Carbon Efficient Network Design:
Evaluating the Trade-Offs Between Carbon Emissions, Transportation Cost, and Delivery Time for a Middle-Mile Distribution Network

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ABSTRACT

The transportation sector is the third largest contributor to greenhouse gas (GHG) emissions, accounting for over 28% of total U.S. emissions and over 14% of global emissions in 2018. As climate change and its negative effects have grown significantly, efforts to reduce GHG emissions have become an important objective on a global, national, and corporate scale. One approach is to design a distribution network that minimizes transportation carbon emissions while meeting its primary Key Performance Indicators (KPI). It is important for companies to understand the trade-offs between those KPIs, which may include minimizing the carbon footprint, minimizing transportation costs, and meeting the network's delivery time requirements. This research introduces a multi-echelon Green facility location problem (FLP) that focuses on the middle-mile. It incorporates intermodal and alternative-fuel transportation modes and optimizes for the tri-objective of variable transportation cost, delivery time and carbon emissions. By using the ε-constraint method, Pareto frontiers for carbon emissions vs. cost and carbon emissions vs. delivery time were plotted, providing the trade-offs between objectives. Optimal scenarios on the Pareto frontiers were identified to align with 1.5°C and well-below 2°C global climate scenarios according to the Science-Based Targets initiatives. The research team found that the trade-offs between carbon emissions vs. delivery time are non-linear and much more significant than carbon emissions vs. transportation variable cost. In order for firms to reach Science-Based Targets, it is necessary for companies that have transportation heavy operations with short delivery timelines to shift all transportation to vehicles powered by lower carbon fuels. This research informs the approach to start incorporating environmental considerations in the strategic decision-making process for supply chain network design.

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- *Namuun Purevdorj*

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1. Introduction

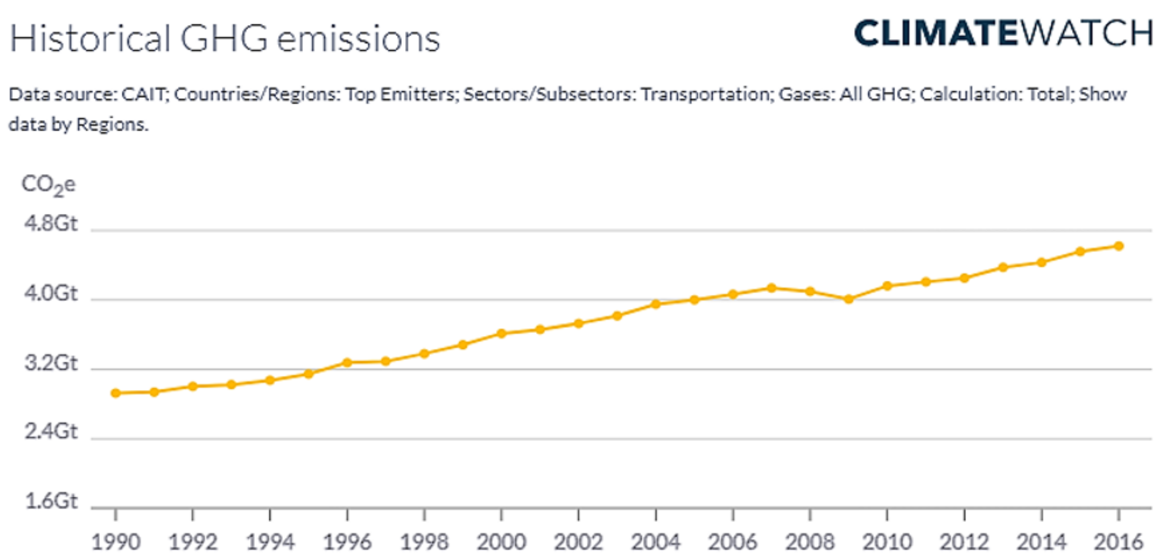
1.1 Motivation for the Study

Traditionally, supply chain network design has focused on economic objectives. However, as climate change is occurring and concerns over its effects have grown significantly over the past few decades, environmental objectives have become an important consideration in supply chain decisions.

The transportation sector is not only vital for supply chains and the global economy but also the third largest contributor of greenhouse gas (GHG) emissions (International Energy Agency, 2019). At the current pace of economic growth, emissions from the transportation sector are set to double by 2050 (ITF, 2019). In 2018, the Intergovernmental Panel on Climate Change (IPCC) warned that it is not possible to avoid catastrophic impacts of climate change if global warming exceeds 1.5ºC above pre-industrial[1] temperatures. Since carbon emissions, a shorthand for GHG emissions, is the leading cause of global warming, efforts to estimate, track and reduce its release in the atmosphere have become integral for global-, government- and corporate-level sustainability goals.

Figure 1

Historical Transportation Sector GHG Emissions in the United States.
Source: Climate Watch, 2019.



[1] The multi-century period prior to the onset of large-scale industrial activity around 1750. The reference period 1850–1900 is used to approximate pre-industrial (IPCC, 2020)

On a global scale, in 2015, 196 countries adopted the Paris Agreement, a legally binding international treaty that's part of the United Nations (UN) Framework to fight climate change. Over the long term, the universal agreement aims to limit the increase in global temperatures to well below 2°C, and preferably to 1.5°C compared to pre-industrial levels (United Nations, 2015). In addition, methodologies and standards to measure and report carbon emissions have been established through joint initiatives between international organizations, governments and corporations. The Greenhouse Gas Protocol (GHGP) Corporate Standard as well as the Global Logistics and Emissions Council (GLEC) Framework are the main carbon accounting methodologies utilized by businesses to quantify their carbon emissions. The Carbon Disclosure Project (CDP), however, serves as the leading reporting platform for enterprise emissions, providing and acknowledging the increasing transparency of participating organizations' carbon emissions accounting and reduction. The CDP along with the UN Global Compact, World Resources Institute (WRI), and the World-Wide Fund for Nature (WWF) partnered to create the Science-Based Targets initiative (SBTi). The initiative provides tools that help businesses world-wide set carbon emissions reduction targets that are in line with the climate goals of limiting global warming to 1.5°C.

In the United States, the transportation sector is the largest contributor to GHG emissions, which accounted for 28.2% in 2018 (Office of Transportation and Air Quality, 2020). Light-duty vehicles, medium- and heavy-duty trucks, and airplanes are among the top three modes of transportation that contribute to GHG emissions - 59%, 23%, and 9%, respectively (Office of Transportation and Air Quality, 2020). Given this fact, stakeholders in logistics and transportations have started to locally strategize and implement policies to achieve these global goals. The United States has set goals of progressively reducing carbon emissions by 50 to 52% by the end of 2030, and reaching net zero carbon emissions by no later than 2050, compared to the emissions level in 2005 (The United States Government, 2021). Past efforts at the national level include President Obama's Climate Action Plan, bills on renewable energy utilization, and GHGs inventory regulation by states. Policies at different levels help all stakeholders to participate and navigate actions to take.

On a corporate level, companies such as Middle-Mile Transportation Network (MMTN), have joined initiatives such as The Climate Pledge that call organizations globally to implement measures that combat climate change. MMTN has pledged to reduce 50% of its total shipments' carbon emissions by 2030 and become net zero carbon by 2040 across their businesses (The Climate Pledge, 2019). Since transportation plays a huge role in MMTN's operations, the company has been investigating ways to design a more carbon-efficient transportation network that further supports its zero-carbon goals.

This research will inform the carbon-efficient network design scenarios in the middle-mile scope for MMTN and other organizations. Global transportation networks are typically divided by three stages: first-mile, middle-mile, and last-mile. The first-mile refers to the outbound delivery from the suppliers and the last-mile refers to the inbound delivery to the customers. The middle-mile is the entire domestic transportation network between the first and last-mile and typically has more stable and predictable flows, providing opportunities for optimization.

1.2 Research Questions

The capstone seeks to solve for the optimal transportation network that will minimize MMTN's transportation carbon emissions while meeting its customer demand. More specifically, the below questions need to be explored to build the optimal network solution:

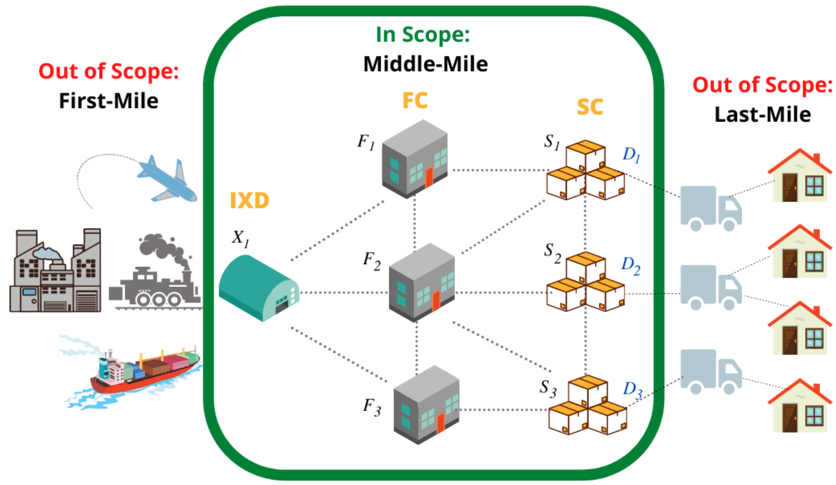
1. What are the best locations for the various nodes that will provide the customer coverage and maximize carbon efficiency opportunities?
2. What are the routes that will best connect the nodes to meet customer demands? What are the best routes given the transportation mode limitations and/or opportunities?
3. What are the modes of transportation for each of the routes that will minimize emissions? How can efficient use of transportation (increased fill rate, or load factor) and alternative carbon-efficient transportation (electrification of the fleet, multi-modal network design) influence absolute emissions?
4. How do we best estimate the GHG emissions of the transportation network? What are the estimated target emissions for the firm?
5. What are the tradeoffs between carbon emissions vs. delivery time and variable transportation cost?

The scope of the capstone only includes the middle-mile of MMTN's supply chain network. A typical middle-mile network consists of three types of nodes: Inbound Cross-Docks (IXD), Fulfillment Centers (FC), and downstream Sorting Centers (SC) (Figure 2). They are connected in a three-echelon model with a forward flow from IXD to FC, and from FC to SC. The IXDs receive inventory from domestic and international vendors. The IXDs then become the point of origin for the fulfillment process. After receiving the shipments, the FCs store the inventory until there is demand. It is a range of warehouse facilities where each specializes in a different size, weight, and product type. Lastly, the SCs consolidate the inventory received from different FC locations before the last mile distribution phase (Rodrigue, 2020).

For the purposes of this research, the scope of the research will include only the transportation flows and vehicles used between these three nodes as seen in Figure 2. The total emissions for this research will only include emissions from vehicles and will exclude emissions from the facilities. The total costs for this research only include variable transportation costs of operating vehicles and excludes all other costs such as capital expense.

