Innovative Green Network Design: Rethinking the Role of Wholesalers in the Distribution Network

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ABSTRACT

In response to global climate warming, corporations have solidified their sustainability commitments and intensified their efforts to reduce greenhouse gas (GHG) emissions. In partnership with a multinational consumer packaged goods (CPG) company, this work assesses the feasibility of engaging wholesalers in the distribution network as third-party logistics providers (3PLs) to reduce emissions. We also investigate which of the current distribution strategies is the most efficient from emissions and cost perspectives. Using shipment data provided by the company, we calculate baseline emissions and costs across the current supply chain. To assess the current network against the alternate network, in which wholesalers function as 3PLs, we build several proof-of-concept models using mixed-integer linear programming (MILP). Within the optimization models, emissions are calculated following both the Global Logistics Emissions Council (GLEC) Framework and the Network for Transport Measures (NTM) methodology. We also explore the financial implications of the alternate network design. Across both calculation methods, our models demonstrate opportunities for cost and emissions savings, but not by utilizing wholesalers as 3PLs. Additionally, the models reveal that plant direct shipping (PDS) is the most emissions- and cost-efficient distribution strategy available. We recommend that these analyses be repeated across different prefectures and business units for validation. As a follow-up to this work, we suggest using the models to explore whether wholesalers may be utilized as strategic partners in specific "emergency" or fire-fighting operational scenarios to reduce emissions.

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"I felt my lungs inflate with the onrush of scenery - air, mountains, trees, people. I thought, 'This is what it is to be happy.'" - Sylvia Plath

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Kavi & Fan
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1 INTRODUCTION

1.1 Motivation

With extreme weather conditions escalating in both intensity and frequency and global temperatures continuing to rise annually, the need to address the climate crisis has never been more urgent. Global temperatures have risen by 1–1.2°C since the "pre-industrial" era (Ritchie et al., 2020) and are projected to increase by 2.6°C by 2100 (United Nations Environment Programme, 2022). Many of the Earth's ecosystems have already suffered irreparable damage and millions of people living in coastal areas risk displacement from rising sea levels (Calvin et al., 2023). In response to mounting scientific evidence about the consequences of inaction, reducing anthropogenic[1] greenhouse gas (GHG) emissions – the primary drivers of climate change – has become a global priority.

The effort to reduce carbon emissions must be collective; however, corporate entities have an opportunity to make a significant impact in this area. As of 2019, nearly 30% of the world's carbon emissions were linked to Fortune 500 companies[2] (Barbato, 2021). In fact, a Carbon Disclosure Project (CDP) report found that just 25 organizations were responsible for 50% of global industrial emissions (Griffin, 2017). Owing to growing stakeholder pressure, climate action has become a business imperative. Sustainable interventions present opportunities for market expansion through product innovation and cost savings through reduced energy consumption (Climate Impact Partners, 2023). Additionally, as more stringent disclosure regulations come down the pike, reducing GHG emissions across operations has become critical to mitigating financial risk and ensuring the long-term health of the business.

Among the different strategies being deployed to tackle sustainability, improving operational efficiency through innovative supply chain management has emerged as a major focus in both academia and industry. Logistics activities, which encompass transportation, warehousing, and inventory management in the supply chain, have significant impacts on the environment in the form of pollution, energy consumption, and waste generation (Bouchery et al., 2017). Roughly 16% of total global emissions are estimated to be transportation-related, of which road transport constitutes nearly 12% (Ritchie & Roser, 2023). Experts believe the demand for transportation will potentially double by 2050 and with it, freight transportation emissions (ITF Transport Outlook 2021: Executive Summary, 2021). As a result, the

[1] Anthropogenic in this context refers to GHG related to or resulting from human activity.
[2] Fortune 500 companies are the top 500 largest companies in the world ranked by revenue.

discipline of green logistics continues to grow with innovations in vehicle routing, inventory strategy, and network design driving systems-level improvement.

In this project, we investigate a new approach to green network design – collaborating with existing value chain partners to reduce transportation and warehousing-related emissions. Research has shown that companies that engage with partners along the value chain are twice as likely to reduce emissions and see financial returns (Carbon Disclosure Project, 2015). We develop proof-of-concept models to test the feasibility of customer collaboration as an emissions-reduction strategy and to evaluate the financial implications of this strategic change.

To do this, we worked with a multinational consumer packaged goods (CPG) company with established operations and a solid commitment to sustainability.

1.2 Sponsor Company: Background

With $100 billion in net sales and 5 billion customers served across 180 countries, our sponsor company, which we refer to as Company A throughout this report, is one of the largest manufacturers of consumer packaged goods in the world. Company A's global supply chain consists of roughly 130 plants, 250 internal shipping locations, and nearly 70,000 external partners. Goods are grouped into five operating sectors and broken down further into business units that include common household and personal care items. With a strong market presence and customer base that has been established over 100 years, Company A is uniquely positioned to impact social, economic, and environmental sectors through its integrated growth strategy (Company A, 2023).

Building upon several years of effort thus far, Company A has solidified its commitment to sustainability by declaring its intention to achieve net zero CO_2 emissions[3] across the supply chain by 2040. The company hopes to accomplish this through a multi-pronged and incremental approach, which it has outlined in a detailed action plan. This ambition falls in line with directives from the Climate Action 100+ Net Zero Benchmark, an independent agency committed to helping companies achieve their net zero goals (Climate Action 100+ Initiative, 2021).

To measure progress toward these sustainability goals, Company A has established metrics across several sectors of its supply chain, of which we focus on transportation. Company A is aiming to reduce finished product freight emissions intensity (in this case, the kg of CO_2 released per km traveled) by 50% against its

[3] Net Zero CO_2 emissions "are achieved when anthropogenic CO_2 emissions are balanced globally by anthropogenic CO_2 removals over a specified period" (Masson-Delmotte, V. et al., 2022, p. 24).

2020 baseline. This metric along with others has been submitted to and validated by the Science-Based Targets initiative (SBTi)[4].

Since declaring its net-zero ambition, Company A has made notable progress in some areas while leaving room for improvement in others. For example, upstream freight emissions intensity increased by 4% in 2023 (*Climate Action*, n.d.). Our project seeks to explore methods of reducing transportation-related emissions, an objective we expound upon in the next section which details Company A's distribution network.

1.3 Sponsor Company: Network Design

This capstone focuses on the household cleaning category of goods (referred to as Category X) in the Kantō region of Japan. Kantō represents Company A's most important market area, as this region has the highest population density and accounts for most of its product demand. Likewise, in 2023, 35% of net sales – the highest of any business segment – were attributed to Category X, solidifying its importance in the overall business portfolio (Company A, 2023). In 2022, this product category had the second highest energy consumption and total GHG emissions, presenting an opportunity for supply chain evaluation and improvement that falls in line with Company A's broader sustainability goals (*Climate Action*, n.d.).

Company A's distribution network for Category X goods consists of several facility locations and value chain partners (**Figure 1**). Category X goods for the entire country are produced in a single plant in the Kantō region; however, this location only has the capacity to store inventory for four hours. As such, finished goods move directly from the plant to its neighboring distribution center, which we refer to as the "Plant DC," for storage. From here, goods are transported to two regional DCs (RDCs) as well as wholesale and retail customers within the network.

At present, Company A utilizes two main strategies to distribute products to customers: 1) standard distribution, where goods move from the Plant DC to a regional DC for storage and finally to the customer; and 2) plant direct shipping (PDS) where goods move directly from the Plant DC to the customer. In these scenarios, customers include both retailers and wholesalers. Company A is interested in exploring how the current network (**Figure 1**) can be modified to reduce overall logistics-related emissions.

[4] The Science Based Targets initiative (SBTi) "defines and promotes best practices in emissions reductions and net-zero targets in line with climate science; provides technical assistance and expert resources to companies that set science-based targets in line with the latest climate science; and brings together a team of experts to provide companies with independent assessments and validation of targets" (Science Based Targets, n.d., About Us section).

A unique feature of Company A's current network is that 70 – 80% of its product volume moves through wholesalers (personal communication with Company A, November 21, 2023). As wholesalers already constitute an integral part of the distribution network, we designed a proof-of-concept model that explores the feasibility of utilizing them as third-party logistics providers to distribute to customers more efficiently. We focus on leveraging two wholesalers that take on the bulk of the products. In the alternate network (**Figure 2**), these high-volume wholesaler locations are categorized as "3PL Candidates." We investigate whether modifying these locations to serve the remaining wholesalers and retail customers, which are captured as "Other Customers", reduces overall emissions.

