Greenhouse Gas Optimization Across a Multi-Echelon Manufacturing and Distribution Network

by

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Abstract

Emissions from the industrial sector are a major contributor to climate change around the world. Many of these industrial emissions are attributable to the supply chain and will need to be drastically reduced to meet emission goals set forth by the United Nations Paris Agreement. Possibilities including renewable energy technologies for manufacturing and sustainable vehicles for transportation already exist and can help to reduce emissions across the supply chain, but few solutions have been evaluated regarding re-organizing supply chains as a whole to minimize carbon footprint. This thesis focuses on adapting sourcing strategies in a multi-echelon supply chain network to minimize Greenhouse Gas emissions. An approach using a multi-objective mixed-integer linear program that balances emission reduction along with other objectives such as sourcing cost, lead time, and supply risk is conducted to test the feasibility of the developed strategy in a business context. Opportunities for improvement of the model and possibilities for implementation in other organizations are evaluated.

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Finally, to the many friends I made over the course of this project, you brought immense joy to me while I was with you. Without you, I am certain this project would have been far more mundane and without such passion. Cheers to you!

"Friendship is unnecessary, like philosophy, like art.... It has no survival value; rather it is one of those things which give value to survival."

– C.S. Lewis

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Note on Proprietary Information

To protect information that is proprietary to the host company of this project, the data presented has been modified to represent relative values rather than actual values. Additionally, the figures and data labels included may have been altered to protect competitive information and should be viewed as illustrative rather than representing actual data.

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Acronyms

CCWG Clean Cargo Working Group

CH_4 Methane

CO_2 Carbon Dioxide

CO_2e Carbon Dioxide Equivalent

CPG Consumer Packaged Goods

DC Distribution Center

EF Emission Factor

EPA Environmental Protection Agency

FGU Finished Good Unit

GEO Customer Port

GLEC Global Logistics Emissions Council

GWP Global Warming Potential

IPCC Intergovernmental Panel on Climate Change

IEA International Energy Agency

LGO MIT Leaders for Global Operations Program

MCO Manufacturing Country of Origin

N_2O Nitrous oxide

PPA Power Purchase Agreement

TEU Twenty Foot Equivalent Unit

TTM Trailing Twelve Months

T1 Tier 1 Manufacturer

T2 Tier 2 Manufacturer

YOY Year Over Year

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Chapter 1

Introduction

For the protection of the host company of this project, the company will be referred to as Iota for the remainder of this thesis.

1.1 Company Overview

Iota is an athletic footwear, apparel, and equipment company based in the United States of America that services countries around the world with its products. It is responsible for the design and marketing of products, but it does not own its manufacturing or upstream distribution network. Historically, its products have been manufactured in Asia using multiple manufacturing partners and then distributed from Asia to the rest of the world. While Iota does not own its suppliers, it does have a degree of influence over where and how its products are made, and which modes of transportation are used to distribute them.

Iota's upstream supply chain is a multi-echelon manufacturing and distribution network. Materials flow from high manufacturing tiers in the network (Tier 3+ or T3+), which are mostly comprised of raw material harvesting and processing, to the network's mid manufacturing tier (Tier 2 or T2), which includes weaving, dying, and finishing processes. From T2 manufacturing, materials flow to the final manufacturing tier (Tier 1 or T1), where finished goods are assembled. After T1 manufacturing, finished goods flow to customer ports called GEOs. The flow of materials through the network has been illustrated in Figure 1-1 below:

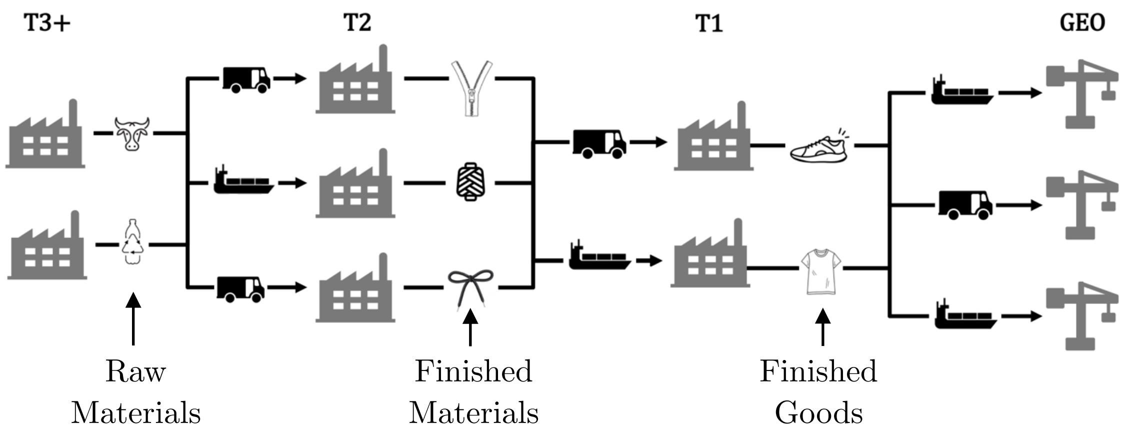


Figure 1-1: Iota's Multi-echelon Manufacturing and Distribution Network

1.2 Project Drivers and Motivation

In 2015, 196 groups at the United Nations Climate Change Conference entered into a legally binding international treaty on climate change called the Paris Agreement. The Paris Agreement was designed to keep the world's average temperature rise within 2 degrees Celsius of pre-industrial levels. In order to meet this goal, the world's greenhouse gas (GHG) emissions must reach their peak before 2025 and drop by at least 43% by 2030.[1] Additional Paris Agreement goals call for net zero GHG emissions by the year 2050.[2]

The aggressive emissions reductions set forth by the Paris Agreement have created pressure for companies to meet ambitious reductions in emissions by 2030 to lead the change. Iota serves consumers across the globe who are demanding these reductions and has pledged to significantly reduce its absolute GHG emissions by 2030, both internally (Scope 1 emissions) and in the upstream, outsourced, supply chain of its operations (Scope 3 emissions). Iota's goal for Scope 3 GHG emissions is a 30% absolute reduction by 2030. It is critical for Iota to strategically plan for the difficult task of reducing the GHG emissions of its outsourced manufacturing and distribution network in order to meet its 30% reduction target.

1.3 Problem Statement

The problem of focus in this thesis is the minimization of GHG emissions across Iota's product manufacturing and distribution network while maintaining desirable levels of alternate objectives such as sourcing cost, lead time, and supply risk across the network. Iota has committed to a percentage reduction of both its own GHG emissions and the GHG emissions of non-Iota manufacturing and distribution entities within its supply chain. Iota has already begun taking steps to reduce the GHG emissions across its supply chain with initiatives such as renewable energy implementation at manufacturing facilities. While Iota is moving in the right direction toward its emissions targets, additional steps will be required to meet the ambitious goals.

The Securities and Exchange Commission (SEC) has proposed regulations to require businesses to provide more detailed disclosures of their Scope 1 - 3 GHG emissions and include detailed plans for emissions reduction. In order to remain compliant with the SEC and maintain their position as an environmentally conscious firm within the market, Iota believes it is critical to develop a complete plan that can be followed to achieve its pledged emissions reduction. While Iota has a well-developed plan to reduce the emissions of its own facilities, a plan to reduce Scope 3 emissions across the supply chain requires additional analysis and optimization.

Iota has already designed a digital twin of its manufacturing and distribution network, hereby referred to as the Digital Twin, with a multi-objective optimization algorithm that considers sourcing cost, lead time, and supply risk across the network as key performance metrics. The focus of this thesis is the addition of GHG emissions as another key performance metric in the optimization algorithm so that GHG emissions can be considered in conjunction with sourcing cost, lead time, and supply risk. Using a multi-objective minimization approach, Iota can determine how much it can reduce its GHG emissions while keeping supply risk, sourcing cost, and lead time in desirable ranges.

1.4 Thesis Overview

This thesis is comprised of seven (7) chapters, including this one. The chapters following this section are outlined below:

Chapter 2 – Literature Review: The literature review outlines the reason for selecting GHG emissions as a focus in this thesis, and describes the motive for focus on corporations, and their supply chains, specifically. Additionally, a review of prior works in supply chain GHG emissions optimization is conducted.

Chapter 3 – Digital Twin Optimization Model Background: This chapter describes the configuration of the Digital Twin model before the commencement of work on this thesis. Motivation for the model and scope are provided along with a high-level description of model variables, constraints, and optimization methodology.

Chapter 4 – Incorporation of Responsibility in the Digital Twin Model: In this chapter, a detailed explanation of the methodology behind the addition of GHG emissions into the Digital Twin model is given. The processes for data collection, emission factor selection, 2030 emission forecasting, and data extrapolation is described along with the calculation method for network GHG emissions and updates to the model objective function.

Chapter 5 – Analysis: The Analysis chapter reviews four (4) scenarios in which Pareto frontiers are generated to explore the optimal supply chain network for Iota along varying weights on the objectives of sourcing cost and GHG emissions. A baseline scenario is compared to a constraint-reduced scenario, a sustainable energy mix scenario, and a combined scenario with both sustainable energies and constraint reduction. All scenarios are compared to Iota's 2030 Scope 3 GHG emissions reduction target. Additionally, example outputs describing an optimized network in further detail are displayed.

Chapter 6 – Recommendations for Model Expansion and Implementation: In the recommendations chapter, future options to improve and add to the model are discussed in depth.