Figure 2

Middle-Mile Distribution for the Transportation Network



1.3 Approach

This capstone aims to design transportation distribution network scenarios that reduce the carbon emissions of MMTN's activities that meet both global carbon emissions reduction targets as well as customer demand. In addition, the research hopes to assess the trade-offs of reducing carbon emissions to transportation cost and on-the-road delivery time.

To optimize a carbon-efficient network design, three key objectives were included in the model: carbon emissions, delivery time, and variable transportation cost. There are several key trade-offs when one variable is maximized over the others. For instance, less carbon intensive long-range vehicles, such as trains, are much slower than carbon intensive airplanes. How does the carbon intensity of a shipment differ for each scenario? How should the company choose one mode of transportation over the other for certain lanes? What is the extent to which transportation by rail, water or air make economic sense? Additionally, how does the utilization of alternative-fuel vehicles such as electric trucks and biofuel planes impact the total carbon emissions of the transportation network?

This project developed a model using Green Facility Location Problem (FLP) to minimize these objectives, and used the ε-constraint method to generate Pareto frontiers that quantified the trade-offs. Additionally, to account for, analyze and determine the reduction targets of MMTN's transportation carbon footprint, the Global Logistics Emissions Council (GLEC) Framework and Science-Based Target Initiative (SBTi) tools have been utilized.

The remainder of the capstone is organized as follows: In Section 2, a thorough literature review is conducted to assess and understand the existing scholarship around network design, the middle-mile, emerging scenarios of carbon-efficient transportation and network design, emerging options for transportation with low carbon intensity in the United States, and the methods of measuring carbon intensity. Following the literature review, the Section 3 and 4 cover the data and methodology of the research as well as the results derived. Finally, Section 5 will delve into the insights, recommendations and limitations of the research.

2. Literature Review

The scope of this research is to solve for the optimal supply chain network within the middle-mile transportation network of MMTN that meets carbon emissions reduction targets as well as customer demand.

There is a significant amount of literature relevant to the scope of this research such as network design, transportation, carbon emissions accounting and Pareto optimality. In this literature review, we explored different network design approaches. Previous studies have utilized existing and emerging real-world scenarios to better understand and optimize for traditional objectives such as minimizing cost. While, the emerging green network design studies have included impacts on the environment such as minimizing carbon emissions as an additional objective.

2.1 Network Design

2.1.1 Traditional Network Design Models and Solutions

Supply Chain Network Design (SCND) is the configuration of the supply chain network by determining the optimal location and size of the facilities (also known as nodes) as well as the flow (also known as arcs) through these facilities to best distribute materials and products (Rezaee et al., 2017; Watson et al., 2012). The SCND, thus, has an influence on supply chain planning decisions at three different levels of an organization: strategic, tactical, and operational. From a strategic perspective, SCND deals with decisions such as the location of facilities and the allocation of customers. The tactical decisions will include the transportation modes among the facilities as well as inventory volume and type in facilities. Lastly, operational-level decisions include the fulfillment of customer demands such as the routing problem (Farahani et al., 2014; Rezaee et al., 2017; Zheng et al., 2019).

To solve for the optimal solutions in decision making, there has been extensive operational and supply chain research conducted on SCND problems (Peng et al., 2016). Since locating the facilities is one of the key strategic decisions made in the SCND problem, Facility Location Problems (FLP) are one of the main researches utilized (Farahani et al., 2014).

The FLP's key goals are to determine the facilities to open and the allocation of the demand (or customers) to these facilities (Melo et al., 2009). The distance-based approach solves for the optimal location of multiple nodes by minimizing the average weighted distance from demand locations (Watson et al., 2012). Traditional SCND and FLP models can be classified based on a variety of considerations, including the uncertainty of demand and cost parameters (i.e., stochastic vs. deterministic models), supply chain scale or echelons (i.e., number of layers), the multiplicity of planning period (i.e., single or multiple periods), forward and/or backward product flows, the number of products (i.e., single or multiple products), the type and number of objective functions (cost minimization, profit or service level maximization, etc.) (Rezaee et al., 2017). FLPs can also be differentiated by their solution space Continuous and Discrete Models (Daskin, 2008).

The multi-echelon (or multi-layer) FLP research is scarce, as much of the research focuses on a specific layer of the supply chain, typically the distribution center or warehouse (Melo et al., 2007). For example, Watson et al. (2012), presented a three-echelon supply chain model that determined warehouse locations with fixed plants and customers, optimizing for the minimization of total transportation and warehouse cost. Moreover, many FLP models have incorporated other supply chain decisions in addition to the described location-allocation decisions, such as capacity, inventory, procurement, production, routing, and transportation modes (Melo et al., 2007). Cordeau et al. (2006) integrated the decisions of inventory, production, and transportation mode in their network design. Carlsson and Ronnqvist (2005) only considered the location and transportation mode decisions in their model, allowing only one transportation mode for each arc. Appendix F outlines additional traditional network design literature.

2.1.2 Carbon Emission in Network Design Models

SCND models traditionally focus on minimizing fixed and operating costs, but because of SCND's role in the economic and environmental performance of a firm as well as the growing need to reduce the emissions within the supply chain, research that integrates carbon emissions decisions into the SCND problem has been increasing in recent years (Peng et al., 2016).

As the transportation sector becomes the largest contributor to carbon emission, SCND plays a role on the strategic level to limit and reduce the impact to the ecosystem. This is because the design of the network strongly influences the transportation performance in terms of cost and emissions (Martínez & Fransoo, 2017). There are three main approaches to how researchers have incorporated carbon emissions as an extension of the traditional SCND problem (Wang et al., 2020). The first method is to reduce emissions in the supply chain when designing the supply chain network by accounting for the emissions by converting it to a cost as a carbon price variable in the economic (total cost) objective(s). Some recent research examples that incorporate carbon price as part of the total cost objective function are from Rezaee et al (2017) and Jiang et al (2019), who solved for optimal discrete, multi-echelon SCND scenarios. The second approach is to treat carbon emissions as a constraint by way of strict emissions caps, emissions taxes, or emissions permission trade. Zhou and Wen (2020) provide a comprehensive review of the most recent studies in this area. The third method treats total emissions as a separate objective function to be minimized in the SCND model.

Bouzembrak et al. (2011) and Wang et al. (2011) adopted multi-objective SCND models to minimize both the total cost and total carbon emission in the supply chain.

The scope of the operational decisions that are included in the total emissions and total cost objectives vary widely in the current literature. For instance, in their single-objective SCND model, Jiang et al. (2019) considered the total cost and the emissions from the operational activities, such as procurement, manufacturing, distribution, and recycling decisions. Peng et al. (2016) introduced a bi-objective optimization model that considered emissions and costs generated exclusively from the product transport and product storage at both factories and sales points. However, in their bi-objective SCND models, Wang et al. (2011) considered the transportation cost, handling cost, fixed facility setup cost, and environmental protection investment costs in their cost objective. For their total emissions objective, they considered emissions generated from the facilities as well as from the flow (or distance) in the network.

Another relevant line of research that also considers minimizing emissions as an objective function is an extension of the FLP. This model is commonly known as the Green FLP (GFLP). The GFLP objective aims to determine the ideal number and location of facilities to reduce the carbon emissions while meeting the demand coverage (Martínez & Fransoo, 2017). Velázquez-Martínez et al (2014) developed a multi-objective FLP model that found the trade-offs between carbon emissions and the cost of transportation while solving for the optimal facility locations of a single-layer (or echelon) of a multi-echelon supply chain network. Their research illustrates that a company can invest more in adjusting the distance and replacing its facilities while reducing the carbon significantly (Velázquez-Martínez et al., 2014). They adapted the p-median problem (discrete FLP model), as the assumptions included deterministic demand and a finite set of candidate locations. For the cost objective, they included the labor cost, transport-related costs such as the use of the truck (i.e., depreciation), and the number of trips between nodes (by taking into account distance and truck capacity between nodes). They also utilized the Network for Transport and Environment (NTM) methodology in formulating the carbon emissions objective function. The NTM methodology estimates carbon emissions through the following parameters: fuel consumption, distance traveled, and weight per shipment (Network for Transportation and Environment, 2008). In addition, the research allowed for multiple truck types with different capacities to be assigned based on the demand node constraints, enabling a better understanding of the different location solutions dependent on transport infrastructure or other constraints apparent at the demand node (Velázquez-Martínez et al., 2014).

Since many of the studies in the past have concluded that an increase in the number of open facilities will reduce emissions, Martínez & Fransoo (2017) presented a bi-objective GFLP that only considered the emissions and cost from mobile sources (i.e., transportation) and excluded the fixed emission and cost from stationary sources such as the facilities. By excluding costs and emissions of stationary sources their formulation enabled a better understanding of the trade-off between the distance and utilization when making location-allocation decisions (Martínez & Fransoo., 2017). Thus, only the cost and emissions from mobile sources, such as transportation mode, capacity, speed, and load factor will be included in the scope of this study's SCND problem.

Although the literature in network design is rich and broad, there currently is not a model with all the parameters and considerations configuration that will directly apply to our research. This research solves for a multi-layer and middle-mile specific SCND problem with a tri-objective to minimize the total transportation costs, carbon emissions, and On-The-Road (OTR) delivery time. Section 2.5 summarizes the key differences of this research compared to previous relevant studies.

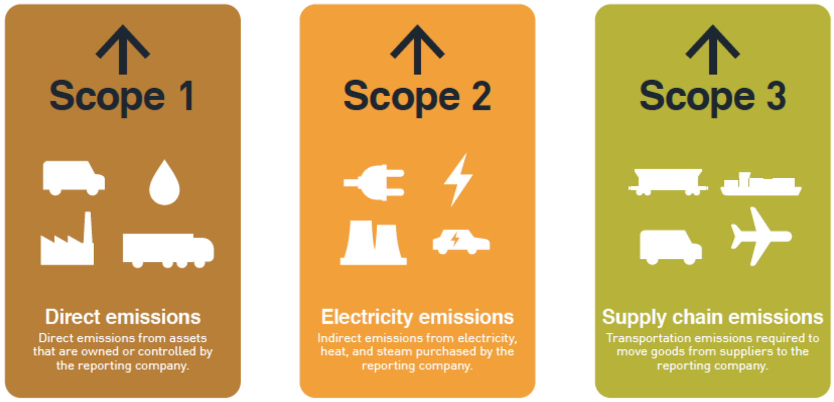
2.2 Measuring Carbon Emissions in Supply Chains

"Carbon" is commonly used as a shorthand for GHGs because carbon dioxide (CO_2) is the largest GHG emitted as well as the most important anthropogenic GHG in total impact. However, the GHGs produced by transportation activity also include the following gases: methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbon (HFC), perfluorocarbons (PFC), nitrogen trifluoride (NF_3), and sulphur hexafluoride. To easily measure the different GHGs in an aggregated manner, a single standard metric expressed as carbon dioxide equivalent (CO_2e) has been established globally (Boukherroub, Tesseda et al., 2017). This standard metric uses the relative impact of a GHG on global warming using the equivalent concentration of CO_2.