Figure 1

Company A's Current Network

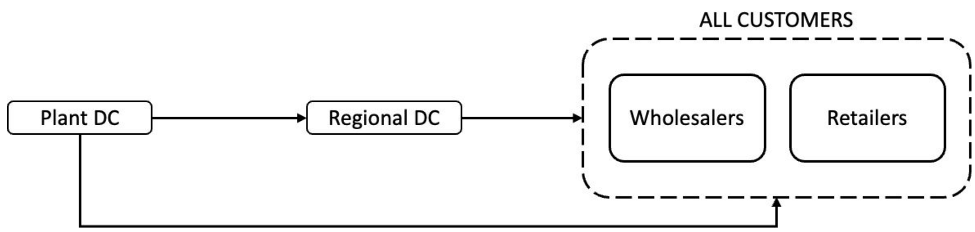
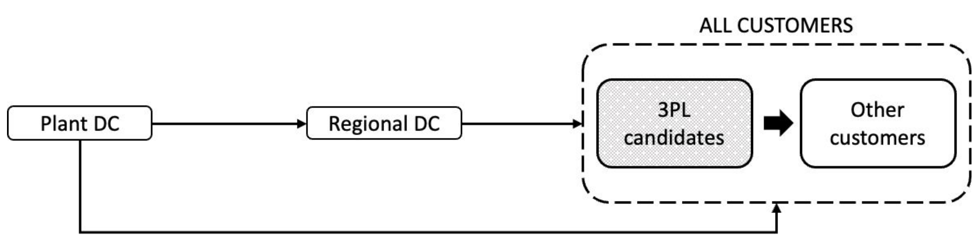


Figure 2

Company A's Alternate Network



1.4 Key Questions

The goal of this project is to develop proof-of-concept (PoC) models that assess the feasibility of collaborating with wholesalers to reduce logistics-related emissions across Company A's supply chain. We aim to answer the following questions:

- What are Company A's baseline emissions?

- Which of the current distribution strategies results in the lowest emissions?
- How will collaborating with wholesalers as 3PLs impact total logistics-related emissions?
- If utilizing wholesalers as 3PLs reduces GHG emissions, what are the significant drivers of this reduction (e.g., distance minimization, improved truck utilization) and how must the contract with wholesalers be structured to result in the greatest emissions and cost savings?

Using data provided by the company, we developed analytical models to assess the cost and emissions implications of these network changes. These models can be used as a basis for further larger-scale network optimization.

1.5 Scope of Project

To limit the scope of this project, we consider the following boundaries:

- As this is a PoC exercise, we consider wholesaler locations and ship-to points in a single prefecture[5] to build the models.
- This work only models single-pick and single-drop shipments, as opposed to multi-pick or multi-drop shipments.
- We focus only on road transportation; intermodal shipments are beyond the scope of this work.
- This work does not investigate an inventory policy that could operationalize converting the wholesalers into 3PLs. It considers only the implications of this strategic change on costs and emissions.
- We do not examine routing within the existing network as a method of reducing emissions and improving operational efficiency.
- We do not differentiate between imported and locally produced Category X goods – all SKUs within this product category are treated the same way.

1.6 Contributions

[5] A prefecture is a region in Japan that can be considered analogous to a state.

In preparation for this analysis and throughout the process, we conducted in-depth interviews with Company A personnel, reviewed literature, and employed out-of-the-box thinking to develop innovative network models. To gain a deeper understanding of Company A's network in the Kantō region, we interfaced weekly with the operations team and presented conceptual models, which we iterated over several months. We also consulted with the sustainability team to ascertain how this project fits into current efforts to achieve Company A's stated climate goals. Our continued communication with the company afforded insight into the most pressing operational challenges, which was instrumental in refining our key project questions and highlighting the broad applicability of these project results.

Combining knowledge from the scientific community on emissions reductions with scenario-specific information from the company, we ran several models which identified the following results: 1) the distribution network can be further optimized to reduce emissions and cost; 2) these reductions are not the result of working with wholesalers as 3PLs; and 3) shipping goods directly from the Plant DC is the most efficient distribution strategy in terms of both emissions and cost.

In this chapter we introduced the problem and provided the context of the sponsor company. In Chapter 2, we review established methodologies for calculating supply chain emissions and the current strategies in use to reduce logistics-related emissions. Chapter 3 details the mathematical formulations of the models and Chapter 4 presents the modeling results. Chapter 5 discusses the implications of these results as well as their limitations. Finally, Chapter 6 concludes with recommendations for future work.

2 STATE OF THE PRACTICE

This chapter covers two topical areas of research that were critical to the conceptualization and execution of this capstone. First, we reviewed various methods of calculating GHG emissions that could be used in this analysis. Second, we explored established strategies for reducing logistics-related emissions to see which, if any, could be applied to Company A's supply chain.

2.1 Calculating and Estimating GHG Emissions

Each year, sustainability becomes more important to organizations and as a result, methods for calculating and estimating GHG emissions continue to be refined. The consensus among scholars is that, in the absence of being able to measure GHG emissions directly, energy-based calculations offer the most accurate results. For example, calculating emissions from electrical energy consumption in a warehouse is done using the kilowatt hours (KwH) of electricity multiplied by a carbon emissions conversion factor. A similar method is used to calculate transportation emissions by multiplying fuel consumption by an emissions factor for the fuel type. When energy data is unavailable, activity-based methods are employed to produce emissions estimates. Here, transportation activity is a function of the gross weight of products being transported and the distance traveled by the shipment. This transportation activity is then multiplied by a mode-specific emissions factor to estimate the emissions associated with the shipment (Bouchery et al., 2017).

The Greenhouse Gas Protocol is widely considered a "classical model" and uses default emission factors by vehicle type to produce estimates. While the GHG Protocol continues to serve as a foundation for calculating value chain emissions for scholars and practitioners alike, several other methods have emerged to capture the nuances of logistics that often significantly impact emissions. Among these, the most important methodologies and frameworks are the EPA SmartWay, the Global Logistics Emissions Council (GLEC) Framework, and the Network for Transport Measures (NTM) methodology. Each framework requires different data and produces results with varying levels of precision.

Developed within the Smart Freight Centre (SFC) and first published in 2016, the GLEC Framework offers a robust approach to estimating transportation emissions that is widely used by multinational companies. Company A is, in fact, a GLEC Participant (Ehrler et al., 2023). Not only is GLEC consistent with the GHG Protocol, but the latest version (v3) has also incorporated requirements of the ISO 14083:2023 standard[6]. Additionally, it has been endorsed by the CDP as a method of tracking and reporting logistics-related emissions (CDP, n.d.). The GLEC Framework differs from other estimation approaches by incorporating emissions from the lifecycle of fuel into the total emissions calculations. For example, the EPA SmartWay focuses primarily on tank-to-wheel emissions (TTW) – the emissions generated during transport activities – while the GLEC Framework also includes well-to-tank (WTT) emissions – the emissions associated with extracting the fuel (US Environmental Protection Agency, 2016). This holistic approach that considers well-to-wheel (WTW) emissions (comprised of both TTW and WTT) offers more accurate overall estimates (Ehrler et al., 2023). Similarly, facility emissions include the lifecycle of the energy used to power them, which are ultimately incorporated into the total emissions calculations for the supply chain.

Considering the data available from Company A and its corresponding assumptions, the GLEC Framework offers a comprehensive methodology for calculating logistics-related emissions. It covers all freight transport and hub operations along the transport chain, including the operational activities executed by

[6] International Organization for Standardization. (2018). Greenhouse gases - Quantification and reporting of greenhouse gas emissions arising from transport chain operations (ISO Standard No. 14083:2023)

3PLs (Ehrler et al., 2023). Since a large portion of Company A's operations are carried out by 3PLs, the GLEC framework allows us to disentangle this ownership structure and simplify our calculation methodology. The roundtrip of each transport activity is also built into GLEC's emissions factors and allocation methods, precluding further calculations.

In addition to using GLEC, we also calculated emissions using the NTM methodology. While GLEC offers a comprehensive method for assessing total emissions including those generated by facilities, the Network for Transportation Measures (NTM) methodology focuses on transportation. Established in 1993, this non-profit organization sought to develop and standardize methods for calculating the environmental impact of transport activities. NTM's initial tools were designed to enable transportation service providers to conduct more robust and credible assessments of their activities. NTM also developed evaluation criteria to assess the performances of these operators. Over the last three decades, the organization has focused on sharpening its calculation tools, even offering an easy-to-use calculator on its website. It has collected relevant data for different traffic modes and fuel types, and meaningfully developed the field of sustainable transportation through knowledge and information exchanges.

Following conversations with the sustainability team in which they signaled interest in investigating truck utilization as a potential driver of emissions, we realized a more granular calculation approach was necessary. The NTM calculation methodology considers fuel consumption as a function of truck type, load factor, and road type and applies a corresponding emission factor (Velázquez Martínez et al., 2014). It has proven to be more accurate when working with shipment-level data. To simplify NTM calculations, we consolidated truck classes into light, medium, and heavy. Emissions factors were then calculated for each of these categories using the comprehensive emissions model explained by Barth et al., 2005 and the parameters documented by Koç et al., 2014.