Chapter 7 – Conclusion: The conclusion chapter reviews the insights from prior chapters and describes how the methodology developed in this thesis could be used in institutions beyond the host company.

Chapter 2

Literature Review

2.1 Greenhouse Gas Emissions as a Key Metric

GHG emissions, primarily the result of burning fossil fuels, are a major contributor to global warming.[3] Rising global temperatures contribute to increasing glacial melt, rising sea levels, and other adverse environmental impacts.[4] The major components of GHG emissions are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases such as hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluoride.[5] These gases trap heat in the Earth's atmosphere, contributing to warming of the planet.

GHG emissions are measured by weight and are multiplied by a Global Warming Potential (GWP). The GWP is a measure of the warming impact of a gas compared to CO_2.[6] For example, N_2O has a warming impact that is 273 times that of CO_2, so it is assigned a GWP of 273. By measuring the weight of emissions of each gas and multiplying by that gas' GWP, a meaningful sum of GHG emissions can be calculated in the units of Carbon Dioxide Equivalent (CO_2e). This thesis focuses heavily on CO_2e as a sustainability metric because it is an aggregated representation of a company's contribution toward global warming. All references to GHGs in the analyses performed in this thesis are measured in units of CO_2e.

2.2 Corporate Industry Environmental Responsibility

In the United States in 2021, the industrial sector's direct and indirect GHG emissions were the largest of any sector and accounted for 30% of the country's GHG emissions.[7] The emissions of the industrial sector are far higher in magnitude than that of the commercial, residential, and agricultural sectors, making it one of the biggest areas of opportunity for climate change mitigation. The Environmental Protection Agency (EPA) lists opportunities such as improved energy efficiency, switching to low GHG fuels, and recycling as core opportunities for emission reductions, along with a multitude of other possibilities.[8] Despite the tangible steps available for corporations in the industrial sector to reduce emissions, a recent trend of greenwashing, which means making misleading statements about a company's environmental practices or benefits, has arisen as a tactic for corporations to appear environmentally friendly but evade the burden of actual emission reduction.[9]

One of the top tactics for corporations to appear environmentally friendly is to pledge net zero carbon using carbon offsets or carbon credits. This strategy allows a corporation to buy a certificate that is linked to an effort to lower GHG emissions somewhere else, outside of their value chain, instead of taking steps to lower their own carbon emissions. Recently, studies have shown that offsets are guilty of promising more emission reductions than they can actually achieve.[10] The carbon credit market lacks appropriate standards and regulations, which makes it concerning and unreliable.[11] Unfortunately, carbon credits are a major tactic leveraged by the industrial sector, where actual emission reduction is urgently needed.

In an attempt to be transparent with consumers and avoid greenwashing, Iota has pledged to reduce its actual emissions instead of relying on carbon offsetting. The focus of this thesis is the reduction of actual GHG emissions within Iota's supply chain. Through the rest of this thesis, carbon offsets are not included in any reports of GHG emissions reduction efforts.

2.3 Greenhouse Gases in the Supply Chain

According to the EPA, an organization's supply chain is often responsible for more than 90 percent of the organization's GHG emissions, making it the biggest source of emissions, by far, for many corporations.[12] Additionally, the Consumer Packaged Goods (CPG) market is anticipated to grow at an average annual rate of 5.3%, which will contribute to additional increases in GHG emissions from their supply chains.[13] Because such a high percentage of corporate emissions stem from the supply chain, in order to meet aggressive GHG emissions reduction, corporations will need to begin making drastic reductions to their supply chain emissions. Analysts such as McKinsey predict that the CPG industry will need to reduce their GHG emissions by more than half to meet 2050 targets.[14] To address the magnitude of change that will be required within the corporate supply chain, specifically, this thesis focuses on emission reductions within the corporate supply chain.

2.4 Prior Work in Supply Chain GHG Emissions Optimization

Optimization modeling for GHG emissions reduction across the supply chain is not a fundamentally new concept. Studies in various countries have been performed to determine how to balance GHG emissions with risks in cost, quality, and lead times.[15,16] In an international study of collaborative supply chains, researchers studied the network GHG emissions of multi-echelon manufacturing networks, very similar to those at Iota, and discovered that a robust optimization approach could be used to reduce the GHG emissions of collaborative networks over non-collaborative networks.[17] While Iota is traditionally a non-collaborative network where each tier of manufacturing in the multi-echelon network is confined to communicate only with the tiers directly above and below them, the Digital Twin project under development by Iota would encourage deeper network collaboration. This platform for collaboration makes the Digital Twin an ideal host for the GHG emissions reduction study undergone in this thesis.

Case-based studies of carbon mitigation in supply chain management have been conducted throughout the foreign automobile industry.[18,19,20] An additional study on global supply chain explored integer programming to strategically optimize location, scheduling, and transportation flow while minimizing GHG emissions, and the authors were able to achieve significant reduction in GHG emissions using this method.[21] Studies demonstrating GHG emissions reduction using similar programing techniques to Iota's Digital Twin are validating that this platform could be used to achieve significant GHG emissions reduction at Iota, itself. In the apparel industry and in the United States in general, research on the topic remains limited, so Iota could be at the forefront of its industry with respect to sustainable supply chain design, which would pose a strategic advantage.

Chapter 3

Digital Twin Optimization Model Background

3.1 Motivation for the Digital Twin Optimization Model

Iota's manufacturing network is highly concentrated in Southeast Asia. This has traditionally served the purpose of providing a low-cost network. However, the historic network was not optimized for resilience, responsiveness, or responsibility. The Digital Twin model was created to enable the re-design of a network that is optimized for sourcing cost, resiliency, and responsiveness. The responsibility element was not included in the first generation of the Digital Twin model and is therefore not discussed further in this background chapter. Instead, it will be discussed in later chapters as a primary focus of the current thesis. It is important to note that the Digital Twin model has been designed to plan growth on the 2030 horizon and is not intended to be used for short term network planning. The Digital Twin model will reconfigure the supply footprint within T1 and T2 factories and will assess the impact of adding factories in existing and new Manufacturing Countries of Origin (MCOs).

3.2 Model Scope

The Digital Twin model is concentrated in scope to the T2 to T1 to GEO segments of the supply chain. This includes T2 material weaving, dying, and finishing processes, transportation of finished materials to T1 facilities where they are assembled into finished goods, and transportation of finished goods to destination ports. Figure 3-1 depicts the series of supply chain operations that are included in the Digital Twin model. Tiers 3 and higher of the supply chain network have not been included in the Digital Twin model at this time. These high tiers have been excluded from the first-generation model because it becomes increasingly more difficult for Iota to trace the sourcing of materials that are multiple tiers in the supply chain beyond their control, and because optimization becomes more complex with additional levels of sourcing. Iota may add higher tiers to the Digital Twin model in future iterations, but for the purpose of this thesis, the scope has been limited to the elements included in the first-generation version of the Digital Twin, shown below:

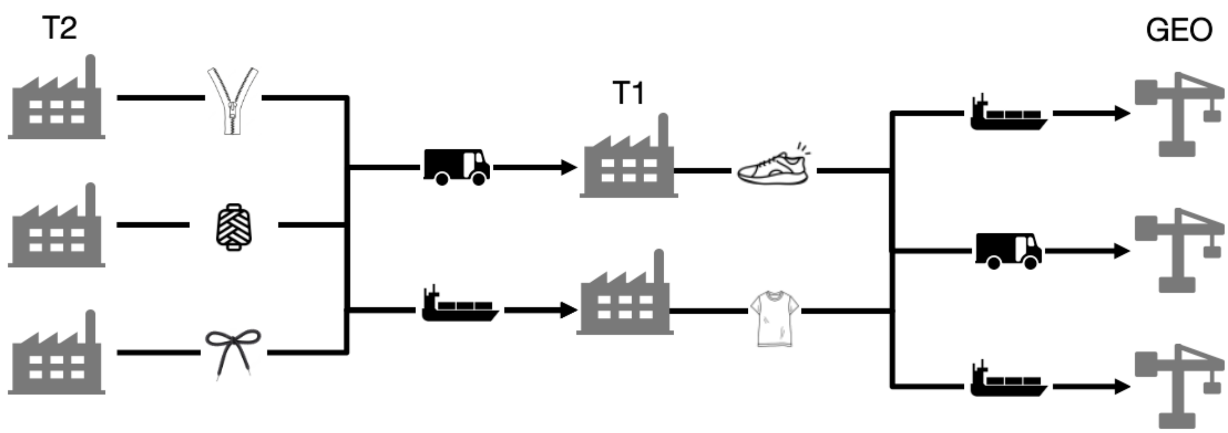


Figure 3-1: Digital Twin Model Scope

3.3 Model Elements

As previously discussed, the Digital Twin model optimizes for cost, resiliency, responsiveness, and responsibility. The element of responsibility is the newest addition to the model and falls under the work of this thesis. The elements of cost, resiliency, and responsiveness were integrated into the Digital Twin prior to the beginning of this thesis. The responsiveness metric is measured by lead time, the resiliency metric is measured by supply risk, and the cost metric is measured by sourcing cost. These three measurements used in the Digital Twin algorithm are discussed in the subsections below.

Additionally, the subsections below describe how the sourcing cost, lead time, and supply risk metrics are all tracked across "units" in the multi-echelon manufacturing and distribution network. At the T2 level of the network, a "unit" refers to a piece of material which undergoes dyeing, weaving, finishing, etc., whereas a "unit" in the T1 level of the network refers to a finished good unit. The total network is comprised of both T2 material "units" and T1 finished good "units," both of which are referred to as "units" below.

