Article

Inventory Transshipment Considering Greenhouse Gas Emissions for Sustainable Cross-Filling in Cold Supply Chains

Hang Thi Thanh Vu and Jeonghan Ko *

Department of Industrial Engineering, Ajou University,
206 Worldcup-ro, Suwon-si 16499, Republic of Korea
* Correspondence: jko@ajou.ac.kr; Tel.: +82-31-219-2335

Abstract: In recent years, sustainable supply chain management has gained increasing attention, and greenhouse gas (GHG) emissions throughout supply chains have been identified as one of the most important sustainability issues. This paper presents an investigation of the problem of transshipment among distribution centers (DCs) in a cold supply chain to achieve sustainable inventory cross-filling. Although transshipment is an effective tool for supply chain pooling, the possibility of increased GHG emissions raises environmental concerns. This study establishes a sustainable cold-chain logistics model that considers GHG emissions from DC storage and transshipment trucks. The new sustainable cold-chain model also reflects laden status and cargo weights of trucks for accurate emission assessment. An optimization model is also developed to minimize both GHG emissions and costs in the cold chain. Numerical simulations are conducted for diverse problem cases to examine important problem characteristics. The result analysis identifies that inventory service levels and demand variability have a strong impact on GHG emissions in transshipment; small *p*-values in the statistical analysis verify the significance of this effect. The different effects of demand variability and service levels on each emission source are also analyzed. The results demonstrate that transshipment among DCs can effectively reduce both GHG emissions and costs in cold supply chains. This study provides useful models and tools to assess GHG emissions and optimize decisions for the design and operation of transshipment. The proposed models will enable the assessment of sustainable alternatives and achieve sustainability objectives effectively for cold supply chains.

Keywords: transshipment; cross-filling; sustainability; greenhouse gas; carbon; emission; green supply chain; cold chain; piecewise linear

1. Introduction

Greenhouse gas (GHG) emissions throughout a supply chain have been one of the most important topics addressed in the research on sustainable supply chains [1–3]. This study investigates a problem of transshipment among distribution centers (DCs) in a cold supply chain to achieve sustainable inventory cross-filling. This paper presents integrated sustainable cold-chain logistics models considering GHG emissions from DC storage and transshipping trucks. The mathematical models incorporate a truck's laden status and cargo weights to evaluate emissions accurately. This study also identifies the impact of operation decisions and conditions on the GHG emissions during transshipment in cold chains. Analysis of this impact helps to clarify the characteristics of operation decisions and GHG emissions in transshipment. Thus, models in this study will help manage logistics operations to successfully achieve sustainable goals and correctly assess sustainable alternatives.

Cold supply chains have become more prevalent in recent years due to the rising demand for fresh products. As living standards rise and average income grows, consumers desire more fresh products, not just cheap ones. These products include fruits, vegetables, flowers, meat, fish, and medicine. Cold chains can meet such demand by prolonging the

life of fresh items as inventory and enabling long-distance logistics. For example, cold chains of fresh fruit have spread across different continents. By extending item variety and transportation distance, cold chains have become a fast-growing sector in supply chains.

Cold supply chains have also enabled responsive supply chains. Quick delivery, such as 2-h delivery, has become one of the most competitive strategies in recent years. For example, the integration of smart purchasing and quick delivery has created a new industry of fresh-food delivery. The cold chain system is an essential part of these responsive last-mile logistics. Thus, the cold chain has potential for further growth.

Despite the numerous benefits of the cold chain, its use of extra energy and equipment may significantly increase cost and GHG emissions. Cold chain logistics requires extra equipment and handling to maintain temperature and humidity. For example, refrigerated containers and vehicles are often used. Environment-controlled storage is also necessary in distribution centers. All of these need more capital investment and operation costs. The cold chain also consumes more energy and packaging for environmental control. These equipment and operations also lead to increased GHG emissions [4]. The cold chain also has risks of refrigerant leakage, a significant source of GHG emissions. In addition, compared with conventional supply chains, the enhanced responsiveness of the cold chain requires increased inventory levels and more transportation, which also contribute to increased costs and GHG emissions.

One solution to the above problems in responsive cold supply chains is transshipment (cross-filling) among DCs. Transshipment serves as an inventory pooling approach. In cross-filling, the surplus items of a DC are shipped to other DCs lacking those items. This transshipping allows coping with demand fluctuations without maintaining high inventory levels. An inventory level may be kept high to reduce shortage possibility and increase responsiveness, because shortage at DCs causes shortage at retail stores and a detrimental impact on sales and customer satisfaction. High inventory often results in increased storage requirements, handling activities, obsolescence risk, and holding costs. These also lead to more energy use and waste disposal, thus elevating GHG emissions. This harmful impact is especially severe in cold chains due to increased energy use and added systems. Therefore, reduced inventory by transshipment has the potential to enhance financial and environmental sustainability [5].

For sustainable and cost-effective transshipment, a variety of aspects of cold supply chains should be evaluated for trade-offs. Transshipment can decrease financial and sustainability impact by reducing the negative effects of high inventory. However, transshipment also incurs added transportation and handling, which may increase cost and environmental impact. Thus, trade-offs between inventory levels and transportation amount should be identified accurately. In addition, diverse characteristics of cold chains affect the trade-off. Important operational decisions such as a service level affect the trade-offs. Operation conditions such as demand variability also affect the trade-offs. The GHG emission pattern unique to cold chains also affects the trade-offs.

Despite the importance of transshipment, the existing parameters and methodologies are insufficient for appropriate sustainable transshipment planning in cold chains [6]. First, only a limited number of emission factors for cold chains are available in the literature and databases. The current emission factors are too simple to accurately reflect conditions in the cold chain. For example, the emission factors of trucks are often in the form of a single value used for a wide range of cargo loads, truck types, and operating conditions. Detailed emission factors or values such as those at Tier 3 [7] are not readily available. Second, the current transshipment transportation model does not consider important characteristics related to GHG emissions. For example, the majority of the existing methods do not distinguish empty miles (runs without cargo) from non-empty miles of the trucks in transportation modeling. Few systematic methods have been developed for incorporating the variable emissions depending on cargo weights in transportation modeling.

This study overcomes such limitations by providing integrated sustainable cold-chain models considering the GHG emissions from storage and transshipment trucks. First,

mathematical models and solutions are provided for the green transshipment for cross-filling in cold chains. This paper presents a method that distinguishes between empty and non-empty miles in complicated transshipment networks. Novel mathematical models are suggested to reflect trucks' empty and laden status. New methods are proposed to reflect cargo-load-dependent emissions rather than a simple single value. A piecewise-linear emission-factor function (PLEF) is introduced to compute the GHG emissions of refrigerated trucks with varying cargo weights. The model can also evaluate the trade-offs between profitability and sustainability.

In addition, this study reveals the impact of transshipment decisions and conditions on GHG emissions. This research investigates how transshipment decisions and operations for cross-filling affect GHG emissions. A variety of numerical case studies are conducted to examine the impact of transshipment-related decisions and operation conditions. This research analyzes the effects of demand variability and inventory service levels on GHG emissions and investigates the extent to which such decisions and conditions contribute to changes in emissions across different emission categories.

The contribution of this study is to provide a set of novel methodologies for green transshipment in cold chains and to help businesses improve environmental operations. (1) This paper provides new optimization models to enable best supply chain decisions under conflicting requirements and achieve best trade-offs for transshipment. Thus, this study demonstrates how to tackle a typical dilemma in transshipment for green logistics in cold chains. (2) The novel approaches in this paper enable the calculation of GHG emissions under different cargo conditions of transshipment trucks. Compared with the previous research, the new comprehensive model will enable more detailed and accurate calculations of GHG emissions from transshipment operations. (3) The results of this study will also improve understanding of how transshipment parameters affect GHG emissions throughout supply chains. This understating allows an organization to estimate an emission beyond its boundary, such as Scope 3 emissions [8]. (4) All of these will support businesses in achieving sustainable goals such as 100 percent renewable energy (RE100) [9] and assess candidates for carbon reduction plans, such as switching to electric vehicles, with confidence. Accurate evaluation will also help prepare for new regulations such as the European Union's carbon border adjustment mechanism (CBAM) [10].

The remainder of this paper is organized as follows. The related literature and practices are reviewed in Section 2. The green transshipment model for cross-filling is described in Section 3. Case studies and statistical analyses are presented in Section 4. Results and practical implications are discussed in Section 5. The paper concludes in Section 6.

2. Review of the State-of-the-Art Research

Transshipment, or cross-filling, has demonstrated effectiveness as an important supply chain pooling method [11–13]. A variety of characteristics of the transshipment problem have been studied [14]. For example, a proactive lateral transshipment model was presented to reduce the overall cost [15]. For replenishing and recycling perishable goods, lateral transshipment was investigated [16,17]. Numerous studies have explored sustainable inventory management with a focus on lateral transshipment [18–21]. Several combined transshipment and production control policies were proposed, including a policy for multi-location systems [22,23]. A transshipment inventory-routing problem was also studied [24]. Transshipment vehicle routing problems were solved using different approaches such as a heuristic algorithm [11] or a mixed-integer programming model [25]. A mathematical model proposed by Vu and Ko permits simultaneous imputation for missing demand data and transshipment decisions, and thus provides proper ways to handle incomplete data situations [5]. However, this mathematical model does not directly consider sustainability issues and the changes in GHG emissions affected by operation decisions.

In the literature, extensive research on green logistics exists and comprehensive reviews can be found in [26,27]. Several studies have investigated the vehicle routing problem (VRP) with electric vehicles as an alternative to conventional internal combustion engine

vehicles [28–30]. The electric recharging station location problem was investigated via stochastic power usage [31]. Similarly, a mathematical model was proposed for pickup and delivery problems with electric vehicles under stochastic power usage [32].

The VPR with cold chain logistics has been the subject of extensive investigation. A low-carbon location–routing model was proposed for a cold chain logistics distribution network with a hybrid genetic algorithm [33]. Stochastic VRPs with time windows [34,35] were proposed for perishable food delivery. A heuristic approach was presented to minimize the total cost and energy use with a time window in a cold chain VRP [36]. A simultaneous delivery and pickup VRP was presented for cold chain logistics, considering vehicle cooling costs [37]. A minimum loss based VRP was also proposed for cold chain logistics [38].

A few studies on green transshipment are also available. GHG emission constraints relying on loading volume and travel distance were presented [39], and those depending on traveling distance with demand uncertainty were also studied [40].