2.2 Reducing Logistics-Related GHG Emissions

Institutions at large are examining their operations from a sustainability lens; however, CPG companies have the unique challenge of meeting consumer demands while reducing supply chain emissions (Felix et al., 2022). To balance the tradeoffs between keeping inventory in stock, delivering products faster, and minimizing the associated carbon footprint of these logistics activities, companies are turning to a portfolio of solutions. While many are making capital investments in electrifying their internal fleets, others have focused on improving supply chain efficiency as an emissions reduction strategy.

Within the latter, several areas of the supply chain present opportunities for emissions reduction. In their chapter on Green Logistics, Blanco and Sheffi (2017) describe the main drivers of the environmental impact of logistics activities as follows: 1) distance traveled; 2) transportation mode used for shipments; 3) fuel consumption of specific equipment types; 4) load planning; and 5) operational efficiency. With these come proven strategies for reducing freight transportation emissions including optimizing delivery sequences and expanding the use of transportation modes with lower GHG emissions, such as rail. Additionally, experts concede that reducing driving distances (Bouchery et al., 2017) and improving asset utilization (McKinnon, 2018) are levers that can be pulled to reduce emissions without completely restructuring a distribution network or disrupting operations.

In this project, we investigate whether supply chain partnerships can be leveraged to achieve both objectives – distance reduction and improved asset utilization – and ultimately lower logistics-related emissions. Up until now, this type of collaboration has reduced empty miles through improved inventory planning and order forms of consolidation. Similarly, shared distribution centers allow collaborators to split warehousing costs and emissions and capitalize on economies of scale. We explore whether a company can utilize the distribution capabilities of wholesalers to reduce driving distances and improve truck utilization.

3 METHODOLOGY

This chapter details the process followed to investigate whether converting wholesalers to 3PLs would result in lower GHG emissions across Company A's supply chain. It outlines data cleaning steps, key assumptions made during the analysis, and mathematical formulations for the models built.

3.1 Data Sources & Preparation

We received two main datasets from Company A's operations and sustainability teams to conduct this analysis. Both datasets offered historical shipment-level information for the 2023 calendar year. Data from the operations team included key details about the flow of goods between Company A's facilities and its customers. This was supplemented by data from the sustainability team, which disaggregated each shipment into products of different business units and included emissions information[7] for each row. The datasets were merged, after which we excluded data for shipments that used modes of transportation

[7] These emissions calculations were done by a third-party vendor, EcoTransit. Our team did not have access to EcoTransit's calculation methodology.

other than road transport; these accounted for about 1.6% of the data volume. Only shipments that contain Category X goods (even if mixed with other business units) were considered in this project. Unless specified, we use the shipment and emission data of the Category X products in most of our data processing steps instead of the total shipment. Additionally, outbound shipments from the manufacturing plant were excluded since it is a fixed location and only serves customers directly on rare occasions.

The datasets also provided longitude and latitude information for all nodes in the supply chain network. We calculated the shortest feasible distance (SFD)[8] between node pairs by inputting the geocoordinates into Google API. The columns that were included in our final dataset can be found in Table A-1.

3.2 Key Assumptions

A key feature of Company A's supply chain is the collaboration with numerous partners, including transportation 3PLs. Data availability, accuracy, and transparency across these entities varied considerably, which required us to make the following key assumptions throughout our analytical process:

- All shipments contain only Company A's products.
- No facility capacity constraint is considered across the supply chain network.
- Plant DC hub emissions and costs are consistent across all the distribution scenarios; therefore, they are excluded from the calculations to maximize the relative differences mathematically.
- Delivery to each ship-to-point is considered a single shipment. Each shipment has a return trip that is assumed to be an empty truckload.
- Intersite and PDS shipments are delivered in 13T or 20T trucks. Company A is responsible for planning these shipments, which follow a fixed cost structure. Emission intensities for 20T and 13T trucks are calculated from historical data.
- RDC outbound shipments, which are planned by 3PLs, travel in two different truck types for which average emission intensities were calculated from historical data. They follow a variable cost structure dependent on shipment weight and distance.
- Candidate 3PLs have the operational capacity to serve as transshipment facilities.
- All the hub emission intensities are taken from the GLEC Framework.

[8] Shortest Feasible Distance (SFD) is a practical estimate of the distance between two points considering specific attributes of the vehicle in use and route being traveled (e.g. topography, congestion) (Ehrler et al., 2023)

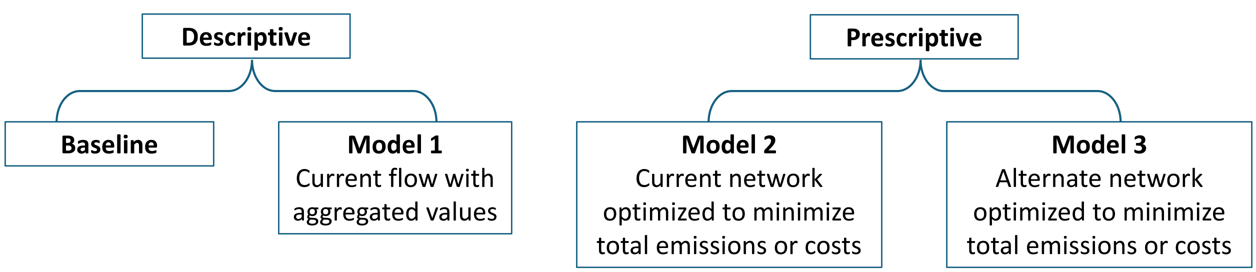
- For the potential distribution from 3PL candidate locations, three smaller truck types – 2T, 4T, and 10T – are considered. These emission factors are taken from the GLEC Framework. The transportation costs for candidate 3PLs to serve the demands of other customers mirror the variable transportation costs at an RDC.
- Truckloads are modeled with regional historical load factors per truck type or load factors derived from GLEC (Appendices A and B).
- Empty trips back are incorporated into the NTM calculation to ensure comparability with GLEC.

3.3 Emissions and Cost Estimations

This section details the descriptive and prescriptive models (**Figure 3**) used to assess Company A's current distribution network and simulate the alternate network design.

Figure 3

Overview of Emissions and Cost Estimation Models



3.3.1 Baseline Emissions Calculations

Shipment data provided by the sustainability team included CO_2 emissions (kg) on the shipment level; therefore, we used a simple, multi-step aggregation method to calculate and allocate baseline emissions of Category X products. Note that the Intersite shipments from the Plant DC to the Regional DCs in the calendar year are not directly linked with the demand served at customers in a particular prefecture. To ensure comparability with other models, we followed an allocation rule to only account for the distribution flows that also leave the RDCs to serve the customer demands in the prefecture.

3.3.2 GLEC Model 1: Current flow

We formulated all the GLEC models with the following sets (**Table 1**) and parameters (**Table 2**). Parameters are extracted from historical shipment-level data.

Table 1

Sets for Emissions Optimization Models

Notation	Definition
P	$Node\ for\ the\ Plant\ DC$
R	$Nodes\ for\ regional\ DCs$
W	$Nodes\ for\ customer\ locations\ that\ are\ Candidate\ 3PLs$
S	$Nodes\ for\ other\ customer\ locations$
C	$Nodes\ for\ all\ customers$
H	$Nodes\ for\ logistics\ hubs\ including\ regional\ DC\ and\ Candidate\ 3PLs$
A	$Arcs$
K	$Truck\ types$

Table 2

Parameters for Emissions Optimization Models

Notation	Definition
D_j	$Annual\ demand\ of\ Category\ X\ products\ at\ customer\ node\ j \in C\ [tonne]$
d_{ij}	$Driving\ distance\ of\ arc\ (i, j) \in A\ [km]$
EF_k	$Transportation\ emission\ factor\ using\ truck\ type\ k \in K$ $[gCO_2e/(tonne * km)]$
EF_i	$Hub\ emission\ factor\ for\ node\ i \in H\ [gCO_2e/tonne]$
FC_k^f	$Diesel\ consumption\ for\ a\ full\ truckload\ using\ truck\ type$ $k \in K\ [l/km]$
FC_k^e	$Diesel\ consumption\ for\ an\ empty\ truckload\ using\ truck\ type$ $k \in K\ [l/km]$
CE	$Emission\ factor\ constant\ [gCO_2e/l\ Diesel]$
C_k	$Maximum\ capacity\ for\ truck\ type\ k \in K$
LF_k	$Average\ load\ factor\ for\ truck\ type\ k \in K$
PDS_ratio	$Percentage\ of\ demand\ served\ through\ plant\ direct\ shipping$
$truck\_ratio_{k1:k2}$	$Ratio\ of\ demand\ served\ by\ truck\ type\ k1\ and\ k2$ $k1 \in K, k2 \in K$
X_ratio_k	$Average\ weight\ ratio\ of\ Category\ X\ products\ in\ truck\ type\ k \in K$

Model 1 was created to calculate emissions using the same historical values as inputs into the following equation.

$$Model\ 1_{emission} = Hub\ emission + Transportation\ emission,$$

in which

$$Hub\ emission = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} (X_{ijk} *\ EF_i),$$

$$Transportation\ emission = \sum_{(i,j)\in A}\sum_{k\in K}\left(X_{ijk} * d_{ij} * EF_k\right).$$

X_{ijk} is the aggregated distribution flow for Category X products on each arc (i,j) for each truck type k.

