduling problem, in which a restriction

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was placed on the number of vehicles serving in the hub facilities. The objective functions of the models included minimizing transportation costs, maximizing food freshness and quality, and minimizing carbon emissions. They used an adopted non-dominated sorting genetic algorithm-II (NSGA-II) to solve the model. Maiyar and Thakkar (2019) presented a hub-and-spoke network for sustainable food grain transportation that considered hub disruption. They formulated their problem as a multi-period mixed integer nonlinear problem by minimizing the costs of hub location and transportation, rerouting, social, and environmental expenses. The Particle Swarm Optimization with DE (PSODE) algorithm was used to solve the model.

Parsa et al. (2019) proposed a multi-objective HLP that minimized the total cost of the network, as well as greenhouse gas emissions, noise, and fuel consumption. Yin et al. (2019) presented a distributionally robust p-hub median problem by considering CCTP. The carbon emission was considered as an uncertain parameter in the model that only involves partially available information. Dukkanci et al. (2019) modeled a nonlinear problem for a green HLP, redesigned it as a second-order cone programming problem, and used several cuts to strengthen the problem. Mokhtarzadeh et al. (2021) modeled a multi-objective non-linear model for the p-mobile HLP. They employed multi-objective particle swarm optimization (MOPSO) and NSGA-II algorithms to solve their proposed model. Tian et al. (2020) presented a p-hub median problem with single assignment. They calculated the network emissions, including CO, HC, and NO_x and aircraft fuel consumption for a real case in china. Golestani et al. (2021) modeled a bi-objective green HLP. The first objective function minimized network costs, while the latter maximized the quality of the delivered commodities. Yin et al. (2022) developed a distributionally robust multi-objective HLP in which economic and environmental factors were incorporated. They considered carbon emissions, transportation costs, and noise levels as uncertain parameters. Carbon regularities have been used widely in other problems (Sherafati et al. 2020; Pan et al. 2021; Modak and Kelle 2021; Hosseini-Motlagh et al. 2021).

Table 1 shows a brief review of sustainability-related subjects within the concept of HLPs. Columns labeled "SO" and "MO" are abbreviations for single-objective and multi-objective, respectively. Columns "ST," "RO," "FU," and "DT" are abbreviations for stochastic programming, robust optimization, fuzzy programming, and deterministic models, respectively. Columns labeled "w," "c," "f," "e," "cap," and "t" represent demand, transportation cost, hub establishment cost, hub capacity, travel time, and emission parameters, respectively. The "emission sector" column indicates that carbon emissions are considered in the transportation (TR) or hub facilities sectors. Finally, the "solution approach" column gives the corresponding solution techniques.

Most studies did not consider carbon policies in HLPs, but three papers incorporated CTPs and CCTPs. Yin et al. (2019) also considered carbon emission as a source of uncertainty and used a commercial solver to solve the problem; additionally, carbon emission was solely considered in the transportation network. The two other carbon policies (i.e., CCP and COP) did not receive any attention in the literature on HLP. As a result, this paper incorporates the entire four carbon policies, and the carbon emission is included in the hub facilities and transportation network. Moreover, a two-stage stochastic programming approach is applied to deal with demand uncertainty. Finally, the L-shaped algorithm (multi-cut framework) augmented with ESAA was used

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to solve large-scale instances more efficiently. Most previous papers concentrated on HLP by minimizing costs. Therefore, the carbon regulations in this paper are based on profit-maximizing HLP considering uncertain demand. In addition, the SOM clustering and k-means clustering algorithm are employed in the SAA method to achieve a good quality solution with fewer scenarios in the proposed models.

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Table 1. Review of sustainable HLPs

Author(s)	Objective		Tackling uncertainty				Uncertain parameter						Carbon policies				Emission sector		Solution approach
	SO	MO	ST	RO	FU	DT	w	c	f	e	cap	t	CTP	CCTP	CCP	COP	TR	Hub	
Mohammadi et al. (2014)		✓	✓		✓			✓	✓		✓	✓					✓		Simulated annealing
Niknamfar and Niaki (2016)		✓				✓											✓		Commercial solver
Zhalechian et al. (2017)		✓			✓		✓	✓	✓		✓	✓					✓		Hybrid differential evolution
Musavi and Bozorgi-Amiri (2017)		✓				✓											✓		NSGA-II
Dukkanci et al. (2019)		✓				✓											✓		Commercial solver
Maiyar and Thakkar (2019)	✓					✓							✓				✓		PSODE
Parsa et al. (2019)		✓				✓											✓		Commercial solver
Yin et al. (2019)	✓			✓						✓				✓			✓		Commercial solver
Tian et al. (2020)	✓					✓											✓		Commercial solver
Golestani et al. (2021)		✓				✓							✓				✓		Commercial solver
Mokhtarzadeh et al. (2021)		✓				✓											✓		NSGA-II
Yin et al. (2022)		✓		✓				✓		✓							✓		Commercial solver
This research	✓		✓				✓						✓	✓	✓	✓	✓	✓	L-shaped algorithm

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3. Problem description and formulation

The stochastic model of profit-maximizing HLP with uncertain demand is presented in this section. In particular, different carbon mechanisms such as CTP, CCTP, CCP, and COP are taken into account. The sets, parameters, and decision variables are presented as follows:

Sets

N Set of non-hub nodes, $i, j \in N$.
H Set of potential hub nodes and $H \subset N$, $k, l \in H$.
Q Set of random samples, $q \in Q$.

Parameters

r_{ij} Revenue by transferring flows from node $i \in N$ to node $j \in N$.
w_{ij} Amount of flows from origin node $i \in N$ to destination node $j \in N$.
f_k Hub establishment cost for potential hub node $k \in H$.
d_{ij} Distance between node $i \in N$ and node $j \in N$.
Γ_k Capacity of potential hub node $k \in H$.
e_k Amount of carbon emission per unit of flows that entered to each hub $k \in H$.
et_{ij} Amount of carbon emission per unit of flows by transferring flows from node $i \in N$ to node $j \in N$.
π Amount of tax paid per unit of carbon.
Cb Carbon buying prices per unit of carbon.
Cs Carbon selling prices per unit of carbon.
MC Maximum permitted amount of carbon that can be emitted.
α Inter hub discount factor.

Variables

z_k Binary variable, equal to 1 when a hub is established in node $k \in H$.
x_{ij}^{kl} Fraction of flows between nodes $i \in N$ and $j \in N$ through hubs $k \in H$ and $l \in H$.
v_k Amount of flows entered to each hub node $k \in H$.
yb Amount of carbon credit bought in a carbon trade market.
ys Amount of carbon credit sold in a carbon trade market.

3.1. *Stochastic capacitated profit-maximizing hub location problem*

The proposed model restricts the total flows entered into each hub facility to those originating at origin nodes and flow from the first hub to other hubs along the path. It is assumed that at least one and at most two hubs can be used in the network to transfer commodities between origins and destinations. A multiple-assignment strategy is considered in the proposed model. In other words, each node can be allocated to any number of hubs. More precisely, each origin-destination can transfer commodities through several different paths. Even different fractions of a flow between a specified origin-destination node can be transferred through various paths due to economic factors or limited hub capacity. In the profit-maximizing HLPs, there is no requirement to satisfy

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entire network flows, and only profitable flows between origin-destination are satisfied; i.e., demand is satisfied if the revenue generated by origin-destination nodes exceeds its associated costs. As a result, certain pre-processing actions can reduce the variables and constraints. In this case, the values of routing decision variables (x_{ij}^{kl}) are fixed to zero if $r_{ij} - c_{ij}^{kl} \leq 0$. Transportation costs are calculated by $c_{ij}^{kl} = d_{ik} + \alpha d_{kl} + d_{lj}$ relation. Moreover, for the economy of scale property, it is assumed that $0 < \alpha < 1$. In other words, to offer economical transferring flows through hubs, a discount factor α is considered within the inter-hub network. According to the proposed model, the location of hub facilities (z_k) is a strategic decision and is considered the first-stage decision (here-and-now decision); importantly, it is determined in the absence of uncertain demand. Let Ξ denotes the support of ξ, and E_ξ denotes the expectation with respect to ξ. It is assumed that $w_{ij}(\xi)$ is a random variable of future demand from origin node $i \in N$ to destination node $j \in N$. Allocation decisions ($x_{ij}^{kl}(\xi)$) are considered as the second-stage decision variables (wait-and-see decisions) and determined in the realization of uncertain demand. The mathematical model of the stochastic profit-maximizing HLP with uncertain demand is as follows:

$$Max\,Z = -\sum_{k \in H} f_k z_k + E_\xi \left[\sum_{i \in N} \sum_{j \in N} \sum_{k \in H} \sum_{l \in H} (r_{ij} - c_{ij}^{kl}) w_{ij}(\xi) x_{ij}^{kl}(\xi) \right] \tag{1}$$

Subject to:

$$\sum_{k \in H} \sum_{l \in H} x_{ij}^{kl}(\xi) \leq 1 \qquad \forall i, j \in N, \xi \in \Xi \tag{2}$$

$$\sum_{l \in H} x_{ij}^{kl}(\xi) + \sum_{l \in H, l \neq k} x_{ij}^{lk}(\xi) \leq z_k \qquad \forall i, j \in N, k \in H, \xi \in \Xi \tag{3}$$

$$\left(\begin{array}{l} \sum_{i \in N} \sum_{j \in N} \sum_{l \in H} w_{ij}(\xi) x_{ij}^{kl}(\xi) \\ + \sum_{i \in N} \sum_{j \in N} \sum_{l \in H, l \neq k} w_{ij}(\xi) x_{ij}^{lk}(\xi) \end{array} \right) \leq \Gamma_k z_k \qquad \forall k \in H, \xi \in \Xi \tag{4}$$

$$x_{ij}^{kl}(\xi) \geq 0 \qquad \forall i, j \in N, k, l \in H, \xi \in \Xi \tag{5}$$

$$z_k \in \{0, 1\} \qquad \forall k \in H \tag{6}$$

The objective function (1) maximizes the total profit in the design of the hub network. The first-stage decision variables (z_k) are taken before revealing uncertain demand, while the second-stage decisions ($x_{ij}^{kl}(\xi)$) are taken after revealing such uncertainties. The first term of the objective function denotes the cost of establishing hubs and the second term is the expected value of revenue minus transportation costs. According to the constraints (2), flows are transmitted through hubs, and it is not necessary to cover the entire demand. Constraints (3) emphasize that non-hub node connections are not allowed. In other words, each node should be allocated to hub nodes, and there is no direct connection between non-hub nodes. Constraints (4) are capacity restriction constraints

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for each hub facility where the incoming flow (from non-hub nodes and other hubs) to hub facilities should be lower than their corresponding capacities. Finally, constraints (5) to (6) determine the domains of decision variables.