In a cold chain, it is difficult to measure precise energy use and GHG emissions, but fairly good estimates have been developed for industrial use [41]. The cold storage in DCs requires a variety of systems and equipment for storage, picking, sorting, and material handling, all with maintained temperature. A DC often accommodates separate facilities with different temperature and humidity levels. Some storage systems use specialized gases to extend the shelf life of fresh food items, called modified atmosphere storage or controlled atmosphere storage [42], for each fruit type.

Various technologies have been used in cold chain logistics but their impact on GHG emissions needs further investigation. Refrigerant has become better in efficiency, with a lower environmental impact, but needs more improvement. The currently popular hydrofluorocarbon adopted for ozone layer protection has large global warming potential (GWP) [43,44]. Thus, new refrigerant is required that is more energy efficient and has a lower GWP. Cold chain trucks or containers are equipped with devices such as compressors, condensers, evaporators, controllers, sensors, and recorders as well as specialized materials such as insulations, refrigerants, and packaging materials [45]. Some cold chain trucks have separate compartments for multi-temperature transportation [46].

GHG emissions can be measured in various ways. Several studies have demonstrated that the GHG emissions of vehicles correspond to actual traveling distance and loading volume. However, accurately estimating GHG emissions can be challenging [47]. To mitigate such difficulties, GHG emissions are commonly transformed into a readily observable energy consumption problem [48]. Numerous emission models have been employed in the green VRP [49], the majority of which utilize the relationship between fuel consumption and GHG emissions [50]. A VRP model for cold chains considering empty vehicles was presented using a linear function for fuel consumption to estimate GHG emissions [51,52]. A heuristic framework was developed for a multi-depot problem with GHG emissions estimated from fuel consumption [53].

Numerous tools and software are available that support tracking and managing GHG emissions. The Carbon Disclosure Project (CDP) is a non-profit organization that comprises investors, governments, companies, and cities to build a sustainable economy [54]. Ecometrica [55] and the Carbon Trust [56] are well-known partners of the CDP that provide tools and software to measure GHG emissions. Other well-known tools include EcoAct [57], Greenhouse Gas Protocol [58], and SAP Sustainability Performance [59]. A GHG emission tool for aircraft, released by Eurocontrol, adopted piecewise linear modeling [60].

Transshipment problems, cold chain logistics, green logistics, and GHG emission measurement methods have been investigated extensively. However, sustainable cold chain transshipment with GHG emission factors has not been adequately addressed by the aforementioned studies. This study attempts to address this research gap.

3. Sustainable Transshipment Model

This section describes a sustainable cold-chain logistics model that considers GHG emissions from DC storage and transshipment trucks. Section 3.1 describes the problem

assumptions in this paper. Section 3.2 presents new emission factors and their mathematical expressions. Section 3.3 describes the aggregated mathematical formulations.

3.1. Problem Assumptions, System Boundary, and Definitions

The mathematical models in this paper represent the optimal sustainable transshipment for cold chains. The new model expresses cost factors and GHG emissions from inventory transshipment including cold storage and transshipment trucks. The overall structure and input to the model are shown in Figures 1 and 2. The problem was modeled using mixed-integer programming (MIP).
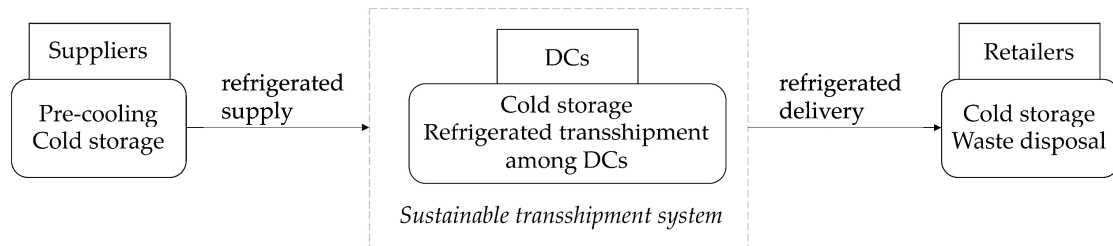

Figure 1. Sustainable transshipment system boundary (dotted box) in a cold supply chain.
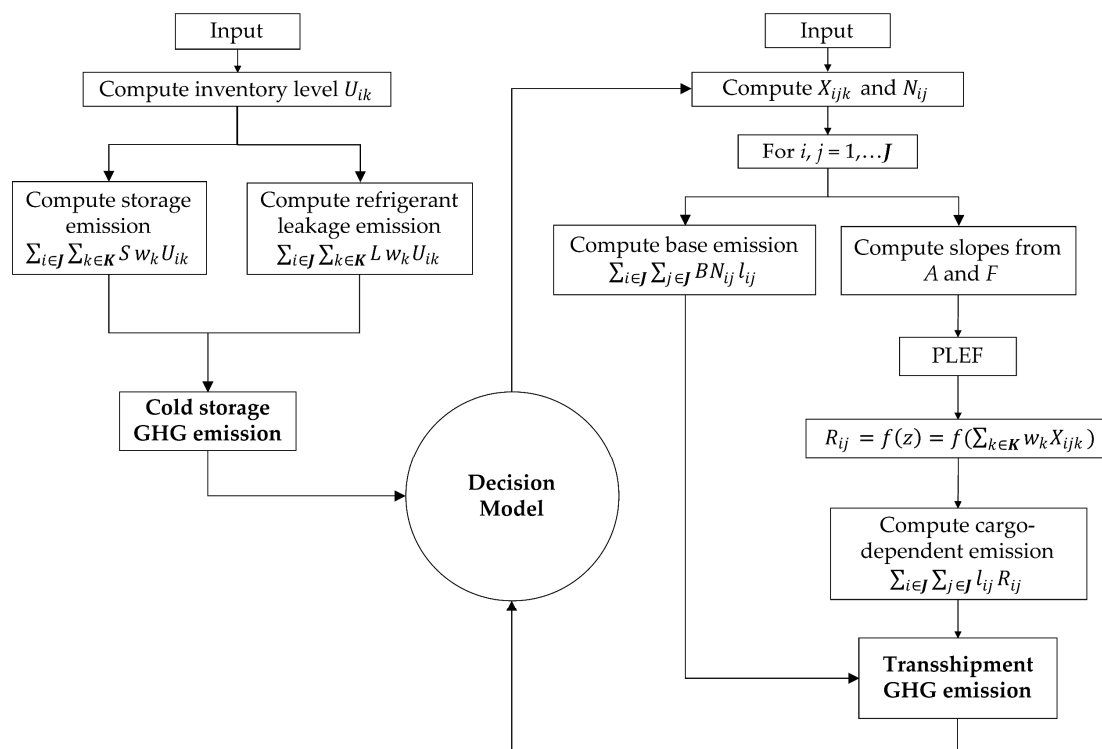
Figure 2. Flowchart of sustainable transshipment decision model considering greenhouse gas (GHG) emissions.

For modeling, the following conditions are assumed. First, we assume that the headquarter (HQ) of a company gathers all relevant data and makes decisions on the cross-filling by the DCs. The demand information for DCs is obtained by the HQ from the retailers in the service region of each DC. The HQ coordinates the optimal transshipment between the DCs based on the inventory level, shortage information, and demand data. The DCs then execute the transshipment plan of the HQ. The HQ also places replenishment orders to upstream suppliers for the DCs. After the transshipment is completed, each DC sends the replenishment orders to its retailers. In addition, we assume that there exist a sufficient

number of refrigerated trucks of the same type at the DCs and the trucks return to the DC from which they depart after completing transshipping.

In a typical transshipment condition as shown in this paper, the time window of transshipment is limited to a short period. In daily transshipment it can be only some hours, determined by operation policies [5]. Moreover, the travel distance for transshipment is the result of optimization. In other words, the average travel distance of trucks is not assumed in advance, unlike existing studies. If the time window increases, longer travel distances are allowed and more pairs of DCs located farther away could transship items from each other.

This study assumes that all the DCs follow an inventory policy with daily replenishment up to a certain value U_{ik}. This policy is known to provide an optimal long-run performance [61]. At DC i, the order-up-to level for product item k is defined as $U_{ik} = \mu_{ik} + z_\alpha \sigma_{ik}$. The z-score z_α corresponds to the target in-stock probability (*ISP*) α in the standard normal distribution. In this study, the in-stock probability or service level is defined as the likelihood of not being stocked out within a certain length of time [62]. The expected inventory and shortage levels before transshipment are calculated using the target *ISP*, order-up-to value, and demand data.

Without loss of generality, this paper considers the GHG emissions from two major sources: (1) a DC's cold storage, mainly including refrigeration energy consumption and refrigerant leakage, and (2) refrigerated transshipment trucks, primarily including fuel consumption. The stable emission amounts regardless of transshipment decisions are not considered as a part of the operational decision model. For instance, the upstream suppliers are assumed to perform pre-cooling processes and supply enough quantity of product items to fulfill the inventory. Thus, the carbon footprint from the supply chain upstream is outside the scope of the operational transshipment decision in this study. The carbon footprint from the supply chain downstream is not considered either; the transportation from DCs to retailers as well as the retailer storage and relevant activities are also beyond consideration. The system boundary of this sustainable transshipment is shown in Figure 1. If the same truck type is used, no difference is assumed for the GHG emissions among trucks. In this paper, GHG, CO_2 equivalent, and carbon are used interchangeably.

The overall procedure of the sustainable transshipment decision model is described in Figure 2. The figure shows that the decision model considers GHG emissions from cold storage and transshipment. The details will be explained in later sections.

3.2. GHG Emission Factors

This section describes the emission factors developed to reflect the transshipment conditions and carbon footprints more accurately than conventional factors. The emission from a truck is dependent on a range of variables, such as the weight of the cargo, vehicle speed, road condition, and other operational parameters. Thus, a single constant emission factor in the majority of the existing research cannot properly reflect these complex operation conditions.

This paper considers two main sources of greenhouse gas emissions: (1) cold storage at DCs and (2) refrigerated transshipment trucks both for temperature and humidity control.

(1) GHG emission from the cold storage at DCs: GHGs are generated by DC's cold storage systems through refrigeration energy use and refrigerant leakage [63]. The leakage depends on equipment, and GWP is also dependent on the refrigerant gas. Thus, separate treatment of leakage will provide flexibility to model the storage emissions. Because daily inventory levels remain as U_{ik} [5], and the logistics operations at DCs are generally stable, the total daily GHG emissions from the cold storage of the DC is calculated based on the weight and quantity of product items as described in Equation (1).

$$\sum_{i \in J} \sum_{k \in K} (S + L) w_k U_{ik} \tag{1}$$

The numerical details are described in Section 4.