Model 1 allows us to assess how accurately the current reality of the distribution network was being captured. Its development is also critical in validating the optimization models structured around the same assumptions.

3.3.3 GLEC Model 2: Current network optimized for minimum total emissions

We created a mixed-integer linear program to find an optimal solution to minimize total emissions in the current distribution network and identify potential areas for improvement through parameter testing.

Model 2 was built with distribution flow (X_{ijk}) on each arc (i,j) for each truck type k as a decision variable.

X_{ijk}: $flow\ of\ Category\ X\ products\ on\ arc\ (i,j) \in A\ with\ truck\ type\ k \in K\ (tonne)$

The objective function was formulated to minimize the sum of hub and transportation emissions of the current network,

$$Model2_{OF} = \min\ (Hub\ emission + Transportation\ emission).$$

in which

$$Hub\ emission = \sum_{i\in R}\sum_{j\in C}\sum_{k\in K}(X_{ijk} *\ EF_i),$$

$$Transportation\ emission = \sum_{(i,j)\in A}\sum_{k\in K}\left(X_{ijk} * d_{ij} * EF_k\right).$$

The model was subject to the following constraints:

$$\textstyle\sum_{i\in P}\sum_{k\in K} X_{ilk} - \sum_{j\in C}\sum_{k\in K} X_{ljk} = 0, \qquad \forall l \in R, \tag{1}$$

$$\textstyle\sum_{i\in(P\cup R)}\sum_{k\in K} X_{ijk} \geq D_j, \qquad \forall j \in C \tag{2}$$

$$\textstyle\sum_{i\in P}\sum_{j\in(W\cup S)}\sum_{k\in K} X_{ijk} \leq ratio_{PDS} *\ \sum_{i\in P}\sum_{k\in K} X_{ijk}, \tag{3}$$

$$\textstyle\sum_{(i,j)\in A} X_{ijk1} =\ \sum_{(i,j)\in A} X_{ijk2} * ratio_{k1:k2}. \tag{4}$$

Transportation emissions were captured by multiplying the flow (X_{ijk}) by the distance of arc (i,j) and the transportation emissions factor for truck type (k). Different truck types were available for each arc, so these emissions were summed over all arcs ($\in A$) and truck types available on these arcs ($\in K$). Hub emissions were calculated by multiplying the flow of goods (X_{ijk}) out of RDCs by a hub-specific emissions factor (EF_i). This objective function was subject to a conservation of flow constraint (1) for the RDCs as well as the constraint that demand (D_j) was being fulfilled for all customers ($\in C$) (2). Constraints (3) and (4) were introduced to limit the maximum ratio of plant direct shipping and the composition of the usage of truck types to make the model better reflect reality.

3.3.4 GLEC Model 3: Alternate network optimized for minimum total emissions

The formulation for Model 3, which minimized total emissions in the alternate network, was very similar to Model 2. The sets (**Table 1**), parameters (**Table 2**), and decision variable remained the same:

$X_{ijk}: flow\ of\ Category\ X\ products\ on\ arc\ (i,j) \in A\ with\ truck\ type\ k \in K\ (tonne)$

However, the objective function was formulated slightly differently.

$Model\ 3_{OF} = \min(Hub\ emission + Transportation\ emission),$

in which,

$$Hub\ emission = \sum_{i \in H} \sum_{j \in C} \sum_{k \in K} (X_{ijk} *\ EF_i)\ ,$$

$$Transportation\ emission = \sum_{(i,j) \in A} \sum_{k \in K} \left(X_{ijk} * d_{ij} * EF_k\right).$$

The model was subject to the following constraints:

$$\sum_{i \in P} \sum_{k \in K} X_{ilk} - \sum_{j \in C} \sum_{k \in K} X_{ljk} = 0\ , \qquad \forall l \in R, \qquad (1)$$

$$\sum_{i \in (P \cup R)} \sum_{k \in K} X_{ilk} - \sum_{j \in S} \sum_{k \in K} X_{ljk} \geq D_l\ , \qquad \forall l \in W, \qquad (2\text{-}1)$$

$$\sum_{i \in (P \cup R \cup W)} \sum_{k \in K} X_{ijk} \geq D_j\ , \qquad \forall j \in S, \qquad (2\text{-}2)$$

$$\sum_{i \in P} \sum_{j \in (W \cup S)} \sum_{k \in K} X_{ijk} \leq ratio_{PDS} *\ \sum_{i \in P} \sum_{k \in K} X_{ijk}\ , \qquad (3)$$

$$\sum_{(i,j) \in A} X_{ijk1} =\ \sum_{(i,j) \in A} X_{ijk2} * ratio_{k1:k2}\ . \qquad (4)$$

Transportation emissions were captured similarly by multiplying the flow (X_{ijk}) with a transportation emissions factor specific to that arc (i,j) and truck type (k). However, in the alternate network, a small number of wholesaler locations, W, were modeled as potential hubs for distribution to other customer locations. Therefore, hub emissions were summed over all hubs ($\in H$), including RDCs and candidate 3PL locations. This objective function was subject once again to a conservation of flow constraint for the RDC (1). The demand constraint ensured that demand for all ship-to points ($\in S$) was being fulfilled from the plant, RDC, or candidate 3PL locations ($P \cup R \cup W$) (2-1). Since the potential 3PL candidate locations, W, have both the function of a hub and a customer, the conservation of flow ensures that demand at W is served. Constraints (3) and (4) were introduced to limit the maximum ratio of plant direct shipping and the composition of the usage of truck types to make the model closer to reality.

3.3.5 NTM Model 1: Current flow

To gain insight into the impact of truck utilization, we formulated models using the NTM estimation methodology. Once again, we created Model 1 using the NTM methodology to serve as a basis for comparison for the optimization models.

The following equations used historical values as inputs to calculate the emissions.

$$Model\ 1_X = Hub\ emission_X + Transportation\ emission_X\ ,$$

in which,

$$Hub\ emission_X = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} (X_{ijk} * EF_i)\ ,$$

$$Transportation\ emission_X = \ Emission\ delivery + Emission\ truck\ return\ ,$$

$$Emission\ delivery = \sum_{(i,j) \in A} \sum_{k \in K} \left(X\_ratio_k * N_{ijk} * CE * d_{ij} * (FC_k^e + \left(FC_k^f - FC_k^e\right) * LF_k\ ) \right)\ ,$$

$$Emission\ truck\ return = \sum_{(i,j) \in A} \sum_{k \in K} \left(X\_ratio_k * CE * d_{ij} * \ N_{ijk} * FC_k^e \right)\ .$$

X_{ijk} is the aggregated distribution flow for Category X products on each arc (i, j) for each truck type k where N_{ijk} represents the number of trucks necessary to deliver the flow.

3.3.6 NTM Model 2: Current network optimized for minimum total emissions

Once again, we sought to find an optimal solution to minimize total emissions in the current distribution network by creating a mixed-integer linear program. NTM Model 2 was formulated with the same sets (**Table 1**) and parameters (**Table 2**) as previous models. In addition to the decision variable used in the GLEC calculations, we introduced a decision variable for the number of trucks on each arc with each truck type (N_{ijk}):

$X_{ijk}: flow\ of\ Category\ X\ products\ on\ arc\ (i,j) \in A\ with\ truck\ type\ k \in K\ (tonne)$

$N_{ijk}: integer\ number\ of\ trucks\ to\ fulfill\ flow\ X_{ijk}$

Since NTM focuses on truck utilization for the shipments instead of part of the cargo, the objective function is set to minimize the sum of transportation and hub emissions for the shipments, as opposed to the partial shipments of Category X products.