There are several methodologies to account for carbon emissions. Most relevant for this study is the GHG Protocol, which established widely-adopted principles for carbon accounting across all sectors, and the Global Logistics Emissions Council Framework, which offers freight transport specific guidance aligned with the GHG Protocol. The GHG Protocol's standardized framework divides the emissions into three scopes (see Figure 3). Scope 1 includes direct emissions, defined as emissions from assets owned or controlled by the reporting company. Scope 2 includes the indirect electricity emissions, defined as the emissions from the production and distribution of electricity. Finally, Scope 3 includes all other indirect emissions, known as the indirect emissions from the reporting company's supply chain. It is estimated that 80% of a business' emissions occur in Scope 3 (WBCSD and WRI, 2011), largely from the transportation and distribution emissions required to move goods from and to the reporting company.

Figure 3

GLEC Framework's Carbon Emissions Calculation Scopes

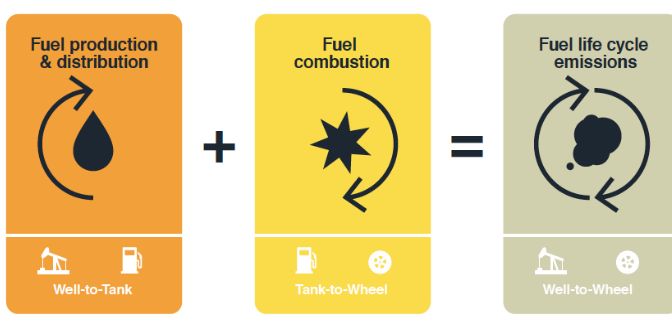


Source: Global Logistics Emissions Council Framework for Logistics Emissions Accounting and Reporting Version 2.0 (p. 16) by S. Greene & A. Lewis, 2019, Smart Freight Centre.

Furthermore, the GHG Protocol and GLEC Framework require the inclusion of emissions from the entire fuel life cycle, known as well-to-wheel (WTW) emissions, in order to capture the full impact of GHG emissions on the environment. As illustrated in Figure 4 below, the full fuel life cycle, or WTW cycle, consists of two processes: well-to-tank (WTT) and tank-to-wheel (TTW). The WTT process includes all the activities, such as extraction, processing, storage and delivery, between the source of the energy (the well) up to the point of use (the tank). However, the TTW emissions are from fuels combusted to power Scope 1 activities (the wheel) (Greene & Lewis, 2019). Hence, the WTW is the sum of WTT and TTW emissions.

Figure 4

The Fuel Life Cycle for Carbon Accounting



Source: Global Logistics Emissions Council Framework for Logistics Emissions Accounting and Reporting Version 2.0 (p. 16) by S. Greene & A. Lewis, 2019, Smart Freight Centre.

For Scope 3 emissions, the GLEC Framework provides an activity-based calculation method to derive total carbon emissions (in kg CO_2 emissions) where primary data are unavailable (see Appendix A for more details):

1. Calculate total tonne-kilometers (tkm): Find and capture the shipment weight and distance traveled of all freight transport activities (see Appendix A, Equation 2).
2. Find the fuel efficiency or CO_2e (carbon equivalent) intensity factors that best represents the transport conditions
3. Convert total activity data (tkms) to GHG emissions by multiplying the activity data with fuel efficiency or CO_2e intensity factors. (See Appendix A, Equation 3 and 4). If using the CO_2e intensity factors, the underlying activity data must account for full WTW and all GHGs.

In addition to the total carbon emissions calculation, carbon emissions intensity (carbon intensity) is another metric that companies use to track, analyze and strategize emissions reduction efforts (Greene and Lewis, 2019). The carbon intensity is derived by the emissions divided by the logistics activity, typically per tonne-kilometer. While we are using industry average carbon intensity factors for our calculations, companies can create their own custom intensity factors to further quantify and evaluate carbon emissions. This metric can be used as a key performance indicator (KPI) of its business' transportation sustainability efforts.

Over 1,000 companies worldwide are working with organizations such as Science-Based Targets (SBT) to establish carbon emissions and carbon intensity targets in line with the Paris Agreement targets of staying within the 1.5-2^oC global warming (Science-Based Targets, 2020). The Science-Based Target initiative (SBTi) has established scientifically-informed target-setting tools, two of which will directly apply to the scope of this research. The first tool, the Science-Based Target Setting Tool, provides a generic Scope 3 tool that uses the Absolute Contraction Approach to set total carbon emissions reduction targets that are in line with global, annual emissions reduction rates that is required to meet the 1.5^oC, well-below 2^oC (WB2^oC) and 2^oC goals by 2050. The second tool, Target Setting Tool for Transport Sector, uses the Sectoral Decarbonization Approach (SDA) that takes International Energy Agency (IEA) Energy Technology Perspectives global sectoral scenarios, comprising emissions and activity projections, to compute sectoral intensity pathways. The Transport Sector tool budgets future carbon emissions and carbon intensity targets for an organization using its current activity and carbon emissions data. These SBT tools and the targets they derive are globally recognized to set short-term (minimum of 5 years) and long-term (maximum till year 2050) targets. SBT requires organizations to use the GLEC framework or equivalent carbon accounting method to derive the initial emissions prior to target-setting.

2.3 Emerging and Existing Carbon Efficient Transportation Modes

To achieve higher carbon efficiency in the SCND problem, different emerging and existing transportation modes need to be explored and incorporated into the optimization model. Hence this section will explore the literature on carbon management and carbon-efficient options in the traditional freight transportation space – train, aircraft, barge, and truck – as well as any emerging, innovative alternatives.

Since the transportation sector is a major contributor to world emissions and, according to the Carbon Trust, emissions from mobile sources are much higher than stationary sources (Martínez & Fransoo, 2017), there has been growing research on carbon management in the transportation sector to help mitigate the environmental impact. Herold and Lee (2017) provided a thorough review of the existing literature in this space. Since vehicle types vary in capacity, carbon intensity, fuel compatibility, and utilization as well as speed, the resulting emissions generated can differ greatly from one to the other. Freight aircraft have the highest average carbon intensity, followed by medium-duty truck, heavy-duty truck, rail, and container ship, respectively (Sims et al., 2014). One leading research area in carbon management and reduction in freight transportation is to determine the most carbon-efficient modal choice. Hoen et al. (2014) studied the reduction of emissions by switching transport modes within an existing network, determining that a 10% reduction in emissions could be achieved with a marginal increase in logistics costs of just 0.7%.

Another research area is the efficiencies gained from the mix of these transportation modes, also known as intermodal transportation. For instance, Bouzembrak et al. (2011) formulated integer linear program solutions to include *m*-number of transportation modes. By taking the case of railway and waterway as an alternative to land vehicles, they found the Pareto solutions for business optimality. In a similar vein, Tsao and Linh (2018) reduced the carbon cost by delivering containers through a multi-modal scenario from seaport to dry port using rail and road transportation. On the other hand, Craig et al. calculated the total carbon efficiency of switching truck transportation to intermodal (Craig et al., 2013). Moreover, Liljestrand et al. (2015) determined that intermodal transportation had the largest potential compared to other variables in transportation to reduce total carbon emissions.

In addition to the carbon management of current modal types, several emerging technologies and innovations are seeking to reduce emissions from freight transportation. The following subsections summarize the brief background as well as corresponding new or upcoming innovations for each transportation mode.

2.3.1 Rail

The U.S. rail cargo network covers up to 140,000 miles and transports around 57 tons of goods per American per year (Association of American Railroads, 2020). While American freight railways are diesel-powered, they are a more efficient and lower carbon option compared to road transport. In the US, advanced developments such as fully electric locomotives and high-speed rail systems are limited to a small subset of passenger rail lines. This is due to the fact that railroads are privately owned and partially funded by the U.S. government (Nunno, 2018). Therefore, there is little incentive to invest in transforming to electric rail lines. The train line-haul option is limited to railway lanes and terminals available in the region and therefore do not have the flexibility that other modes such as trucking does. Further, rail shipments will always require a transfer process from the terminal to the receiver's facility. Typically, this transfer process, also known as drayage, utilizes truck trailers and adds extra lead time as well as transportation cost. If the facility is too far from the station, both the total cost and emissions may not have significant cutbacks compared to exclusively shipping with trucks.

2.3.2 Air

Air cargo is a great option for long hauls across the country, especially to serve fulfilment network where a limited time window is expected to fulfill customer demand. The International Air Transportation Association (IATA) reports an increasing demand for air freight with 9.7% growth in 2017 (IATA, 2019). Although aircraft have competitive advantages, they also have a major drawback: they are among the top three contributors to transportation carbon emissions in the U.S. (OTAQ, 2020). The extent of the carbon emissions is influenced by the size of the aircraft, fuel efficiency, and the load factor (Miyoshi & Mason, 2009). A study of the evolution of U.S. air cargo productivity between 1990 and 2010 showed that the air cargo industry has only made minor fuel improvement, and that the fuel efficiency is not only determined by the type of fuel, but also the structure of the aircraft and the engine technology, the payload it carries, and the traffic of the route (Donatelli, 2012). As substitutes for fossil jet fuels, innovative fuels have emerged within the industry, such as sustainable aviation fuels (SAF) which is produced from waste oils from a biological origin, or agricultural residues; Lower Carbon Aviation Fuels (LCAF); and hydrogen (ICAO, 2017).

Khoo and Teoh (2014) proposed a Green Fleet Index to indicate the environmental impact of an aircraft. They concluded that increasing the load factor and reducing the flight frequency will reduce carbon emissions (Khoo & Teoh, 2014). To relate their research to the FLP in network design, Parsa et al. (2019) solved the hub-and-spoke location problem by optimizing cost, air pollution, fuel consumption, and sound pollution which results in cutting the carbon emission by almost 10%. This research examines a medium Boeing 737 aircraft and a large Boeing 767 aircraft traveling between the existing airports available in the U.S., which requires intermodal connectivity between the airport and the facility location.

2.3.3 Ocean and River

Ocean shipping accounts for over 80% of world trade and 27% of global logistics carbon emissions (ITF, 2019). Although vessels are the most carbon-efficient mode out of the four traditional modes of transportation (Sims et al., 2014), the sheer volume of goods shipped provides the industry with the critical potential to support the reduction of carbon emissions in the transportation industry. Designing carbon-neutral or carbon-efficient, vessels has been a major field of research as firms and scientists are investing in developing innovative fuel and vessel technologies that are also viable for utilization on ocean and waterways. For instance, one study illustrates wind propulsion systems that provide more lift and propulsion, effectively reducing fuel consumption by up to 30% (Kleiner, 2007). Container logistics firms like Maersk have also developed lower fuel consumption vessels such as the Maersk Triple E class, a ship that incorporates the "slow steaming" strategy (McKinnon, 2016). This strategy is the practice of operating vessels at lower speeds to reduce cost and carbon emissions (Kloch, 2013). Moreover, Maersk recently piloted a new biofuel in its operations that is set to reduce total transportation carbon emissions for its customers (Johnson, 2019).