(2) GHG emissions during transshipment by refrigerated trucks: GHGs are emitted during truck operation, mainly through fuel consumption. Trucks transship between a pair of DCs: trucks can ship items both ways and must return to their departing locations. Sometimes, a truck may run empty (without cargo), especially on the returning route. An accurate estimation of GHG emissions should differentiate between empty and non-empty miles. Thus, this study divides the GHG emissions into two parts: base and cargo-dependent emissions. The base emission accounts for moving the truck itself (tare weight for each truck) and is proportional to the total traveling distance; it can also be used for accounting the empty miles. The additional emissions with the loaded cargo vary with the cargo weight (laden weight minus tare weight) and travel distance. The total daily emissions from transshipment are shown in Equation (2).

$$\sum_{i \in J} \sum_{j \in J} \left(BN_{ij} l_{ij} + l_{ij} R_{ij} \right), \tag{2}$$

where the first term represents the base emissions and the second term expresses the cargo-dependent emissions. The terms are explained in more detail below.

In addition to the separate emission factors for empty trucks and loaded cargos, this study also considers the varying emission factor with the cargo weight. First, fuel consumption is not simply proportional to the weight, because engine fuel efficiency changes with load. Thus, the rate of emission per cargo weight changes as the cargo weight changes. Second, multiple trucks can operate simultaneously on the same route. When the transshipment weight exceeds the truck capacity, multiple trucks are required in a specific route. This nonlinear rate is denoted in Equation (3) as a function of the total weight of the cargo between a pair of DCs.

$$R_{ij} = f(z) = f\left(\sum_{k \in K} w_k X_{ijk} \right) \forall i, j \in J. \tag{3}$$

This nonlinear rate can be accurately approximated using piecewise linear functions. The piecewise linear emission factor (PLEF) is defined by a set of slopes, breakpoints at which the slopes change, and fixed values of the functions. For example, the PLEF accounting for only the cargo weight is expressed by Equation (4) for a two-rate case:

$$f(z) = \begin{cases} a_1^b z, & \text{for } 0 \le z \le \gamma_1^b, \\ a_2^b \left(z - \gamma_1^b \right) + \delta_1^b, & \text{for } \gamma_1^b < z \le \gamma_2^b, \\ \quad \vdots \\ a_{n-1}^b \left(z - \gamma_{n-2}^b \right) + \delta_{n-2}^b, & \text{for } \gamma_{n-2}^b < z \le \gamma_{n-1}^b, \\ a_n^b \left(z - \gamma_{n-1}^b \right) + \delta_{n-1}^b, & \text{for } \gamma_{n-1}^b < z \le \gamma_n^b. \end{cases} \tag{4}$$

Figure 3 illustrates the portion of the PLEF corresponding only to the cargo weight (laden weight minus the tare weight). Here, the number of piecewise function intervals per one truck is two. There are two slopes: when the cargo weight is (1) less than γ_1^b (e.g., an average value) and (2) between γ_1^b and γ_2^b (e.g., full truck load). At every increase by γ_2^b in the horizontal axis, a new two-line segment is used to represent the cargo emission factor of an added truck. By representing the emission measurement or fuel consumption data using multiple intervals, the PLEF can model the nonlinear emission rates quite accurately.
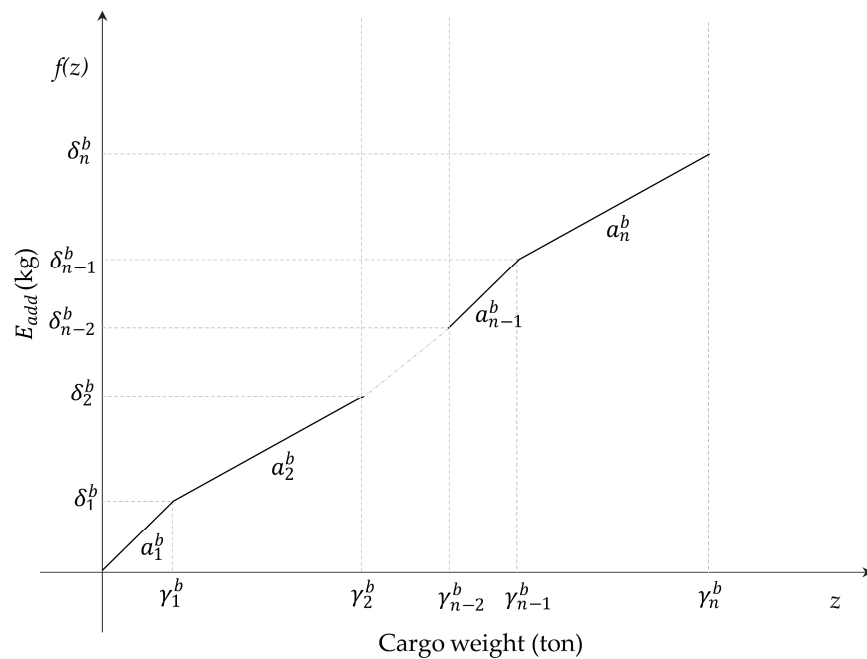
Figure 3. Piecewise linear emission factor (PLEF) for calculating emissions only from the loaded cargos.

Figure 4 illustrates the complete generic emission factors from different truck types, including the base and cargo-dependent emissions. Even when there is no cargo, trucks still emit a base amount of pollution corresponding to moving the tare weight of a truck. Therefore, the emission begins with a non-zero value when the cargo weight is zero. At every increment by cargo weight W tons (truck capacity), the emission jumps by the amount of the base emission of the next truck. Truck emissions can vary based on the type of trucks due to their differences in engines and bodies. The model depicted in Figure 4 can be applied to multiple truck types. When there is no cargo, Truck Type 1 has a base emission factor B_1. At the point of the cargo weight W tons (γ_2^1 for Truck Type 1), the emission jumps by the amount of the base emission of another truck (B_2 of Truck Type 2).
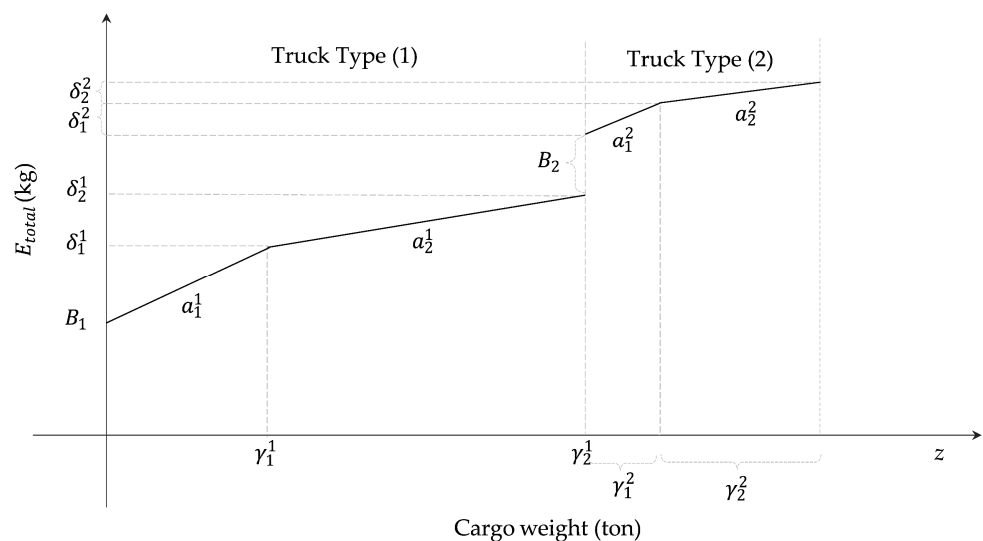

Figure 4. An illustration of generic emission factors for different truck types. Note: for Truck Type 2, δ_n^2 and γ_n^2 are the lengths of the intervals, not the accumulated values.

3.3. Optimization Model

The following MIP model represents the optimal sustainable transshipment for cold chains. The new MIP model expresses cost factors for GHG emissions from inventory transshipment including cold storage and transshipment trucks, and constraints for calculating and restricting the GHG emissions from transshipment operation. Some equations partially use the vehicle routing and transshipment models previously developed by the authors [5].

$$Min\ Z = \sum_{i \in J}\sum_{j \in J} c_{ij}N_{ij} + m\sum_{i \in J}\sum_{j \in J}\sum_{k \in K} X_{ijk} + \sum_{i \in J}\sum_{k \in K} p_k r_k S_{ik}^+ + \sum_{i \in J}\sum_{k \in K} hp_k U_{ik}$$
$$+ \theta\sum_{i \in J}\sum_{k \in K} (S + L)w_k U_{ik} + \theta\sum_{i \in J}\sum_{j \in J} (BN_{ij}l_{ij} + l_{ij}R_{ij}) \tag{5}$$

subject to

$$\sum_{j \neq i} X_{ijk} \leq U_{ik} \forall i, j \in J,\ \forall k \in K \tag{6}$$

$$S_{ik}^+ \geq d_{ik} - U_{ik} + \sum_{j \neq i} X_{ijk} - \sum_{j \neq i} X_{jik}\ \forall i, j \in J, \forall k \in K \tag{7}$$

$$R_{ij} = f\left(\sum_{k \in K} w_k X_{ijk}\right) \forall i, j \in J \tag{8}$$

$$\sum_{i \in J}\sum_{k \in K} (S + L)w_k U_{ik} + \sum_{i \in J}\sum_{j \in J} (BN_{ij}l_{ij} + l_{ij}R_{ij}) \leq C_{MAX} \tag{9}$$

$$\sum_{k \in K} w_k X_{ijk} \leq WN_{ij}\ \forall i, j \in J \tag{10}$$

$$\sum_{k \in K} v_k X_{ijk} \leq v^0 N_{ij}\ \forall i, j \in J \tag{11}$$

$$N_{ij} = N_{ji}\ \forall i, j \in J \tag{12}$$

$$(t_{ij} - T)N_{ij} \leq 0\ \forall i, j \in J \tag{13}$$

$$X_{ijk}, S_{ik}^+, N_{ij} \geq 0,\ \text{integer}\ \forall i, j \in J,\ \forall k \in K \tag{14}$$

$$R_{ij} \geq 0\ \forall i, j \in J \tag{15}$$

Equation (5) represents the objective function of the proposed model, which seeks to minimize the overall costs, including the pure financial costs (the first four terms on the right-hand side) and converted costs from emissions (the fifth and sixth terms for DC storage and transshipment trucks).