$Model\ 2_{OF} = Hub\ emission_{total} + Transportation\ emission_{total}$

in which,

$$Hub\ emission_{total} = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} \left(\frac{X_{ijk} * EF_i}{X\_ratio_k}\right),$$

$$Transportation\ emission_{total} = Emission\ delivery + Emission\ truck\ return,$$

$$Emission\ delivery = \sum_{(i,j) \in A} \sum_{k \in K} \left(N_{ijk} * CE * d_{ij} * \left(FC_k^e + \left(FC_k^f - FC_k^e\right) * LF_k\right)\right),$$

$$Emission\ truck\ return = \sum_{(i,j) \in A} \sum_{k \in K} \left(CE * d_{ij} * N_{ijk} * FC_k^e\right).$$

The model and was subject to the following constraints:

$$\sum_{i \in P} \sum_{k \in K} X_{ilk} - \sum_{j \in C} \sum_{k \in K} X_{ljk} = 0, \qquad \forall l \in R, \qquad (1)$$

$$\sum_{i(P \cup R)} \sum_{k \in K} X_{ijk} \geq D_j, \qquad \forall j \in C, \qquad (2)$$

$$\sum_{i \in P} \sum_{j \in (W \cup S)} \sum_{k \in K} X_{ijk} \leq ratio_{PDS} * \sum_{i \in P} \sum_{k \in K} X_{ijk} \qquad (3)$$

$$\sum_{(i,j) \in A} X_{ijk1} = \sum_{(i,j) \in A} X_{ijk2} * ratio_{k1:k2} \qquad (4)$$

$$N_{ijk} * LF_k * C_k \geq X_{ijk}/X\_ratio_k, \qquad \forall (i,j) \in A, \forall k \in K. \qquad (5)$$

In the objective function, hub emissions calculations mirrored those used in GLEC Model 2 using the total flow calculated from the flow of Category X products. Transportation emissions were calculated using parameters different than in GLEC Framework. This includes the average load factor (LF_k), which is a ratio of the total cargo over the capacity of a specific truck type (C_k) for all truck types ($\in K$). Then, the emission for a single truck on a specific arc (i,j) is calculated based on the fuel consumption per kilometer and the distance of the arc. Fuel consumption of a full truckload FC_k^f and of an empty truck FC_k^e were both calculated in advance for every truck type and input as parameters. The actual fuel consumption for this truck type at a certain load factor is then calculated utilizing linear interpolation. Fuel consumption multiplied by the emission factor constant CE gives the emission values. Multiplying the emission for a single truck by the number of trucks required gives the total transportation emissions to deliver the flow on the arc (i, j) using the truck type k. Also, emissions for the return trip are calculated using the fuel consumption for an empty truckload. It is essential to consider the return trip to ensure comparability with models using the GLEC Framework.

The objective function minimizes total emissions and is subject to similar conservation of flow (1), demand (2), PDS ratio (3), and truck composition (4) constraints as GLEC Model 2. Constraint (5) ensures that the model includes the minimum number of trips (N_{ijk}) necessary to transport the flow (X_{ijk}) by considering the load factor (LF_k).

Once an optimal solution is found, transportation emissions for Category X products are allocated using the following formula:

$$Model2_{FHC} = (Hub\ emission_{total} + Transportation\ emission_{total}) * X\_ratio_k$$

Here, hub and transportation emissions are multiplied by the average ratio of Category X products in each truck type (X_ratio_k).

3.3.7 NTM Model 3: Alternate network optimized for minimum total emissions

NTM Model 3 adapts Model 2 to reflect the alternate network with the same decision variables:

$X_{ijk}: flow\ of\ Category\ X\ products\ on\ arc\ (i, j) \in A\ with\ truck\ type\ k \in K\ (tonne)$

$N_{ijk}: integer\ number\ of\ trucks\ to\ fulfill\ flow\ X_{ijk}$

The objective function is the same as in Model 2:

$$Model\ 3_{OF} = Hub\ emission_{total} + Transportation\ emission_{total}$$

in which,

$$Hub\ emission_{total} = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} (\frac{X_{ijk} * EF_i}{X\_ratio_k}) ,$$

$$Transportation\ emission_{total} = Emission\ delivery + Emission\ truck\ return ,$$

$$Emission\ delivery = \sum_{(i,j) \in A} \sum_{k \in K} \left(N_{ijk} * CE * d_{ij} * (FC_k^e + \left(FC_k^f - FC_k^e \right) * LF_k) \right) ,$$

$$Emission\ truck\ return = \sum_{(i,j)\in A}\sum_{k\in K}\left(CE * d_{ij} * N_{ijk} * FC_k^e\right).$$

The model minimizes the objective function and is subject to the following constraints:

$$\sum_{i\in P}\sum_{k\in K} X_{ilk} - \sum_{j\in C}\sum_{k\in K} X_{ljk} = 0, \qquad \forall l \in R, \qquad (1)$$

$$\sum_{i\in(P\cup R)}\sum_{k\in K} X_{ilk} - \sum_{j\in S}\sum_{k\in K} X_{ljk} \geq D_l, \qquad \forall l \in W, \qquad (2\text{-}1)$$

$$\sum_{i\in(P\cup R\cup W)}\sum_{k\in K} X_{ijk} \geq D_j, \qquad \forall j \in S, \qquad (2\text{-}2)$$

$$\sum_{i\in P}\sum_{j\in(W\cup S)}\sum_{k\in K} X_{ijk} \leq ratio_{PDS} * \sum_{i\in P}\sum_{k\in K} X_{ijk} \qquad (3)$$

$$\sum_{(i,j)\in A} X_{ijk1} = \sum_{(i,j)\in A} X_{ijk2} * ratio_{k1:k2} \qquad (4)$$

$$N_{ijk} * LF_k * C_k \geq X_{ijk}/X\_ratio_k, \qquad \forall (i,j) \in A, \forall k \in K. \qquad (5)$$

This model was subject to similar conservation of flow (1), demand (2-1) and (2-2), PDS ratio (3), and truck composition (4) constraints as GLEC Model 3. Constraint (5) mirrors NTM Model 2 and ensures that the model includes the minimum number of trips (N_{ijk}) necessary to transport the flow (X_{ijk}) by considering the load factor (LF_k).

3.3.8 Baseline Cost Calculations

Cost data on a shipment level was provided by Company A. We used a simple, multi-step aggregation method to calculate the current costs.

3.3.9 Cost Model 1: Current costs with aggregated values

We formulated all the cost models with previously used sets (**Table 3**) and parameters including additional cost variable (**Table 4**).

Table 3

Sets for Cost Optimization Models

Notation	Definition
P	$Node\ for\ the\ Plant\ DC$
R	$Nodes\ for\ regional\ DCs$
W	$Nodes\ for\ customer\ locations\ that\ are\ Candidate\ 3PLs$
S	$Nodes\ for\ other\ customer\ locations$
C	$Nodes\ for\ all\ customers$
H	$Nodes\ for\ logistics\ hubs\ including\ regional\ DC\ and\ Candidate\ 3PLs$
A	$Arcs$
K	$Truck\ types$

Table 4

Parameters for Cost Optimization Models

Notation	Definition
D_j	$Annual\ demand\ of\ Category\ X\ products\ at\ customer\ node\ j \in C\ [tonne]$
d_{ij}	$Driving\ distance\ of\ arc\ (i,j) \in A\ [km]$
c_k^f	$Fixed\ shipment\ cost\ for\ truck\ type\ k \in K^f, [JPY/shipment]$
c_k^v	$Unit\ shipment\ cost\ for\ truck\ type\ k \in K^v, [JPY/(tonne * km)]$
c_i	$Hub\ cost\ for\ node\ i \in H\ [JPY/tonne]$
C_k	$Maximum\ capacity\ for\ truck\ type\ k \in K$
LF_k	$Average\ load\ factor\ for\ truck\ type\ k \in K$
PDS_ratio	$Percentage\ of\ demand\ served\ through\ plant\ direct\ shipping$
$truck\_ratio_{k1:k2}$	$Ratio\ of\ demand\ served\ by\ truck\ type\ k1\ and\ k2$ $k1 \in K, k2 \in K$

The following equations used historical values as inputs to calculate the costs. X_{ijk} is the aggregated flow for Category X Products on each arc (i,j) for each truck type k.

$Model1_{Costs} = \min\ (Hub\ costs + Transportation\ costs\ variable + \ Transportation\ costs\ fix,$

In which,

$Hub\ costs = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} (X_{ijk} * \ c_i),$

$Transportation\ costs\ variable = \sum_{(i,j) \in A} \sum_{k \in K^v} \left(X_{ijk} * d_{ij} * c_k^v\right),$

$$Transportation\ costs\ fix = \sum_{(i,j) \in A} \sum_{k \in K^f} \left(N_{ijk} * c_k^f\right).$$

3.3.10 Cost Model 2: Current network optimized on total cost

We created another mixed-integer linear program to gain insight into where logistics-related costs may be reduced. Cost Model 2 uses the same decision variables as in NTM models.