In the US, river barge transportation carries over 53% of U.S. imports and 38% of U.S. exports by dollar value (Bureau of Transportation Statistics, 2012). In addition, the inland waterways carry approximately 14% of all intercity freight in the U.S. (Waterways Council, 2006), over 12,000 miles across 38 different states. Figure 6 in Appendix D illustrates the major ports and inland waterways in the US. This research will incorporate barge shipment along the ports and inland waterways as an option in our SCND model.

2.3.4 Truck

Globally, on-the-road transportation makes up over 62% of total logistics carbon emissions (ITF, 2019). The two main truck types utilized for on-the-road freight transportation are medium-duty and heavy-duty trucks. Medium-duty trucks are trucks between the Class 4 and Class 6 weight categories, equivalent to 14,000 to 26,000 pounds. Heavy-duty trucks are any vehicle exceeding 26,000 pounds, including all Class 7 to Class 9 trucks (Soard, 2017). Over 70% of all freight tonnage in the U.S. is hauled by heavy-duty trucks and they contribute about 5% of all carbon emissions in the U.S. (Deng et al., 2018).

As emissions from transport continue to rise, on average an increase of 1.9% annually from all transportation and an increase of 2.6% annually from trucks and buses since 2000 (International Energy Agency, 2020), efforts such as the Modern Truck Scenario have developed to reduce emissions (International Energy Agency, 2017). The Modern Truck Scenario sets out targeted efforts to reduce emissions by three key approaches: systematic improvements in operations and logistics in road freight, vehicle efficiency improvements, and the use of alternative fuels (International Energy Agency, 2017). Increased vehicle efficiency improvements can be achieved by designing more fuel-efficient trucks, with such improvements as better engine designs, drivetrains, aerodynamics, and tires (Harrington & Krupnick, 2012; Mohamed-Kassim & Filippone, 2010). There have also been recent developments of low-carbon alternative fuels as energy sources for trucks. For instance, Plug Power and Lighting Systems in the U.S. have developed fuel-cell powered Class 6 electric trucks, while Plug Power has also launched its 125kW heavy-duty ProGen fuel cell engines that will expand their technology to Class 7 and Class 8 trucks (Global News Wire, 2020). These alternative fuel trucks will allow for travel ranges from 200 miles in the standard version to up to 400 miles in the extended-range version, enabling capabilities to support middle-mile delivery and logistics (Fuel Cells Bulletin, 2020). Since the scope of our research includes Class 6 and Class 8 trucks, these new technologies will be comparable alternatives to evaluate in optimizing the SCND model.

2.4 Business Impact of Carbon Efficient Network Design

Optimizing the facility location that minimizes total carbon emission by reconfiguring the vehicle mix and distance between the facility nodes will impact the network's transportation costs, affecting business decisions and strategy. Thus, the resulting scenarios from the SCND problem require a trade-off analysis to provide managerial insights. Since optimizing total cost and carbon emissions are common objectives among carbon-efficient SCND studies, the trade-off between both objectives as an effect of multiple variables have been considered and illustrated by several researchers (Huang et al., 2020; Palacio et al., 2018).

The trade-offs for all the optimal solutions can be illustrated using a Pareto frontier graph. This is also known as Pareto-optimal when no one variable or factor (such as cost or total emissions) could be made better off without making other variables worse off (Vélazquez-Martínez et al., 2014). For instance, Wang et al. (2011) proposed a network design model to see the trade-off between the total cost and the optimum quantity of CO_2 transported by using a two-dimension Pareto frontier. The result from their study illustrated that the organization's cost increased if it wanted to emit less carbon (Wang et al., 2011). With the Pareto frontier graph, they were able to present the minimum and maximum threshold for cost and carbon emission that the model could carry. Pareto solutions provide predictable configurations that help decision-makers design the optimal supply chain network (Bouzembrak et al., 2011). For this research study, not only are total cost and carbon emissions being assessed, but also the third objective of delivery speed. This will result in a three-dimensional Pareto graph. The Pareto frontier resulting from this study will help support the effort to better understand the trade-offs between reducing carbon emissions, speed (or distance), and transportation cost when navigating a more carbon-efficient SCND.

2.5 Summary

The literature on SCND has been widely studied over the past several decades. These studies have solved a variety of challenges. This research contributes primarily to the stream of carbon-efficient network design research but differs from previous relevant studies in the following aspects:

1. Our scope of the supply chain is limited to the middle-mile distribution, which is a three-echelon network that includes Inbound Cross-Docks (IXD), Fulfillment Centers (FC), and Sorting Center (SC) nodes.
2. The research will be a multi-objective GFLP that sequentially minimizes three objective functions: emission, cost, and delivery time. Typically, GFLP considers a bi-objective approach with carbon emission and cost reduction only.
3. Although the demand at the SC nodes is deterministic, a finite set of candidate locations for all three node types (IXD, FC, and SC) will need to be estimated first, requiring a 2-step modeling process. The model will first need to determine the optimal candidate locations before determining optimal locations that minimize the objective functions of total emissions, cost, and speed (or distance).
4. Considering the scope of our research and limited data access, the model will only include costs and emissions from mobile (or transportation) sources. All other supply chain decisions such as the cost of opening and operating a facility (i.e., processing of packages, inventory management) and the energy usage of facilities (emissions from activities at the nodes) will be excluded. Thus, only cost and emissions derived from the distance traveled between nodes as well as the transportation modal type, capacity and load size will be relevant for our calculations.
5. There are sixteen choices of transportation to consider for multi-modal linehaul (see Appendix B).
6. The research will use the GLEC Framework as the carbon emission accounting method as it offers the most comprehensive carbon accounting method and is the primary carbon accounting method used by MMTN.

3. Data and Methodology

This section provides background on the research methods and data used to solve for the optimal middle-mile transportation network scenarios that minimize total carbon emissions while fulfilling customer demand. To accomplish this, the research consisted of the following steps:

1. Build Network Design models:
    a. Determine candidate locations for all three echelons of IXD, FC and SC.
    b. Formulate the three objectives of minimizing carbon emissions, transportation cost and on-the-road delivery time.
    c. Incorporate other business constraints for middle-mile network
    d. Determine Baseline vs. alternative network design scenarios
2. Plot Pareto frontiers:
    a. Identify the extreme boundaries of each Pareto frontier from objective output
    b. Generate and plot observations between boundaries using ε-constraint method
3. Identify optimal target scenarios:
    a. Calculate the target total carbon emissions that meet Science-Based Targets of 1.5^{o}C, WB2^{o}C and 2^{o}C.
    b. Identify and analyze the optimal targets scenarios from the Pareto frontiers that meet the calculated Science-Based Target carbon emissions,

Due to the scope and limited data access of this research, the model includes costs and emissions from mobile sources. All other supply chain decisions such as the cost of opening and operating a facility and the energy usage of facilities (emissions from activities at the nodes) have been excluded.

The data that informs the research is limited to the following in Table 1:

Table 1

Data Provided from MMTN

Type	Data
Transportation Modes	Current modes utilized and corresponding load size per trip
	Average speed of vehicles
Facilities and Network Design	Maximum processing capacities of all facility types in the middle mile
	Minimum processing requirements of all facility types
	Maximum number of within-layer FC and SC facilities
Demand	Monthly customer demand aggregated by U.S. 3-digit ZIP code level

3.1 Assumptions

Our proposed methodology has made the following assumptions to clearly demonstrate the problem and the mathematical solution.

3.1.1 Facilities and Network Design Assumptions

The following assumptions describe the facilities and the flow between these facilities:

- All nodes (facilities) are located on a Euclidean plane with x and y coordinates.
- The middle-mile network design is formed of three layers: Inbound Cross-Docks (IXD), Fulfilment Center (FC), and Sorting Center (SC).
- All flows in the scope of the model are forward flows (IXD to FC to SC). Backward flows or reverse logistics are not considered.
- Each node type (IXD, FC or SC) has a fixed minimum and maximum processing capacity.
- The network excluded the inter-layer flows such as FC-FC and SC-SC.

3.1.2 Transportation Modes Assumptions

The following assumptions relate to the transportation modes in the network design:

- There are sixteen types of transportation choice considered in the model. A detailed breakdown can be found in Appendix B.

- The Baseline Model only includes the current transportation modes utilized in the middle-mile. This includes the Class 6 and Class 8 Trucks, as well as Boeing 737 and Boeing 767 freighter airplanes.
- The model assumes that there will be no fixed schedules for all transportation (including barge and train) and assumes all transportation is available on demand.
- All transportation types are assumed to have a uniform and constant speed per transportation mode. For example, all trucks are assumed to have the same speed of 40 MPH. Speed breakdown of each vehicle type can be found in Appendix B Table 13.
- All transportation types are assumed to have the average fill rate as specified for each type Appendix B Table 13. The fill rate of a vehicle can be defined as the ratio of the actual capacity used in a vehicle to the total capacity available in terms of weight and volume.
- Average weight or average capacity per trip for all vehicle types are pre-determined with the following additional assumptions for vehicles modes that are not currently utilized:
    - Short-haul and medium-haul air have the same capacity and weight per trip.
    - Each rail car's capacity is equivalent to a 53-foot trailer.
    - Each barge's capacity is equivalent to eight 53-foot trailers.

3.1.3 Other General Assumptions

The following assumptions relate to other assumptions for the network optimization:

- In order to determine the distance of travel between nodes (facilities), a circuity factor has been applied to the Euclidean distance (straight-line distance). The circuity factor will differ depending on transportation mode and region.
- Demand is deterministic and aggregated in a single period of time for a single commodity in a specific 3-digit ZIP code region.
- All shipments (packages) are uniform in weight and size. For example, each package has the same X weight and Y dimensions so no packages have distinctive features that will affect the cost and loading capacity of the different transportation types.
- The fuel price uses the U.S. average pricing, as described in Appendix C Table 15.
- Fixed transportation costs are excluded from this model, as investments for alternative fuels and transportation mode types are out of scope for this research.
- SC to customer node lanes have to be incorporated into the model in order to determine the open or close decisions for SC candidate locations. Therefore, the model is optimized based on the whole network (IXD-Customer nodes) and not just middle-mile (IXD-SC).

3.2 Candidate Locations

In order to solve for the GFLP that minimizes the three objectives of carbon emissions, transportation cost and delivery time, the model first needs to determine a finite set of candidate locations for all node types (IXD, FC and SC). This section illustrates the approach taken to determine these candidate locations for each node type.