Equations (6) and (7) indicate that a DC is permitted to simultaneously ship in and out through DCs for each product item up to U_{ik}. Equation (8) calculates emission factors for the items that trucks transship between two DCs in each direction, as defined by the PLEF in Section 3.2. Equation (9) restricts the total considered GHG emissions so as not to exceed a regulatory or company limit. This constraint will be useful when the emission cost factor (θ) in the objective function is relatively too small and has insignificant effect on determining optimal solutions. Equations (10)–(12) limit the transshipment weight and volume not to exceed the truck's capacity in either direction between a pair of DCs. Equation (13) prevents unnecessary long-distance transshipment between DCs. Equations (14) and (15) define the types of variables.

4. Simulations and Statistical Analysis

This section analyzes the GHG emissions from cold-chain transshipment using numerical simulations and discusses the statistical models of the emissions and parameters.

4.1. Numerical Simulations and Parameter Setting

To verify the optimization models and operation parameter relationships in generic conditions, this study conducted numerical simulations with a wide range of parameters and generalized conditions. These numerical simulations are not a specific case study dictated by a particular business situation, parameter setting, or company. Namely, the numerical cases were generated to examine common and broad conditions of transshipment in cold chains. Thus, the parameters and data were taken from existing scientific research or assumed for typical industrial situations. Otherwise, the optimization model and results will be meaningful for only a single case but would not be applicable for a broad range of operational conditions.

To analyze the characteristics of the problem in diverse conditions, this study examines a great number of instances with 10 DCs and 20 product items. Proper parameters were chosen to simulate practical situations for sustainable transshipment (Appendix A). The data of market prices, pallet sizes, and weights of 20 fruit types were collected to compute these parameters. Please note that the parameters will vary depending on the country and region.

The demand data were simulated using the following parameters. Because the normality assumption is appropriate enough in many real instances, it is assumed that the demand of product item k at DC i follows a normal distribution $N(\mu_{ik}, \sigma_{ik}^2)$. The mean values μ_{ik} of 20 product items were assumed to be 10% of the daily average consumption of 20 different fruits [64] (listed in Appendix A). The ratio of the demand to the mean, also known as the coefficient of variation (CV), is used to express the demand variability to evaluate generic scenarios without being constrained by a particular standard deviation value. Given that c denotes the CV, the representative standard deviation σ_{ik} is set as $c \cdot \mu_{ik}$. The corresponding order-up-to level of inventory is calculated as $U_{ik} = \mu_{ik} + \sigma_{ik} z_\alpha$.

The GHG emission parameters are shown in Table 1. These parameters were chosen based on existing scientific research. Please note that these emission factors are used to evaluate emissions using cargo weight. This is different from some of the existing studies that use average distances and loads or convert fuel or energy consumption to emissions.

Table 1. Parameters of GHG emissions.

Symbol	Data	Use	Source
C_{MAX}	137,000 (kg)		[65]
θ	0.08149 (USD/kg *)	GHG emissions cost	[66,67]
S	0.2355 (kg/ton·day)	refrigeration emissions from cold storage	[63]
L	0.0564 (kg/ton·day)	refrigerant-leakage emissions from cold storage	
B	0.236 (kg/km)	base emissions from a transshipment truck	
A	0.016 (kg/km)	cargo-dependent emissions (average-laden truck)	[68]
F	0.053 (kg/km)	cargo-dependent emissions (full-laden truck)	

* Calculated from the average carbon price and exchange rate from May to November 2022. The average carbon price was 80 EUR/ton, and the average exchange rate was 1 EUR = 1.0186 USD.

The emission factors for cold storage at DCs are functions of product weight and time period. These numbers come from scientific research on a fruit and vegetable cold chain [63]. Although the main electricity mix is different by country, electricity emission factors are not greatly different among some countries, ranging from 0.4 to 0.5 kg CO_2 equivalent per kWh [69]. The electricity mix is also different by region in each country. Other factors also influence the emission factors of cold storage, including climate and

specific equipment efficiency. Therefore, for parameter reliability, the numbers in the reference are used without further modification.

The emission factors for trucks in Table 1 are calculated as follows. The GHG emission factors were evaluated for a single-type light refrigerated truck using diesel with a capacity of 1.5 tons. The base GHG emissions from tare weight trucks is set by averaging the emission factors from the un-laden trucks over the suburban free-flow and peak-hour conditions [68]. Please note that these numbers are based on scientific research on vehicles, by considering cargo weight and refrigeration but not converting fuel consumption to emission factors. The cargo-dependent emission factors are represented by a piecewise linear function with two intervals. Two emission factors for the two intervals were chosen for the average and full truck loads. For example, the GHG emission factors for the average-(0.4 tons) and full-laden (1.5 tons) trucks are 0.016 and 0.053, respectively. Using these emission values and Equation (4), the parameters of the piecewise linear function (slope $a_1 = 1/25$ and $a_2 = 37/1100$) are calculated for the cargo dependent GHG emissions. At every 1.5-ton increase in the cargo weight, an additional truck is required. If the same truck type is used, as the number of trucks increases, the same slope is applied for the next truck with added intercepts. Because the transshipment is carried out daily in this study, the calculated emission is the amount per day. The small capacity (e.g., 1.5 tons) is common for transshipment trucks, because transshipment is usually conducted for a small portion of the total inventory. This study assumes that a short time window for transshipment also leads to not using large capacity trucks for many DCs. This value was also common in the collected data. Diesel is also common for such trucks.

The simulations were conducted for 12 cases with different values of *CV* and *ISP*. Thirty samples were simulated for each demand scenario. For each instance of the problems, the MIP model in Section 3 was solved, and the optimal transshipment plan was determined.

4.2. Statistical Analysis

In this section, the GHG emission results from the numerical simulations are analyzed, and the effect of different demand variability and service levels on GHG emissions is discussed from various perspectives.

The GHG emissions were analyzed using a linear regression model. The following equation was obtained for the linear regression model:

$$\begin{aligned} \text{GHG emissions} \quad &\approx 617 + 921 \times CV - 4.6 \times ISP - 6.2 CV \times ISP \\ &= 617 + (921 - 6.2 \times ISP) \times CV - 4.6 \times ISP \\ &= 617 - (4.6 + 6.2 \times CV) \times ISP + 921 \times CV \end{aligned} \quad (16)$$

where:

GHG emissions: total GHG emission amount in kilograms;
CV: demand variability as coefficient of variation (value between 0 and 1);
ISP: target in-stock probability (value in percentage, from 0 to 100).

The predicted GHG emissions can be calculated using the regression model in Equation (16). The statistical properties of the coefficients are shown in Table 2.

Table 2. Statistical properties of the regression model coefficients.

	Coefficient	**Standard Error**	***p*-Value**
Intercept	617	55.4	<0.01
CV	921	257	<0.01
ISP	−4.6	0.6	<0.01
CV × *ISP*	−6.2	2.9	0.034

The regression analysis reveals that the main effects of demand variability and target *ISP* are significant. In Table 2, the *p*-values associated with main effects (*CV* and *ISP*) are very small, which suggests effect significance.

The coefficient of the slopes ($\beta_1 = 921$ and $\beta_2 = -4.6$) in the first line of Equation (16) shows the relationships of GHG emissions with *CV* and *ISP*. According to this model, an increase of 0.1 in *CV* causes an additional 92.1 kg of daily GHG emissions, while an increase of 10% in *ISP* decreases GHG emissions by 46 kg.

The significance of the interaction effect is not clear. The *p*-value of the interaction $CV \times ISP$ is 0.034; as this is near the decision bound of 0.05, the level of significance is inconclusive. R^2 increases from 75.6% by the model without the interaction term to 76% by the model with the interaction. This implies that $(76 - 75.6)/(100 - 75.6)$ = 1.6% of the GHG emission variability is explained by the interaction term.

The second and third lines in Equation (16) show the effect of the interaction term $CV \times ISP$ on GHG emissions. According to the second line, an increase in *CV* of 0.1 is linked to an increase in GHG emissions of $92.1 - 0.62 \times ISP$ units. It means that the effect of *CV* on GHG emission decreases as the *ISP* increases. As can be seen in the third line of the equation, an increase in the *ISP* of 10% is linked to a decrease in GHG emissions by $46 + 62 \times CV$ units. Thus, the more uncertain the demand, the stronger the effect of the *ISP* on the GHG emissions.

Additional analyses from the linear regression model are shown in Figures 5 and 6. Figure 5 shows the main (blue circles) and conditional effects (red circles) of the *CV* and *ISP*. The main effect is the impact of a change of one term with averaging over the other, whereas the conditional effect is the impact of a change in one term while the other is fixed. The lines on the circles represent the confidence intervals for the effects. Considering the main effects, with all else being constant, an increase in *CV* from 0.1 to 0.3 increases the expected GHG emissions by approximately 75 kg (upper blue circle). By contrast, a change in *ISP* from 80 to 95 decreases the expected GHG emissions by approximately 87 kg (lower blue circle). These results are similar to the overall trend shown later in Section 5. In the upper right part of Figure 5 (conditional effect plot), an increase in *CV* from 0.1 to 0.3 with a fixed *ISP* = 80 causes an increase of approximately 80 kg in the expected GHG emissions, while the effect of a fixed *ISP* = 95 causes an increase of approximately 65 kg in the expected GHG emissions. In the bottom left part of Figure 5, an increase in *ISP* from 80% to 95% with a fixed *CV* = 0.1 causes a decrease in expected emissions of approximately 80 kg, and fixed *CV* = 0.3 causes a larger decrease in GHG emissions.
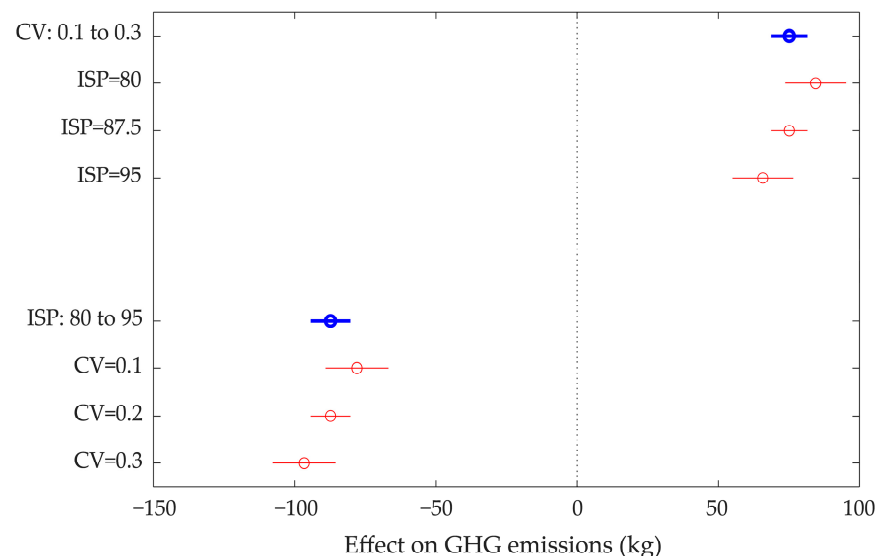