$X_{ijk}: flow\ of\ Category\ X\ products\ on\ arc\ (i,j) \in A\ with\ truck\ type\ k \in K\ (tonne)$

$N_{ijk}: integer\ number\ of\ trucks\ to\ fulfill\ flow\ X_{ijk}$

The objective function is formulated to minimize the sum of hub costs plus fixed and variable transportation costs of the current network,

$Model2_{OF} = \min\ (Hub\ costs + Transportation\ costs\ variable +\ Transportation\ costs\ fix)$

in which,

$Hub\ costs = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} (X_{ijk} *\ c_i),$

$Transportation\ costs\ variable = \sum_{(i,j) \in A} \sum_{k \in K^v} \left(X_{ijk} * d_{ij} * c_k^v\right),$

$Transportation\ costs\ fix = \sum_{(i,j) \in A} \sum_{k \in K^f} \left(N_{ijk} * c_k^f\right).$

The model was subject to the following constraints:

$$\sum_{i \in P} \sum_{k \in K} X_{ilk} - \sum_{j \in C} \sum_{k \in K} X_{ljk} = 0, \qquad \forall l \in R, \qquad (1)$$

$$\sum_{i (P \cup R)} \sum_{k \in K} X_{ijk} \geq\ D_j, \qquad \forall j \in C, \qquad (2)$$

$$\sum_{i \in P} \sum_{j \in (W \cup S)} \sum_{k \in K} X_{ijk} \leq ratio_{PDS} *\ \sum_{i \in P} \sum_{k \in K} X_{ijk} \qquad (3)$$

$$\sum_{(i,j) \in A} X_{ijk1} =\ \sum_{(i,j) \in A} X_{ijk2} * ratio_{k1:k2} \qquad (4)$$

$$N_{ijk} * LF_k * C_k\ \geq\ X_{ijk}, \qquad \forall (i,j) \in A, \forall k \in K. \qquad (5)$$

Hub costs at the RDCs are calculated by multiplying the total outbound flow at these nodes with the cost factor at the node (c_i). Transportation costs were calculated as a combination of fixed and variable costs. Certain truck types are planned as fixed costs (c_k^f) which are only impacted by the number of trips required to deliver a specific load (N_{ijk}). Other truck types have variable costs (c_k^v) that are proportional to the weight of the goods transported (X_{ijk}) and the distance. This objective function was subject to the same constraints as those used in previous models of the current network. Note that the return trip never incurs additional cost, therefore it was not included in the calculations.

3.3.11 Cost Model 3: Alternate network optimized for minimum total cost

Our final model sought to minimize cost in the alternate network. Cost Model 3 was formulated with the same sets (**Table 3**), parameters (**Table 4**), and decision variables used in Cost Model 2.

$X_{ijk}: flow\ of\ Category\ X\ products\ on\ arc\ (i,j) \in A\ with\ truck\ type\ k \in K\ (tonne)$

$N_{ijk}: integer\ number\ of\ trucks\ to\ fulfill\ flow\ X_{ijk}$

The objective function is formulated to minimize the sum of hub costs plus fixed and variable transportation costs of the current network.

$Model3_{OF} = \min\ (Hub\ costs + Transportation\ costs\ variable + \ Transportation\ costs\ fix)$,

in which,

$$Hub\ costs = \sum_{i \in R} \sum_{j \in C} \sum_{k \in K} (X_{ijk} *\ c_i)\ ,$$

$$Transportation\ costs\ variable = \sum_{(i,j) \in A} \sum_{k \in K^v} \left(X_{ijk} * d_{ij} * c_k^v\right),$$

$$Transportation\ costs\ fix = \sum_{(i,j) \in A} \sum_{k \in K^f} \left(N_{ijk} * c_k^f\right).$$

This model was subject to the following constraints that were defined earlier for the alternate network:

$\sum_{i \in P} \sum_{k \in K} X_{ilk} - \sum_{j \in C} \sum_{k \in K} X_{ljk} = 0,$	$\forall l \in R,$	(1)
$\sum_{i \in (P \cup R)} \sum_{k \in K} X_{ilk} - \sum_{j \in S} \sum_{k \in K} X_{ljk} \geq D_l,$	$\forall l \in W,$	(2-1)
$\sum_{i \in (P \cup R \cup W)} \sum_{k \in K} X_{ijk} \geq D_j,$	$\forall j \in S,$	(2-2)
$\sum_{i \in P} \sum_{j \in (W \cup S)} \sum_{k \in K} X_{ijk} \leq ratio_{PDS} *\ \sum_{i \in P} \sum_{k \in K} X_{ijk},$		(3)
$\sum_{(i,j) \in A} X_{ijk1} =\ \sum_{(i,j) \in A} X_{ijk2} * ratio_{k1:k2}\ ,$		(4)
$N_{ijk} * LF_k * C_k \geq\ X_{ijk},$	$\forall (i,j) \in A, \forall k \in K.$	(5)

4 RESULTS

In this section, we discuss the results of our models and begin to contextualize them in Company A's operations.

4.1 Emissions Optimization Results

This section details the results of the descriptive analyses and simulation models. As described in Section 3.3, baseline results were calculated using a year of historical data provided by the company. Baseline calculations revealed that distributing Category X goods within a single prefecture generates 1,385 tonnes of CO_2 emissions annually. The associated costs of these logistics activities amount to roughly ¥297 million per year ($2.7 million) (**Table 5**).

Using the GLEC Framework as a calculation method, we found that emissions estimations in Model 1 were 23% different than baseline emissions calculations (**Table 5**). By contrast, using the NTM methodology resulted in a difference of 42% against the baseline (**Table 6**). In these calculations where cost was a function of the modeled demand, Model 1 showed a difference of 23% against the baseline.

Table 5

Emissions Estimated Using the GLEC Framework and Associated Costs (JPY)

GLEC Framework Constraint: Max PDS Ratio	**EMISSIONS (tonne CO_2)** (% change)	**COST (JPY)** (% change)
Baseline	1,385	¥296,484,410
Model 1 (Current network)	1,069 (-23% against Baseline)	¥365,505,032 (23% against Baseline)
Model 2 (Optimized for current network)	1,023 (-4% against Model 1)	¥263,148,522 (-28% against Model1)
Model 3 (Optimized for alternate network)	1,023 (0.00% against Model 2)	¥263,096,466 (0.02% against Model 2)

Table 6

Emissions Estimated Using the NTM Methodology and Associated Costs (JPY)

NTM Methodology Constraint: Max PDS Ratio	**EMISSIONS (tonne CO_2)** (% change)	**COST (JPY)** (% change)
Baseline	1,385	¥296,484,410
Model 1 (Current network)	1,970 (42% against Baseline)	¥365,505,032 (23% against Baseline)
Model 2 (Optimized for current network)	1,488 (-25% against Model 1)	¥262,394,051 (-28% against Model 1)
Model 3 (Optimized for alternate network)	1,484 (0% against Model 2)	¥265,896,183 (1.33% against Model 2)

Within the simulation models, which first optimized the current network (Model 2) and then the alternate network (Model 3), several constraints were introduced. Among these, the most important was the ratio of demand being distributed through plant direct shipping (PDS). This was set to a maximum value of 65%, which matches the historical data provided for this prefecture. Within this parameter, the alternate network (Model 3) did not offer meaningful reductions in emissions or cost when compared with the current optimized network (Model 2). This result was consistent across methodologies of emissions estimation.

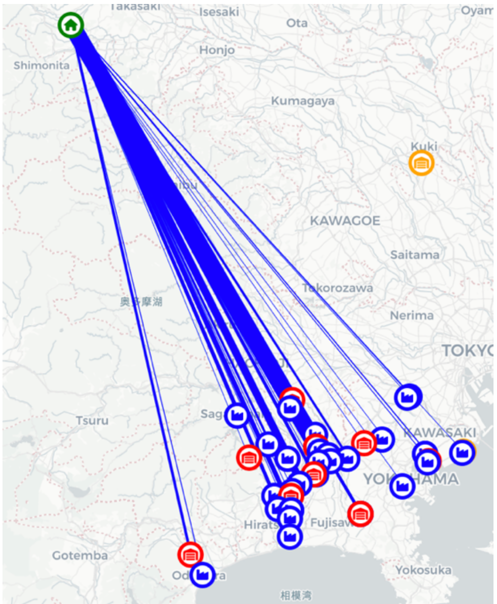
Although the models show no effect from engaging wholesalers, they reveal opportunities to optimize the current network. GLEC shows a 4% decrease in emissions and a 28% decrease in costs when the current network is optimized for emissions. The NTM Methodology also showed potential cost savings of 28% but demonstrated a more dramatic difference between Models 1 and 2 than GLEC, showing a decrease in emissions of 25%.

To gain further insights, we modeled additional scenarios; however, they did not change the outcome that engaging wholesalers offered no emissions reductions. For example, the optimization models were all initially run with no constraints. As a result, emissions were reduced by 41% in the GLEC model and 52% in the NTM model. In both scenarios, costs were reduced by 41%. Digging into these results, we found that 100% of the demand was being fulfilled through PDS (**Figure 4**). This was consistent for both the current and alternate networks, suggesting that changing the function of wholesalers did not alter the optimal solution in an unconstrained model. Similarly, a truck composition constraint was introduced to ensure that the model only assigned 13T and 20T trucks in a ratio that mirrors reality. Despite constraining the model further, the alternate network did not offer a solution with lower emissions that utilizes the 3PL candidates. The absolute values and percentage changes of each modeling scenario can be found for both the GLEC Framework and the NTM Methodology in Appendix C.

When examining the breakdown of fulfillment by distribution strategy, the GLEC models and NTM models produced different results with the addition of constraints (Appendix D). With PDS set to a maximum, the GLEC model produced the same results in Models 2 and 3. However, the NTM model funneled 11.5% of the demand through the candidate 3PL locations. Similarly, once added, the truck composition constraint did not affect the results of the GLEC model. However, the NTM model funneled 22.4% of the demand through candidate 3PLs (**Figure 5**). While this change in the breakdown of distribution strategies is notable, it ultimately did not result in reduced emissions.