3.3.1 Sourcing Cost

The sourcing cost metric is quantified by total sourcing cost. The total sourcing cost is measured as the sum of the cost to manufacture and distribute each unit in the network, which includes material cost, labor cost, transportation cost, and duty rate. The equation for total sourcing cost is expressed in equation 3-1 below.

$$\textit{Total Sourcing Cost} = \Sigma\ [(\textit{Material Cost} + \textit{Labor Cost}) \times (1 + \textit{Duty Rate}) + \textit{Transportation Cost}] \tag{3-1}$$

Material cost, labor cost, and transportation cost are measured on a per-unit basis and summed over all units in the network to calculate the total sourcing cost.

3.3.2 Lead Time

A unit's lead time is calculated at a finished good unit level and is comprised of four components including: 1) T2 materials production time, 2) transit time of materials from T2 node to T1 node, 3) T1 finished good production time, and 4) transit time from T1 node to marketplace GEO. Because the lead time is calculated at a finished good unit level and finished goods are comprised of multiple materials coming from different T2 nodes, the maximum lead time for all the required materials used for each finished good is utilized in the calculation of each finished good lead time. The exact equation and methodology of the finished good unit lead time is outside of the scope of this thesis, proprietary to Iota, and not discussed in further detail. Once each unit's lead time is calculated, total lead time of the network is then measured as the sum of each finished good unit's lead time over all units in the network. Because the total lead time of the network aggregates a set of times to manufacture and distribute many kinds of materials and finished goods, which can occur in parallel, the total lead time is not a 1 to 1 representation of actual time to get a set of goods from point to point and should not be interpreted as such. The equation for total lead time is expressed in equation 3-2 below.

$$Total\ Lead\ Time = \Sigma\ (Unit\ Lead\ Time) \tag{3-2}$$

3.3.3 Supply Risk

Each unit is given a country-specific unit supply risk score that is based on a Country Risk Index created by Iota. The Country Risk Index is a weighted average of nine (9) factors including climate risk, corruption risk, natural disaster risk, economics risk, cargo risk, labor risk, business risk, property risk, and individual risk. These nine (9) factors are updated by Iota for each country on a quarterly basis. Total supply risk is then measured as the sum of each unit's supply risk score over all units in the network. Further details behind the supply risk metric are also proprietary to Iota, and the metric is not the primary metric of focus in this thesis, so it is not discussed in further detail. The equation for total supply risk is expressed in equation 3-3 below.

$$Total\ Supply\ Risk = \Sigma\ (Unit\ Supply\ Risk\ Score) \tag{3-3}$$

3.4 Model Decision Variables

The Digital Twin optimization model aims to determine the optimal sourcing plan for Iota and therefore must provide Iota with the following information:

1) The quantity and type of each material to be manufactured in each T2 factory (or the decision to not use the factory);

2) The quantity and type of each finished good to be manufactured in each T1 factory (or the decision to not use the factory);

3) Transportation routes and modes between T2 and T1 factories and the quantity and types of materials being transported in each route and mode; and

4) Transportation routes and modes between T1 factories and GEOs and the quantity and types of finished goods being transported in each route and mode.

These four (4) pieces of information constitute the decision variables in the Digital Twin algorithm and comprise the optimal sourcing plan for Iota once optimization has occurred.

3.5 Model Constraints

The Digital Twin optimization model employs multiple constraints that help guide the algorithm toward practical solutions. The constraints employed in the original Digital Twin model are outlined below:

1) Demand by GEO. Iota is able to estimate consumer demand of all products in each of their GEOs. The model is constrained to exactly meet the estimated demand in each GEO so there are no supply shortages nor excess supply compared to the demand estimate in any region.

2) Maximum number of new MCOs. This constraint limits the number of new MCOs that can be added to the existing supply chain infrastructure. This constraint is in

place because of additional expenditure, negotiation, and research required for Iota to expand into new countries. It would be impractical to suggest moving into an all-new set of countries at once and abandoning existing partnerships, so the Digital Twin model limits the number of new MCOs that can be suggested.

3) Maximum or minimum demand fulfilled by a factory or factory group. Some of Iota's historic factory partnerships require that a minimum amount of demand be fulfilled by certain factories or groups of factories. To ensure relations with factory partners remain healthy, the Digital Twin model ensures those historic agreements are not broken using a minimum demand constraint. Additionally, Iota desires to avoid risk stemming from factories closing unexpectedly, so Iota limits the percent of their total demand that can be served from any one factory or factory group. As a result, the Digital Twin model includes maximum demand percentage constraints for factory groups.

4) Maximum demand percentage fulfilled by MCO. Iota wants to diversify the risk from factory shutdowns by limiting the percentage of its demand that is fulfilled by any one MCO. If any MCO ceases fulfilling orders due to political shutdown, natural disaster, or other country-wide problems, Iota can continue operating from factories in other MCOs by spreading the demand fulfillment over the remaining non-disrupted MCOs.

5) Minimum percentage of GEO demand fulfilled by nearshore T1 capacity. Iota hopes to move toward a nearshoring approach for its finished goods. To this end, the Digital Twin model imposes a minimum demand percentage constraint to make sure nearshore production reaches an acceptable level.

6) Maximum or minimum factory capacity. Each factory can only accommodate a certain level of capacity, limited by the factory's size and labor force. In order to ensure more capacity is not allotted to a factory than is physically possible, the Digital Twin model limits the maximum capacity of each factory. Additionally, factories have minimum order size limits that must be met in order to place orders from those factories, so the Digital Twin model requires that the minimum capacity be ordered from a factory if orders are placed at the factory.

3.6 Model Multi-Objective Optimization

The current Digital Twin model optimizes for total sourcing cost, total supply risk, and total lead time using a single, weighted objective function. Because total sourcing cost, total supply risk, and total lead time are all measured in different units, the weighted objective function normalizes the individual objectives before they are added together using the maximum and minimum possible values for each objective. The model calculates the extreme values for each objective by solving the model for each objective individually then uses those calculated values in the weighted objective function. The multi-objective function is expressed in equation 3-4 below.

$$
\begin{aligned}
&min(\ W_C \times \frac{Total\ Sourcing\ Cost\ \text{-}\ Min\ Possible\ Total\ Sourcing\ Cost}{Max\ Possible\ Total\ Sourcing\ Cost\ \text{-}\ Min\ Possible\ Total\ Sourcing\ Cost} \\
&\quad + W_{LT} \times \frac{Total\ Lead\ Time\ \text{-}\ Min\ Possible\ Total\ Lead\ Time}{Max\ Possible\ Total\ Lead\ Time\ \text{-}\ Min\ Possible\ Total\ Lead\ Time} \\
&\quad + W_R \times \frac{Total\ Supply\ Risk\ \text{-}\ Min\ Possible\ Total\ Supply\ Risk}{Max\ Possible\ Total\ Supply\ Risk\ \text{-}\ Min\ Possible\ Total\ Supply\ Risk}\ ) \\
&\quad where\ W_C + W_{LT} + W_R = 1
\end{aligned} \tag{3-4}
$$

In the weighted objective function, each individual objective is assigned its own weight based on priority of that objective. The weighting of total sourcing cost is represented by W_C, the weighting of total lead time is represented by W_{LT}, and the weighting of total supply risk is represented by W_R. The weighting of the three objectives must add to one (1), and the weights can be changed to generate a set of optimal solutions based on priority. If any one weight is set to one (1) and the others set to zero (0), the model can be executed to optimize for just that one objective to reveal the cheapest, fastest, or least risky solution without the influence of the other objectives. Alternatively, each weight could be set to one third to result in a solution balanced equally across all three objectives. By testing different combinations of weightings, a three-dimensional Pareto frontier can be generated to visualize the set of optimal solutions along the three performance metrics.

Chapter 4

Incorporation of Responsibility in the Digital Twin Model

This section focuses on the addition of the responsibility element to the Digital Twin model. As previously discussed, GHG emissions were selected as the metric of interest to measure responsibility. In order to minimize Iota's GHG emissions in the Digital Twin model, the model requires GHG emissions information on a per-unit basis for each facility and for each transportation route considered by the model. Additionally, because the model is designed to produce an optimal network for the year of 2030, the per-unit GHG emissions were forecasted to the year of 2030 before integration into the Digital Twin. The following subsections review the detailed methodology for data and emission factor sourcing, data extrapolation, emission calculations, emission forecasting, and optimization.

4.1 Data Collection

An initial collection of internal GHG emissions related data was required so GHG emissions measures could be incorporated in the Digital Twin model. The following sources of internal data were the foundation of information that fed the Digital Twin model:

1) <u>T1 and T2 Manufacturing Energy Data</u>. For all T1 and T2 manufacturing facilities, Iota had received reports of actual energy usage from the facilities for the previous five (5) years. To maintain an accurate depiction of the most recent

energy trends, only the trailing twelve months (TTM) of data were used in the model. This energy usage includes both on-site energy usage and energy purchased from the grid. On-site energy usage includes the combustion of fossil fuels and biofuels, on-site renewable energy generation, and other on-site energy sources. Energy purchased from the grid includes both purchased renewable energy and purchased standard grid energy.

2) Transportation Distances, Loads, and Fuel Types. For all cargo routes occurring by truck and ship in Iota's transportation network, Iota had collected information on the historic load quantities, load masses, travel distances, and fuel types used.