Figure 5. Main (blue) and conditional (red) effects of demand coefficient of variation (*CV*) and in-stock probability (*ISP*).
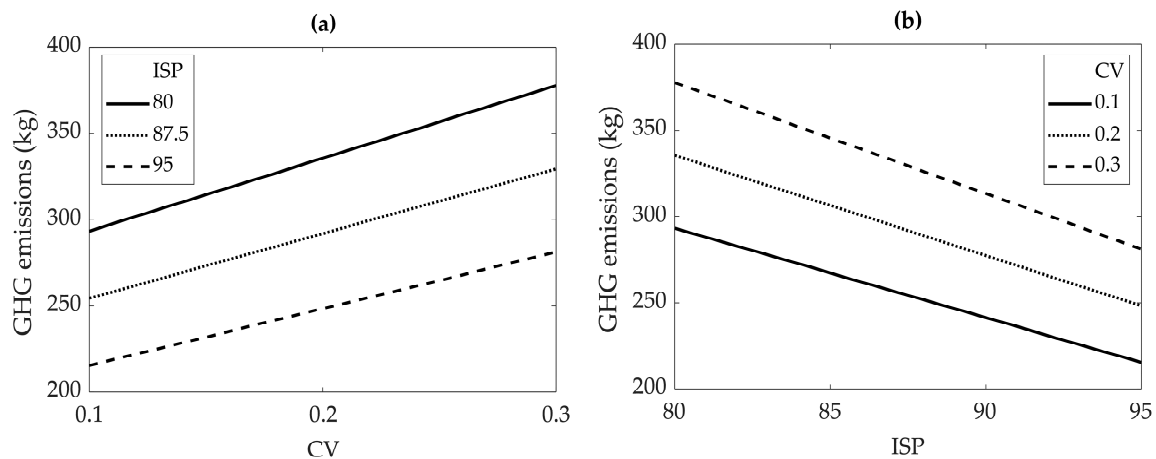
Figure 6. GHG emissions for (**a**) *CV* moderated by *ISP*, and (**b**) *ISP* moderated by *CV*. Note: the figure legends display the minimum, average and maximum value of the moderators.

Figure 6 shows a detailed look of the interaction between *CV* and *ISP*. The effect of moderation between *CV* and *ISP* exists as the line slopes are not the same. In Figure 6a, the expected GHG emissions increase as the *CV* increases at each *ISP* value. Specifically, the slope of each line increases from *ISP* = 95 to *ISP* = 80. This indicates that the GHG emissions are generated more with lower service level as more transshipment is required. In Figure 6b, the expected GHG emissions decrease as the *ISP* increases at each *CV* value. The slope of each line decreases from *CV* = 0.1 to *CV* = 0.3. These show that more GHG emissions are generated when demand is more uncertain as more transshipment is required.

5. Result Analysis and Discussion

This section analyzes the GHG emissions in more detail and discusses the trade-offs among operation decisions. This section also discusses practical implications.

5.1. Individual Effects of Demand Variability and Service Levels on Emission Sources

The GHG emissions are further analyzed by the two sources: cold storage at DCs and transshipment trucks. Thus, the emission amount is divided into the two sources.

Figure 7 illustrates the overall trend of the daily GHG emissions generated from the two sources with different (a) demand variabilities and (b) service levels. In Figure 7a, for each *CV* the emission values are averaged over all service levels. In Figure 7b, for each ISP the values are averaged over all *CV*s. The mean GHG emissions per day is 292 kg. In most cases with the given data, the GHG emissions from DC storage are higher than those from transshipment trucks. The GHG emission from storage is from maintaining the total inventory level. The emission from transshipment is from transporting a small portion (shortage quantity) of the total inventory level. Thus, with some typical parameters in this study, the GHG emission from storage can be higher than that from transshipment.

As can be seen in Figure 7a, demand variability (*CV*) has a strong impact on the carbon footprint in transshipment. Figure 7a shows the overall average of the storage and transshipment GHG emissions by different demand variabilities (*CV*). Overall, an increase in *CV* leads to rising GHG emissions. The averages of GHG emissions vary by 75 kg as *CV* changes. The emissions are lowest with *CV* = 0.1 (around 257 kg), and highest with *CV* = 0.3 (around 332 kg). This implies that less transshipment and storage lead to lower GHG emissions when demand is less uncertain.

Although their overall increasing trend is similar, the impact of *CV* on emissions is different for the two emission sources. Figure 7a allows this comparison. When *CV* increases from 0.1 to 0.3, the rate of increase in the storage GHG emissions becomes slightly lower (10.7% to 9.5%), but rate of increase in transshipment emissions becomes significantly higher (12.5% to 25.7%). This implies that, to compensate for higher demand

fluctuation so that expected shortage can be avoided, increased transshipment is more effective than an increased service level. Thus, this leads to much more increased emissions from transshipment than storage.
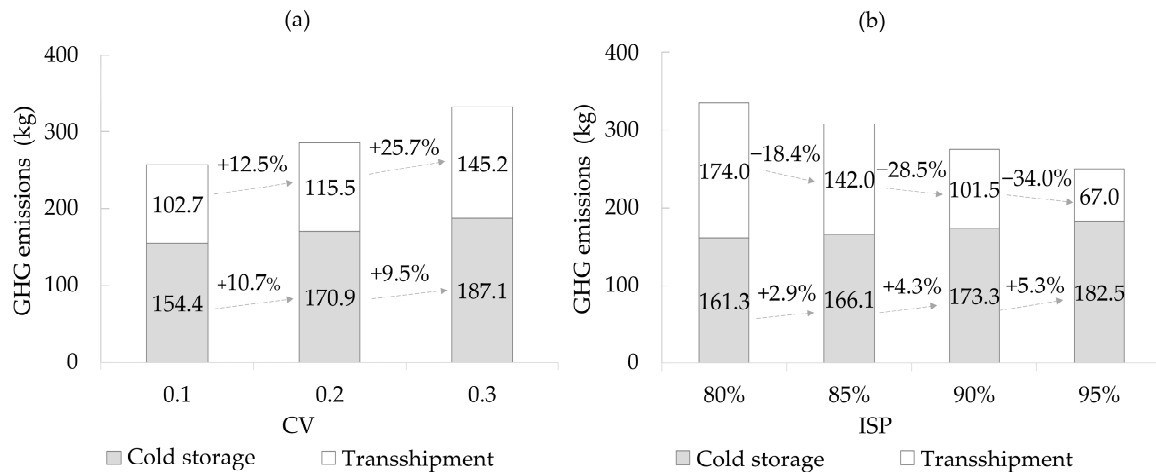

Figure 7. Overall daily GHG emission trends with different (**a**) *CV* and (**b**) *ISP*.

Similarly, the service level (*ISP*) has a strong impact on the carbon footprint, as can be seen in Figure 7b. The overall average GHG emissions of storage and transshipment are shown at different service levels in Figure 7b. An increase in *ISP* leads to a decrease in overall GHG emissions. The range of emission difference is 86 kg, with the largest emissions at *ISP* = 80% (around 335 kg) and the lowest at *ISP* = 95% (around 249 kg).

Unlike that of *CV*, the effects of *ISP* on emissions are opposite for the two emission sources and are more significant for transshipment emissions. When the service level increases, the GHG emissions from cold storage at DCs are high because more inventory stocking is required. On the other hand, GHG emissions from transshipment are lower when the service level increases. As less shortage is expected, fewer items are transshipped. Therefore, less transshipment leads to less GHG emissions when the service level is high. In Figure 7b, as *ISP* increases from 80% to 95%, the rate of increase in storage GHG emissions slightly increases (from 3% to 5%), whereas the rate of decrease in transshipment emissions significantly increases (from 18% to 34%). Because the reduction in transshipment emissions is higher than the increase in storage emissions, the overall emissions become less as *ISP* increases.

5.2. Combined Effects of Demand Variability and Service Levels on Emission Sources

The combined effect of demand variability and target in-stock probability shows interesting emission characteristics. The combined effects can be observed in Figures 8 and 9. Figure 8 shows the average GHG emissions from different target *ISP* values grouped by different *CV* values. In Figure 9, the average GHG emissions are grouped by different target *ISP* values.

The range of the total emission differences is 161 kg. The highest amount is emitted from the case of *CV* = 0.3 and *ISP* = 80%. The lowest amount is emitted from the case *CV* = 0.1 and *ISP* = 95%. The storage emissions vary by 55 kg, with the highest amount emitted at *CV* = 0.3 and *ISP* = 95%, and lowest amount at *CV* = 0.1 and *ISP* = 80%. The transshipment emissions vary by 148 kg, with the highest amount emitted at *CV* = 0.3 and *ISP* = 80%, and lowest amount at *CV* = 0.1 and *ISP* = 95%.

As can be seen in Figures 8 and 9, the combined effects show patterns consistent with the previous analyses. The combined effect graphs show consistently increasing emissions by an increase in *CV* and a decrease in *ISP*. First, in Figure 8, for any value of *CV*, an increase in *ISP* from 80% to 95% causes a decrease in the expected GHG emission because of

less transshipment required. In Figure 9, for any value of *ISP*, an increase in *CV* from 0.1 to 0.3 causes an increase in the expected GHG emissions due to more transshipment required.

Second, among all combinations of *CV* and *ISP* values, as *CV* increases, the emissions from transshipment increase more than those from the DC storage increase. Similar patterns are observed for *ISP* changes. (In Figures 8 and 9, the white bars change heights more than the grey bars do in all variable combinations.) These trends match the overall trends in Figure 7.

The combined effect graphs also demonstrate the interaction effect suggested by the regression analysis in Section 4. Although the change is small, the emission amount decreases as both *CV* and *ISP* increase in Figures 8 and 9. This pattern is expected by the sign of the interaction term in the regression equation.