3.2. *Profit-maximizing HLP under carbon tax policy (CTP)*

In this section, a profit-maximizing HLP is developed under a carbon tax policy. Carbon emissions are released during the transfer of flows between origin-destination nodes and during material handling in hubs. Accordingly, a tax is imposed on the carbon emissions released by the hub network (hubs or transportation). The SAA method is a scenario generation-based sampling that is widely used in stochastic optimization problems, especially in the literature on HLPs to obtain a proper number of discrete scenarios (Shapiro and Homem-de-Mello 1998). According to the known probability distribution of uncertain parameters, several scenarios are generated based on the probability distribution; moreover, the expected stochastic value function is approximated by the sample average function. The two-stage stochastic mathematical model of the proposed model by considering CTP and the SAA description is presented in Appendix A in order not to lengthen the paper. Let x_{ij}^{klq} and v_k^q be the second-stage decision variables related to the sample $q \in Q$, and let w_{ij}^q represent demand between node $i \in N$ and node $j \in N$ in sample $q \in Q$. The SAA problem for the CTP model can be stated as follows:

$$Max\,Z = -\sum_{k\in H} f_k z_k + \frac{1}{|Q|}\sum_{q\in Q}\left(\begin{array}{l}\sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H}(r_{ij}-c_{ij}^{kl})w_{ij}^q x_{ij}^{klq} - \pi\sum\limits_{k\in H} e_k v_k^q \\ -\sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H}\pi(et_{ik}+et_{kl}+et_{lj})w_{ij}^q x_{ij}^{klq}\end{array}\right) \tag{7}$$

Subject to:

$$\sum_{k\in H}\sum_{l\in H} x_{ij}^{klq} \le 1 \qquad \forall i,j\in N, q\in Q \tag{8}$$

$$\sum_{l\in H} x_{ij}^{klq} + \sum_{l\in H, l\neq k} x_{ij}^{lkq} \le z_k \qquad \forall i,j\in N, k\in H, q\in Q \tag{9}$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{l\in H} w_{ij}^q x_{ij}^{klq} + \sum_{i\in N}\sum_{j\in N}\sum_{l\in H,l\neq k} w_{ij}^q x_{ij}^{lkq} \le v_k^q \qquad \forall k\in H, q\in Q \tag{10}$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{l\in H} w_{ij}^q x_{ij}^{klq} + \sum_{i\in N}\sum_{j\in N}\sum_{l\in H,l\neq k} w_{ij}^q x_{ij}^{lkq} \le \Gamma_k z_k \qquad \forall k\in H, q\in Q \tag{11}$$

$$x_{ij}^{klq} \ge 0 \qquad \forall i,j\in N, k,l\in H, q\in Q \tag{12}$$

$$v_k^q \ge 0 \qquad \forall k\in H, q\in Q \tag{13}$$

$$z_k \in \{0,1\} \qquad \forall k\in H \tag{14}$$

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The objective function (7) consists of hub establishment costs and the approximation of the second stage value which consists of total revenue minus total transportation and carbon emission costs. Constraints (10) calculate the amount of flows entered into each hub facility, beginning with the non-hub nodes or the first hubs. Constraints (12) - (14) determine the type of decision variables. Hereafter, the problem (7) - (14) is considered as an approximate problem with uncertain demand for the CTP model.

3.3. *Profit-maximizing HLP under carbon cap-and-trade policy (CCTP)*

In this section, a profit-maximizing HLP is developed under a carbon cap-and-trade policy. As part of this model, carbon emissions from firms are limited, yet to a greater extent allowed. In other words, the model takes into account the trade of carbon (buy or sell). The two-stage stochastic mathematical model of the proposed model by considering CCTP and the SAA description is presented in Appendix B. Let yb^q and ys^q be the second-stage decision variables with $q \in Q$. Accordingly, the SAA problem for the CTP model can be stated as follows:

$$Max\,Z = -\sum_{k\in H} f_k z_k + \frac{1}{|Q|}\sum_{q\in Q}\left(\begin{array}{l}\sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H}(r_{ij} - c_{ij}^{kl})w_{ij}^{q}x_{ij}^{klq}\\ -Cb\times yb^q + Cs\times ys^q\end{array}\right) \qquad (15)$$

Subject to:
Constraints (8)-(14)

$$\left(\begin{array}{l}\sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H} w_{ij}^{q}x_{ij}^{klq}(et_{ik} + et_{kl} + et_{lj})\\ +\sum\limits_{k\in H} e_k v_k^q + ys^q - yb^q\end{array}\right) \le MC \qquad \forall q\in Q \qquad (16)$$

$$yb^q \ge 0 \qquad \forall q \in Q \qquad (17)$$

$$ys^q \ge 0 \qquad \forall q \in Q \qquad (18)$$

In the objective function (15), the approximation of the second stage value consists of total revenue (i.e., revenue which is obtained either from satisfying demand or selling carbon) minus total transportation costs and carbon buying from the market. Constraints (16) restrict carbon emissions while considering the ability to sell and buy carbon in each scenario. Constraints (17) and (18) determine the domains of decision variables. Hereafter, this model is considered as an approximate problem with uncertain demand for the CCTP model.

Importantly, the CCP and COP models are similar to the CCTP model. The CCP model is the same as the CCTP model, except those trade decisions (carbon buys and sells) are ignored. In other words, carbon trading is not allowed in CCP ($yb(\xi) = 0, ys(\xi) = 0$). Additionally, the COP model is the same as CCTP model in which selling carbon is not allowed ($yb(\xi) \ge 0, ys(\xi) = 0$). To avoid overwhelming the context of the paper, the related mathematical models are not provided.

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In the SAA method (with maximization objective function), samples are classified into M classes ($M = \{b_1, b_2, ..., b_{|M|}\}$) in which each class contains Q scenarios ($b_m = \{q_m^1, q_m^2, ..., q_m^{|Q|}\}$). In the first step, the SAA model for each M class of samples is solved, and OFV_m denotes the optimal associated objective value for $m \in M$. Then, the average of the optimal values is calculated for each class of samples, and an upper bound is provided for the original problem (SAA_{UB}). In the second step, several samples (Q') are generated so that $Q' >> Q$. Afterward, the first-stage decision variables ($\bar{z}_k$) are fixed in the SAA model and solved based on the Q' samples generated. The optimal objective value for this problem provides a lower bound for the original problem (SAA_{LB}) (Shapiro and Homem-de-Mello 1998).

4. Enhanced sample average approximation method (ESAA)

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Emelogu et al. (2016) presented a stochastic facility location problem. The SAA was used to determine the appropriate number of scenarios in their stochastic model. As unsupervised machine learning algorithms, they used k-means, k-means ++, k-means $||$, and fuzzy c-means algorithms to cluster samples for the SAA method. Compared to the classical SAA method without pre-processing, these clustering methods produce better results. Consequently, in this paper, the k-means algorithm is used to cluster scenarios to assist the SAA method named ESAA-I. Algorithm 1 gives a pseudo-code representation of the k-means algorithm. For the SAA method, $|M|$ dependent class of samples with $|Q|$ scenarios are needed. Hence, for each $m \in M$ class, samples are generated randomly based on the simple sampling method. It is assumed that $\Xi = \{\xi_1, \xi_2, ..., \xi_\omega\}$ shows the set of samples, μ_b denotes the center of each cluster and t_b represents the set of samples belonging to each cluster.

Algorithm 1: k-means clustering algorithm

$\Xi \leftarrow$ a set of samples (scenarios), $\{\xi_1, \xi_2, ..., \xi_\omega\}$;
$q \leftarrow$ total number of clusters;
for $m = 1 : M$ **do**
    randomly generate the set of scenario Ξ (simple sample method based Monte Carlo simulation);
    randomly select q centers from $\xi_\omega \in \Xi$;
    $\mu_b \leftarrow q$ clusters centers, $b = 1, 2, ..., q$;
    $t_b \leftarrow$ set of samples belongs to the cluster b, $b = 1, 2, ..., q$;
    repeat
        assign each sample to its nearest cluster;
    until *centroids do not changed*;
    calculate the mean of each cluster member as follows;
    $w_{ij}^{qm} \leftarrow \frac{1}{|t_b|} \sum_{j \in t_b} \xi_j, \forall b$;
end

The self-organizing map (SOM) algorithm was presented by Kohonen (1982). The training of the SOM algorithm consists of two repetitive phases: first, selecting the best mapping unit (the best neural network neuron) to adapt to any of the input data, and second, updating this mapping to provide the best representation and display of the input data. The pseudo-code of the SOM clustering algorithm is presented in Algorithm 2. Hereafter, the SAA algorithm involving the use of the SOM method is named ESAA-II.

Algorithm 2: Self-organizing map clustering algorithm

$\Xi \leftarrow$ a large set of samples (scenarios), $\{\xi_1, \xi_2, ..., \xi_\omega\}$;
$\Lambda \leftarrow$ a set of neurons, $\{\lambda_1, \lambda_2, ..., \lambda_q\}$;
for $m = 1 : M$ **do**
    randomly generate the set of scenario Ξ (simple sample method based Monte Carlo simulation);
    initialize $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_q\}$, randomly;
    repeat
        select $\xi \in \Xi$ randomly;
        find λ^* such that $d(\xi, \lambda^*) = \min\{d(\xi, \lambda) | \lambda \in \Lambda\}$;
        for *all* $\lambda \in \omega(\lambda^*)$ **do**
            $\lambda = \lambda + \gamma(\xi - \lambda)$;
            reduce learning rate γ;
        end
    until *termination condition is true*;
    $w_{ij}^{qm} \leftarrow$ the mean of each neurons (clusters) members, $\lambda_q \in \Lambda$;
end

5. L-shaped algorithm

Benders decomposition algorithm was introduced by Benders (1962). The algorithm divides the model into two detached problems named 'sub' and 'master'. In mixed-integer linear problems (MILPs), binary or integer variables should exist in the master problem, while continuous variables should appear in the sub problem. Therefore, the sub problem is a linear programming (LP) model, while the master problem is either an integer programming (IP) model or mixed-integer programming (MIP) model. In stochastic problems, the first-stage decision variables and associated constraints are placed in the master problem, while the second-stage decision variables and their associated constraints are found in the sub problem.

Increasing the number of scenarios reduces the performance of the classic Benders decomposition algorithm. In the proposed models, the most computational time is spent solving the sub problem instead of the master problem. There is, therefore, a need for specific accelerating techniques and variable fixing methods to enhance the performance of the Benders decomposition algorithm. The decomposition of stochastic scenario-based problems into Q dependent problems can be achieved by fixing the first-stage decision variables in the model. As a result, the sub problem can be divided into Q sub-models,

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resulting in an algorithm called the L-shaped algorithm. Furthermore, the $|Q|$ optimality cut is applied to the master problem in each iteration. Magnanti and Wong (1981) presented an accelerating technique that generates a stronger optimality cut called the 'Pareto-optimal cut'. In this method, the optimality cut of the dual of the multiple sub problem solutions is selected, leading to a better upper bound (in maximization problems). Consequently, the algorithm converges to the optimal solution in fewer iterations. A disadvantage of this method is that it involves solving an additional problem, which leads to a longer computation time. Papadakos (2008) modified the Pareto model and proposed a method that solved it more efficiently and in a shorter amount of time. In this paper, the L-shaped algorithm is implemented to solve the proposed models and the Pareto-optimal cut Benders decomposition algorithm is not used.