Figure 4

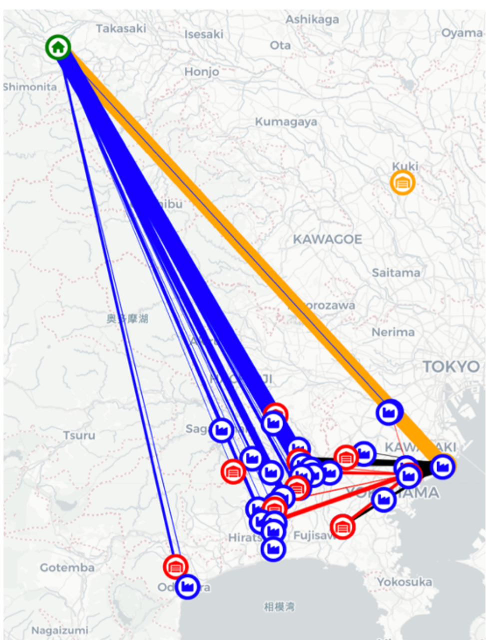
Visualization of 100% PDS Distribution, Model 1



NOTE: Green Node= Plant DC; Yellow Nodes = RDCs; Red Nodes = Candidate 3PLs; Blue Nodes = Other Customers; Blue line = PDS, where the width of the line is proportional to the total volume of flow on that arc.

Figure 5

Visualization of Flow Through Candidate 3PLs, Model 4-3

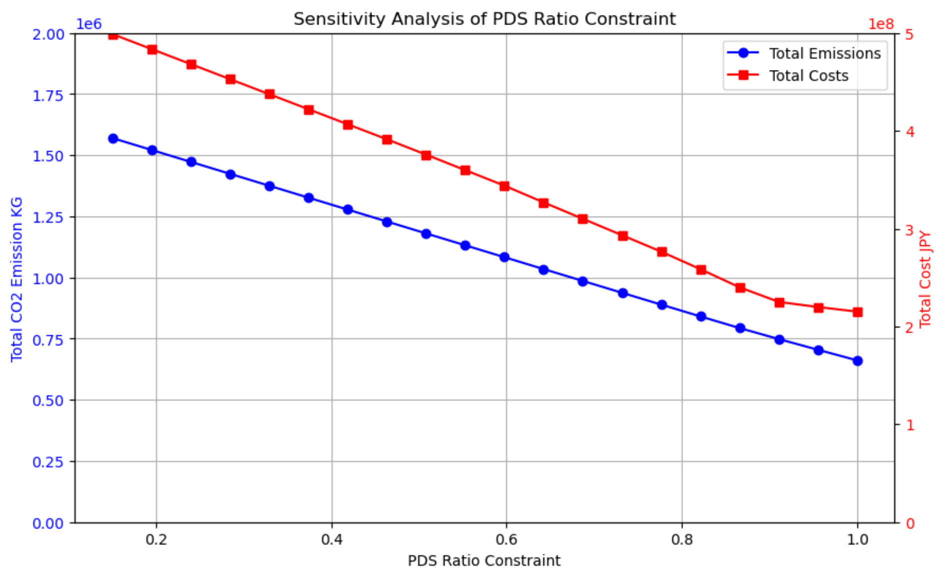


NOTE: Green Node= Plant DC; Yellow Nodes = RDCs; Red Nodes = Candidate 3PLs; Blue Nodes = Other Customers; Blue line = PDS; Yellow line = Intersite; Black line = Standard shipping; Red line = Distribution through Candidate 3PL locations; width of the line represents the total volume of flow on that arc.

We also conducted a sensitivity analysis to better understand the impact of the PDS ratio on total emissions and total costs. Our results (**Figure 6**) suggested that a higher PDS ratio would result in lower total CO_2 emissions as well as lower total costs. These results were consistent across the current and alternate networks.

Figure 6

Sensitivity Analysis of PDS Ratio on Total Emissions and Total Costs, Models 1-2 & 2-2



4.2 Cost Optimization Results

As described in **Table 5**, the estimated costs captured by Model 1 were 23% higher than the baseline calculations. However, the optimization models demonstrated significant potential for cost reductions (**Table 7**). Model 2, which optimized the current network, showed a 28% drop in operational costs. Model 3, which optimized the alternate network, showed an additional decrease of 12% in costs.

Table 7

Results of Cost Models (JPY)

Cost Models	COST (JPY) (% change)
Baseline	¥296,484,410
Model 1 (Current)	¥365,505,032 (23% against Baseline)
Model 2 (Current Optimized with Max PDS Ratio)	¥261,693,967 (-28% against Model 1)
Model 3 (Proposed with Max PDS Ratio)	¥229,575,407 (-12% against Model 2)

In the following section, we discuss the interpretability of these findings.

5 DISCUSSION

Despite testing numerous parameters, our models revealed unequivocally that engaging wholesalers in the value chain as 3PLs did not reduce logistics-related emissions. Since emissions were calculated using two different methods, it is significant to consider which offers more reliable operational insights even though the ultimate conclusions were the same. The GLEC model, for example, will always prioritize the truck type with the lowest emission factor regardless of the size of the load.

The other notable takeaway of these analyses is that in every scenario where plant direct shipping was utilized to its full capacity, both emissions and costs were reduced. In recent years, Company A has invested significant resources in increasing the percentage of shipments that are distributed directly from the Plant DC. We recommend that Company A continues to expand this strategy to improve the efficiency of its network.

While consistent, the modeling results should be interpreted with some degree of caution. First and foremost, the data provided included emissions factors that were calculated by an independent agency. Without visibility of these calculation methods, we can only surmise which values were used. Secondly, we aggregated the historical data for a year and used this demand as an input for the modeling. In doing so, we may have lost important time-specific nuances in the data. For example, if emissions were higher in certain months or periods of time in the year, those features were lost in the process of aggregation.

Additionally, Model 1, which offered insight into the accuracy of our simulation models, showed significantly different values than the baseline results. These discrepancies may be attributable to the fact that we used the shortest feasible distance (SFD) in the calculations while baseline calculations were based on the actual distance traveled. Similar discrepancies were observed between baseline cost calculations and Cost Model 1. We attribute them to the distillation of a complex and highly situational operation into a simple network model with fixed and variable costs.

Finally, based on the scope of this project we made assumptions to facilitate the analysis, but those assumptions also complicate the interpretation of results. For example, shipments leaving the Plant DC travel to the entire Kantō region, but the rest of the network was modeled to fill prefecture-specific demand. While the emissions of this arc were allocated, the additional calculation may have introduced some error into the results. Similarly, we assumed that all truckloads traveled with only Company A's goods; however, interviews with the company revealed that shipments traveling from the RDCs are likely less-than-truckload (LTL) and contain products from other brands. Without direct access to this data (since the RDC is operated by a 3PL), we were unable to allocate emissions accordingly. Focusing on a specific business unit added another dimension to the allocation process. Taken together, our models were unable to capture an LTL truckload that is filled with Company A products across different business units, although this scenario is commonplace.

6 CONCLUSION

In this project, we were tasked with investigating whether logistics-related emissions could be reduced by collaborating with wholesalers in the distribution network. We explored whether utilizing wholesalers within the network to fill demand, particularly small shipments, could potentially reduce total driving distances and thus, transportation-related emissions. Rather than modeling this strategic shift across the entire distribution network, we created several proof-of-concept models to test its feasibility and assess the impact of implementing such a change. Using data from a single prefecture of Japan, we measured the emissions and costs of Company A's operation in the 2023 calendar year. We then formulated a mixed-integer linear program to reflect the current network and used it to calculate baseline emissions and costs. Once the descriptive analytics were completed, this model was used to optimize the flow of goods in the current distribution network. These results were compared with a model of the alternate network to see if engaging wholesalers offered any benefit. Across multiple emissions calculations and after adjusting several parameters, our models showed that this would not be a successful strategy for emissions-reduction.

As a follow-up, we recommend that these results be validated by running the models with data from different prefectures. In doing so, we suggest modeling all business units in a single region to make the interpretation of truck utilization and its impact on emissions more informative. Additionally, this analysis should be conducted using both weight fill rate and volume fill rate as components of truck utilization. We also recommend conducting a sensitivity analysis on the load factor per truck type, as it may provide some insights that can be used in contract negotiations with existing 3PL partners. The models could also be expanded to include intermodal transportation and explore whether modeling wholesalers as 3PLs would be beneficial in a larger, more complex network.

Finally, we recommend repeating these analyses with data aggregated over a month or specific quarter, rather than values aggregated over an entire year. Along the same lines, there are specific "emergency" operational scenarios, such as out-of-area shipments, same-day shipments, and instances of double-handling where emissions are higher than average. We recommend expanding this work to determine whether utilizing wholesalers to fulfill demand in these specific scenarios results in emissions reductions.