The analysis of the combined effects reveals other aspects that are not observable in Figure 7. One aspect observable from Figures 8 and 9 is the balance between emissions from both sources. The balance point between storage and transshipment GHG emissions is at approximately *ISP* = 80%. Further decreasing *ISP* beyond this point would cause higher GHG emissions from transshipment compared with those from cold storage.

ISP	80%	85%	90%	95%	80%	85%	90%	95%	80%	85%	90%	95%
CV		0.1				0.2				0.3		
☐ Transshipment	149.0	115.6	87.2	59.0	166.6	137.5	96.9	61.1	206.5	173.1	120.4	81.0
▨ Cold storage	149.4	152.3	155.8	160.2	161.1	166.4	173.5	182.6	173.5	179.6	190.7	204.6
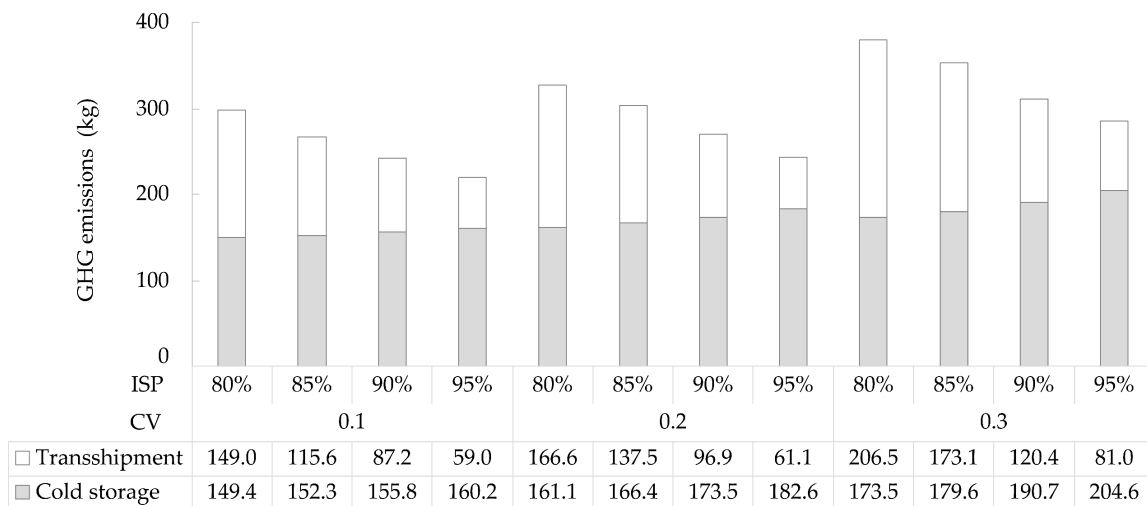
Figure 8. GHG emissions per day (kg) at different *ISP*s grouped by different *CV*s.

CV	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3
ISP		80%			85%			90%			95%	

Figure 9. GHG emissions per day (kg) at different *CV*s grouped by different target *ISP*s.

5.3. Insights for Practice

The results in Sections 4 and 5 provide insights on how to plan an eco-friendly transshipment using relatively straightforward but accurate methods to evaluate GHG emissions

in the cold chain. The GHG emission calculation method can be useful for a variety of situations. For example, under recent regulations, such as CBAM, the developed methodology can be used to calculate a portion of the GHG emissions in a supply chain.

The results also demonstrate that the developed methodologies can be used to strike a trade-off among different operation parameters or environmental decisions. This study can be used to examine the operation plans and environmental strategies under different demand scenarios. This suggests that managers can find an appropriate inventory transshipment strategy to simultaneously save costs and protect the environment. The analysis can suggest a suitable inventory strategy for compromising between cost saving and a green approach in transshipment decision and operation.

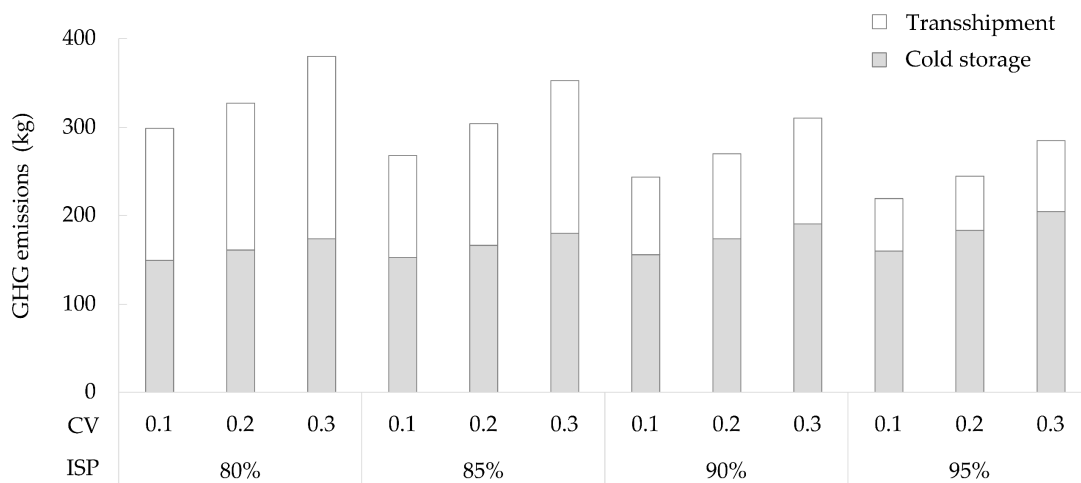These results also suggest that with proper methodology we can identify the contribution of each emission source to the total carbon footprint. The results in the previous sections show that neither of the two sources dominates the GHG emissions in the cold supply chain. The identification of such contributions is important for planning emission reduction as well as eco-friendly transshipment. We can also use this information to estimate how much we can reduce emissions from each source by choosing alternative fuel or equipment.

The analysis of the results also indicates that we can assess the sensitivity of operation parameters in different emission sources. In Section 5, the emissions from DC storage stay relatively constant regardless of the operation parameter changes. However, the emissions from trucks vary significantly as the operation parameter changes. Supply chain managers and planners can always conduct such analyses and implement different strategies using the information on source sensitivity. For a stable emission source, regular emission reduction activities may be meaningful. For a source greatly affected by operation parameters, optimized planning will be effective.

The results indicate that the accuracy of evaluating carbon footprints can be improved in several ways. First, this study developed decision models that can account for empty and non-empty miles in supply chain planning. It is known within industry that a significant portion of truck operation is empty miles. The GHG emissions during the empty miles differ significantly from those during laden miles. This study shows that the emission factors can be separated into a base emission factor for tare weight and a cargo-dependent factor so that they can be used for evaluating GHG emissions properly.

The second way to improve accuracy demonstrated in this paper is an enhanced representation of cargo dependent GHG emissions. Many existing methods estimate GHG emissions by converting fuel consumption. The conversion often relies on a single emission factor with truck capacity or average cargo weight. This single factor based method prevents considering the variation of fuel efficiency depending on cargo weight or truck types. This study proposes a piecewise linear representation that can incorporate various emission factors. This new representation can handle multiple trucks with different cargo weights. This new expression can be developed further for more sophisticated modeling by considering trucks with different conditions.

Another insight on accuracy improvement is a new direction for data collection. This study suggests that managers should find appropriate base and extra emission factors for their truck types. More advanced models can suggest what type of data should be measured to support the advanced models.

6. Conclusions

This study investigated the problem of transshipment among distribution centers (DCs) for a cold supply chain to achieve sustainable inventory cross-filling.

First, this study established the problem of sustainable transshipment for cold chains and developed an optimal decision model. The key factors contributing to GHG emissions in the cold chain were described. The limitations of the existing emission factors and methodologies were also identified. This paper provided new models for emission factors in cold chain logistics. The new sustainable cold-chain models reflect trucks' laden status and cargo weights for accurate emission evaluation. By combining these models, this study

established integrated sustainable cold-chain logistics models considering GHG emissions from DC storage and transshipment trucks. A mathematical optimization model was established to minimize both GHG emissions and costs in the cold chain.

Second, this research identified the impact of operation decisions and conditions on GHG emissions in transshipment. Many numerical simulations were conducted to generate diverse problem cases with different operation conditions. These numerical experiments enabled the examination of the critical problem characteristics. The statistical model and analysis revealed the key relationships between the operation variables and the GHG emissions in the cold chain. The statistical analysis verified the significance of the effects of demand variability and service levels on GHG emissions. This is verified by the p-values that are much smaller than 0.01 for the main effects of demand variability and service levels. The relatively insignificant combined effects of demand variability and service levels on emission were also uncovered. A p-value of around 0.05 indicated this inconclusive characteristic. The individual effects of demand variability and service levels on each emission source were identified. It turned out that the emissions from DC storage showed relatively small differences against operation parameter changes. On the contrary, the emissions from transportation were sensitive to the change in operation parameters.

Third, this study provided a deeper understanding of the characteristics of operation decisions and GHG emissions in transshipment. The results indicate that the transshipment among DCs could effectively reduce both GHG emissions and costs in cold supply chains. The analysis also shows that the reduction of GHG emissions and cost strongly depends on transshipment conditions and operation parameters such as demand variability and service levels. The results imply that reducing service levels below a certain level such as 80% would result in increased GHG emissions from transshipment in comparison to those from cold storage.

The proposed models and results can be used to evaluate the trade-offs for sustainable transshipment. This research provides useful models and tools for evaluating GHG emissions and optimizing operation decisions. This research also provides valuable insights for transshipment operations to successfully accomplish environmental goals and assess alternative green plans. The models and results of this study can help make reliable decisions in the design and operation of cold supply chains to achieve sustainable goals.

This research can be extended in a variety of ways. Different transportation modes can be considered, ranging from a minor change to major ones. Because GHG emissions are sensitive to operation parameters, as can be seen in previous sections, the transportation mode will affect emission amount. For instance, different truck types can be considered if cargo weight is high. Completely different methods of transportation such as rail could be considered, although it is usually outside the scope of the short distance transportation common in transshipment among nearby DCs. This research can be extended to incorporate the local production of fresh produce and associated city planning.