5.1. *Applying L-shaped algorithm for the CTP model*

First, the sub problem of the CTP model is presented. In this problem, continuous decision variables such as x_{ij}^{klq} and v_k^q, along with their associated constraints, are considered. Let z_k^u be the solution of the first-stage decision variables in iteration $u \in U$. The sub problem of the CTP model is presented as follows:

$$Max\, Z = \sum_{q \in Q} \left(\sum_{i \in N} \sum_{j \in N} \sum_{k \in H} \sum_{l \in H} (r_{ij} - c_{ij}^{kl} - \pi(et_{ik} + et_{kl} + et_{lj})) w_{ij}^q x_{ij}^{klq} - \pi \sum_{k \in H} e_k v_k^q \right) \tag{19}$$

Subject to:
Constraints (8), (10), (12), (13)

$$\sum_{l \in H} x_{ij}^{klq} + \sum_{l \in H, l \neq k} x_{ij}^{lkq} \leq z_k^u \qquad \forall i,j \in N, k \in H, q \in Q \tag{20}$$

$$\sum_{i \in N} \sum_{j \in N} \sum_{l \in H} w_{ij}^q x_{ij}^{klq} + \sum_{i \in N} \sum_{j \in N} \sum_{l \in H, l \neq k} w_{ij}^q x_{ij}^{lkq} \leq \Gamma_k z_k^u \qquad \forall k \in H, q \in Q \tag{21}$$

It is assumed that a_{ij}^q, θ_k^q, g_{ij}^{kq}, and μ_k^q are dual variables of constraints (8), (10), (20) and (21), respectively. The dual of sub problem can be written as follows:

$$Min\, Z = \sum_{i \in N} \sum_{j \in N} \sum_{q \in Q} a_{ij}^q + \sum_{i \in N} \sum_{j \in N} \sum_{k \in H} \sum_{q \in Q} z_k^u g_{ij}^{kq} + \sum_{k \in H} \sum_{q \in Q} \Gamma_k z_k^u \mu_k^q \tag{22}$$

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Subject to:

$$\begin{pmatrix} a_{ij}^q + g_{ij}^{kq} + g_{ij}^{lq} \\ +w_{ij}^q \mu_k^q + w_{ij}^q \mu_l^q \\ +w_{ij}^q \theta_k^q + w_{ij}^q \theta_l^q \end{pmatrix} \geq \begin{pmatrix} (r_{ij} - c_{ij}^{kl}) w_{ij}^q \\ -\pi w_{ij}^q (et_{ik} + et_{kl} + et_{lj}) \end{pmatrix} \quad \forall i,j \in N, k,l \in H, q \in Q, k \neq l \tag{23}$$

$$\begin{pmatrix} a_{ij}^q + g_{ij}^{kq} \\ +w_{ij}^q \mu_k^q + w_{ij}^q \theta_k^q \end{pmatrix} \geq \begin{pmatrix} (r_{ij} - (d_{ik} + d_{kj})) w_{ij}^q \\ -\pi w_{ij}^q (et_{ik} + et_{kj}) \end{pmatrix} \quad \forall i,j \in N, k \in H, q \in Q \tag{24}$$

$$-\theta_k^q \geq -\pi e_k \quad \forall k \in H, q \in Q \tag{25}$$

$$a_{ij}^q \geq 0 \quad \forall i,j \in N, q \in Q \tag{26}$$

$$g_{ij}^{kq} \geq 0 \quad \forall i,j \in N, k \in H, q \in Q \tag{27}$$

$$\theta_k^q \geq 0 \quad \forall k \in H, q \in Q \tag{28}$$

$$\mu_k^q \geq 0 \quad \forall k \in H, q \in Q \tag{29}$$

Constraints (23) and (24) represents using exactly two and one hubs in the network, respectively. Given a_{ij}^{qu}, g_{ij}^{kqu}, and μ_k^{qu} as the dual of the sub problem solutions in iteration $u \in U$, the master problem of the CTP model can be written as follows:

$$Max\, Z = -\sum_{k \in H} f_k z_k + \frac{1}{|Q|} \sum_{q \in Q} \eta_q \tag{30}$$

Subject to:

$$\eta_q \leq \sum_{i \in N} \sum_{j \in N} a_{ij}^{qu} + \sum_{i \in N} \sum_{j \in N} \sum_{k \in H} z_k g_{ij}^{kqu} + \sum_{k \in H} \Gamma_k z_k \mu_k^{qu} \quad \forall q \in Q, u \in U \tag{31}$$

$$z_k \in \{0,1\} \quad \forall k \in H \tag{32}$$

Constraints (31) represent the optimality cuts added in each iteration to the master problem based on the dual sub problem solutions.

5.2. *Applying the L-shaped algorithm for the CCTP model*

In the CCTP model, the second-stage decision variables such as x_{ij}^{klq}, v_k^q, yb^q and ys^q and their associated constraints exist in the sub problem. The sub problem of the CCTP model can be expressed as follows:

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$$Max\,Z = \sum_{q\in Q}\left(\sum_{i\in N}\sum_{j\in N}\sum_{k\in H}\sum_{l\in H}(r_{ij}-c_{ij}^{kl})w_{ij}^{q}x_{ij}^{klq} - Cb\times yb^{q} + Cs\times ys^{q}\right) \tag{33}$$

Subject to:

Constraints (8), (10), (12), (13), (16)-(18), (20), (21)

It is assumed that τ_q is the dual variable associated with the constraints (16). Other dual variables for the sub problem constraints are presented in the previous section. The dual of the sub problem for the CCTP model is presented below:

$$Min\,Z = \sum_{i\in N}\sum_{j\in N}\sum_{q\in Q}a_{ij}^{q} + \sum_{i\in N}\sum_{j\in N}\sum_{k\in H}\sum_{q\in Q}z_k^u g_{ij}^{kq} + \sum_{k\in H}\sum_{q\in Q}\Gamma_k z_k^u \mu_k^q + \sum_{q\in Q}MC\times\tau_q \tag{34}$$

Subject to:

Constraints (26)-(29)

$$\begin{pmatrix} a_{ij}^{q}+g_{ij}^{kq}+g_{ij}^{lq}+w_{ij}^{q}\theta_k^q+ \\ w_{ij}^{q}\theta_l^q+w_{ij}^{q}\mu_k^q+w_{ij}^{q}\mu_l^q+ \\ w_{ij}^{q}(et_{ik}+et_{kl}+et_{lj})\tau_q \end{pmatrix} \geq (r_{ij}-c_{ij}^{kl})w_{ij}^{q} \qquad \forall i,j\in N, k,l\in H, q\in Q, k\neq l \tag{35}$$

$$\begin{pmatrix} a_{ij}^{q}+g_{ij}^{kq}+w_{ij}^{q}\theta_k^q+ \\ w_{ij}^{q}\mu_k^q+w_{ij}^{q}(et_{ik}+et_{kj})\tau_q \end{pmatrix} \geq \begin{pmatrix} r_{ij}w_{ij}^{q}-w_{ij}^{q}d_{ik} \\ -w_{ij}^{q}d_{kj} \end{pmatrix} \qquad \forall i,j\in N, k\in H, q\in Q \tag{36}$$

$$e_k\tau_q - \theta_k^q \geq 0 \qquad \forall k\in H, q\in Q \tag{37}$$

$$\tau_q \geq Cs \qquad \forall k\in H, q\in Q \tag{38}$$

$$-\tau_q \geq -Cb \qquad \forall k\in H, q\in Q \tag{39}$$

$$\tau_q \geq 0 \qquad \forall q\in Q \tag{40}$$

Given τ_q^u as the dual of the sub problem solution in iteration $u\in U$, the master problem of the CCTP model is stated as follows:

$$Max\,Z = -\sum_{k\in H}f_k z_k + \frac{1}{|Q|}\sum_{q\in Q}\eta_q \tag{41}$$

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Subject to:

$$\eta_q \leq \sum_{i\in N}\sum_{j\in N} a_{ij}^{qu} + \sum_{i\in N}\sum_{j\in N}\sum_{k\in H} z_k g_{ij}^{kqu} + \sum_{k\in H}\Gamma_k z_k \mu_k^{qu} + MC \times \tau_q^u \quad \forall q \in Q, u \in U \tag{42}$$

$$z_k \in \{0,1\} \quad \forall k \in H \tag{43}$$

Constraints (42) are the optimality cuts added in each iteration of the L-shaped algorithm to the master problem. Due to the similarities between CCTP, CCP, and COP, and to prevent excessive model definitions, the sub and master problems of CCP and COP are not discussed.

Algorithm 3 shows the pseudo-code of the L-shaped algorithm augmented with the ESAA-I and ESAA-II methods. Because the pseudo-codes for both models (CTP and CCTP) are very similar, only the pseudo-code for CTP is provided to keep the paper concise. The L-shaped algorithm is an iterative method; accordingly, first, the dual of the sub problem is solved for each scenario with an initial value for the first-stage decision variables. Then, the lower bound is calculated according to the dual of the sub problem objective functions plus the cost of hub establishment. In each iteration, the solutions obtained from the dual sub problem will add Q optimality cuts to the master problem. The objective function of the master problem gives an upper bound to the original optimal solution. This iterative procedure is continued until convergence is achieved (i.e., the difference between upper and lower bounds is less than the upsilon). The sub problem of the proposed models is always feasible; therefore, there is no need for any feasibility cuts for the master problem.

5.3. *Variable fixing*

The L-shaped algorithm can be sped up, and the number of iterations required to achieve convergence is reduced by variable fixing. Contreras et al. (2011a) presented variable fixing in an uncapacitated HLP to solve large-scale instances, where the sizes of the sub and master problems are reduced by taking advantage of the information realized during the inner iterations of the Benders decomposition algorithm.

Two variable fixing strategies are used in this paper to speed up the L-shaped algorithm. In the first strategy, the LP relaxation of the master problem (MP) is solved in each iteration of the L-shaped algorithm. Let MP_{LP}^u represent the LP relaxation of MP in iteration u, and OB_{LP}^u its optimal objective function value; furthermore, let rc_k represent the reduced cost of z_k variables. LB is assumed to be a lower bound on the optimal solution value of MP. If in an optimal solution of MP_{LP}^u, z_k becomes a non-basic variable and $OB_{LB}^u + rc_k < LB$, then z_k cannot be opened as a hub facility. Therefore, the associated nodes can be removed from the set of hub nodes in the subsequent iterations of the L-shaped algorithm. Furthermore, the corresponding decision variables and constraints are removed from both the sub and master problems.