For each of these facilities, the estimated number of nodes needed is a division of total daily demand per the minimum capacity of node type. Total daily demand for each node is estimated as follows:

*Total Daily Demand = Monthly Total Units (provided by MMTN) * 1.4 (conversion to packages) * 30 (average days per month).*

Number of Nodes = Total Daily Demand / Minimum Capacity

Using Coupa's Supply Chain Guru X (SCGX) software, the greenfield analysis tool generated the best placement of candidate locations coordinates that are aligned with the distance-based approach (Coupa, 2021). To optimize for the best facility locations, the model requires enough candidate locations to draw from. Therefore, the number of candidate locations need to double the estimated number of nodes required for each type of location. Fortunately, the program's map visualization tools help ensure the facilities generated are located close to main roads and not at unreachable locations. The following sections on candidate locations gather the input details on each type of the facilities and the distance-based approach formulation.

3.2.1 Inbound Cross-Dock (IXD) Candidate Locations

The IXD candidate locations can be solved by using the basic FLP distance-based approach. This approach locates the optimal location of multiple nodes by minimizing the average weighted distance from the demand. The demand locations in this case are the current major ports in the U.S. as well as the top locations of domestic sellers that currently sell to the sponsoring company. The number of demand for these locations is the aggregated volume processed at these ports and the percent of total domestic sellers' volumes per location.

The mathematical formulation to solve for the IXD candidate locations is closely follow Watson et al.,'s (2012) formulation as follows:

$$Min. \sum_{x} \sum_{a} d_{xa} D_a Y_{xa} \tag{1}$$

This formula is subject to a number of constraints such as constraint (2) which make sure that every customer is fulfilled.

$$\sum_{x} Y_{xa} = 1 \qquad \forall a \tag{2}$$

Constraint (3) is used to generate the number of candidate locations L in the network using the values that have been calculated before.

$$\sum_{x} X_{x} = L \tag{3}$$

Constraint (4) ensures that a facility must process between its minimum and maximum capacities.

$$U_{x\,min}\, X_x \leq \sum_{a} D_{xa} Y_{xa} \leq U_{x\,max}\, X_x \qquad \forall x \tag{4}$$

The shipment between the two nodes cannot be made unless the facility is opened as reflected in constraint (5)

$$Y_{xa} \leq X_x \qquad \forall x \ \forall a \tag{5}$$

Constraint (6) is a binary linking whether a lane is created between the candidate locations and its input.

$$Y_{xa} \in \{0,1\} \tag{6}$$

Constraint (7) is a binary linking whether to open the facility or not.

$$X_x \in \{0,1\} \tag{7}$$

3.2.2 Fulfillment Center (FC) Candidate Locations

The FC candidate locations can be solved by also utilizing the distance-based approach. The demand locations in this case, however, will be based on 830 cities across the U.S. with populations above 50,000 residents. This method is used in order to avoid the tendencies of having FC closer towards the IXD candidate locations due to the distance-based approach.

Similarly, the mathematical formulation to solve for the FC candidate locations is closely follow Watson et al.'s (2012) formulation as follows:

$$Min. \sum_{f} \sum_{b} d_{fb} D_b Y_{fb} \tag{8}$$

This formula is subject to a number of constraints such as constraint (9) which make sure that every customer is fulfilled.

$$\sum_{f} Y_{fb} = 1 \qquad\qquad \forall b \tag{9}$$

Constraint (10) is used to generate the number of candidate locations L in the network using the values that have been calculated before.

$$\sum_{f} X_f = L \tag{10}$$

Constraint (11) ensures that a facility must process between its minimum and maximum capacities.

$$U_{f\,min}\, X_f \le \sum_{b} D_{fb} Y_{fb} \le U_{f\,max}\, X_f \qquad\qquad \forall f \tag{11}$$

The shipment between the two nodes cannot be made unless the facility is opened as reflected in constraint (12)

$$Y_{fb} \le X_{fb} \qquad\qquad \forall f \;\; \forall b \tag{12}$$

Constraint (13) is a binary linking whether a lane is created between the candidate locations and its input.

$$Y_{fb} \in \{0,1\} \tag{13}$$

Constraint (14) is a binary linking whether to open the facility or not.

$$X_f \in \{0,1\} \tag{14}$$

3.2.3 Sorting Center (SC) Candidate Locations

The sorting center candidate location can also be solved by using the same approach taken to locate IXD and FC candidate locations. The customer demand input in this case is provided as a U.S. 3-digit ZIP code format, aggregating demand by sectional divides within each state. This method selects candidate locations closer to zip codes with higher demands.

The minimum capacity requirements will limit the number of SC candidate locations, aggregating demand in certain ZIP-codes to be served by fewer SC. Maximum capacity limitations, however, may increase the number of candidate locations necessary to meet certain zip-codes' demand.

Similarly, the mathematical formulation to solve for the SC candidate locations is closely follow Watson et al.'s (2012) formulation as follows:

$$Min. \sum_{s} \sum_{c} d_{sc} D_c Y_{sc} \tag{15}$$

This formula is subject to a number of constraints such as constraint (16) which make sure that every customer is fulfilled.

$$\sum_{s} Y_{sc} = 1 \qquad \forall c \tag{16}$$

Constraint (17) is used to generate the number of candidate locations L in the network using the values that have been calculated before.

$$\sum_{s} X_s = L \tag{17}$$

Constraint (18) ensures that a facility must process between its minimum and maximum capacities.

$$U_{s\,min}\, X_s \leq \sum_{c} D_{sc} Y_{sc} \leq U_{s\,max}\, X_s \qquad \forall s \tag{18}$$

The shipment between the two nodes cannot be made unless the facility is opened as reflected in constraint (19)

$$Y_{sc} \leq X_{sc} \qquad \forall s \ \forall c \tag{19}$$

Constraint (20) is a binary linking whether a lane is created between the candidate locations and its input.

$$Y_{sc} \in \{0,1\} \tag{20}$$

Constraint (21) is a binary linking whether to open the facility or not.

$$X_s \in \{0,1\} \tag{21}$$

3.2.4 Annotations and Mathematical Formulations

a_i : Public terminals or domestic supplier number *i* as Greenfield input for IXD

b_j : Cities above 50,000 population number *j* as Greenfield input for FC

c_k : Customer demand number *k* as Greenfield input for SC

x_i : Inbound Cross-Docks (IXD) number *i*

f_j : Fulfillment Center (FC) number *j*

s_k : Sorting Center (SC) number *k*

D_a, D_b, D_c : Facility supply capacity, number of populations, or customer demand for Greenfield input

D_{xa}, D_{fb}, D_{sc} : Supply capacity assigned to IXD, number of populations assigned to FC, or customer demand assigned to SC

d_{xa}, d_{fb}, d_{sc} : Distance of travel between candidate locations and its Greenfield input (public terminals and domestic suppliers, cities above 50,000 population, or customer demand

U_x, U_f, U_s : Capacity of each facility

Y_{xa},Y_{fb},Y_{sc} : Binary linking, 1 if candidate locations *x/f/s* serve the Greenfield input *a/b/c*

X_x, X_f, X_s : Binary linking, 1 if candidate locations *x/f/s* are opened

L : Number of candidate locations for each facility to be generated (IXD = 30, FC = 206, SC = 154)

Locating facilities using the distance-based approach can be generalized as the following objectives and constraints where *xa* indicates a pairing for IXD and it's Greenfield input from public terminals or domestic suppliers information. Use *fb* annotation pairing to find candidate locations for FC and *sc* annotation pairing to find candidate locations for SC.

$$Min. \sum_x \sum_a d_{xa} D_a Y_{xa} \tag{1}$$

s.t.

$$\sum_x Y_{xa} = 1 \qquad \forall a \tag{2}$$

$$\sum_x X_x = L \tag{3}$$

$$U_{x\,min}\, X_x \leq \sum_a D_{xa} Y_{xa} \leq U_{x\,max}\, X_x \qquad \forall x \tag{4}$$

$$Y_{xa} \leq X_x \qquad \forall x \ \forall a \tag{5}$$

$$Y_{xa} \in \{0,1\} \tag{6}$$

$$X_x \in \{0,1\} \tag{7}$$

3.3 Formulating Objectives

Once candidate locations for IXD, FC, and SC are identified as a fixed set of number of facilities, the network optimization model is then categorized as a discrete model. Discrete models mean that the number of nodes is restricted to a finite number of locations (Daskin, 2008). Additionally, one of the key variables that build-up to each objective is the distance between the nodes. Thus, under the umbrella of discrete models, optimizing the distance between nodes in this model is categorized as a p-median discrete model (Daskin, 2008). This constraint applies to the GFLP optimization to achieve the three objectives in minimizing carbon emission, transportation cost, and delivery time.

3.3.1 Carbon Emissions

The first objective function is to minimize total carbon emissions of the network. The model utilizes the GLEC Framework to account for carbon emissions. Per the GHG Protocol and GLEC Framework, all the emissions in scope for this research, the transportation emissions required to move goods, is calculated using the method for Scope 3 emissions. As explained in Section 2.2, Scope 3 is used to estimate transportation emissions in the supply chain when the actual fuel burn data is unavailable, and when the split between company-owned vs. subcontracted transportation is unknown.

To accurately calculate carbon emissions from transportation, the GLEC Framework includes the full fuel life cycle, also known as the well-to-wheel (WTW) carbon intensity factors (Greene and Lewis, 2019). The WTW emissions is the sum of both the fuel emissions from well-to-tank (fuel production and distribution) and from tank-to-wheel (fuel combustion). Carbon intensity factors were selected from the GLEC Framework that most closely align with the transportation vehicles and activities used in this study. For electric-powered vehicles, electricity use is converted to carbon emissions by accounting for the sources of energy used to create electricity, expressing its emissions factors in mass carbon emissions (CO_2e) per kilowatt-hours (kWh) of electricity used.

Scope 3 emissions are calculated based on the following formula:

$$kg\ CO_2e\ emissions\ = \sum total\ t\ *\ km\ *\ CO_2e\ intensity\ factor \tag{23}$$

Thus, total emissions per trip can be calculated following the below steps:

1. Calculate total tonne-kilometer(tkm) by estimating total weight (t) per trip per transportation type and the total distance (km) traveled by the same transportation type between nodes
2. Determine carbon intensity factor(s) of transportation types (*CO_2e intensity factor)*
3. Convert tonne-kilometer to CO_2e emissions per transportation type (*total tkm * CO_2e intensity factor)*

The average weight per shipment is pre-determined for each vehicle type per MMTN's requirements. Distance between nodes will be derived from the optimization of the model itself as certain nodes from the candidate locations open and/or close per each objective function. In addition, the total carbon intensity factors can be determined from transportation mode-specific reference tables calculated by the GLEC Framework. Table 11 and Table 12 in the Appendix B illustrate the 16 different transportation types utilized in the model with their corresponding categorization and fuel emission intensity factors derived from the GLEC Framework.

Since all vehicles have certain capacity limitations, not all demand per period can be met by one trip. Therefore, the objective function to minimize total emissions in the model will require an additional variable that accounts for the number of trips or in other words, the number of vehicles required to fully serve the customer demand (D_s). This variable is annotated as N, which is a function of total demand (D_s) divided by capacity of vehicles traveling between two nodes using vehicle T (U^T).