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8 APPENDICES

Appendix A

Table A-1

Relevant Columns in the Dataset Used for Analysis.

shipment_number	Shipment number
ship_from	The starting point of a shipment
ship_to	The end point of a shipment
cust_lvl_2_name	Name of a customer
prefecture	Prefecture location of customer
truck_type	Truck type used for shipment (JPXX, JPSP, etc.)
actual_goods_movement_Date	Shipment date
total weight	Transport gross weight [kg]
distance (provided)	Distance traveled [km]
Shipment_cost_JPY	Cost per shipment [JPY]
truck_class	Truck class (Class 44, Class 20, etc.)
weight_X_tonne	Weight of only Category X goods in each shipment [tonne]
weight_total_tonne	Total weight of shipment [tonne]
emissions_X_kgCO2	Emissions associated with only Category X goods in each shipment [tonne CO_2]
emissions_total_kgCO2	Total emissions associated with shipment [tonne CO_2]
shipment subsector	Business unit of goods (Category X, others)
driving_distance (calculated)	Distance traveled [km]
Route	Unique routes (ship-from and ship-to)

Appendix B

Table B-1

Current Use Truck Classes and Types with Corresponding Historical Average Load Factors.

Truck Class	Truck Type	Average Load Factor[9]
Class 20	JP13	0.7312
	JPSP	0.2050
	JPXX	0.3229
Class 26	JP13	0.5309
Class 40	JP20	0.4806
Class 44	JPSP	0.1124
	JPXX	0.1381

Table B-2

Truck Classes and Types Potentially Used by Candidate 3PLs with Standardized Load Factors.

Truck Class	Truck Type	Average Load Factors[10]
Class 3.5	JP2T	0.36
Class 7.5	JP4T	0.60
Class 20	JP10T	0.60

[9] Calculated using historical shipment data from the entire Kantō region.
[10] Load Factors derived from GLEC v3. (Ehrler et al., 2023)

Appendix C

Table C-1

Emissions Estimated Using the GLEC Framework and Associated Costs (JPY): All Scenarios.

Model	Description	Constraints	CO_2 Emissions (tonne)	Change (basis)	Cost (JPY)	Change (basis)
M0	Baseline	N/A	1385		¥296,484,410	
M1	Current flow	N/A	1069	-23% (M0)	¥365,505,032	+23% (M0)
M2-1	Optimized for current network	No constraints	628	-41% (M1)	¥215,169,827	-41% (M1)
M2-2		Max. PDS ratio	1023	-4% (M1)	¥263,148,522	-28% (M1)
M2-3		Max. PDS ratio Truck composition	1177	+10% (M1)	¥338,490,835	-7% (M1)
M3-1	Optimized for alternate network	No constraints	628	0% (M2-1)	¥215,169,827	0% (M2-1)
M3-2		Max. PDS ratio	1023	0% (M2-2)	¥263,096,466	0% (M2-2)
M3-3		Max. PDS ratio Truck composition	1177	0% (M2-3)	¥338,490,835	0% (M2-3)

Table C-2

Emissions Estimated Using the NTM Methodology and Associated Costs (JPY): All Scenarios

Model	Description	Constraints	CO_2 Emissions (tonne)	Change (basis)	Cost (JPY)	Change (basis)
M0	Baseline	N/A	1385		¥296,484,410	
M1	Current flow	N/A	1970	+42% (M0)	¥365,505,032	+23% (M0)
M2-1	Optimized for current network	No constraints	949	-52% (M1)	¥216,250,837	-41% (M1)
M2-2		Max. PDS ratio	1488	-25% (M1)	¥262,394,051	-28% (M1)
M2-3		Max. PDS ratio Truck composition	1602	-19% (M1)	¥275,528,200	-25% (M1)
M3-1	Optimized for alternate network	No constraints	947	0% (M2-1)	¥217,116,835	0.4% (M2-1)
M3-2		Max. PDS ratio	1484	0% (M2-2)	¥265,896,183	1.3% (M2-2)
M3-3		Max. PDS ratio Truck composition	1598	0% (M2-3)	¥288,157,957	4.6% (M2-3)

Appendix D

Table D-1

Breakdown of Fulfillment Volume by Distribution Strategy Across Model Type and Constraints: GLEC Results.

Model Constraints	**Distribution Strategy**	**Model 2** Optimized for current network	**Model 3** Optimized for alternate network
No Constraints	Plant Direct Shipping	100%	100%
	Standard	0%	0%
	Through Candidate 3PLs	0%	0%
Max. PDS ratio	Plant Direct Shipping	63.5%	63.5%
	Standard	36.5%	36.5%
	Through Candidate 3PLs	0%	0%
Max. PDS ratio Truck composition	Plant Direct Shipping	63.5%	63.5%
	Standard	36.5%	36.5%
	Through Candidate 3PLs	0%	0%

Table D-2

Breakdown of Fulfillment Volume by Distribution Strategy Across Model Type and Constraints: NTM Results.

Model Constraints	**Distribution Strategy**	**Model 2** Optimized for current network	**Model 3** Optimized for alternate network
No Constraints	PDS	100%	100%
	Standard	0%	0%
	Through Candidate 3PLs	0%	0%
Max. PDS ratio	PDS	63.5%	63.5%
	Standard	36.5%	24.5%
	Through Candidate 3PLs	0%	11.5%
Max. PDS ratio Truck composition	PDS	63.5%	63.5%
	Standard	36.5%	14.1%
	Through Candidate 3PLs	0%	22.4%

Appendix E

Table E-1

Comprehensive Modeling Results.

Category	Network	Model	Description	Tonne CO2 Total	Change	Tonne CO2 Transportation	Change	Transportation % in all	Costs JPY	Change	Costs JPY Transportation	Change	Transportation % in all
Baseline	Current	0	Actual data	1385		1037		74.89%	¥296,484,410		¥296,752,200		100.09%
Emission GLEC	Current	1-0	Current flow	1069	-22.77%	761	-26.63%	71.15%	¥365,505,032	23.3%	¥365,455,281	23.2%	99.99%
		1-1	No constraint	628	-41.24%	628	-17.41%	100.00%	¥215,169,827	-41.1%	¥215,169,827	-41.1%	100.00%
		1-2	Constraint: max. PDS ratio	1023	-4.34%	700	-7.98%	68.44%	¥263,148,522	-28.0%	¥263,096,466	-28.0%	99.98%
		1-3	Constraint: Max. PDS ratio Truck composition	1177	10.11%	855	12.33%	72.58%	¥338,490,835	-7.4%	¥338,438,779	-7.4%	99.98%
	Proposed	2-1	No constraint	628	0.00%	628	-17.41%	100.00%	¥215,169,827	0.0%	¥215,169,827	0.0%	100.00%
		2-2	Constraint: max. PDS ratio	1023	0.00%	700	-7.98%	68.44%	¥263,096,466	0.0%	¥263,148,522	0.0%	100.02%
		2-3	Constraint: Max. PDS ratio Truck composition	1177	0.00%	855	12.33%	72.58%	¥338,490,835	0.0%	¥338,438,779	0.0%	99.98%
Emission NTM	Current	3-0	Current flow	1970	42.31%	1662	60.27%	84.34%	¥365,505,032	23.3%	¥365,455,281	23.2%	99.99%
		3-1	No constraint	949	-51.85%	949	-42.92%	99.99%	¥216,250,837	-40.8%	¥216,250,821	-40.8%	100.00%
		3-2	Constraint: max. PDS ratio	1488	-24.50%	1165	-29.91%	78.30%	¥262,394,051	-28.2%	¥262,341,995	-28.2%	99.98%
		3-3	Constraint:Max. PDS ratio Truck composition	1602	-18.71%	1279	-23.05%	79.85%	¥275,528,200	-24.6%	¥275,476,143	-24.6%	99.98%
	Proposed	4-1	No constraint	947	-0.15%	946	-43.06%	99.91%	¥217,116,835	0.4%	¥217,116,835	0.4%	100.00%
		4-2	Constraint: max. PDS ratio	1484	-0.25%	1158	-30.34%	78.01%	¥265,896,183	1.3%	¥265,844,127	1.3%	99.98%
		4-3	Constraint: Max. PDS ratio Truck composition	1598	-0.25%	1268	-23.69%	79.37%	¥288,157,957	4.6%	¥288,105,901	4.6%	99.98%
Costs	Current	5-0	Current flow						¥365,505,032	23.3%	¥365,455,281	23.2%	99.99%
		5-1	No constraint						¥215,169,827	-41.1%	¥215,169,827	-41.1%	100.00%
		5-2	Constraint: max. PDS ratio						¥261,693,967	-28.4%	¥261,641,911	-28.4%	99.98%
	Proposed	6-1	No constraint						¥215,169,827	0.0%	¥215,169,827	-41.1%	100.00%
		6-2	Constraint: max. PDS ratio						¥229,575,407	-12.3%	¥229,566,613	-37.2%	100.00%