Additionally, public sources of data were collected to fill knowledge gaps in internal data sources. The following public data were fed into the Digital Twin algorithm:

1) European Energy Mix. Because Iota is not currently operating any manufacturing facilities in Europe, a reasonable extrapolation of the energy mix in this region could not be made using actual T1 and T2 manufacturing energy data. Instead, data was sourced from Eurostat,[22] an official database of the European Union which contains publicly available energy information. Records detailing the total consumption of energy by industry in the European Union, separated by energy source and industrial sector, was retrieved from Eurostat and was filtered to the textile and leather sector, the closest option of industrial

sector to Iota, and was filtered to the most recent available year, 2020. The types and ratios of historic consumption of energy were used to extrapolate the available energy mix.

2) Oceania Energy Mix. Similar to Europe, Iota does not currently operate any manufacturing facilities in Oceania. As such, data detailing the total consumption of energy by industry in Oceania, separated by energy source and industrial sector, were also outsourced for this region. This information was sourced from the Australian Government's Department of Climate Change, Energy, the Environment and Water.[23] Final energy consumption was filtered by the most recent available date range, 2020-2021, and was filtered by the closest industrial sector to Iota, which was food, beverages, and textiles. The types and ratios of historic consumption of energy were used to extrapolate the available energy mix.

4.2 Emission Factors

Emission factors were used to calculate GHG emissions from energy and fuel usage. The following databases were used to source emission factors:

1) Intergovernmental Panel on Climate Change (IPCC): For stationary sources of emissions, such as those at the T1 and T2 manufacturing levels, emission factors for on-site energy generation were sourced from IPCC,[24] the United Nations

body for assessing the science related to climate change. Emission factors were provided on a kg CO_2e per kwh basis.

2) International Energy Agency (IEA): To calculate emissions from T1 and T2 factory consumption of off-site energy from the grid, emission factors were sourced from IEA[25] on a country-specific basis. Factors were provided in grams of CO_2e per kwh.

3) Global Logistics Emissions Council (GLEC) Framework: Emissions from the truck and ship-based transportation of materials between T2 and T1 manufacturing facilities were calculated using emission factors from the GLEC Framework.[26] Emission factors were provided for material transport on a kg CO_2e per tonne-kilometer basis.

4) The United States Department of Transportation Research and Special Programs Administration: Emissions from the truck transport of finished goods between T1 manufacturing facilities and GEOs were calculated using emission factors from The United States Department of Transportation Research and Special Programs Administration.[27] These emission factors were sourced on a grams of CO_2e per Twenty Foot Equivalent Unit (TEU)-mile basis.

5) Clean Cargo Working Group (CCWG): Finally, the emissions from the ship-based transport of finished goods between T1 manufacturing facilities and GEOs were calculated using emission factors from CCWG.[28] Factors were

provided in units of grams of CO_2e per TEU-kilometer and were specific to the origin region to destination region route.

4.3 Grid Emission Factor Forecasting

As described in section 4.2, emission factors for T1 and T2 factory consumption of off-site energy from the grid were sourced from IEA on a country-specific basis. These emission factors are estimates of grid energy for the year 2020 and require forecasting to estimate grid emissions for the year 2030. Year over year (YOY) predicted percent changes to grid emission factors were sourced from IHS Markit[29] and applied to 2020 Emission Factors (EF_{2020}) to estimate 2030 Emission Factors (EF_{2030}), as shown in equation 4-1, below.

$$EF_{2030} = EF_{2020} \times YOY_{2020\text{-}2021} \times YOY_{2021\text{-}2022} \times YOY_{2022\text{-}2023} \times YOY_{2023\text{-}2024} \times YOY_{2024\text{-}2025} \times YOY_{2025\text{-}2026} \times YOY_{2026\text{-}2027} \times YOY_{2027\text{-}2028} \times YOY_{2028\text{-}2029} \times YOY_{2029\text{-}2030} \tag{4-1}$$

4.4 Regional Extrapolation

All MCOs considered by the Digital Twin algorithm had corresponding IEA 2020 emission factors for consumption of off-site grid energy. However, not all of the MCOs had corresponding YOY percent changes in the IHS database. In order to arrive at an estimate of 2030 emission factors for those countries, the YOY percent changes were regionally extrapolated by averaging the known YOY percent changes from other MCOs in the same region (e.g. Central America, South America, Middle East, etc.). The regional average YOY percent changes were then applied to IEA 2020 emission factors using equation 4-1 to arrive at 2030 emission factors for the MCOs with missing YOY percent change values.

With the exception of Europe and Oceania, Iota contracts with T1 and T2 manufacturing facilities in all other global regions where MCOs are being considered by the Digital Twin. For the MCOs being considered with no current T1 or T2 manufacturing facilities in the country, a regional average of T1 and T2 manufacturing energy data was calculated to extrapolate the mix of energy that would most likely be used by the facility (e.g. 82% standard grid energy, 3% on-site solar, 8% on-site diesel energy generation, 7% purchased renewable energy from the grid). Additionally, the efficiency, measured as kilowatt-hours of energy required to make one unit (kwh/unit), was regionally averaged as an extrapolation for those same facilities with no current manufacturing data.

4.5 Energy Mix Forecasting

After the present-day energy mixes were extrapolated to include all T1 and T2 facilities, these energy mixes could be manually altered to better represent the 2030 renewable energy plans of the facilities. For example, if a facility had disclosed to Iota that it planned to switch completely to renewable power via a Power Purchase Agreement (PPA) by 2030, the energy mix for that facility could be changed to 100% renewable power in the Digital Twin model. Iota is able to change the energy mixes manually as it continues to receive information from its facilities about their 2030 sustainability efforts. This lever allows for a higher degree of predictive accuracy to be used as information becomes available.

As an added benefit to the energy mix being optionally manually altered in the model, Iota can test scenarios in which its T1 and T2 facilities meet aggressive renewable energy targets, and scenarios in which they fail to meet targets. The comparison of these scenarios gives Iota an understanding of how upstream facility actions will impact their own success.

4.6 Manufacturing GHG Emissions Calculation

Once the energy mix (percentage of each energy type used by a facility), emission factors (kg CO_2e/kwh), and efficiency (kwh/unit) were estimated for all facilities, a calculation of CO_2e/unit could be performed for each facility using equation 4-2, below:

$$\begin{aligned} kg\ CO_2e/unit \ = & \\ & [Percent\ Energy\ A \times Emission\ Factor\ Energy\ A\ + \\ & Percent\ Energy\ B \times Emission\ Factor\ Energy\ B\ + \\ & Percent\ Energy\ C \times Emission\ Factor\ Energy\ C\ + \ldots\ ] \times Efficiency \end{aligned} \tag{4-2}$$

Note that kg CO_2e/unit can take the form of kg CO_2e per finished good unit (FGU) or kg CO_2e per kilogram of material, depending on the scenario described in Section 4.7 below.

4.7 Final Data Entry

The final GHG emissions data fed into the Digital Twin model to facilitate GHG emissions optimization takes the following forms:

1) T1 Manufacturing GHG Emissions: The final T1 Manufacturing GHG emissions data used as inputs for the Digital Twin model are in the form of kg CO_2e per finished good unit. These data are factory specific for MCOs where there are current Iota T1 manufacturing operations and country specific for MCOs where regional extrapolations were used in place of actual energy data because of lack of Iota T1 manufacturing operations in the MCO. These data are also product specific (i.e., differentiated by footwear vs. apparel vs. equipment). The data are all forecasts for the year 2030.

2) T2 Manufacturing GHG Emissions: The final T2 Manufacturing GHG emissions data used as inputs for the Digital Twin model are in the form of kg CO_2e per kilogram of material. These data are factory specific for MCOs where there are current Iota T2 manufacturing operations and country specific for MCOs where regional extrapolations were used in place of actual energy data because of lack of Iota T2 manufacturing operations in the MCO. These data are also material specific. The data are all forecasts for the year 2030.

3) T2 to T1 Transportation GHG Emissions: T2 to T1 transportation emissions were inputted into the Digital Twin model in the units of kg CO_2e per kilogram

of material shipped. These emissions were inputted on a route-specific and mode-specific (i.e., truck vs. ship) basis, independent of material type.

4) T1 to GEO Transportation GHG Emissions: T1 to GEO transportation emissions were inputted into the Digital Twin model in the units of kg CO_2e per finished good unit shipped. The average number of Iota's finished good units per TEU in their historic supply network was used to convert the emission factors with TEU to finished good units in calculations. The kg CO_2e per finished good unit emissions were then inputted on a route-specific, mode-specific, and product-specific basis.

The final calculation of total network GHG emissions including the above four (4) listed elements is shown in equation 4-3, below:

$$\begin{aligned}&\textit{Total GHG Emissions} = \\ &\sum_{i=1}^{u} (\textit{T1 Manufacture GHG Emissions}/\textit{FGU}_i + \textit{T1 to GEO Transportation GHG Emissions}/\textit{FGU}_i) + \\ &\sum_{j=1}^{k} (\textit{T2 Manufacture GHG Emissions/kg material}_j + \textit{T2 to T1 Transportation GHG Emissions/kg material}_j) \\ &\qquad \textit{Where } i \textit{ is in the set of all } u \textit{ FGUs and } j \textit{ is in the set of all } k \textit{ materials} \qquad (4\text{-}3)\end{aligned}$$

4.8 Optimization

4.8.1 Optimization Strategies Considered

Two approaches were considered for the optimization of the Digital Twin model with GHG emissions included:

1) Add GHG Emissions as a Weighted Objective: One approach was to re-optimize the Digital Twin model with GHG emissions added as an additional objective in the weighted objective function. Using this method, a weight of 100% could be selected for the GHG emissions objective to determine the configuration with the lowest possible GHG emissions. Alternatively, a weight of 25% could be used on each objective to identify a network balanced over sourcing cost, lead time, supply risk, and GHG emissions. The drawback of this method is that solutions become much more difficult to interpret and visualize on a Pareto frontier when a fourth axis is added, so weights become more difficult to select. Adding GHG emissions as a weighted objective is attractive, though, because it allows for the identification of the best possible scenario for GHG emissions reduction.