In the second variable fixing strategy, a set of hubs $E \subset H$ is proven not to be opened in an optimal solution, so these nodes are removed from the set H. It is assumed that $MP^u(E)$ represents MP in iteration u by considering the set $E \subset H$ as potential hub

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Algorithm 3: ESAA-I and II methods augmented with the L-shaped algorithm for the CTP model

Go to algorithm 1 for the ESAA-I or algorithm 2 for the ESAA-II;
for $m = 1 : M$ **do**
  $LB \leftarrow -\infty$;
  $UB \leftarrow +\infty$;
  $u \leftarrow 1$;
  $z_k^u \leftarrow \bar{z}_k$ initial random solution;
  $w_{ij}^q \leftarrow w_{ij}^{qm}$;
  $LBcurrent_q \leftarrow 0$;
  while UB - $LB > \varepsilon$ **do**
    for $q = 1 : |Q|$ **do**
      Step 1: Solve the dual of sub problem and obtain (a_{ij}^{qu}, g_{ij}^{kqu}, μ_k^{qu});
      $LBcurrent_q \leftarrow \sum_{i\in N}\sum_{j\in N} a_{ij}^{qu} + \sum_{i\in N}\sum_{j\in N}\sum_{k\in H} z_k^u g_{ij}^{kqu} + \sum_{k\in H} \Gamma_k z_k^u \mu_k^{qu}$;
    end
    $LB \leftarrow \max\{LB, \frac{1}{|Q|}\sum_{q\in Q} LBcurrent_q - \sum_{k\in H} f_k z_k^u\}$;
    Step 2: Add constraints (31) as optimality cuts in the master problem;
    Step 3: Solve master problem;
    $UB \leftarrow -\sum_{k\in H} f_k \bar{z}_k + \frac{1}{|Q|}\sum_{q\in Q} \bar{\eta}_q$;
    $u \leftarrow u + 1$;
    $z_k^u \leftarrow \bar{z}_k$;
  end
  $zm_k^m \leftarrow \bar{z}_k$;
  $OFV_m \leftarrow UB$;
end
$SAA_{UB} \leftarrow \sum_{m\in M} OFV_m/|M|$;
$Var_{UB} \leftarrow \frac{1}{|M|(|M|-1)} \sum_{m\in M} (OFV_m - SAA_{UB})^2$;
$\bar{z}_k \leftarrow$ a random feasible solution (first-stage decision variables);
for $q' = 1 : |Q'|$ **do**
  Step 4: Solve SAA model for each Q' scenario;
  $OFVN_{q'} \leftarrow$
  $\sum_{i\in N}\sum_{j\in N}\sum_{k\in H}\sum_{l\in H} (r_{ij} - c_{ij}^{kl} - \pi(et_{ik} + et_{kl} + et_{lj})) w_{ij}^{q'} \bar{x}_{ij}^{klq'} - \sum_{k\in H} \pi e_k \bar{v}_k^{q'}$
  $\forall q' \in Q'$;
end
$SAA_{LB} \leftarrow -\sum_{k\in H} f_k \bar{z}_k + \frac{1}{|Q'|}\sum_{q'\in Q'} OFVN_{q'}$;
$Var_{LB} \leftarrow \frac{1}{|Q'|(|Q'|-1)} \sum_{q'\in Q'} (OFVN_{q'} - SAA_{LB})$;
$Gap \leftarrow \frac{SAA_{UB} - SAA_{LB}}{SAA_{UB}}$;
$Gap_{\text{var}} \leftarrow Var_{LB} + Var_{UB}$;

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nodes. Additionally to the MP constraints, a new constraint ($\sum_{k \in E} z_k \geq 1$) is considered for the $MP^u(E)$ problem, and $OB^u(E)$ represents its optimal objective function value. Like the first variable fixing method, let LB be a lower bound on the optimal value of the master problem. Furthermore, $MP^u(E)$ gives a lower bound for MP in iteration u (MP^u). The potential hub nodes E are closed in an optimal solution if $OB^u(E) < LB$. In other words, the hub nodes E and their associated variables and constraints are eliminated from the subsequent iterations of the L-shaped algorithm. To improve the performance of the variable fixing strategy, the set E should be taken into account properly since, in earlier iterations of the L-shaped algorithm, non-optimal hubs are eliminated. For this purpose, the ratio of hub establishment costs to their capacities is calculated and sorted in descending order. Nodes with a smaller ratio value (bottom of the list) have a higher potential to become hubs. Because of the time-consuming nature of this variable fixing strategy, only %80 of the top list is considered for set E. The hubs obtained from solving the MP in iteration u and nodes from the first variable fixing strategy are discarded from the set E. The $MP^u(E)$ model is then solved, and if the second test condition is unsuccessful, the open hubs obtained from this model are excluded from the set E. After several iterations of the L-shaped algorithm, set E becomes empty and should be reinitialized due to the discarding of open hubs or a successful test. In this case, the hubs (which are discarded from the set E according to the successful tests in the previous iterations) are not taken into account in the new set.

6. Computational experiments

In this section, several tests are provided to assess the performance of the proposed models. In this regard, a well-known set of instances, such as the Australian Post (AP) data set, widely used in HLPs, was employed for analysis (Ernst and Krishnamoorthy 1996). The AP data set consists of several items, such as origin-destination flows and the distances between nodes. In addition, it contains two sets of hub establishment costs and hub capacities, which are referred to as loose (L) and tight (T). A tight capacity instance has fewer available capacity options than a loose capacity instance. The hub establishment cost is higher in instances with tight installation costs than in instances with loose installation costs. Due to the revenue elasticity of demand and the price of shipping a parcel based on its size and the distance between origin-destination pairs, the revenue per unit demand is determined by the distance and flow volume being transferred. Hence, revenues for each origin-destination pair are randomly generated based on the following equation $r_{ij} = \bar{\varphi}\frac{d_{ij}}{w_{ij}}$, where $\bar{\varphi} \sim U[40, 50]$ (Taherkhani et al. 2020).

Carbon is priced on the carbon market, which fluctuates instantly based on several conditions. Therefore, the trend in carbon prices for the past year in Australia has been reviewed according to the Carbon Credits. (n.d.), and its average has been used for further analysis. In the past year, the carbon price has ranged from \$17 to \$55. Hence, the price of carbon was assumed as \$33.25 for carbon trading schemes ($\pi = Cb = Cs =$ \$33.25). The carbon emission data for the transportation sector were extracted from the EcoTransIT World. (n.d.). Hub facilities can be categorized as logistics sites that

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connect transport chains. Logistics sites refer to any hubs that combine different origin-destination pairs or start or end transportation chains. As a result of the data provided by Dobers et al. (2018), the carbon emission per unit flow is calculated as 0.0054 per ton. Regarding the economy of scale property, the value of α is to be from $\{0.3, 0.5, 0.8\}$. In stochastic models, the demand probability distribution was assumed to follow a normal distribution ($w_{ij}^q \sim N(w_{ij}, (\tau w_{ij})^2)$), in which τ represents the coefficient of variation value and considered equal 0.5 ($\tau = 0.5$).

The number of input samples for the k-means and SOM algorithms were considered 6,000 and 30,000 samples, respectively. Notably, these samples were taken into account for k-means and SOM methods as a result of their computation time and their performances. Moreover, $|Q'| = 10,000$ scenarios were considered for SAA problems. The proposed models and algorithms (L-shaped algorithm and SAA) were coded in GAMS software. Additionally, the k-means clustering algorithm and the SOM method were coded in MATLAB software, which ran on a system with the following specs: Intel Core i7 with 3.7 GHz CPU and 32 GB of RAM. Notably, the dual sub problem in the L-shaped algorithm was solved by the OSIXPRESS solver. This solver is used because it solves LP models more quickly than CPLEX. To reduce the number of tables, evaluations have been done for loose capacities in Sections 6.1 and 6.2, while both loose and tight capacities have been analyzed in Section 6.3.

6.1. *Performance analysis of the L-shaped algorithm with variable fixing strategy*

In this section, several tests are developed to evaluate the performance of the commercial solver (CPLEX) and L-shaped algorithm. The algorithms are evaluated based on the solution quality and the computational time. In this section, scenarios are generated using the SOM method only and the same scenarios are used for both the CPLEX solver and the L-shaped algorithm. It is assumed that $|M| = 1$ and samples are clustered into q clusters.

First, the performance of variable fixing strategies is evaluated in the L-shaped algorithm. Table 2 shows the results for the CTP model with different instances. In the L-shaped algorithm, variable fixing was able to solve problems in a reasonable computing time and with fewer iterations than without using them. Therefore, for further analysis, variable fixing will be used in the L-shaped algorithm.

Table 3 shows the comparison between methods in solving the CTP and CCTP models. For the analysis, several sets of AP instances (N) and scenarios (S) were considered. Hence, the number of nodes to be from $|N| \in \{10, 20, 25, 40, 50, 60, 70\}$, while the number of scenarios is different from 40 to 70 nodes instances compared to other instances (e.g., 10, 20, and 25 node instances). Notably, CPU time (second) was increased by increasing the number of scenarios and nodes. Therefore, selecting a larger number of scenarios requires more execution time and is not cost-effective. Mentioned methods were compared based on CPU time (in seconds) and the number of iterations for the CTP and CCTP models. As soon as the commercial solver (CPLEX) or the L-shaped algorithm run out of memory, "Memory" appears in the "CPU time (s)" column. The CPLEX solver was not capable of solving certain instances and ended up with "out of

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Table 2. Evaluation of variable fixing in the CTP model for AP $|N|$LL instances and $\alpha = 0.8$

		With Variable fixing		Without variable fixing	
$\|N\|$	$\|S\|$	CPU time (s)	Iteration	CPU time (s)	Iteration
20	10	16.69	17	19.27	28
	20	40.35	24	72.23	31
	30	63.62	28	134.87	39
	40	63.62	21	147.67	32
	50	85.81	21	236.12	41
25	10	45.04	22	197.43	64
	20	95.40	22	323.34	53
	30	138.20	22	499.41	55
	40	185.25	22	585.49	48
	50	230.82	24	1,132.40	73
40	5	178.36	26	1,304.75	113
	10	369.72	28	3,004.91	121
	15	836.72	28	4,697.05	127
	20	1,178.36	27	6,523.73	136
	25	1,735.27	28	8,067.82	140
Average		350.88	24.00	1,796.43	73.40

memory". Even for a lower number of scenarios (e.g., for 5 or 10) in AP 40LL, 50LL, 60LL, and 70LL instances, the commercial solver cannot find any feasible solution. In smaller instances (10LL and 20LL), CPLEX showed better results according to CPU time (s). The results showed the superiority of the L-shaped algorithm compared to the CPLEX when the size of the nodes and scenarios are increased. Therefore, the L-shaped algorithm is used to solve the SAA-based models in further analysis.