To fulfill the customer demand, each node in the middle-mile network should be connected with one another subject to conditional limitation and the objective function (24). In this case, constraint (25) illustrates that demand always exists and through candidate location selection, the SC should have covered the aggregated number of demands in the region.

$$Min. \sum_x \sum_f w^T d_{xf} F^T N_{xf} + \sum_f \sum_s w^T d_{fs} F^T N_{fs} \tag{24}$$

$$D_s \geq 0 \tag{25}$$

Each IXD is randomly connected to one of the 5 FC groups consisting of about 40 FC reflected in constraint (26).

$$G_{x_i} = \sum_j f_j /5 \tag{26}$$

On the other side of the network, constraint (27) ensures the supply product quantity transported from IXD has to be equal or greater to the total demand at SC, otherwise, the demand is not fulfilled.

$$\sum_x Q_x \geq \sum_s Q_s \qquad \forall x \; \forall s \tag{27}$$

Constraint (28) ensures that the total number of products coming into FC should also be the same as the products coming out of it.

$$Q_{xf} = Q_{fs} \qquad \forall f \tag{28}$$

Constraints (29-30) ensure that the number of product quantities transported between two nodes has to be less than or equal to the number of vehicles in each lane multiplied by the capacity of each vehicle.

$$Q_{xf} \leq N_{xf} U_{xf}^T \qquad \forall x \, \forall f \tag{29}$$

$$Q_{fs} \leq N_{fs} U_{fs}^T \qquad \forall f \, \forall s \tag{30}$$

Additionally, each type of facility (IXD, FC, and SC) has minimum and maximum capacity constraints to open a facility bounded by constraints (31-33).

$$B_x U_{x\,min} \leq \sum_f Q_{xf} \leq B_x U_{x\,max} \qquad \forall x \tag{31}$$

$$B_f U_{f\,min} \leq \sum_s Q_{fs} \leq B_f U_{f\,max} \qquad \forall f \tag{32}$$

$$B_s U_{s\,min} \leq \sum_f Q_{fs} \leq B_s U_{s\,max} \qquad \forall s \tag{33}$$

Later to create Pareto frontier, the total emissions objective is bounded by the total carbon emission produced in the observed scenario using constraint (34).

$$Min. \sum_x \sum_f w^T d_{xf} F^T N_{xf} + \sum_f \sum_s w^T d_{fs} F^T N_{fs} \; \leq \; T_e \tag{34}$$

A binary linking of 0 and 1 in constraint (35) will be used to indicate if a candidate location should be opened or closed. Hence, the total cost will indirectly reflect the number of facilities that are open.

$$B_x \,, B_f \,, B_s \; \in \{0,1\} \tag{35}$$

Lastly, constraint (36-37) tells that all these flows are non-negative.

$$Q_{xf}, Q_{fs} \; \geq \; 0 \qquad \forall x \, \forall f \, \forall s \tag{36}$$

$$U, Q, N \; \geq \; 0 \qquad integer \tag{37}$$

3.3.2 Transportation Cost

The transportation cost -- in addition to the facility cost -- usually becomes a primary parameter in designing a distribution network (Daskin, 2008; Palacio et al., 2018). Daskin and Palacio chose transportation cost as an input variable which will lead to the objective function of minimizing the overall costs. Typically, the total transportation cost covers the fixed cost and the variable cost. The fixed cost includes, but is not limited to, the cost of vehicles, the labor costs, the operational costs, and the vehicle maintenance costs. Considering a more sustainable vehicle and new advanced technology such as electric trucks, electric trains, and others, its transportation fixed cost will be much higher than the existing diesel-powered vehicles (García-Olivares et al., 2018) .

The market for alternative transportation is still limited and thus adds another burden for companies to make investments to proceed. Since one of the objectives of this research is to minimize the cost while considering low carbon transportation, this fixed cost will bias the model such that it will always choose the cheaper traditional vehicles. Hence, in this scope of research, the objective function (37) on transportation cost will only consider the variable costs to generate a fair comparison between all modes of transportation.

$$Min. \sum_{x}\sum_{f} c_{xf}^{T} d_{xf} \eta^{T} N_{xf} (w^{T} + W^{T}) + \sum_{f}\sum_{s} c_{xf}^{T} d_{xf} \eta^{T} N_{xf} (w^{T} + W^{T}) \tag{38}$$

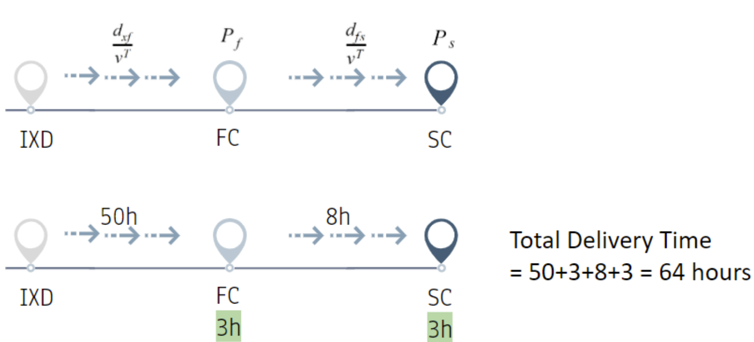
The variable cost covers the efficiency of each vehicle, the price of fuel or source of power, and the distance of travel. For fuel-powered vehicles, the vehicle efficiency is indicated by the average miles per gallon and may utilize the average factors from the GLEC Framework. As the vehicles travel to many regions, the price of fuel in Appendix C Table 15 uses the average fuel price across the United States in July 2020, as published by the U.S. Department of Energy and International Air Transport Association. Lastly, the distance of travel for each vehicle is determined by several constraints to meet the demand while minimizing the transportation cost and carbon emission.

3.3.3 On-The-Road Delivery Time

The last objective that this research oversees is the delivery time of a shipment or the time it takes for an item to travel from IXD to SC. The time is measured starting from the outbound delivery from the IXD to FC, then FC to SC, and additional processing time in FC and SC. Figure 5 visualizes how the total delivery time is calculated and its example.

Figure 5

On-The-Road Delivery Time Calculation Example



How fast an item is being transported is critical to a transportation network company. These companies offer a guaranteed shipment for their customers to receive packages within a certain number of days. As a result of choosing a combination of transportation modes, the time they take to ship packages may vary. Similarly, if the fastest mode of vehicles is chosen in order to meet the customer requirement, then the carbon emission and the cost may be impacted. Hence, the delivery time is observed along with the previous two objectives as objective function (38).

$$Min. \sum_{x} \sum_{f} \frac{d_{xf}}{v^T} N_{xf} + \sum_{f} \sum_{s} \frac{d_{fs}}{v^T} N_{fs} + \sum_{f} P_f + \sum_{s} P_s \tag{39}$$

The variables that construct the delivery time are the average vehicle velocity, the distance of travel, and the average under the roof processing time. Another variable to consider is how fast the overall demand in a region can be fulfilled with the limited capacity of each vehicle type. The number of demands over the vehicle capacity generates the number of vehicles needed or it can also be interpreted as the number of trips that a single vehicle should make. The larger the capacity, the fewer vehicles needed, and thus the faster it takes for the package to arrive. To minimize the delivery time, the same constraints for transportation costs will be used.

3.3.4 Summary of Annotations and Mathematical Formulations

The following are annotations used for Multi-objective network design formulations:

x_i : Inbound Cross-Docks (IXD) number *i*

f_j : Fulfillment Center (FC) number *j*

s_k : Sorting Center (SC) number *k*

D_s : Customer demand aggregated in Sorting Center

U_x, U_f, U_s : Capacity of each facility

U_{xf}^T , U_{fs}^T : Capacity of vehicle traveling between two nodes using vehicle T

Q_{xf} , Q_{fs} : Quantity of items required to be transported between two nodes

c_{xf}^T , c_{fs}^T : Fuel cost for vehicle T traveling between two nodes

E_{xf}^T , E_{fs}^T : Carbon Emission of vehicle T traveling between two nodes

B_x , B_f , B_s : Binary linking for facilities to open

N_{xf}, N_{fs} : Number of vehicle needed between two nodes (e.g., $N_{xf} = D_f / U_{xf}^T$)

G_{x_i} : Number of FC being served by IXD number i

d_{xf}, d_{fs} : Distance of travel between two nodes

P_f , P_s : Average additional processing time in facility

η^T : Consumption factor of vehicle T

F^T : Fuel emission intensity factor of vehicle T

T_e : Targeted total carbon emission

v^T : Average velocity of vehicle T

w^T : Average weight per shipment of vehicle T

W^T : Average weight per vehicle T

The following are formulas to minimize carbon emission, transportation cost, and delivery time subject to several constraints used to build the network design:

$$Min. \sum_x \sum_f w^T d_{xf} F^T N_{xf} + \sum_f \sum_s w^T d_{fs} F^T N_{fs} \tag{24}$$

$$Min. \sum_x \sum_f c_{xf}^T d_{xf} \eta^T N_{xf}(w^T + W^T) + \sum_f \sum_s c_{xf}^T d_{xf} \eta^T N_{xf}(w^T + W^T) \tag{38}$$

$$Min. \sum_x \sum_f \frac{d_{xf}}{v^T} N_{xf} + \sum_f \sum_s \frac{d_{fs}}{v^T} N_{fs} + \sum_f P_f + \sum_s P_s \tag{39}$$

s.t.