2) Add GHG Emissions as a Constraint: An alternative approach is to leave the objective function as-is with only sourcing cost, lead time, and supply risk included, then add a maximum amount of acceptable GHG emissions as a constraint to the model. Iota's target of 30% Scope 3 GHG emissions reduction by 2030 could be used as the constraint, meaning the model would not be allowed to produce solutions in which Iota would fail its 2030 GHG emissions pledge. This strategy is attractive because it allows the model to optimize for traditional corporate priorities such as sourcing cost, lead time, and supply risk while meeting the exact maximum acceptable levels of emissions. The main drawback of this approach is

that the model will never provide a solution that helps Iota reduce its emissions to the largest extent, so Iota would never get an idea of how well it could be doing with respect to sustainability. Additionally, meeting the exact maximum allowable GHG emissions for 2030 may not adequately prepare Iota to meet its aggressive 2050 GHG emissions targets the way the minimization approach could.

4.8.2 Implemented Optimization Strategy

Ultimately, the option to add GHG emissions as an additional objective was selected for use in the Digital Twin model. Because Iota wanted to reduce their emissions as much as feasible rather than simply achieving their 2030 disclosed target, it was essential to understand how much they could feasibly reduce their emissions.

The objective function described in Section 3.6 was updated with a fourth weighted term with GHG emissions added. The new objective function is outlined in equation 4-4, below.

$$\begin{aligned} min\ (\ W_C \times & \frac{Total\ Sourcing\ Cost\ \text{-}\ Min\ Possible\ Total\ Sourcing\ Cost}{Max\ Possible\ Total\ Sourcing\ Cost\ \text{-}\ Min\ Possible\ Total\ Sourcing\ Cost} \\ + W_{LT} \times & \frac{Total\ Lead\ Time\ \text{-}\ Min\ Possible\ Total\ Lead\ Time}{Max\ Possible\ Total\ Lead\ Time\ \text{-}\ Min\ Possible\ Total\ Lead\ Time} \\ + W_R \times & \frac{Total\ Supply\ Risk\ \text{-}\ Min\ Possible\ Total\ Supply\ Risk}{Max\ Possible\ Total\ Supply\ Risk\ \text{-}\ Min\ Possible\ Total\ Supply\ Risk} \\ + W_{GHG} \times & \frac{Total\ GHG\ Emissions\ \text{-}\ Min\ Possible\ Total\ GHG\ Emissions}{Max\ Possible\ Total\ GHG\ Emissions\ \text{-}\ Min\ Possible\ Total\ GHG\ Emissions}) \\ & where\ W_C + W_{LT} + W_R + W_{GHG} = 1 \end{aligned} \tag{4-4}$$

Again, each objective is assigned its own weight based on priority of that objective. The weighting of total GHG emissions is added and represented by W_{GHG}. The weighting of the four objectives must add to one (1), and the weights can be changed to generate a set of optimal solutions based on priority. By testing different combinations of weightings, now a four-dimensional Pareto frontier could be generated to understand the set of optimal solutions along the four performance metrics. Because four-dimensional Pareto frontiers are difficult to conceptualize, other strategies can be used to visualize outcomes, such as setting two of the weights to zero and visualizing the tradeoff between the remaining two metrics in isolation. This strategy was used to visualize results for the purpose of this thesis and is discussed in the following chapter.

Chapter 5

Analysis

This section shows various results of solving the responsibility-integrated Digital Twin optimization model described in the previous section. In all of the results discussed in the subsections below, a 2030 footwear demand forecast generated by Iota's business stakeholders was used as the customer demand constraint. The demand was limited to footwear for all model runs and excluded apparel and equipment to showcase the results in a simplified manner and to avoid redundant discussions of similar results across the apparel and equipment categories.

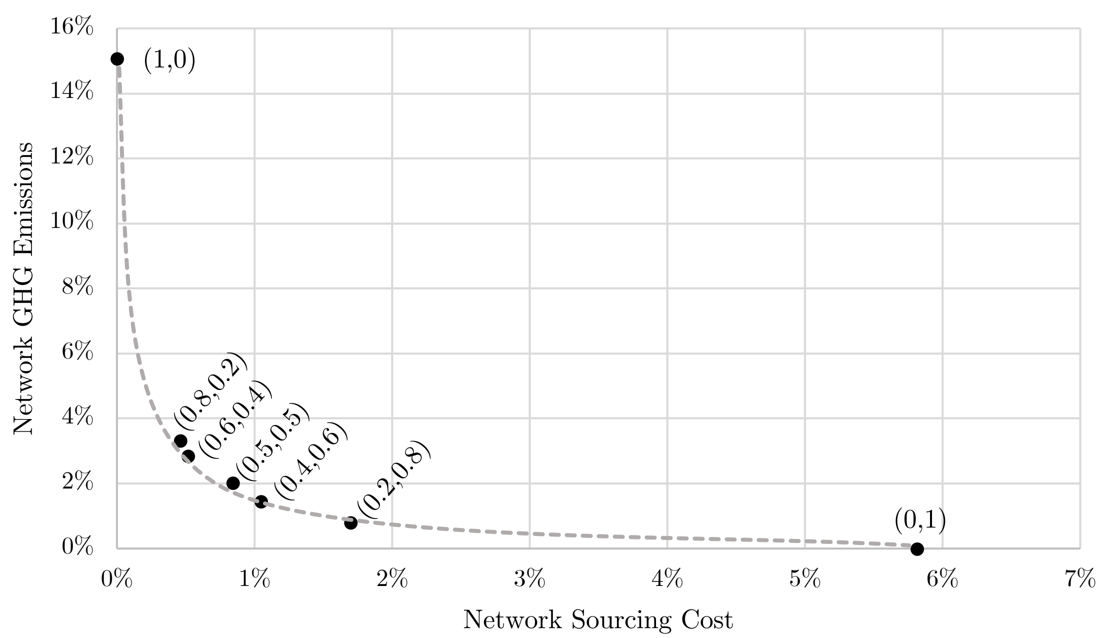
Additionally, the results discussed in the following subsections showcase the difference between model runs with GHG emissions as the sole objective, sourcing cost as the sole objective, and a weighted sum of GHG emissions and sourcing cost as the objective. The results do not include model runs with supply risk and lead time as additional objectives (though network supply risk and network lead time values were still calculated) for the purpose of simplifying illustration in the thesis (i.e., visualizing a two-dimensional Pareto frontier versus a three- or four-dimensional pareto frontier). Sourcing cost was chosen as the objective to balance with GHG emissions because it produces the most interesting tradeoffs on a Pareto frontier. Solutions that are ideal for GHG emissions also tend to be ideal for both supply risk and lead time, so less interesting tradeoffs tend to be produced with those metrics. Additionally, the transportation GHG emissions model inputs correlate strongly with lead time inputs, and there was concern about running the model with correlated variables in the objective function. This concern is discussed in more detail in Section 6.1. For all the model results showcased below, the lead time weight (W_{LT}) and the supply risk weight (W_R) were set to zero.

5.1 Baseline 2030 Scenario

In this subsection, the Baseline 2030 Scenario results are discussed. In the Baseline 2030 Scenario, the estimated emission factors for country energy grids in the year 2030 were used, but the present-day ratios of each of the energy types used were assumed to stay unchanged. To illustrate, if a factory currently uses 20% onsite diesel fuel with the remaining 80% of energy coming from the grid, the baseline scenario would preserve this 20%/80% ratio, while the emission factor used for the 80% of energy coming from the grid would be forecasted to that of the year 2030. Additionally, Iota's historic partner sourcing contract quantities with factories in its supply chain are preserved in this scenario. This means that if Iota has historically contracted to source a certain number of finished goods from a factory each year and wishes to maintain a healthy partnership with that factory into the long-term future, the historic contract quantity has been used as a constraint in the optimization. This scenario was designed to represent the 2030 emissions that would occur if neither Iota nor its suppliers took any action to alter the emissions of the supply chain.

Presented in Figure 5-1, below, is the Pareto frontier generated from running the digital twin optimization model with various combinations of weights on the GHG emissions and sourcing cost objectives. The x-axis displays the network sourcing cost, measured as a percentage increase from the lowest-cost scenario. The y-axis displays the network GHG emissions, measured as a percentage increase from the lowest GHG emissions scenario. Each point represents an optimized scenario with objective function weights labeled as (sourcing cost weight, GHG emissions weight).

Figure 5-1: Baseline 2030 Scenario - Network GHG Emissions & Sourcing Cost Tradeoff



As depicted, the network sourcing cost increases as the network GHG emissions decreases scenario-by-scenario, revealing a non-linear trade-off between sourcing cost and GHG emissions. By comparing the (1,0) and (0,1) weight points, the Baseline 2030 Scenario reveals that Iota could reduce its projected 2030 GHG emissions by as much as

15% just by re-organizing the supply allocation within its available supply chain, but at a nearly 6% increase in sourcing cost.