6.2. *Carbon regulations analysis*

To control carbon emissions, governments attempt to impose carbon regulations on different companies of transportation businesses. Accordingly, given different politics, each country may apply a different carbon policy compared to other nations. Table 4 for the AP 50LL instance contains the results of the stochastic CTP model with the different ranges of price per ton ($\$0, \$10, ..., \$80$), and discount factor $(0.3, 0.5, 0.8)$. The SOM method is used in this section to generate scenarios for the stochastic model where only one class of samples is considered ($|M| = 1$). In addition, the L-shaped algorithm is employed to solve the stochastic models.

The "emission components" column gives the carbon emissions from hub facilities and transportation sectors, while the "overall emission" column shows the total emissions. The "% satisfied demand" column gives the percentage of demand satisfied through the hub network. The "profit" column contains the net profit resulting from the proposed problems. Finally, the last column represents the nodes that are selected as hubs. Results showed that raising the discount factor resulted in fewer established hubs and decreased

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Table 3. Comparison between commercial solver and the L-shaped algorithm for two carbon policies, AP $|N|$LL instances and $\alpha = 0.8$

$\|N\|$	$\|S\|$	CTP			CCTP		
		CPU time (s)		Iteration	CPU time (s)		Iteration
		CPLEX	L-shaped		CPLEX	L-shaped	
10	10	0.58	2.22	5	0.64	0.78	4
	20	1.08	1.47	6	1.12	1.16	4
	30	1.52	1.79	5	1.70	2.02	6
	40	1.72	2.30	5	2.40	2.13	4
	50	4.14	2.72	5	3.13	3.44	5
20	10	10.69	16.69	17	14.67	18.09	21
	20	36.91	40.35	24	46.65	37.07	21
	30	56.92	63.62	28	89.84	50.87	17
	40	90.72	63.62	21	115.32	76.64	24
	50	79.61	85.81	21	Memory	41.60	20
25	10	47.36	45.04	22	61.47	60.18	16
	20	130.63	95.40	22	178.10	129.37	26
	30	252.61	138.20	22	255.79	167.52	27
	40	455.84	185.25	22	638.06	210.72	23
	50	640.56	230.82	24	Memory	246.74	18
40	5	477.72	178.36	26	Memory	261.11	34
	10	Memory	369.72	28	Memory	399.80	28
	15	Memory	836.72	28	Memory	913.85	31
	20	Memory	1,178.36	27	Memory	1,096.64	29
	25	Memory	1,735.27	28	Memory	1,827.36	28
50	5	Memory	586.74	36	Memory	544.12	39
	10	Memory	1,056.13	34	Memory	1,046.95	41
	15	Memory	1,642.86	36	Memory	1,452.86	38
	20	Memory	2,288.29	38	Memory	2,067.65	38
	25	Memory	3,051.05	37	Memory	2,811.77	37
60	5	Memory	1,195.85	32	Memory	1,128.34	28
	10	Memory	1,997.86	30	Memory	2,031.01	26
	15	Memory	3,042.47	33	Memory	3,159.35	27
	20	Memory	4,536.74	32	Memory	4,386.69	28
	25	Memory	5,247.89	32	Memory	5,190.36	28
70	5	Memory	2,056.78	21	Memory	2,136.24	25
	10	Memory	4,326.22	25	Memory	4,453.04	29
	15	Memory	6,993.03	32	Memory	6,835.96	28
	20	Memory	8,021.42	28	Memory	7,904.08	28
	25	Memory	10,078.19	31	Memory	10,894.82	30
Average			1,754.15	24.66		1,759.72	24.69

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net profit, while the percentage of satisfied demand remained constant or decreased. In addition, by raising the discount factor without a specific trend, the overall emission increases or decreases. The increase in carbon price also reduces overall emissions, the percentage of satisfying demand, and the net profit. CTP charges significant financial distress to firms to achieve target carbon emissions.

Table 5 shows the results of the stochastic CCTP model for the AP 50LL instance. The analyses were conducted using different discount factors and the maximum allowed carbon emission. The "% carbon" column represents the maximum percentage of carbon that can be emitted. In addition, the column labeled "MC" gives the maximum amount of carbon in a ton. In this case, a CTP model with a carbon price of $0 is used; the MC parameter is a percentage of the overall emissions of the CTP model. Furthermore, the "CB" and "CS" columns indicate the amount of carbon bought or sold on the trade market. Lastly, the other columns are similar to the previous CTP table. When the discount factor is equal to 0.3 and "% carbon" is between 80 and 100, the overall emission is constant and equal to 32,571.22. In other words, the demand is not satisfied entirely, and carbon is sold in the market. However, when "% carbon" is between 10 and 70, carbon is bought from the market. For all ranges of MC, the overall carbon emissions are constant regardless of the discount factor $\{0.3, 0.5, 0.8\}$. Moreover, profit is reduced by increasing the discount factor and decreasing MC.

Similarly, Tables C1 and C2 present the results for the CCP and COP models, respectively in Appendix C. In the CCP model, there is no column for buying or selling carbon; in the COP model, there is a buying column. According to Table C1, decreasing the amount of MC resulted in a lower amount of overall emission, percentage of satisfying demand, and net profit. Table C2 indicates that when "% carbon" is between 10 and 70, carbon was purchased on the market. By decreasing the MC, the percentage of satisfied demand and the net profit also decreased. The reduction in profit for the CTP model is much more than for the CCTP one. The CCTP model provides higher profits and benefits for companies, but customer satisfaction decreases as a result of unfulfilled demand. Compared to other models, the CCP model reduces demand and carbon emissions the most. Comparisons based on parameters such as carbon price or MC may not make a lot of sense; nevertheless, different countries use different policies, and companies can exploit analyses based on carbon policies.

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Table 4. Numerical results for the CTP model, AP 50LL instance

α	Carbon price	Emission components		Overall emission	% satisfied demand	Profit	Hub configuration
		Hubs	Transportation				
0.3	0	1,660.32	40,879.48	42,539.80	97.54	16,879,763.89	6,22,27,35
	10	1,469.13	36,381.47	37,850.60	91.84	16,476,933.38	3,15,22,28,35
	20	1,428.83	34,821.77	36,250.60	89.03	16,108,466.14	3,15,22,28,35
	30	1,260.52	31,310.70	32,571.22	79.65	15,762,283.99	3,9,15,27,32,35
	40	1,180.84	30,225.89	31,406.73	76.19	15,444,243.94	3,9,15,27,32,35
	50	1,079.17	28,855.71	29,934.88	71.24	15,135,468.66	3,9,15,27,33,37
	60	1,071.39	27,410.56	28,481.94	68.00	14,842,612.75	3,9,15,22,28,33,37
	70	1,029.97	26,837.86	27,867.83	65.98	14,560,500.42	3,9,15,22,28,33,37
	80	1,002.67	26,275.55	27,278.23	64.47	14,285,161.95	3,9,15,22,28,33,37
0.5	0	1,443.60	39,351.84	40,795.45	97.22	16,832,561.51	15,27,35
	10	1,291.52	36,153.24	37,444.76	91.10	16,442,019.89	6,22,27,35
	20	1,229.96	34,654.74	35,884.70	85.46	16,073,686.67	15,22,27,35
	30	1,158.91	31,127.08	32,285.99	78.86	15,730,310.01	3,15,27,32,35
	40	1,138.57	30,080.43	31,219.00	76.19	15,412,090.99	3,9,15,27,32,35
	50	970.33	28,708.88	29,679.21	70.62	15,109,148.54	3,9,15,27,33,48
	60	933.77	27,830.40	28,764.18	67.66	14,816,373.43	3,9,15,27,33,48
	70	947.56	26,559.07	27,506.62	65.53	14,531,679.39	3,9,15,22,27,33,48
	80	921.95	26,272.53	27,194.48	64.39	14,257,595.80	3,9,15,22,27,33,48
0.8	0	1,177.91	40,098.38	41,276.29	97.22	16,800,518.22	15,35
	10	1,172.94	37,018.51	38,191.45	90.44	16,407,623.03	15,27,35
	20	1,113.55	34,074.95	35,188.50	84.62	16,043,389.11	15,22,27,35
	30	997.18	31,838.24	32,835.41	77.33	15,705,752.00	15,22,27,35
	40	923.25	30,195.00	31,118.25	73.53	15,387,668.36	3,15,27,33,48
	50	884.42	29,236.32	30,120.74	70.78	15,083,213.16	3,15,27,33,48
	60	866.11	27,671.70	28,537.81	67.17	14,790,153.89	3,9,15,27,32,48
	70	836.05	26,921.32	27,757.37	65.29	14,508,079.84	3,9,15,27,32,48
	80	821.28	26,599.59	27,420.87	63.93	14,231,612.28	3,9,15,27,32,48

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Table 5. Numerical results for the CCTP model, AP 50LL instance