$$D_s \geq 0 \tag{25}$$

$$G_{x_i} = \sum_j f_j /5 \tag{26}$$

$$\sum_x Q_x \geq \sum_s Q_s \qquad \forall x \, \forall s \tag{27}$$

$$Q_{xf} = Q_{fs} \qquad \forall f \tag{28}$$

$$Q_{xf} \leq N_{xf} U_{xf}^T \qquad \forall x \, \forall f \tag{29}$$

$$Q_{fs} \leq N_{fs} U_{fs}^T \qquad \forall f \, \forall s \tag{30}$$

$$B_x U_{x\,min} \leq \sum_f Q_{xf} \leq B_x U_{x\,max} \qquad \forall x \tag{31}$$

$$B_f U_{f\,min} \le \sum_s Q_{fs} \le B_f U_{f\,max} \qquad \forall f \tag{32}$$

$$B_s U_{s\,min} \le \sum_f Q_{fs} \le B_s U_{s\,max} \qquad \forall s \tag{33}$$

$$Min. \sum_x \sum_f w^T d_{xf} F^T N_{xf} + \sum_f \sum_s w^T d_{fs} F^T N_{fs} \le T_e \tag{34}$$

$$B_x\,, B_f\,, B_s \in \{0,1\} \tag{35}$$

$$Q_{xf}, Q_{fs} \ge 0 \qquad \forall x\ \forall f\ \forall s \tag{36}$$

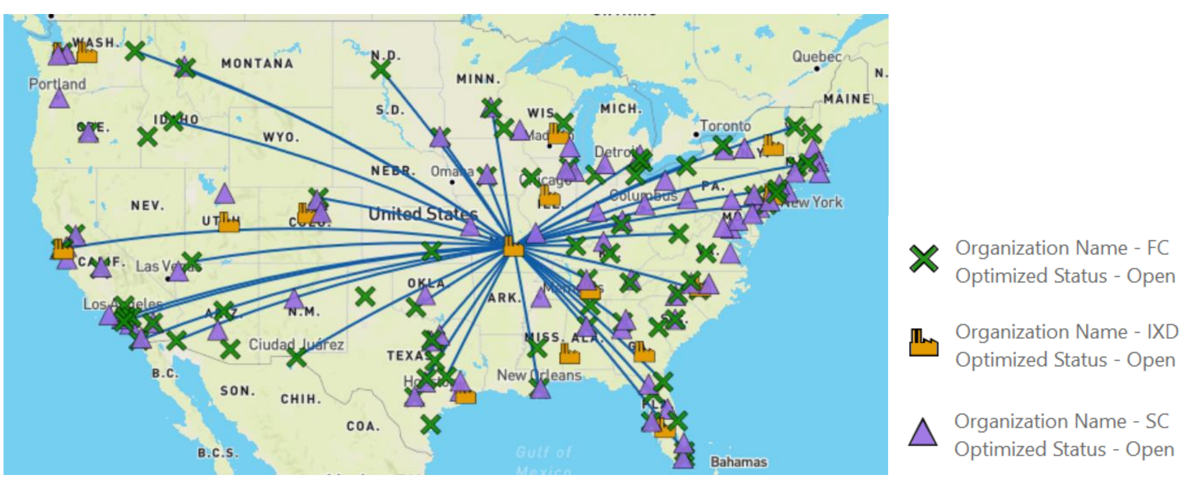
$$U, Q, N \ge 0 \qquad integer \tag{37}$$

3.4 Other Service Constraints

To make the models behave more realistically following the existing fulfillment practice, additional constraints can be applied. Based on the business requirement, the distribution from IXD has to be spread to roughly 40 FC with an average distance of 1,200 miles from IXD. There are 206 FC candidate locations that are randomly assigned to 5 groups. Each IXD is then randomly connected to one of these 5 groups. The Figure 7 below visualizes how this constraint takes place in the model using Coupa SCGX. Hence, the optimization between IXD and FC is no longer based on the closest locations anymore like in an ideal optimization but rather depends on this connection assignment constraint.

Figure 7

Connection Constraint on One IXD to a group of FC Constraint



Additionally, each of these facilities has its own minimum and maximum capacity requirement to be filled for open and close decisions. At least 50% of the total capacity has to be fulfilled in order to open a facility and the maximum is 80%. The remaining 20% of capacity is left as inventory storage which will not be considered further for this optimization process. To summarize, Table 2 below shows the number of packages per day as capacity constraint of each facility to be used in this model.

Table 2

Capacity Constraint as Number of Packages Per Day

Node Type	Total Capacity at 100%	Min Capacity at 50%	Max Capacity at 80%
SC	230,000	115,000	184,000
FC	172,000	86,000	137,600
IXD	910,000	455,000	728,000

3.5 Network Design Scenarios

Once candidate locations, objective functions and additional constraints were defined, the key network design scenarios were determined.

First, a Baseline Model optimizing the current network using current available transportation modes was necessary to compare and contrast with an optimal solution. Next, the research defined a Future State Model optimized by additional alternative transportation modes. Finally, since MMTN had plans to procure additional renewable energy for its electrical fleet, a Future State Model that incorporated lower cost and carbon intensity for electrical modes was added.

Therefore, the research has three key network design scenarios: Baseline Model (Baseline), Future State Model - Market rate (FM-M) and, Future State Model - MMTN rate (FM-C). Table 3 below provides the main difference between the models in detail.

Table 3

Summary of Network Design Models

Node Type	Baseline Model	Future State Model - Market Rate	Future State Model - MMTN Rate
Transport Modes	● Class 6 and Class 8 trucks (diesel), ● Boeing 737 and 767 planes (AvF)	● Class 6 and Class 8 trucks (diesel and electric) ● Boeing 737 and 767 planes (AvF) ● Rail (diesel and electric) ● Vessels (diesel and biofuel) ● Small and Large Air Cargo (biofuel)	
Electricity Variable Cost ($/kWh)	Not Applicable	$0.13	$0.10
Electricity Emissions Intensity Factor (g CO_2e/tkm)	Not Applicable	Varies by mode; See Appendix B for more details	0
Intermodal Drayage	Utilize Class 8 Truck (diesel)	Utilize Class 8 Truck (diesel)	Utilize Class 8 Truck (electric)

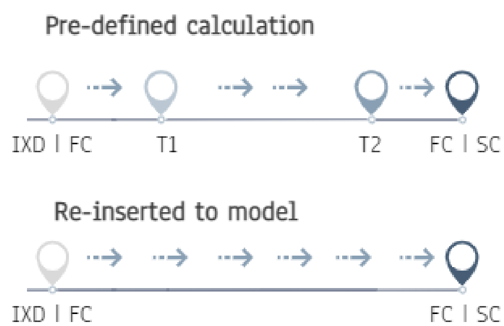
Each of these key network design models was optimized three times to generate the objectives of minimum carbon emissions (min carbon), minimum transportation cost (min cost), and minimum On-The-Road (OTR) transportation time (min time). Coupa's Supply Chain Guru X (SCGX) was utilized for the network optimization, incorporating the described objective formulations in Section 3.3, the constraints in Section 3.4, and the intermodal transport options in Section 3.5.

3.5.1 Intermodal Transportation Options

The Future State Models incorporate both fossil fuel and alternative fuel-powered rails, vessels, and airplanes. These modes have designated terminals or ports throughout the United States, thus limiting their capabilities to travel directly from and to the node locations in the network. Class 8 Trucks are used for drayage shipment between the terminals and facilities. This movement of goods using two or more modes of transportation is called intermodal transportation. The complexity of including intermodal options in the model is simplified by pre-calculating all the metrics separately in Python and inserting them into the model as a single-packaged forward lane from IXD to FC or FC to SC. Figure 8 illustrates this simplification process.

Figure 8

Intermodal Calculation Simplification



The following steps describe how intermodal connections and the corresponding time, cost and carbon emissions required are accurately captured in the models:

1. Find the terminals and ports coordinates
    a. Vessel: Top 30 seaports by export volume in the U.S. (also used for IXD candidate locations) and ports in 10 relevant river systems in the U.S. (Appendix D Figure 6).
    b. Rail: Top 6 cargo rail terminals across mainland U.S. owned by BNSF, CSX, UP, CN, NS and KCS, encompassing 167 rail terminals.
    c. Air: 49 international and 25 domestic airports for cargo
2. Find the distance between terminal-to-terminal and terminal-to-facility. The vessel ports have to be within the same river system or connected through the ocean.
3. Down select all connections by adding the following distance constraints:
    a. Distance between terminals and facilities cannot exceed 50 miles for rail and vessel terminals, and not more than 100 miles for airports.
    b. Distance between terminals must be more than 50 miles for rail and vessel terminals, and more than 100 miles for air.
4. Pair all possible end-to-end connections (from the origin to the first terminal to the second terminal and finally to the destination).
5. Calculate the transportation cost, carbon emissions, and OTR delivery time for both drayage and terminal to terminal connections.
6. Insert these metrics values to the model as end-to-end, origin to destination connections. As the above calculation is done in Python, the model itself does not recognize each terminal or port, but rather recognizes a set of lane options.

Appendix B Table 14 summarizes the assumptions and details of inputs considered for incorporating intermodal transportation into the models.

3.6 Pareto Frontiers

The methodology used to represent the trade-offs between carbon emission, transportation costs, and delivery time is the ε-constraint method for the Pareto frontier (Palacio et al., 2018). To visualize the trade-offs more clearly, two two-dimensional Cartesian coordinate systems showing the Pareto frontier are created instead of a single three-dimensional graphic. These plots illustrate carbon emissions vs. transportation cost, and carbon emissions vs. average on-the-road delivery time. Optimizing each of the three objectives independently will result in finding the coordinate for the Pareto extreme boundary. For instance, when the total transportation cost is fully minimized, its corresponding carbon emissions value is not necessarily the lowest possible emissions value, but the transportation cost is at the lowest possible value and the model will not derive a lower cost value.

As the observation is done in a two-dimensional Cartesian coordinate system, the minimization process is carried out sequentially using Coupa SCGX between the two objectives being observed. Initially, two coordinates of boundary points corresponding to the two objectives examined for the Pareto frontiers need to be determined. The boundary points are the carbon emissions values derived from the optimized network design scenarios from each objective. The next step is to constrain the primary objective of carbon emissions in one axis to be divided by ε numbers where ε is the number of observations and ε_i is a fixed value of carbon emissions at the i^{th} observation.

In this case, to produce ε_i carbon emissions value, the model is run again by this ε_i constraint to minimize the other outcome values (transportation cost or average on-the-road delivery time, respectively). Hence, both x-y coordinate values in the Cartesian coordinate system are found which then can be plotted as carbon emissions vs. transportation cost, and carbon emissions vs. average on-the-road delivery time. Each of these observation points (scenarios) will be connected to create the Pareto frontier line (Palacio et al., 2018). The smaller ε number or the larger the number of observations being calculated, the smoother the Pareto frontier line is.

3.7 Science-Based Targets Calculation

The SBTi provides the guidelines and decarbonization pathway models to be populated with relevant information for both of its tools: Science-Based Target Setting Tool, and the Target Setting tool for Transport Sector. Using the Excel models provided, the outputs from the optimized Baseline minimum carbon emissions (min emissions) objective model are inputted to evaluate which scenarios in the Pareto frontier will help meet the Science-Based Targets that align with 2ºC, WB2ºC and 1.5ºC climate goals in 2030. The Baseline min emissions objective model is the scenario we will use for benchmarking because it represents the current best-case scenario from a total carbon footprint perspective.

The Target Setting Tool - Scope 3, using the absolute contraction approach, provides a non-sector specific decarbonization pathway in line with 1.5ºC, WB2ºC and 2ºC goals for 2030, assuming no change in activity level (tkm). These target numbers help identify the scenarios on the Future State Model's Pareto Frontiers that meet these goals.

The Transport Sector tool provides sector-specific carbon emissions and carbon intensity decarbonization pathways for 2030 considering an activity level increase subscribed by the user of the tool - in this case, a 10% increase in tkms year over year (YoY). Similar to the more generic tool, activity and carbon emissions data from the Baseline Model can be inputted into the Transport Sector tool to find the 2030 carbon emissions and intensity targets for each l mode of transport. The input data required for both SBTi tools are described in Appendix E, Table 16.