While it is Iota's prerogative to determine if the 15% reduction in GHG emissions is worth the near 6% increase in sourcing cost, Figure 5-1 reveals more cost-effective solutions. When comparing the (1,0) point, representing the scenario optimized solely for sourcing cost, to the (0.8,0.2) point, a reduction of approximately 12% in GHG emissions can be achieved at less than half a percent increase in sourcing cost. This (0.8,0.2) point, representing an 80% objective weight for sourcing cost and 20% objective weight for GHG emissions, reveals a far more cost-effective solution for GHG emissions reduction than optimizing solely for GHG emissions, though the final reduction in GHG emissions is slightly smaller. Iota must consider all the points along the Pareto frontier and select the point that best fits their needs for sourcing cost and GHG emissions reduction.

Below in Figure 5-2, Iota's 2030 target of a 30% reduction in GHG emissions compared to their 2015 GHG emissions is plotted with the 2030 baseline Pareto frontier from Figure 5-1. The y-axis has been re-marked such that the 2015 actual GHG emissions fall at the 100% mark, the 2030 target of a 30% reduction in GHG emissions is plotted at the 70% mark, and the Pareto frontier falls where the optimized points lie compared to these two standards.

Figure 5-2: Baseline 2030 Scenario with 2015 GHG Emissions & 2030 GHG Emissions Target

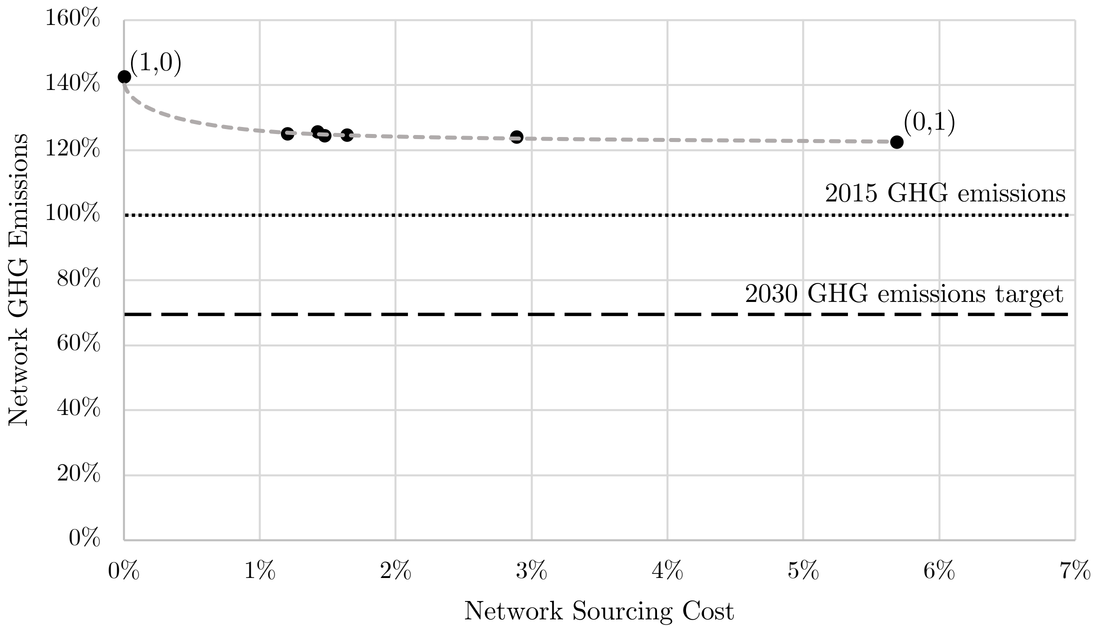


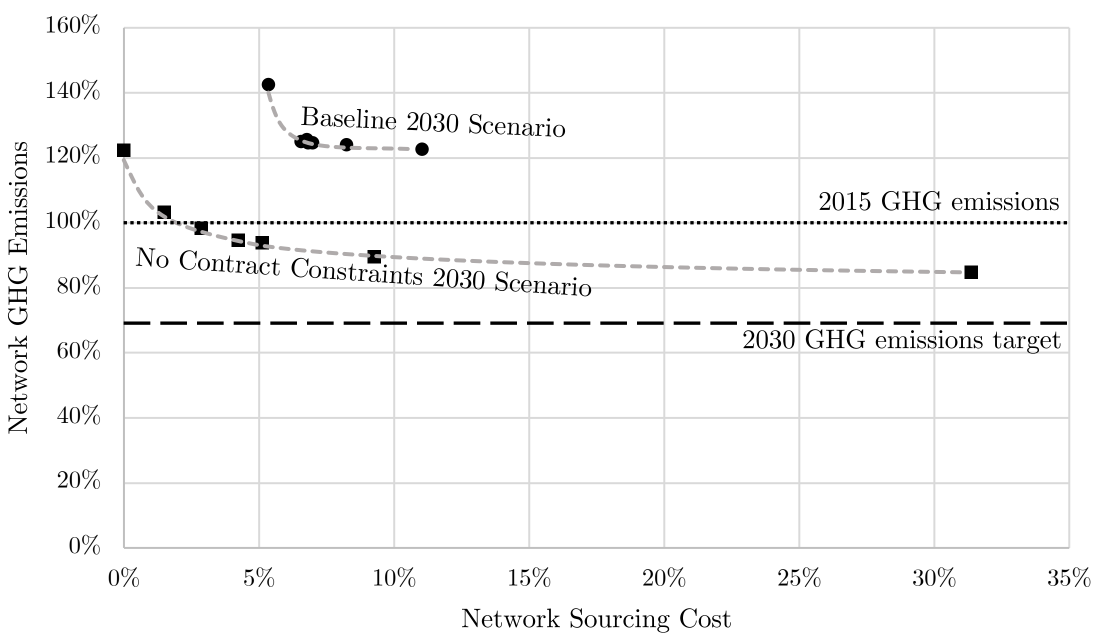
Figure 5-2 reveals that the entire Pareto frontier corresponding to the Baseline 2030 Scenario lies far above the 2015 GHG emissions line and farther yet from the 2030 GHG emissions target. This result is largely attributed to the increase in product demand from 2015 to 2030. Because Iota is producing more products year-over-year, its total emissions will grow if no steps are taken to deliberately reduce those emissions. Given this insight, Iota hoped to explore additional strategies to reduce its emissions. Those additional strategies are discussed in the subsections below.

5.2 No Contract Constraints 2030 Scenario

In this subsection, a new scenario that builds on the Baseline 2030 Scenario is discussed. The No Contract Constraints 2030 Scenario is the same as the Baseline 2030

Scenario except that the contract constraints, which represent Iota's historic agreements to source minimum quantities of finished goods from certain partner factories in its supply chain, are removed. This modified scenario allows Iota to understand the potential impact on emissions if it considers re-evaluating the historic contracts with its partners. In Figure 5-3 below, the No Contract Constraints 2030 Scenario is plotted with squares along with the Baseline 2030 Scenario, 2015 GHG emissions, and 2030 GHG emissions target from Figure 5-2. In Figure 5-3, the x-axis has been re-marked such that the new lowest network sourcing cost represents the 0% mark, and all other sourcing costs are shown as a percentage increase from that point.

Figure 5-3: No Contract Constraints 2030 Scenario



As shown in Figure 5-3, the No Contract Constraints 2030 Scenario shows a reduction in GHG emissions compared to the Baseline 2030 Scenario. Additionally, the

No Contract Constraints 2030 Scenario's Pareto frontier is more extensive in length along the sourcing cost and GHG emissions axes because it reveals a more diverse set of solutions as constraints are removed. The No Contract Constraints 2030 Scenario does not, however, cross the 2030 GHG emissions target line, meaning that re-evaluation of sourcing contracts itself is not sufficient to satisfy the target. In order to meet the aggressive GHG emissions reduction target, Iota again has to consider additional measures to reduce its emissions.

5.3 Sustainable Energy Mix 2030 Scenario

The next scenario is another that builds from the Baseline 2030 Scenario. In order to create this scenario, Iota surveyed factories in its supply chain about plans, realistic expectations, and ambitious expectations for sustainable energy additions and other changes to their energy mixes for the year 2030, given that Iota is placing pressure on them to improve sustainability metrics by that year. In the Sustainable Energy Mix 2030 Scenario, the present-day energy mixes for factories were substituted with the factories' realistic expectations for 2030. All other details were equivalent to that of the Baseline 2030 scenario, meaning contract constraints were utilized. The Sustainable Energy Mix 2030 Scenario is intended to depict the realistic picture of the supply chain in 2030 in which Iota is pressuring its factories to be more sustainable, and it can be compared to the Baseline 2030 Scenario in which there is no change to factory energy mixes from the present. In Figure 5-4 below, the Sustainable Energy Mix 2030 Scenario is plotted with diamonds along with the Baseline 2030 Scenario, 2015 GHG emissions, and 2030 GHG emissions target from Figure 5-2. In Figure 5-4, the x-axis has been re-marked such that the new lowest network sourcing cost represents the 0% mark, and all other sourcing costs are represented as a percentage increase from that point.