α	% Carbon	MC	CB	CS	Emission components		Overall	% Satisfied	Profit	Hub
					Hubs	Transportation	emission	demand		configuration
0.3	100	42,539.80	0.00	9,968.58	1,260.52	31,310.70	32,571.22	79.65	17,038,477.93	3,9,15,27,32,35
	90	38,285.82	0.00	5,714.60	1,260.52	31,310.70	32,571.22	79.65	16,910,858.53	3,9,15,27,32,35
	80	34,031.84	0.00	1,460.62	1,260.52	31,310.70	32,571.22	79.65	16,783,239.13	3,9,15,27,32,35
	70	29,777.86	2,793.36	0.00	1,260.52	31,310.70	32,571.22	79.65	16,655,619.73	3,9,15,27,32,35
	60	25,523.88	7,047.34	0.00	1,260.52	31,310.70	32,571.22	79.65	16,528,000.33	3,9,15,27,32,35
	50	21,269.90	11,301.32	0.00	1,260.52	31,310.70	32,571.22	79.65	16,400,380.93	3,9,15,27,32,35
	40	17,015.92	15,555.30	0.00	1,260.52	31,310.70	32,571.22	79.65	16,272,761.53	3,9,15,27,32,35
	30	12,761.94	19,809.28	0.00	1,260.52	31,310.70	32,571.22	79.65	16,145,142.13	3,9,15,27,32,35
	20	8,507.96	24,063.26	0.00	1,260.52	31,310.70	32,571.22	79.65	16,017,522.73	3,9,15,27,32,35
	10	4,253.98	28,317.24	0.00	1,260.52	31,310.70	32,571.22	79.65	15,889,903.33	3,9,15,27,32,35
0.5	100	42,539.80	0.00	10,253.81	1,158.91	31,127.08	32,285.99	78.86	17,006,503.95	3,15,27,32,35
	90	38,285.82	0.00	5,999.83	1,158.91	31,127.08	32,285.99	78.86	16,878,884.55	3,15,27,32,35
	80	34,031.84	0.00	1,745.85	1,158.91	31,127.08	32,285.99	78.86	16,751,265.15	3,15,27,32,35
	70	29,777.86	2,508.13	0.00	1,158.91	31,127.08	32,285.99	78.86	16,623,645.75	3,15,27,32,35
	60	25,523.88	6,762.11	0.00	1,158.91	31,127.08	32,285.99	78.86	16,496,026.35	3,15,27,32,35
	50	21,269.90	11,016.09	0.00	1,158.91	31,127.08	32,285.99	78.86	16,368,406.95	3,15,27,32,35
	40	17,015.92	15,270.07	0.00	1,158.91	31,127.08	32,285.99	78.86	16,240,787.55	3,15,27,32,35
	30	12,761.94	19,524.05	0.00	1,158.91	31,127.08	32,285.99	78.86	16,113,168.15	3,15,27,32,35
	20	8,507.96	23,778.03	0.00	1,158.91	31,127.08	32,285.99	78.86	15,985,548.75	3,15,27,32,35
	10	4,253.98	28,032.01	0.00	1,158.91	31,127.08	32,285.99	78.86	15,857,929.35	3,15,27,32,35
0.8	100	42,539.80	0.00	9,704.39	997.18	31,838.24	32,835.41	77.33	16,981,945.94	15,22,27,35
	90	38,285.82	0.00	5,450.41	997.18	31,838.24	32,835.41	77.33	16,854,326.54	15,22,27,35
	80	34,031.84	0.00	1,196.43	997.18	31,838.24	32,835.41	77.33	16,726,707.14	15,22,27,35
	70	29,777.86	3,057.55	0.00	997.18	31,838.24	32,835.41	77.33	16,599,087.74	15,22,27,35
	60	25,523.88	7,311.53	0.00	997.18	31,838.24	32,835.41	77.33	16,471,468.34	15,22,27,35
	50	21,269.90	11,565.51	0.00	997.18	31,838.24	32,835.41	77.33	16,343,848.94	15,22,27,35
	40	17,015.92	15,819.49	0.00	997.18	31,838.24	32,835.41	77.33	16,216,229.54	15,22,27,35
	30	12,761.94	20,073.47	0.00	997.18	31,838.24	32,835.41	77.33	16,088,610.14	15,22,27,35
	20	8,507.96	24,327.45	0.00	997.18	31,838.24	32,835.41	77.33	15,960,990.74	15,22,27,35
	10	4,253.98	28,581.43	0.00	997.18	31,838.24	32,835.41	77.33	15,833,371.34	15,22,27,35

6.3. *Analyzing the performance of the ESAA*

For further analysis, one of the SAA, ESAA-I, and ESAA-II methods were required, as well as a proper value for M and Q. Table 6 shows the results of the SAA and ESAA variations for the AP 20LL instances. The "% gap" column indicates the percentage difference between the lower and upper bounds of the approximated models, calculated by $(SAA_{UB} - SAA_{LB})/SAA_{UB}$. Furthermore, the "$LB$" and "$UB$" columns represent the lower and upper bounds, respectively, of the absolute standard deviations (ASD). Finally, the "CPU time" column gives the computational time (in seconds) for each technique. The "k-means", "Opt", and "Total" columns represent the CPU time for pre-processing (k-means method), optimization phase, and total time, respectively. The "SOM" column indicates the CPU time for pre-processing phase (SOM method).

According to the results, the absolute standard deviation value of the UB is decreased by increasing the number of classes and scenarios. In light of the values reported in the UB columns, the results indicated the superiority of the ESAA-II compared to other variations. Specifically, the UB average is 395.07, 65.12, and 4.75 for the SAA, ESAA-I, and ESAA-II, respectively. Additionally, the gap percentage for the ESAA-II is generally better than the other two. In addition, the computational time of ESAA-I and ESAA-II techniques includes the CPU time required for the optimization phase as well as the time needed for the k-means and SOM procedures. Results show that the ESAA-II is faster than the ESAA-I, while slightly slower than the SAA. The ESAA-II algorithm performs better in clustered samples than the ESAA-I method, which can be discussed from two perspectives. SOM clusters the objects more quickly than the k-means algorithm, and 2) increasing the sample size reduced the capability of the k-means algorithm, while the SOM clustering method showed superior performance. Based on the results presented in Table 6 (% gap, absolute standard deviation, and CPU time (s)), ESAA-II is considered for further analysis over large-scale instances. Moreover, $|M| = 20$ and $|Q| = 20$ were chosen for further analysis.

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Table 6. Comparison between the SAA and ESAA variations for the CTP model with $\alpha = 0.8$, AP 20LL instance

$\|M\|$	$\|Q\|$	SAA				ESAA-I						ESAA-II					
		% gap	ASD		CPU time (s)	% gap	ASD		CPU time (s)			% gap	ASD		CPU time (s)		
			LB	*UB*			*LB*	*UB*	*k*-means	Opt	Total		*LB*	*UB*	SOM	Opt	Total
5	10	0.27	1.32	1,549.15	212.38	0.17	1.46	166.42	242.27	197.27	439.54	0.02	1.27	10.34	52.41	206.16	258.57
	20	-0.20	1.24	1,311.39	221.38	0.12	1.43	77.28	239.48	228.34	467.82	0.14	1.37	9.76	54.29	224.93	279.22
	30	-0.31	1.35	558.97	239.27	-0.03	1.35	172.78	243.28	246.38	489.66	-0.01	1.19	10.14	53.19	233.32	286.51
	40	-0.04	1.22	930.13	243.29	0.11	1.56	104.66	241.27	256.73	498.00	0.07	1.21	8.34	56.76	252.59	309.35
	50	0.14	1.47	234.94	320.42	0.20	1.24	150.22	258.75	316.02	574.77	-0.12	1.14	7.28	58.29	318.01	376.30
10	10	-0.08	1.43	451.16	238.18	0.19	1.15	66.22	490.50	245.36	735.86	0.24	1.23	5.79	146.64	246.25	392.89
	20	0.05	1.53	405.12	272.99	0.11	1.36	48.36	482.50	268.19	750.69	0.10	1.33	6.03	145.34	273.07	418.41
	30	0.14	1.28	272.26	319.37	-0.04	1.24	78.72	486.20	317.59	803.79	-0.05	1.14	5.94	147.25	312.13	459.38
	40	0.03	1.27	301.75	350.48	0.11	1.42	82.84	475.51	358.16	833.67	-0.14	1.27	3.28	146.28	354.30	500.58
	50	0.28	1.24	319.09	413.76	0.21	1.15	62.52	501.01	402.46	903.47	0.06	1.08	3.49	152.38	404.94	557.32
20	10	-0.03	1.22	252.45	365.33	-0.17	1.23	51.64	967.23	381.56	1,348.79	0.08	1.20	3.12	243.52	366.95	610.47
	20	-0.11	1.38	250.08	471.20	0.10	1.34	40.44	963.27	462.54	1,425.81	-0.20	1.12	2.43	248.23	483.92	732.15
	30	-0.12	1.67	186.13	553.48	-0.04	1.47	33.44	960.97	567.28	1,528.25	0.13	1.40	3.78	245.27	563.96	809.23
	40	-0.02	1.13	156.55	657.83	0.09	1.64	38.29	998.40	659.35	1,657.75	-0.21	1.37	2.13	245.39	662.29	907.68
	50	-0.11	1.32	122.59	757.38	0.13	1.29	43.89	1,038.85	773.22	1,812.07	0.07	1.18	1.87	246.29	766.02	1,012.31
30	10	0.54	1.25	204.31	473.29	0.17	1.23	18.95	1,521.61	454.39	1,976.12	0.19	1.46	3.24	548.60	462.65	1,011.25
	20	-0.04	1.28	135.99	668.29	0.11	1.22	16.18	1,446.41	679.15	2,125.56	0.03	1.37	3.17	546.31	672.46	1,218.77
	30	-0.15	1.37	89.27	849.63	-0.09	1.32	13.28	1,546.96	834.36	2,381.32	-0.07	1.21	2.14	547.10	844.14	1,391.24
	40	0.06	1.21	90.83	1,003.28	0.14	1.27	15.90	1,536.29	896.58	2,432.87	-0.13	1.22	1.28	552.39	903.72	1,456.11
	50	0.25	1.14	79.34	1,043.28	0.10	1.17	20.36	1,524.52	1,049.35	2,573.87	0.14	1.34	1.47	551.28	1,040.74	1,592.02
Average		0.03	1.32	395.07	483.73	0.08	1.33	65.12	808.26	479.71	1,287.98	0.02	1.26	4.75	249.36	479.63	728.99

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Table 7 shows the quality of the ESAA-II solution compared to the EVP for the CTP and CCTP models and various AP instances. In this table, the column labeled “EVP” gives the optimal solution value for the expected value model. In other words, the deterministic model was solved using the expected value for demand parameters. In addition, sub-columns “LB” and “UB” for the “ESAA-II” column represent the approximate lower and upper bound solution values for the ESAA-II models. The “EVP gap” column displays the percentage gap for the expected value model. The “% gap” column indicates the difference between the lower and upper bounds of the approximated models. In addition, sub-columns represented by LB and UB for the ASD column give the lower and upper bounds for the absolute standard deviation, respectively, in ESAA-II models. The “CPU time” column displays the computational time (in seconds) for the ESAA-II model. Finally, the last column, “hub configuration,” represents the hubs that have been opened in ESAA-II. The results confirm the superiority of the ESAA-II method over that of the EVP method. When the LT instances are considered, the hubs have changed compared to the LL instances. However, in 25 nodes the hubs have not changed. Due to the smaller capacity of LT instances, profit has also decreased compared to LL instances. Table C3 compares the quality of the ESAA-II solution to the EVP for the COP and CCP models and various AP instances in Appendix C.