Nomenclature

Indices and sets

K	set of product items, indexed by k
J	set of distribution centers (DCs), indexed by i, j

Decision variables

X_{ijk}	transshipped quantity of product item k from DC i to j
S_{ik}^{+}	expected shortage of product item k at DC i after transshipment
N_{ij}	transshipped truck count between DCs i and j
R_{ij}	GHG emission factor with different cargo loading from refrigerated transshipping trucks between DCs

Parameters

U_{ik}	order-up-to level of product item k at DC i
d_{ik}	daily demand information of product item k received by DC i
l_{ij}	distance between DCs i and j
t_{ij}	duration of one transshipment round trip, including loading and unloading items, between DCs i and j
p_k	unit price of product item k
w_k	unit weight of product item k
v_k	unit volume of product item k
C_{MAX}	maximum emission allowance
W	maximum loading weight of one truck
v_0	maximum volume of one truck
T	maximum time permitted for one round trip transshipment
S	GHG emission factor of energy consumption at DC cold storage
L	GHG emission factor of refrigerant leakage at DC cold storage
B	base GHG emission factor from refrigerated transshipment trucks between DCs i and j
A	average-laden emission factor from refrigerated transshipment trucks between DCs i and j
F	full-laden emission factor from refrigerated transshipment trucks between DCs i and j
h	inventory holding cost per day ($= 0.25/365 = 0.000684$)
r_k	shortage cost of product item k
c_{ij}	trucking cost per round trip transshipment between DCs i and j
m	handling cost per transshipped product item
θ	cost factor of environment emission or carbon tax

Other notations

α	target in-stock probability (*ISP*)
c	demand's coefficient of variation (*CV*) reflecting demand variability
n	number of breakpoints in a piecewise linear function; positive integer
a_n^b	slope in a piecewise linear function $f(z)$ of truck type b
γ_n^b	x-coordinate of breakpoints in function $f(z)$ of truck type b
δ_n^b	y-coordinate of breakpoints in function $f(z)$ of truck type b
E_{add}	emission factor corresponding to loaded cargo of a refrigerated truck
E_{total}	factor of the total emission from a refrigerated truck

Acronyms

CBAM	carbon border adjustment mechanism
CDP	carbon disclosure project
CO_2	carbon dioxide
CV	coefficient of variation
DCs	distribution centers
GHG	greenhouse gas
GWP	global warming potential
HQ	headquarter
ISP	in-stock probability
MIP	mixed-integer programming
PLEF	piecewise-linear emission factor
VRP	vehicle routing problem

Appendix A. Parameters for Numerical Simulations

k	1	2	3	4	5	6	7	8	9	10
μ_k	319	77	224	37	170	128	74	629	102	77
w_k	0.06	0.20	0.16	0.42	0.09	0.12	0.20	0.20	0.15	0.20
v_k	0.62	0.79	0.41	0.54	0.29	0.25	0.21	0.33	0.10	0.26
p_k	360	3000	1120	2940	720	720	2800	800	1950	800

k	11	12	13	14	15	16	17	18	19	20
μ_k	99	61	47	479	153	256	256	74	170	224
w_k	0.15	0.25	0.10	0.08	0.10	0.06	0.06	0.20	0.09	0.16
v_k	0.29	0.49	0.24	0.16	0.30	0.24	0.24	0.21	0.20	0.41
p_k	1350	1050	900	525	700	600	300	2200	810	1440

p_k	$U(300, 3000)$ in \$
v_k	$U(0.1, 1)$ in m^3
μ_k	Estimated pallets per day [64]
v_0	12.4 m^3
h	$0.25/365 = 0.00068$ per day
m	\$0.50
T	3 h
r_k	0.3 per shortage
w_k	$U(0.05, 0.5)$ in ton
W	1.5 tons

t_{ij}	1	2	3	4	5	6	7	8	9	10
1	0	2.2	1.1	1.2	1.2	1.5	2.4	2.8	1.9	2.8
2	0	0	1.2	2.6	2.5	1.3	1.2	3.1	3.9	4.0
3	0	0	0	1.9	1.3	1.2	1.3	2.4	2.7	3.0
4	0	0	0	0	2.4	1.3	3.2	3.9	2.7	4.0
5	0	0	0	0	0	2.4	2.0	1.6	1.5	1.7
6	0	0	0	0	0	0	2.2	3.6	3.4	4.1
7	0	0	0	0	0	0	0	2	3.5	3.2
8	0	0	0	0	0	0	0	0	2.7	1.4
9	0	0	0	0	0	0	0	0	0	1.8
10	0	0	0	0	0	0	0	0	0	0

c_{ij}	1	2	3	4	5	6	7	8	9	10
1	0	134.5	67.1	70.7	70.7	92.2	143.2	166.4	111.8	170
2	0	0	72.1	155.2	148.7	80.0	72.1	184.4	233.2	240.8
3	0	0	0	111.8	80.6	72.1	80.0	144.2	161.2	181.1
4	0	0	0	0	141.4	80.6	191.1	236	162.8	238.5
5	0	0	0	0	0	143.2	120.4	98.49	92.2	104.4
6	0	0	0	0	0	0	134.2	216.3	204	247.4
7	0	0	0	0	0	0	0	120	212.6	189.7
8	0	0	0	0	0	0	0	0	161.2	84.85
9	0	0	0	0	0	0	0	0	0	107.7
10	0	0	0	0	0	0	0	0	0	0

y_{ij}	1	2	3	4	5	6	7	8	9	10
1	0	67.3	33.5	35.4	35.4	46.1	71.6	83.2	55.9	85.0
2	67.3	0	36.1	77.6	74.3	40.0	36.1	92.2	116.6	120.4
3	33.5	36.1	0	55.9	40.3	36.1	40.0	72.1	80.6	90.6
4	35.4	77.6	55.9	0	70.7	40.3	95.5	118.0	81.4	119.3
5	35.4	74.3	40.3	70.7	0	71.6	60.2	49.2	46.1	52.2
6	46.1	40.0	36.1	40.3	71.6	0	67.1	108.2	102.0	123.7
7	71.6	36.1	40.0	95.5	60.2	67.1	0	60.0	106.3	94.9
8	83.2	92.2	72.1	118.0	49.2	108.2	60.0	0	80.6	42.4
9	55.9	116.6	80.6	81.4	46.1	102.0	106.3	80.6	0	53.9
10	85.0	120.4	90.6	119.3	52.2	123.7	94.9	42.4	53.9	0

References

1. Hariga, M.; As, R.; Shamayleh, A. Integrated economic and environmental models for a multi stage cold supply chain under carbon tax regulation. *J. Clean. Prod.* **2017**, *166*, 1357–1371. [CrossRef]
2. Lee, K.-H. Integrating carbon footprint into supply chain management: The case of Hyundai Motor Company (HMC) in the automobile industry. *J. Clean. Prod.* **2011**, *19*, 1216–1223. [CrossRef]
3. He, B.; Liu, Y.; Zeng, L.; Wang, S.; Zhang, D.; Yu, Q. Product carbon footprint across sustainable supply chain. *J. Clean. Prod.* **2019**, *241*, 118320. [CrossRef]
4. Parashar, S.; Sood, G.; Agrawal, N. Modelling the enablers of food supply chain for reduction in carbon footprint. *J. Clean. Prod.* **2020**, *275*, 122932. [CrossRef]
5. Vu, H.T.T.; Ko, J. Integrated Inventory Transshipment and Missing-Data Treatment Using Improved Imputation-Level Adjustment for Efficient Cross-Filling. *Sustainability* **2022**, *14*, 12934. [CrossRef]
6. Wong, E.Y.C.; Tai, A.H.; Zhou, E. Optimising truckload operations in third-party logistics: A carbon footprint perspective in volatile supply chain. *Transp. Res. Part D Transp. Environ.* **2018**, *63*, 649–661. [CrossRef]
7. IPCC. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Available online: https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/ (accessed on 14 February 2023).
8. We Set the Standards to Measure and Manage Emissions. Greenhouse Gas Protocol. Available online: https://ghgprotocol.org/ (accessed on 14 February 2023).
9. We Are Accelerating Change towards Zero Carbon Grids at Scale. RE100. Available online: https://www.there100.org/ (accessed on 13 February 2023).
10. Taxation and Customs Union. Carbon Border Adjustment Mechanism. Available online: https://taxation-customs.ec.europa.eu/green-taxation-0/carbon-border-adjustment-mechanism_en (accessed on 14 February 2023).
11. Rim, S.-C.; Vu, H.T.T. Transshipment Vehicle Routing with Pickup and Delivery for Cross-Filling. *Math. Probl. Eng.* **2021**, *2021*, 6667765. [CrossRef]
12. Ballou, R.H.; Burnetas, A. Planning multiple location inventories. *J. Bus. Logist.* **2003**, *24*, 65–89. [CrossRef]
13. Evers, P.T. Filling customer orders from multiple locations: A comparison of pooling methods. *J. Bus. Logist.* **1999**, *20*, 121.
14. Chiou, C.-C. Transshipment Problems in Supply ChainSystems: Review and Extensions. In *Supply Chain*; Kordic, V., Ed.; InTech: Rijeka, Croatia, 2008; ISBN 978-3-902613-22-6.
15. Kumari, A.G.K.C.; Wijayanayake, A.N.; Niwunhella, D.H.H. An Effective Lateral Transhipment Model for A Multi-Location Inventory Setting to Minimize Stockouts. In Proceedings of the 2022 International Research Conference on Smart Computing and Systems Engineering (SCSE), Colombo, Sri Lanka, 1 September 2022; Volume 5.
16. Wei, Y.; Yang, M.; Chen, J.; Liang, L.; Ding, T. Dynamic lateral transshipment policy of perishable foods with replenishment and recycling. *Comput. Ind. Eng.* **2022**, *172*, 108574. [CrossRef]
17. Fattahi, P.; Tanhatalab, M. Stochastic inventory-routing problem with lateral transshipment for perishable product. *J. Model. Manag.* **2022**, *17*, 539–568. [CrossRef]
18. Shokouhifar, M.; Sabbaghi, M.M.; Pilevari, N. Inventory management in blood supply chain considering fuzzy supply/demand uncertainties and lateral transshipment. *Transfus. Apher. Sci.* **2021**, *60*, 103103. [CrossRef] [PubMed]
19. Becerra, P.; Mula, J.; Sanchis, R. Sustainable inventory management in supply chains: Trends and further research. *Sustainability* **2022**, *14*, 2613. [CrossRef]
20. Sohrabi, M.; Zandieh, M.; Shokouhifar, M. Sustainable inventory management in blood banks considering health equity using a combined metaheuristic-based robust fuzzy stochastic programming. *Socio-Econ. Plan. Sci.* **2022**, *86*, 101462. [CrossRef]
21. He, Q.; Shi, T.; Liu, B.; Qiu, W. The Ordering Optimization Model for Bounded Rational Retailer with Inventory Transshipment. *Mathematics* **2022**, *10*, 1079. [CrossRef]
22. Dhahri, A.; Gharbi, A.; Ouhimmou, M. Integrated production-transshipment control policy for a two-location unreliable manufacturing system. *Int. J. Prod. Econ.* **2022**, *247*, 108440. [CrossRef]

23. Bhatnagar, R.; Lin, B. The joint transshipment and production control policies for multi-location production/inventory systems. *Eur. J. Oper. Res.* **2019**, *275*, 957–970. [CrossRef]

24. Coelho, L.C.; Cordeau, J.-F.; Laporte, G. The inventory-routing problem with transshipment. *Comput. Oper. Res.* **2012**, *39*, 2537–2548. [CrossRef]

25. Rim, S.-C.; Jiang, J. Multi-item, multi-location transshipment model for cross-filling. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Pilsen, Czech Republic, 23–26 July 2019.