Figure 5-4: Sustainable Energy Mix 2030 Scenario

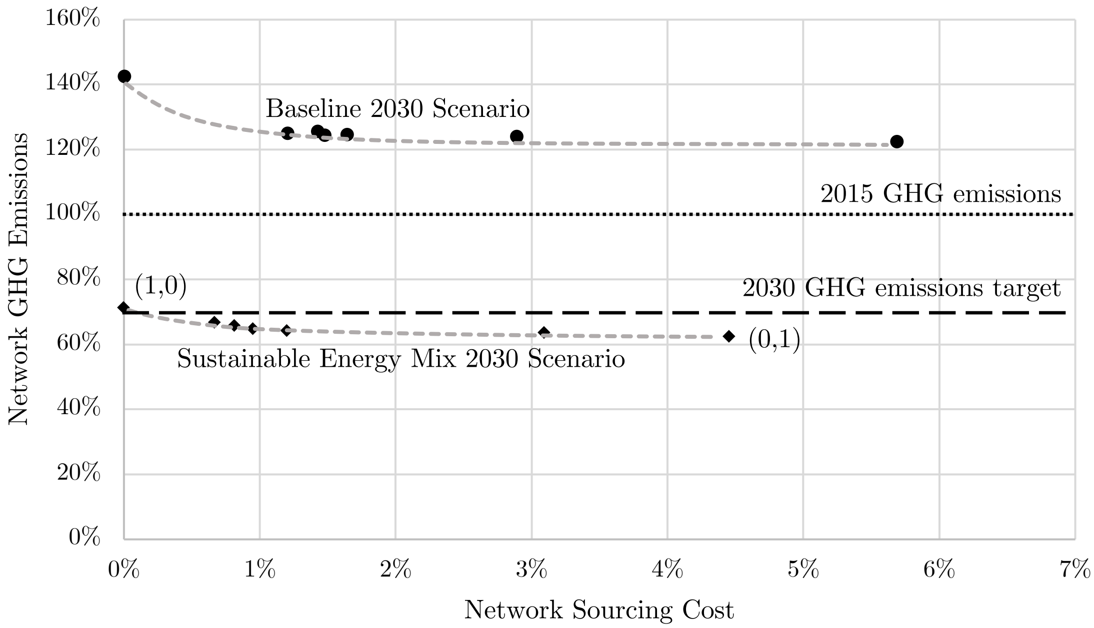
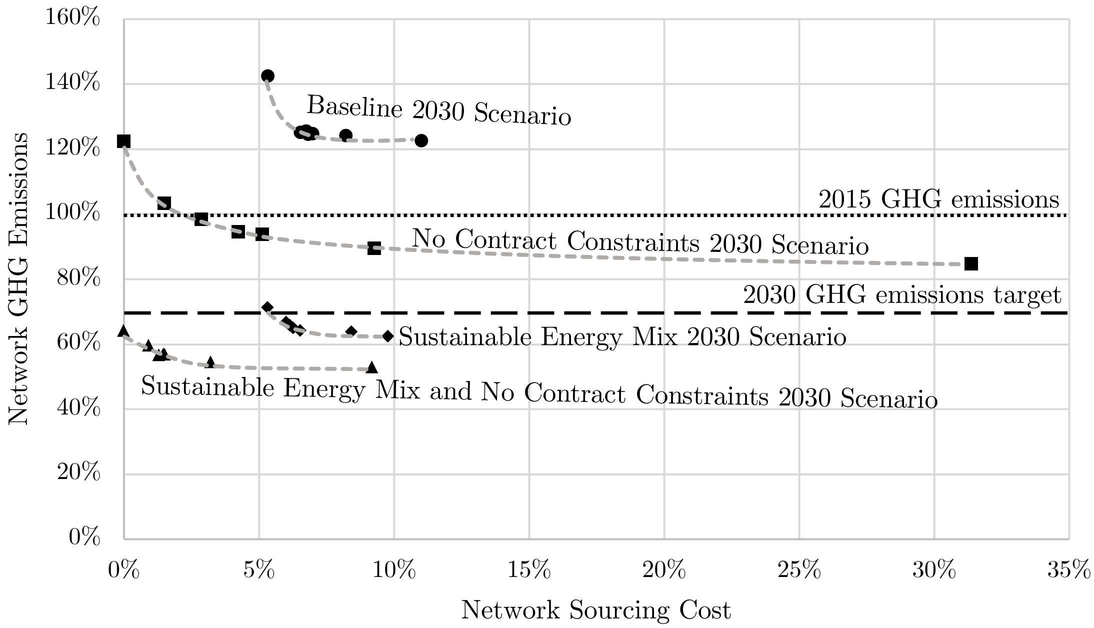


Figure 5-4 reveals that six of the seven cases analyzed within the Sustainable Energy Mix 2030 Scenario meet the 2030 GHG emissions target set by Iota. All but point (1,0), which corresponds to optimizing solely for sourcing cost, allow Iota to meet the target. This result is exciting for Iota because it means that with their realistic expectations for the factories' energy mixes by 2030, they are on-track to meet their emissions reduction target as long as they do not optimize solely for sourcing cost. Because optimization for sourcing cost only is a tempting and common strategy in the industry, this result highlights the importance of explicitly considering emissions performance during sourcing optimization as proposed in this thesis. Without that explicit consideration, Iota would not be on track to meeting its GHG emissions target.

5.4 Sustainable Energy Mix and No Contract Constraints 2030 Scenario

The final scenario discussed is the Sustainable Energy Mix and No Contract Constraints 2030 Scenario. This scenario adapts from the Baseline 2030 Scenario with both the exclusion of contract constraints described in Section 5.2, and the substitution for realistic 2030 energy mixes described in Section 5.3. The Sustainable Energy Mix and No Contract Constraints 2030 Scenario presents the possible outcomes if Iota considers both the future likely outlook of its factories' energy mixes and re-evaluating its historic sourcing contracts with factories. In Figure 5-5, the Sustainable Energy Mix and No Contract Constraints 2030 Scenario has been plotted with triangles along with the Baseline 2030 Scenario in circles, the No Contract Constraints 2030 Scenario in squares, and the Sustainable Energy Mix 2030 Scenario in diamonds. These four scenarios, along with the 2015 GHG emissions and 2030 GHG emissions target give the full picture of emissions reduction possibilities for Iota's supply chain. In Figure 5-5, the x-axis has been re-marked such that the new lowest network sourcing cost represents the 0% mark, and all other sourcing costs are shown as a percentage increase from that point.

Figure 5-5: Sustainable Energy Mix and No Contract Constraints 2030 Scenario



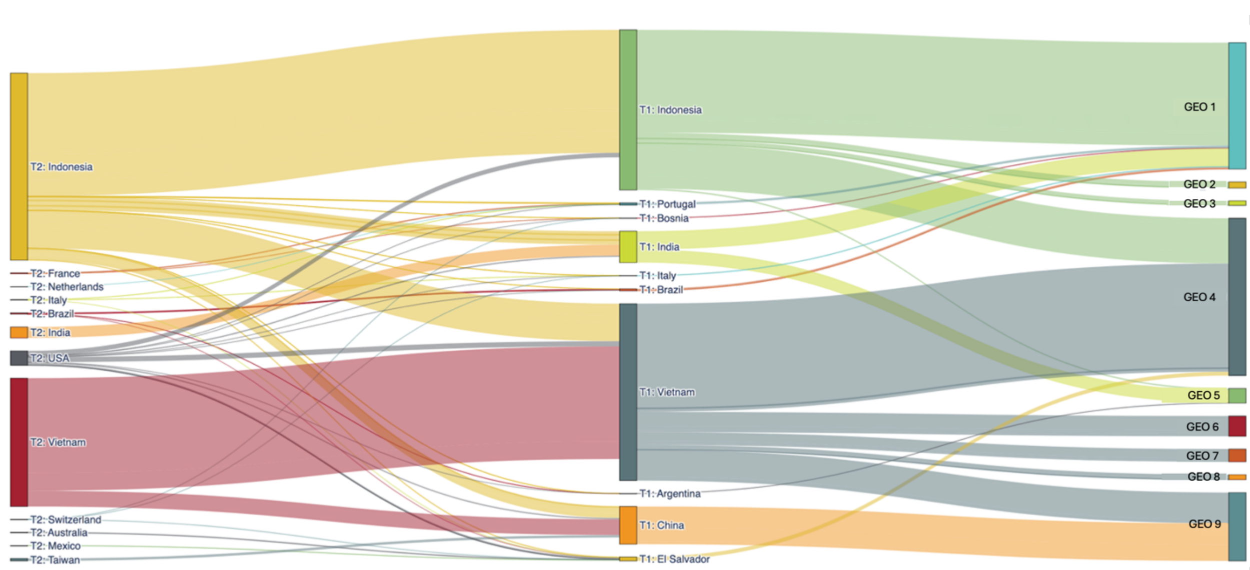
As depicted in Figure 5-5, the Sustainable Energy Mix and No Contract Constraints 2030 Scenario reveals the lowest possible GHG emissions for 2030. In all seven (7) cases examined within the scenario, Iota is projected to meet its 2030 GHG emissions target. This scenario would allow Iota to optimize for sourcing cost and meet its emissions targets. The downside to re-evaluating contracts with factories could be diminished relations with existing factory partners. Iota has the flexibility to continue its historic contracts and optimize its supply chain partially for GHG emissions if it wishes to meet its targets without re-evaluation. Even if it is undesirable for Iota to re-evaluate the current contracts, the methods and analysis developed in this thesis can provide helpful insights when the company negotiates new long-term contracts with its suppliers going forward.