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Table 7. Comparison between ESAA-II and EVP for the CTP and CCTP models and various AP instances (LL and LT), $\alpha = 0.8$

Model	Instance	EVP	ESAA-II		EVP gap	% gap	ASD		CPU time (s)			Hub configuration
			LB	*UB*			*LB*	*UB*	SOM	Opt	Total	
CTP	20LL	1,165,577.09	1,197,205.36	1,194,787.54	2.44	-0.20	1.12	2.43	248.23	483.92	732.15	7,11,13
	20LT	1,151,314.06	1,187,078.43	1,187,905.98	3.08	0.07	1.32	2.47	248.23	608.30	856.53	8,10
	25LL	2,587,693.17	2,656,520.17	2,657,543.19	2.63	0.04	1.24	2.53	896.27	2,086.85	2,983.12	8,14,16
	25LT	2,580,383.76	2,647,676.96	2,644,766.37	2.43	-0.11	1.34	2.49	896.27	2,381.78	3,278.05	8,14,16
	40LL	9,201,028.21	9,469,129.25	9,468,526.13	2.83	-0.01	1.36	2.86	5,043.26	20,420.23	25,463.49	12,22,25,29
	40LT	9,114,521.66	9,328,990.89	9,329,926.61	2.31	0.01	1.45	2.56	5,043.26	21,110.92	26,154.18	12,19,23,25
	50LL	14,986,214.17	15,769,170.00	15,769,100.00	4.96	0.00	2.34	3.24	8,713.20	39,339.88	48,053.08	15,22,27,35
	50LT	15,020,431.00	15,741,390.00	15,745,970.00	4.61	0.03	1.98	2.97	8,713.20	39,612.59	48,325.79	6,26,32,48
	60LL	22,132,457.00	23,532,140.00	23,514,960.00	5.88	-0.07	2.48	3.68	10,653.47	74,725.07	85,378.54	6,8,28,33,38
	60LT	22,179,634.00	23,397,020.00	23,422,830.00	5.31	0.11	1.43	3.46	10,653.47	75,981.81	86,635.28	6,20,38,42
	70LL	31,653,351.00	33,525,730.00	33,501,300.00	5.54	0.09	2.32	4.53	13,456.02	111,357.38	124,813.40	8,16,38,51,60
	70LT	31,233,497.00	33,476,640.00	33,508,270.00	6.79	0.09	2.31	3.89	13,456.02	111,507.25	124,963.27	20,26,45,51
CCTP	20LL	1,823,856.32	1,889,452.94	1,889,460.78	3.47	0.00	7.69	8.36	248.23	514.49	762.72	7,11,13
	20LT	1,819,673.14	1,895,352.27	1,889,621.80	3.70	-0.30	8.13	8.13	248.23	498.09	746.32	8,10
	25LL	3,413,628.13	3,561,765.78	3,560,245.62	4.12	-0.04	7.42	8.68	896.27	2,224.02	3,120.29	8,14,16
	25LT	3,401,320.46	3,560,245.62	3,551,102.94	4.22	-0.26	7.75	8.36	896.27	2,301.49	3,197.76	8,14,16
	40LL	9,874,517.00	10,406,880.00	10,406,620.00	5.11	0.00	8.42	8.46	5,043.26	21,435.10	26,478.36	12,22,25,29
	40LT	9,973,328.00	10,356,110.00	10,355,240.00	3.69	-0.01	7.64	8.43	5,043.26	22,283.43	27,326.69	12,19,23,25
	50LL	15,840,879.00	16,799,910.00	16,806,780.00	5.75	0.04	8.12	9.13	8,713.20	37,645.69	46,358.89	15,22,27,35
	50LT	15,696,375.00	16,629,770.00	16,645,070.00	5.70	0.09	7.84	8.68	8,713.20	37,723.08	46,436.28	6,26,32,48
	60LL	23,143,628.00	24,466,320.00	24,457,040.00	5.37	-0.04	7.89	8.36	10,653.47	75,704.71	86,358.18	6,16,33,38,55
	60LT	23,345,867.00	24,447,330.00	24,496,260.00	4.70	0.20	7.86	8.92	10,653.47	75,782.74	86,436.21	6,20,38,42
	70LL	32,297,639.00	34,523,680.00	34,567,740.00	6.57	0.13	8.19	8.79	13,456.02	111,940.16	125,396.18	8,16,38,49,60
	70LT	32,634,285.00	34,353,350.00	34,428,850.00	5.21	0.22	8.14	9.08	13,456.02	112,676.06	126,132.08	20,26,45,51

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7. Conclusion

It is necessary for countries to expand their transportation infrastructure to achieve economic development, but this causes environmental problems such as carbon emissions. A variety of carbon policies and regulations were presented in this paper to control carbon emissions for profit-maximizing HLPs, such as carbon tax, carbon cap, carbon cap-and-trade, and carbon offset. Additionally, in the proposed models, two-stage scenario-based stochastic programming was used to address uncertain demand. In stochastic programming problems, the main challenge is to include the probability distribution of the uncertain parameters correctly. Therefore, the ESAA method was employed to obtain the number of samples with a good percentage of gap and standard deviation. ESAA-I and ESAA-II were presented as relevant to k-means clustering algorithms and SOM clustering algorithms within the SAA method. Furthermore, the L-shaped algorithm was employed to solve the proposed models more efficiently. In order to solve the L-shaped algorithm more effectively, several variable fixing methods were introduced. The main findings of this research are summarized below: 1) Governments can use the results of the entire carbon policies to reduce overall carbon emissions. 2) CCTP was more cost-effective compared to the other carbon policies. 3) Compared to the classical SAA and ESAA-I, a SOM inside the ESAA (ESAA-II) produced better results. 4) It was found that the L-shaped algorithm (multi-cut scheme) had better results than the commercial solver (CPLEX). 5) The value of inter-hub flow discount factors had the opposite effect on the number of hub facilities. Future studies can focus on modeling carbon regulations for the HLPs with multi-commodity and multi-vehicles, in which several vehicles can be employed between each allocation link. The uncertainty of other parameters such as transportation costs, carbons, hub capacities, hub establishment costs, revenue, etc can be taken into account for future studies. Additionally, the economy of scale discount factor can be considered dependent on flows to make the problem more real.

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Appendix A SAA method for the stochastic CTP model

The mathematical model of the two-stage stochastic CTP model can be written as follows:

$$MaxZ = -\sum_{k\in H} f_k z_k + E_\xi \left[\begin{array}{l} \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H}(r_{ij} - c_{ij}^{kl})w_{ij}(\xi)x_{ij}^{kl}(\xi) - \pi \sum\limits_{k\in H} e_k v_k(\xi) \\ -\pi \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H} w_{ij}(\xi) \times x_{ij}^{kl}(\xi) \times (et_{ik} + et_{kl} + et_{lj}) \end{array} \right] \tag{A1}$$

Subject to:
Constraints (2)-(6)

$$\sum_{i\in N}\sum_{j\in N}\sum_{l\in H} w_{ij}(\xi)x_{ij}^{kl}(\xi) + \sum_{i\in N}\sum_{j\in N}\sum_{l\in H, l\neq k} w_{ij}(\xi)x_{ij}^{lk}(\xi) \leq v_k(\xi) \quad \forall k \in H, \xi \in \Xi \tag{A2}$$

$$v_k(\xi) \geq 0 \quad \forall k \in H, \xi \in \Xi \tag{A3}$$

The main challenge of stochastic programming lies in the expected value term in the objective function (A1) of the CTP model. To address this issue, the SAA method is deployed, in which a set of Q random scenarios is generated based on the probability distribution of the uncertain parameters. The second-stage expectation related to the CTP model

$$E_\xi \left[\begin{array}{l} \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H}(r_{ij} - c_{ij}^{kl})w_{ij}(\xi)x_{ij}^{kl}(\xi) - \pi \sum\limits_{k\in H} e_k v_k(\xi) \\ -\pi \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H} w_{ij}(\xi) \times x_{ij}^{kl}(\xi) \times (et_{ik} + et_{kl} + et_{lj}) \end{array} \right]$$

is approximated by the sampling function

$$\frac{1}{|Q|}\sum_{q\in Q}\left(\sum_{i\in N}\sum_{j\in N}\sum_{k\in H}\sum_{l\in H}(r_{ij} - c_{ij}^{kl} - \pi(et_{ik} + et_{kl} + et_{lj}))w_{ij}^q x_{ij}^{klq} - \pi \sum_{k\in H} e_k v_k^q\right)$$

Appendix B SAA method for the CCTP model

The mathematical model of the two-stage stochastic CCTP model can be written as follows:

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$$MaxZ = -\sum_{k\in H} f_k z_k + E_\xi \left(\begin{array}{l} \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H} (r_{ij} - c_{ij}^{kl}) w_{ij}(\xi) x_{ij}^{kl}(\xi) \\ -Cb \times yb(\xi) + Cs \times ys(\xi) \end{array} \right) \quad \text{(B1)}$$

Subject to:
Constraints (2)-(6), (A2), (A3)

$$\left(\begin{array}{l} \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H} w_{ij}(\xi) x_{ij}^{kl}(\xi)(et_{ik} + et_{kl} + et_{lj}) \\ + \sum\limits_{k\in H} e_k v_k(\xi) + ys(\xi) - yb(\xi) \end{array} \right) \leq MC \qquad \forall \xi \in \Xi \quad \text{(B2)}$$

$$yb(\xi) \geq 0 \qquad \forall \xi \in \Xi \quad \text{(B3)}$$

$$ys(\xi) \geq 0 \qquad \forall \xi \in \Xi \quad \text{(B4)}$$

Similarly, the expectation term in the objective function (B1) of the CCTP model can be approximated by the sample average function. The second-stage expectation related to the CCTP model

$$E_\xi \left[\begin{array}{l} \sum\limits_{i\in N}\sum\limits_{j\in N}\sum\limits_{k\in H}\sum\limits_{l\in H} (r_{ij} - c_{ij}^{kl}) w_{ij}(\xi) x_{ij}^{kl}(\xi) \\ -Cb \times yb(\xi) + Cs \times ys(\xi) \end{array} \right]$$

is approximated by the sampling function

$$\frac{1}{|Q|} \sum_{q\in Q} \left(\sum_{i\in N}\sum_{j\in N}\sum_{k\in H}\sum_{l\in H} (r_{ij} - c_{ij}^{kl}) w_{ij}^q x_{ij}^{klq} - Cb \times yb^q + Cs \times ys^q \right)$$

Appendix C Results for the CCP and COP models

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Table C1. Numerical results for the CCP model, AP 50LL instance