26. Islam, M.S.; Moeinzadeha, S.; Tseng, M.-L.; Tan, K. A literature review on environmental concerns in logistics: Trends and future challenges. *Int. J. Logist. Res. Appl.* **2021**, *24*, 126–151. [CrossRef]

27. Yadav, V.; Gaur, P.; Jain, R. On adoption of green logistics: A literature review. *Int. J. Logist. Syst. Manag.* **2021**, *40*, 193–219. [CrossRef]

28. Ye, C.; He, W.; Chen, H. Electric vehicle routing models and solution algorithms in logistics distribution: A systematic review. *Environ. Sci. Pollut. Res.* **2022**, *29*, 57067–57090. [CrossRef]

29. Erdelić, T.; Carić, T. A survey on the electric vehicle routing problem: Variants and solution approaches. *J. Adv. Transp.* **2019**, *2019*, 5075671. [CrossRef]

30. Kucukoglu, I.; Dewil, R.; Cattrysse, D. The electric vehicle routing problem and its variations: A literature review. *Comput. Ind. Eng.* **2021**, *161*, 107650. [CrossRef]

31. Kchaou-Boujelben, M.; Gicquel, C. Locating electric vehicle charging stations under uncertain battery energy status and power consumption. *Comput. Ind. Eng.* **2020**, *149*, 106752. [CrossRef]

32. Soysal, M.; Çimen, M.; Belbağ, S. Pickup and delivery with electric vehicles under stochastic battery depletion. *Comput. Ind. Eng.* **2020**, *146*, 106512. [CrossRef]

33. Wang, S.; Tao, F.; Shi, Y. Optimization of location–routing problem for cold chain logistics considering carbon footprint. *Int. J. Environ. Res. Public Health* **2018**, *15*, 86. [CrossRef] [PubMed]

34. Hsu, C.-I.; Hung, S.-F.; Li, H.-C. Vehicle routing problem with time-windows for perishable food delivery. *J. Food Eng.* **2007**, *80*, 465–475. [CrossRef]

35. Amorim, P.; Parragh, S.N.; Sperandio, F.; Almada-Lobo, B. A rich vehicle routing problem dealing with perishable food: A case study. *Top* **2014**, *22*, 489–508. [CrossRef]

36. Song, M.-X.; Li, J.-Q.; Han, Y.-Q.; Han, Y.-Y.; Liu, L.-L.; Sun, Q. Metaheuristics for solving the vehicle routing problem with the time windows and energy consumption in cold chain logistics. *Appl. Soft Comput.* **2020**, *95*, 106561. [CrossRef]

37. Ji, Y.; Yang, H.; Zhou, Y. Vehicle routing problem with simultaneous delivery and pickup for cold-chain logistics. In Proceedings of the 2015 International Conference on Modeling, Simulation and Applied Mathematics, Phuket, Thailand, 23–24 August 2015; Atlantis Press: Amsterdam, The Netherlands, 2015.

38. Qi, C.; Hu, L. Optimization of vehicle routing problem for emergency cold chain logistics based on minimum loss. *Phys. Commun.* **2020**, *40*, 101085. [CrossRef]

39. Mirzapour Al-e-hashem, S.M.J.; Rekik, Y. Multi-product multi-period Inventory Routing Problem with a transshipment option: A green approach. *Int. J. Prod. Econ.* **2014**, *157*, 80–88. [CrossRef]

40. Mirzapour Al-e-hashem, S.M.J.; Rekik, Y.; Hoseinhajlou, E.M. A hybrid L-shaped method to solve a bi-objective stochastic transshipment-enabled inventory routing problem. *Int. J. Prod. Econ.* **2019**, *209*, 381–398. [CrossRef]

41. Chaudhuri, A.; Dukovska-Popovska, I.; Subramanian, N.; Chan, H.K.; Bai, R. Decision-making in cold chain logistics using data analytics: A literature review. *Int. J. Logist. Manag.* **2018**, *29*, 839–861. [CrossRef]

42. Rao, C.G. *Engineering for Storage of Fruits and Vegetables: Cold Storage, Controlled Atmosphere Storage, Modified Atmosphere Storage*; Academic Press: Cambridge, MA, USA, 2015.

43. Di Filippo, R.; Bursi, O.S.; Di Maggio, R. Global warming and ozone depletion potentials caused by emissions from HFC and CFC banks due to structural damage. *Energy Build.* **2022**, *273*, 112385. [CrossRef]

44. Salehy, Y.; Delahaye, A.; Hoang, H.M.; Fournaison, L.; Cluzel, F.; Leroy, Y.; Yannou, B. Choosing an optimized refrigeration system based on sustainability and operational scenarios applied to four supermarket architectures in three European countries. *J. Clean. Prod.* **2023**, *392*, 136307. [CrossRef]

45. Dincer, I. *Heat Transfer in Food Cooling Applications*; CRC Press: Boca Raton, FL, USA, 2023.

46. Awad, M.; Ndiaye, M.; Osman, A. Vehicle routing in cold food supply chain logistics: A literature review. *Int. J. Logist. Manag.* **2020**, *32*, 592–617. [CrossRef]

47. Erdoğan, S.; Miller-Hooks, E. A green vehicle routing problem. *Transp. Res. Part E Logist. Transp. Rev.* **2012**, *48*, 100–114. [CrossRef]

48. Huzayyin, O.A.; Salem, H.; Hassan, M.A. A representative urban driving cycle for passenger vehicles to estimate fuel consumption and emission rates under real-world driving conditions. *Urban Clim.* **2021**, *36*, 100810. [CrossRef]

49. Moghdani, R.; Salimifard, K.; Demir, E.; Benyettou, A. The green vehicle routing problem: A systematic literature review. *J. Clean. Prod.* **2021**, *279*, 123691. [CrossRef]

50. Asghari, M.; Mohammad, S.; Al-e, J.M. Green vehicle routing problem: A state-of-the-art review. *Int. J. Prod. Econ.* **2021**, *231*, 107899. [CrossRef]

51. Wang, S.; Tao, F.; Shi, Y.; Wen, H. Optimization of vehicle routing problem with time windows for cold chain logistics based on carbon tax. *Sustainability* **2017**, *9*, 694. [CrossRef]

52. Qin, G.; Tao, F.; Li, L. A vehicle routing optimization problem for cold chain logistics considering customer satisfaction and GHG emissions. *Int. J. Environ. Res. Public Health* **2019**, *16*, 576. [CrossRef] [PubMed]
53. Xue, G. A two-stage heuristic solution for multi-depot collaborative pickup and delivery network with transfers to reduce GHG emissions. *J. Clean. Prod.* **2022**, *373*, 133839. [CrossRef]
54. CDP. CDP Homepage. Available online: https://www.cdp.net/en (accessed on 14 February 2023).
55. Emission Factors: Comprehensive Database. Ecometrica. Available online: https://ecometrica.com/solutions/measuring/emission-factors/ (accessed on 17 January 2023).
56. Guides, Reports and Tools. The Carbon Trust. Available online: https://www.carbontrust.com/our-work-and-impact/guides-reports-and-tools (accessed on 6 February 2023).
57. EcoAct. Carbon Footprinting Factsheet: Download Now. EcoAct Climate Consultancy. Available online: https://info.eco-act.com/en/carbon-footprinting-standards-factsheet-download-now (accessed on 6 February 2023).
58. Calculation Tools. Calculation Tools | Greenhouse Gas Protocol. Available online: https://ghgprotocol.org/calculation-tools (accessed on 14 February 2023).
59. SAP. SAP Product Footprint Management: Sustainability. Available online: https://www.sap.com/products/scm/product-footprint-management.html (accessed on 7 February 2023).
60. Small Emitters Tool (SET)—2022. EUROCONTROL. Available online: https://www.eurocontrol.int/publication/small-emitters-tool-set-2022 (accessed on 7 February 2023).
61. Herer, Y.T.; Tzur, M.; Yücesan, E. The multilocation transshipment problem. *IIE Trans.* **2006**, *38*, 185–200. [CrossRef]
62. Chen, F.Y.; Krass, D. Inventory models with minimal service level constraints. *Eur. J. Oper. Res.* **2001**, *134*, 120–140. [CrossRef]
63. Liu, B.; Jiawei, L.; Aiqiang, C.; Theodorakis, P.E.; Zongsheng, Z.; Jinzhe, Y. Selection of the cold logistics model based on the carbon footprint of products and vegetables in China. *J. Clean. Prod.* **2022**, *334*, 130251.
64. Fresh Fruits—South Korea: Statista Market Forecast. Statista. Available online: https://www.statista.com/outlook/cmo/food/fruits-nuts/fresh-fruits/south-korea (accessed on 10 November 2022).
65. Canadian Government Carbon and Greenhouse Gas Legislation. Osler, Hoskin & Harcourt LLP. Available online: https://www.osler.com/en/resources/regulations/2021/carbon-ghg/canadian-government-carbon-and-greenhouse-gas-legi. (accessed on 10 November 2022).
66. EU Carbon Permits. Trading Economics. Available online: https://tradingeconomics.com/commodity/carbon (accessed on 10 November 2022).
67. Euro (EUR) to US Dollar (USD) Exchange Rate History. Exchange-Rates.org. Available online: https://www.exchange-rates.org/history/USD/EUR/T. (accessed on 10 November 2022).
68. Yang, Z.; Tate, J.E.; Morganti, E.; Shepherd, S.P. Real-world CO_2 and NOX emissions from refrigerated vans. *Sci. Total Environ.* **2021**, *763*, 142974. [CrossRef]
69. The Climate Transparency Report 2021. Climate Transparency. 2022. Available online: https://www.climate-transparency.org/g20-climate-performance/g20report2021 (accessed on 8 January 2023).