5.5 Detailed Findings Underlying the Optimal Solutions

The preceding subsections detailed four (4) scenarios in which Pareto frontiers were generated with points that each represented an optimized network based on a given set of weights used on the two objectives (sourcing cost and GHG emissions). This subsection describes the underlying insights behind those points. Within each optimized point is a sourcing solution detailing how many of each finished good and material should come from each factory in the multi-echelon manufacturing network, and how many of each finished good and material should use each transportation route and mode within the distribution network. This solution can be used by Iota to create a mapping of the ideal flow of goods throughout the network. When Iota selects the optimized point that meets their sourcing cost and GHG emissions needs, they can use its detailed material flow as a sourcing plan within their supply network.

The subsequent discussion illustrates an example of the detailed solution underlying one of the optimized points. The output can be visualized in many different ways. Aside from a detailed table of sourcing quantities, transportation routes, and modes, a Sankey diagram can be generated to help visualize the quantities of goods flowing from T2 factories to T1 factories, and eventually to GEOs. Sankey diagrams display the flow of resources through networks and are useful for depicting high-level views of complex networks.[30] These diagrams can be interpreted as flows of goods from upstream (left) to downstream (right) and the thickness of each line indicates the relative quantity of goods flowing from a source (left) to a destination (right). An example Sankey diagram of an optimized network is displayed in Figure 5-6. The Sankey diagram presented here has been aggregated to the country-GEO level for the protection of Iota's factory network, but it can be viewed on a factory-GEO basis by Iota to gain a detailed understanding of the flow of goods throughout the optimized network. In this diagram, the countries with utilized T2 factories are listed on the left side of the figure, the quantity and direction of goods flowing from T2 factories to T1 factories are depicted by the bars extending from left to center figure, the countries with utilized T1 factories are shown in the center of the figure, and the quantity and direction of goods flowing from T1 factories to GEOs are shown by the bars extending from center to right figure.

Figure 5-6: Example Optimized Network Sankey Diagram



This kind of Sankey diagram provides insight to Iota about the manufacturing locations that are being most heavily utilized in their optimized network. It also provides a high-level depiction of which trade lanes are being identified as optimal so Iota can grasp the overall strategy that would be required to employ the optimized network in its supply chain.

In addition to the Sankey diagram, a more geographically-oriented map can be generated to visualize the network's configuration and the locations generating the most GHG emissions. Bar charts or lists of the most heavily emitting factories per unit or highest contributors to emissions total can also be generated to raise awareness of the most heavily emitting elements of the optimized network. These visuals provide aide to Iota's management to recognize the parts of the network that require the most attention to reduce emissions. Management can use this information to either divert manufacturing and distribution away from high emitting factories or negotiate with those factories to encourage them to reduce their GHG emissions. For Iota's protection, detailed maps will not be depicted in this thesis.

Chapter 6

Recommendations for Model Expansion and Implementation

This section provides recommendations for Iota's current model improvements and expansion along with suggestions for model implementation should other entities decide to adapt the methodology described in this thesis.

6.1 Explore Supply Risk and Lead Time as Concurrent Objectives with GHG Emissions

In the results discussed in the Analysis section, the objective function weights for supply risk and lead time were set to zero and the model was optimized only for combinations of GHG emissions and sourcing cost. The business stakeholders at Iota were most concerned about the trade-off between these two objectives, so most of the time dedicated to model runs and analysis were focused on these objectives.

It is recommended that Iota take further steps to explore GHG emissions vs supply risk and GHG emissions vs lead time objectives in the future, given more time, to check for meaningful results. A cautionary remark is warranted for this study, though. In many instances, travel distance is used to calculate both transportation GHG emissions and lead time, making these two metrics strongly correlated. When optimizing for GHG emissions and lead time, the algorithm may be double-counting the effects of travel distance in the optimization, and results may be unintentionally skewed as an effect. Because total GHG emissions are not solely comprised of transportation GHG emissions (i.e., manufacturing GHG emissions also contribute to total GHG emissions and are not affected by travel distance), it is unclear how much of an effect the double-counting of travel distance will have in the overall optimization results. In order to make this determination, it is recommended that Iota perform a study to clarify the magnitude of correlation between total GHG emissions and lead time variables before performing the optimization with both GHG emissions and lead time as weighted objectives.

6.2 Input Data Improvements

One of the biggest challenges faced in the integration of GHG emissions as a metric in the Digital Twin model was data availability. Data was available on a granular level for T1 manufacturing facilities, but it became less granular and less reliable at the T2 manufacturing level. This is because T2 data is reported by a T2 facility to its corresponding T1 facilities before being provided to Iota, so there is a muti-step chain of reporting occurring in the data collection process. Iota considers the T2 data to be less reliable than T1, which makes the model's results less reliable when including T2 in scope. Iota is taking steps to improve the granularity and reliability of this T2 data, which will improve confidence in the Digital Twin's results in future iterations. This effort is critical for Iota to gain more accurate GHG emissions predictions for comparison to GHG emissions reduction targets, especially as it nears its 2030 target year.

It is recommended that any institution beginning to use the methodology described in this thesis for multi-echelon networks first ensure that it has sufficient and reliable data from upper echelons in its network. Without reliable data, the institution cannot be confident in the exact values of the results of the model.

It is also recommended that Iota conduct a formal sensitivity analysis on the Digital Twin model to adequately understand its variability and reliability. Iota should first understand the sensitivity of the model so its management team understands the risks and degree of accuracy before using the model for its supply planning efforts.

6.3 Additional Tier Scope

In the future, as more information on higher echelons of Iota's network becomes available, it is recommended that Iota integrate higher tiers in the Digital Twin model to optimize all of its Scope 3 emissions, traceable to the farm level. At this point, Iota's emissions data above the Tier 2 level may not be granular enough to be added to the Digital Twin model, but it is recommended that Iota make additional high-tier data gathering efforts to make this a possibility.

Additionally, as a next step, Iota would benefit from integrating its middle and last mile distribution network into the Digital Twin model. Integration of these elements would allow for an end-to-end optimization of the entire network. With both higher tier capability and middle/last mile capabilities, the Digital Twin model could help to optimize GHG emissions for the entire supply chain.

6.4 Refresh Energy Mix Forecasting

The projections of network GHG emissions utilized in the Sustainable Energy Mix 2030 Scenario are dependent on the energy mix forecasting from the T1 and T2 factories. As 2030 approaches, the factories' estimations of their feasible changes to energy mixes will evolve. Refreshing those forecasts in the model as they change at the factory level will allow for a more accurate network GHG emissions estimate into 2030.

6.5 Allocate Supply According to Optimized Plan

The final recommendation for Iota and any other entity attempting to make use of the methodology described herein is to integrate the GHG emissions optimized supply plan created by the Digital Twin into business supply planning decisions. This seems like an intuitive suggestion, but some businesses experience a disconnect between tech-focused divisions and stakeholders making planning decisions. It is imperative for Iota to ensure that the Digital Twin's supply planning outputs make it into the hands of the right stakeholders to support decisions for Iota to meet its 2030 GHG emissions targets.

Chapter 7

Conclusion

This thesis strove to use a multi-objective optimization strategy to minimize GHG emissions across Iota's multi-echelon product manufacturing and distribution network while maintaining desirable levels of alternate objectives such as sourcing cost, lead time, and supply risk. GHG emissions were incorporated as a new element into Iota's existing multi-objective mixed-integer linear program Digital Twin model and the minimization of GHG emissions was added as a new part of the multi-objective function. Execution of the revised multi-objective mixed-integer linear program with GHG emissions resulted in multiple scenarios for Iota to utilize in their supply planning and emissions reduction efforts.

The Baseline 2030 Scenario analyzed in this thesis revealed that without any action on Iota or its factories' part, it would not likely be able to meet its supply chain 2030 Scope 3 GHG emissions targets given the growth of the company. The Sustainable Energy Mix 2030 Scenario demonstrated that, with the current plans for more sustainable energy options at the factories, Iota will likely be able to achieve its 2030 Scope 3 GHG emissions targets despite its growth. With the current projections for energy mixes, it is recommended that Iota stray from the option to optimize solely for sourcing cost, and that it begins using the Digital Twin model described in this thesis to optimize in part for GHG emissions to meet its target. If Iota wishes to optimize solely for sourcing cost, opportunity to meet GHG emissions targets also exists by negotiation of sourcing contracts and promoting low carbon energy options to those factories with contracts.

At the commencement of this project, a path to meet the 2030 Scope 3 GHG emissions target was unclear, though Iota was determined to do whatever it took to meet the target. This project was a large success in providing sourcing strategies to meet the GHG emissions target and validating that the sustainable energy efforts of Iota's network factories would be sufficient to support Iota in meeting the target. The Digital Twin model can be used to help make sourcing roadmaps for Iota's future sustainability efforts, such as its 2050 net zero GHG emissions target, so it has clear direction and can make early strides toward meeting the target.

It is worth acknowledging that the Digital Twin model is not perfect, but it provides value nonetheless. The model could be improved with better data inputs and additions of upstream and downstream tiers within the multi-echelon network. Because of limitations in data inputs, the exact magnitudes of GHG emissions estimates may not come to precise fruition, but they are helpful in making strategic sourcing decisions and selecting certain factories over others in the network.

This thesis served as a proof of concept for the idea of optimization of GHG emissions within a global multi-echelon manufacturing and distribution network. The Digital Twin model was the in-situ implementation of this concept within Iota's network. The product will continue to serve Iota, but its concept could be instituted within networks of other organizations. With good access to data, other organizations could utilize the framework described herein to reduce their carbon footprints, which would be a great service to the planet and help in meeting the Paris Agreement.

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