α	% Carbon	MC	Emission components		Overall	% Satisfied	Profit	Hub configuration
			Hubs	Transportation	emission	demand		
0.3	100	42,539.80	1,660.32	40,879.48	42,539.80	97.54	16,879,763.89	6,22,27,35
	90	38,285.82	1,500.20	36,785.61	38,285.82	93.06	16,859,125.78	3,15,22,28,35
	80	34,031.84	1,355.39	32,676.45	34,031.84	84.08	16,780,623.34	3,9,15,27,32,35
	70	29,777.86	1,073.63	28,704.22	29,777.86	71.02	16,622,705.15	3,9,15,27,32,35
	60	25,523.88	872.02	24,651.86	25,523.88	59.27	16,302,026.07	3,9,15,22,27,32,35
	50	21,269.90	686.83	20,583.06	21,269.90	47.89	15,699,482.18	3,9,15,22,27,32,35
	40	17,015.92	523.52	16,492.40	17,015.92	36.70	14,660,303.97	3,9,15,22,27,32,35
	30	12,761.94	376.05	12,385.89	12,761.94	26.20	13,098,084.02	3,9,15,22,27,32,35
	20	8,507.96	242.33	8,265.63	8,507.96	16.41	10,699,119.61	3,9,15,22,27,32,35
	10	4,253.98	109.76	4,144.22	4,253.98	7.43	6,950,297.55	3,9,15,22,27,48
0.5	100	42,539.80	1,443.60	39,351.84	40,795.45	97.22	16,832,561.51	15,27,35
	90	38,285.82	1,356.40	36,929.42	38,285.82	94.31	16,823,204.60	6,22,27,35
	80	34,031.84	1,198.88	32,832.96	34,031.84	81.54	16,747,657.05	3,15,22,27,35
	70	29,777.86	978.24	28,799.62	29,777.86	71.16	16,597,780.30	3,9,15,27,33,48
	60	25,523.88	846.53	24,677.35	25,523.88	59.57	16,280,484.37	3,9,15,22,27,32,35
	50	21,269.90	672.84	20,597.06	21,269.90	47.97	15,683,097.06	3,9,15,22,27,32,35
	40	17,015.92	513.97	16,501.95	17,015.92	36.75	14,647,429.06	3,9,15,22,27,32,35
	30	12,761.94	374.76	12,387.18	12,761.94	26.20	13,087,891.81	3,9,15,22,27,32,35
	20	8,507.96	240.12	8,267.84	8,507.96	16.42	10,692,093.20	3,9,15,22,27,32,35
	10	4,253.98	103.21	4,150.77	4,253.98	7.37	6,947,359.73	9,15,22,27,48
0.8	100	42,539.80	1,177.91	40,098.38	41,276.29	97.22	16,800,518.22	15,35
	90	38,285.82	1,181.18	37,104.64	38,285.82	91.17	16,790,409.12	15,27,35
	80	34,031.84	1,058.69	32,973.15	34,031.84	81.48	16,720,840.99	15,22,27,35
	70	29,777.86	868.53	28,909.33	29,777.86	69.62	16,571,458.39	3,15,27,33,48
	60	25,523.88	802.53	24,721.35	25,523.88	59.82	16,254,243.51	3,9,15,22,27,33,48
	50	21,269.90	649.87	20,620.02	21,269.90	48.01	15,661,866.03	3,9,15,22,27,33,48
	40	17,015.92	504.87	16,511.04	17,015.92	36.76	14,629,651.47	3,9,15,22,27,33,48
	30	12,761.94	368.42	12,393.51	12,761.94	26.22	13,073,472.80	3,9,15,22,27,33,48
	20	8,507.96	224.07	8,283.89	8,507.96	16.24	10,683,105.53	3,9,15,22,27,48
	10	4,253.98	101.84	4,152.14	4,253.98	7.37	6,943,479.79	9,15,22,27,48

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Table C2. Numerical results for the COP model, AP 50LL instance

α	% Carbon	MC	CB	Emission components		Overall emission	% Satisfied demand	Profit	Hub configuration
				Hubs	Transportation				
0.3	100	42,539.80	0.00	1,660.32	40,879.48	42,539.80	97.54	16,879,763.89	6,22,27,35
	90	38,285.82	0.00	1,500.20	36,785.61	38,285.82	93.06	16,859,125.78	3,15,22,28,35
	80	34,031.84	0.00	1,355.39	32,676.45	34,031.84	84.08	16,780,623.34	3,9,15,27,32,35
	70	29,777.86	2,793.36	1,260.52	31,310.70	32,571.22	79.65	16,655,619.73	3,9,15,27,32,35
	60	25,523.88	7,047.34	1,260.52	31,310.70	32,571.22	79.65	16,528,000.33	3,9,15,27,32,35
	50	21,269.90	11,301.32	1,260.52	31,310.70	32,571.22	79.65	16,400,380.93	3,9,15,27,32,35
	40	17,015.92	15,555.30	1,260.52	31,310.70	32,571.22	79.65	16,272,761.53	3,9,15,27,32,35
	30	12,761.94	19,809.28	1,260.52	31,310.70	32,571.22	79.65	16,145,142.13	3,9,15,27,32,35
	20	8,507.96	24,063.26	1,260.52	31,310.70	32,571.22	79.65	16,017,522.73	3,9,15,27,32,35
	10	4,253.98	28,317.24	1,260.52	31,310.70	32,571.22	79.65	15,889,903.33	3,9,15,27,32,35
0.5	100	42,539.80	0.00	1,443.60	39,351.84	40,795.45	97.22	16,832,561.51	15,27,35
	90	38,285.82	0.00	1,356.40	36,929.42	38,285.82	94.31	16,823,204.60	6,22,27,35
	80	34,031.84	0.00	1,198.87	32,832.96	34,031.84	81.54	16,747,657.05	3,15,22,27,35
	70	29,777.86	2,508.13	1,158.90	31,127.08	32,285.99	78.86	16,623,645.75	3,15,22,27,35
	60	25,523.88	6,762.11	1,158.90	31,127.08	32,285.99	78.86	16,496,026.35	3,15,22,27,35
	50	21,269.90	11,016.09	1,158.90	31,127.08	32,285.99	78.86	16,368,406.95	3,15,22,27,35
	40	17,015.92	15,270.07	1,158.90	31,127.08	32,285.99	78.86	16,240,787.55	3,15,22,27,35
	30	12,761.94	19,524.05	1,158.90	31,127.08	32,285.99	78.86	16,113,168.15	3,15,22,27,35
	20	8,507.96	23,778.03	1,158.90	31,127.08	32,285.99	78.86	15,985,548.75	3,15,22,27,35
	10	4,253.98	28,032.01	1,158.90	31,127.08	32,285.99	78.86	15,857,929.35	3,15,22,27,35
0.8	100	42,539.80	0.00	1,177.91	40,098.38	41,276.29	97.22	16,800,518.22	15,35
	90	38,285.82	0.00	1,181.18	37,104.64	38,285.82	91.17	16,790,409.12	15,27,35
	80	34,031.84	0.00	1,058.69	32,973.15	34,031.84	81.48	16,720,840.99	15,22,27,35
	70	29,777.86	3,057.55	997.18	31,838.24	32,835.41	77.33	16,599,087.74	15,22,27,35
	60	25,523.88	7,311.53	997.18	31,838.24	32,835.41	77.33	16,471,468.34	15,22,27,35
	50	21,269.90	11,565.51	997.18	31,838.24	32,835.41	77.33	16,343,848.94	15,22,27,35
	40	17,015.92	15,819.49	997.18	31,838.24	32,835.41	77.33	16,216,229.54	15,22,27,35
	30	12,761.94	20,073.47	997.18	31,838.24	32,835.41	77.33	16,088,610.14	15,22,27,35
	20	8,507.96	24,327.45	997.18	31,838.24	32,835.41	77.33	15,960,990.74	15,22,27,35
	10	4,253.98	28,581.43	997.18	31,838.24	32,835.41	77.33	15,833,371.34	15,22,27,35

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Table C3. Comparison between ESAA-II and EVP for the CCP and COP models and different AP instances (LL and LT), $\alpha = 0.8$

Model	Instance	EVP	ESAA-II		EVP gap	% gap	ASD		CPU time (s)			Hub configuration
			LB	*UB*			*LB*	*UB*	SOM	Opt	Total	
CCP	20LL	1,783,248.07	1,814,960.66	1,814,650.66	1.73	-0.02	7.68	9.43	248.23	316.23	564.46	7,15
	20LT	1,783,214.79	1,812,178.29	1,809,182.25	1.44	-0.17	7.42	9.62	248.23	331.09	579.32	8,10
	25LL	3,379,342.72	3,463,411.13	3,467,213.91	2.53	0.11	7.54	9.27	896.27	1,539.91	2,436.18	8,14,17
	25LT	3,386,443.02	3,486,653.42	3,485,939.95	2.85	-0.02	7.49	9.29	896.27	1,517.60	2,413.87	8,14,16
	40LL	10,010,793.00	10,402,640.00	10,396,300.00	3.71	-0.06	7.72	9.37	5,043.26	21,799.11	26,842.37	12,22,25,29
	40LT	9,965,983.00	10,349,860.00	10,338,730.00	3.61	-0.11	7.38	9.35	5,043.26	21,949.75	26,993.01	12,19,23,25
	50LL	16,173,829.00	16,737,280.00	16,739,720.00	3.38	0.01	8.18	9.54	8,713.20	37,722.53	46,435.73	15,22,27,35
	50LT	15,964,286.00	16,721,220.00	16,727,300.00	4.56	0.04	8.13	9.32	8,713.20	37,850.08	46,563.28	6,26,32,48
	60LL	23,107,961.00	24,425,980.00	24,447,030.00	5.48	0.09	8.13	9.48	10,653.47	76,115.81	86,769.28	6,16,33,38,55
	60LT	23,263,479.00	24,404,530.00	24,385,020.00	4.60	-0.08	8.42	9.48	10,653.47	75,242.85	85,896.32	6,20,38,42
	70LL	32,127,860.00	34,414,400.00	34,410,140.00	6.63	-0.01	7.98	9.62	13,456.02	113,902.28	127,358.30	8,16,38,49,60
	70LT	32,473,452.00	34,366,570.00	34,395,090.00	5.59	0.08	8.39	9.76	13,456.02	114,789.77	128,245.79	20,26,45,51
COP	20LL	1,811,346.43	1,842,443.69	1,844,438.97	1.79	0.11	7.53	9.32	248.23	558.15	806.38	7,15
	20LT	1,766,439.76	1,804,606.69	1,805,793.87	2.18	0.07	7.46	9.72	248.23	473.16	721.39	8,10
	25LL	3,342,351.02	3,473,039.00	3,468,546.17	3.64	-0.13	7.52	9.42	896.27	2,282.16	3,178.43	8,14,17
	25LT	3,342,389.17	3,453,221.61	3,451,202.54	3.15	-0.06	7.42	9.35	896.27	2,060.49	2,956.76	8,14,16
	40LL	9,986,792.00	10,403,830.00	10,413,390.00	4.10	0.09	7.64	9.34	5,043.26	21,471.87	26,515.13	12,22,25,29
	40LT	9,839,716.00	10,369,620.00	10,380,020.00	5.21	0.10	7.68	9.36	5,043.26	21,998.83	27,042.09	12,19,23,25
	50LL	15,812,438.00	16,740,640.00	16,736,670.00	5.52	-0.02	8.12	9.31	8,713.20	37,406.14	46,119.34	15,22,27,35
	50LT	15,943,997.00	16,714,510.00	16,726,180.00	4.68	0.07	7.72	9.34	8,713.20	37,732.03	46,445.23	6,26,32,48
	60LL	22,798,634.00	24,614,550.00	24,491,280.00	6.91	-0.50	8.22	9.56	10,653.47	75,003.92	85,657.39	6,16,33,38,55
	60LT	23,143,528.00	24,327,750.00	24,314,710.00	4.82	-0.05	8.38	9.61	10,653.47	76,054.70	86,708.17	6,20,38,42
	70LL	32,134,574.00	34,523,880.00	34,504,080.00	6.87	-0.06	8.14	9.65	13,456.02	112,384.06	125,840.08	8,16,38,49,60
	70LT	32,439,187.00	34,291,910.00	34,282,310.00	5.38	-0.03	8.53	9.63	13,456.02	112,676.12	126,132.14	20,26,45,51

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