4. Results and Key Findings

The objective of this research is to find the optimal middle-mile distribution network scenarios that optimize for the objectives of minimum carbon emission (min carbon), transportation cost (min cost) and on-the-road delivery time (min time) while meeting MMTN's customer demand. A total of 400 candidate locations were successfully identified using the Greenfield analysis. The network optimization based on these candidate locations generated the optimal, or in other words, extreme boundary values for each of the three objectives for each model. Using these boundaries, two 2-D Pareto frontiers for the Baseline and Future Models were created to plot the Pareto frontiers and observe the trade-offs between carbon emissions vs. transportation cost, and carbon emissions vs. OTR delivery time. Finally, the observations on the Pareto frontiers that meet the future carbon emissions targets, calculated through the Science-Based Target Setting tool, were identified. The model outputs also provided the corresponding network design configuration of vehicle mix and facility types for these optimal observations (scenarios) along the Pareto frontiers.

4.1 Greenfield Facility Locations Output

Table 4 shows the summary of candidate locations and its inputs. First, from the 895 customer demand locations based on the 3-digit ZIP codes provided by MMTN, the model generated 154 candidate locations for Sorting Centers (SC). Second, bounded by the population of 830 cities (with populations over 50,000) across the US, 206 candidate locations for Fulfillment Centers (FC) were generated. Lastly, based on the 30 largest ports in the US, and the volume of domestic sellers in 51 states, 40 candidate locations for Inbound Cross-Docks (IXD) were identified. Each of these facilities has minimum and maximum capacity requirements that determine open or close decisions, which were used for the next steps in the network optimization.

Table 4

Summary of Candidate Locations

Node Type	Minimum Capacity (# of packages/day)	Maximum Capacity (# of packages/day)	Number of Demand Nodes	Estimated # of Nodes	# of Candidate Locations
SC	115,000	184,000	895	77	**154**
FC	86,000	137,600	830	103	**206**
IXD	455,000	728,000	81	19	**40**

4.2 Optimized Network Outputs

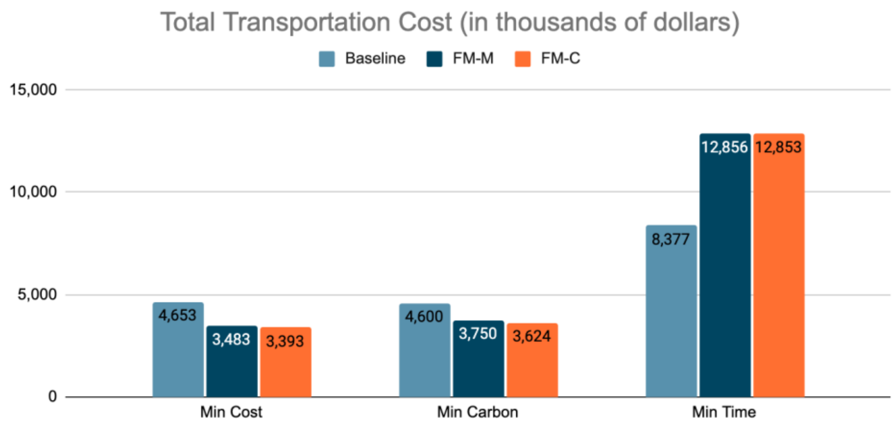
After generating the candidate locations, the model is then optimized three times to reach the three objectives of minimum transportation cost (min cost), carbon emissions (min carbon) and on-the-road delivery time (min time) as outlined in Section 3.3. As discussed in Section 3.5, the research has three key network design models: Baseline Model (Baseline), Future State Model using market electricity rate (FM-M), and Future State Model using MMTN electricity rate (FM-C).

As described in Table 3, the Baseline Model and Future State Models differ in vehicle models utilized. The Baseline Model only consists of diesel trucks and diesel-fuel planes, and is generally not as optimal as the Future State models which include all vehicle options. The difference in electricity costs and carbon intensity, as well as the utilization of Class 8 electric trucks for FM-C's intermodal drayage lanes resulted in FM-C being slightly more optimal than FM-M in costs, carbon emissions and OTR time. This section outlines the key results of the optimized networks.

In terms of transportation costs, the minimum cost objective (min cost) did not always provide the lowest cost compared to the results of the other objectives. As illustrated in Figure 9, the Baseline Model's min carbon scenario's total transportation costs ($4.6M) were less than the min cost scenario's transportation costs ($4.65M). The primary reason is that the model included the customer demand nodes which helped determine the open and close decisions for the SC candidate locations. The lanes from SC to customer nodes were therefore considered part of the network optimization. Although the Baseline Model's min cost scenario for the entire network (IXD-customer) is the lowest cost (see Appendix G, Figure 19), the same scenario's transportation cost for the middle-mile specific network is not. This illustrates that the optimization results of the middle-mile specific network do not always align with the entire network's optimization results.

Figure 9

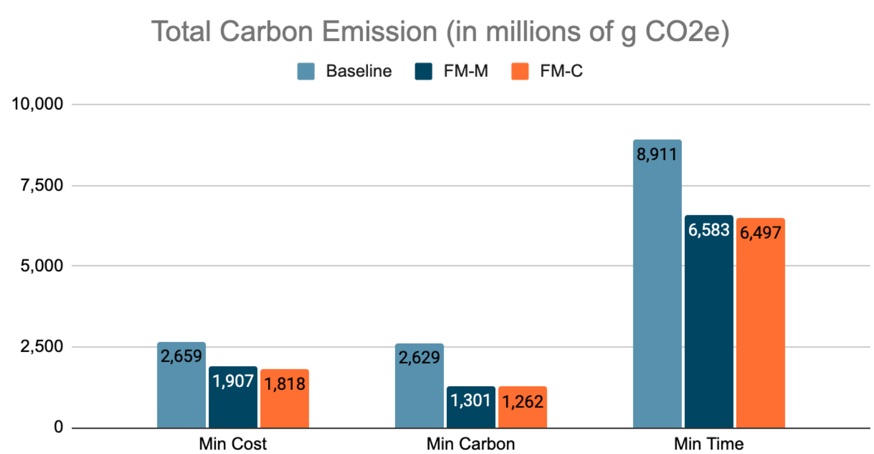
Total Transportation Cost at the Extreme Boundaries



The trade-off in total transportation cost and carbon emissions are minimal for the Baseline Model compared to the Future State Models. As illustrated in Figure 9, the Baseline Model's transportation cost for the min carbon and min cost scenarios are only $53K apart. The difference in carbon emissions between the min cost and min carbon scenarios for the Baseline Model is only 30 tCO_2e, as shown in Figure 10. For both objectives of min carbon and min cost, Class 8 diesel trucks were selected for the entire Baseline Model network scenarios, as they are less costly and carbon-intensive compared to airplanes. The only reason the model produces slightly different values is that it utilizes different routes to achieve lower carbon emissions.

Figure 10

Total Carbon Emissions at the Extreme Boundaries

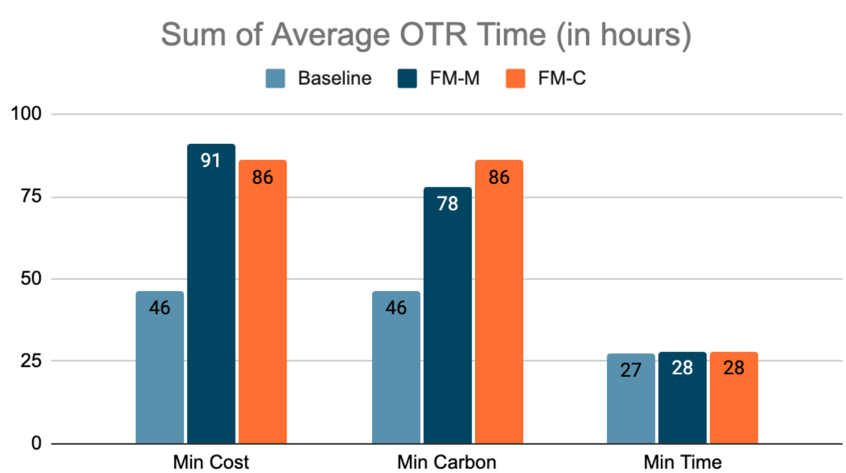


Overall, the two Future State Models present similar results for transportation cost, carbon emissions and delivery time. However, due to the slight input differences between FM-M and FM-C, the FM-C saves up to $126K in transportation cost and up to 89 tCO_2e compared to the FM-M. In contrast to the Baseline Model, both Future Models show a more observable gap between the two objectives. For example, Figure 10 illustrates that the FM-M's min cost (1,907 tCO_2e) and min carbon (1,301 tCO_2e) differ by 606 tCO_2e. The variety of transportation choices in the Future Models influences the model to select extreme values because certain modes such as Class 8 electric trucks are less carbon efficient than others (i.e., Class 8 diesel trucks) but more costly.

In terms of delivery time, all three models illustrated significant trade-offs when minimizing transportation cost and carbon emissions (Figure 9 through 11). This demonstrates that faster transportation modes such as airplanes are not the most cost- or carbon-efficient options.

Figure 11

Total On-the-Road (OTR) Delivery Time at the Extreme Boundaries



The Baseline Model's average On-The-Road (OTR) delivery time outperforms both Future Models' OTR times for all three objective scenarios, as shown in Figure 11. Although at the min time objective scenario, all three models resulted in relatively identical OTR time, the shortest OTR time was the Baseline Model's at 27 hours. However, Figure 10 illustrates that the Baseline Model's carbon emissions for the min time objective scenario is significantly higher than the two Future State Models' carbon emissions even though the min time scenario illustrated in Figure 11 shows identical OTR time. This is because only traditional aviation fuel-powered (AvF) airplanes are available for faster transit. By contrast, the Future

Models have alternative-fuel vehicles that can achieve the same speed as AvF airplanes such as biofuel-powered planes.

Overall, for Future Models, OTR time is longer than the Baseline Model. This can be explained by the different vehicles incorporated that a) are less costly but are not the fastest such as intermodal transportation or b) are the fastest on the market but much more expensive than other alternatives. For example, the fuel costs for biofuel-powered airplanes are three times more expensive than AvF airplanes but are identical in speed. Comparing the Future Models, Figure 11 illustrates that FM-M's OTR time decreased by 13 hours between the min cost and min carbon objectives, while FM-C's OTR time stayed constant at 86 hours for both objective scenarios. This result further demonstrates the significance of how electricity cost and its carbon intensity can influence network design and its configuration of vehicle mix. FM-M had to adjust for less carbon-intensive vehicles when optimizing for the min carbon objective scenario compared to the min cost objective scenario. However, FM-C was able to select the same vehicle mix, as the vehicles that were the least costly were also more carbon-efficient. For example, the Class 8 Electric Truck in the FM-C is 0 g CO_2e/tkm and less costly than slower or faster alternatives such as vessels and airplanes.

4.3 Pareto Frontiers

Using the ε-constraint method to build Pareto frontiers for each model, the results show obvious observations about how carbon emissions reduction influences transportation cost and OTR time. The Pareto frontiers were plotted by finding the optimal scenarios between the carbon emissions extreme boundaries generated by the min cost, min carbon and min time scenario models. In this section, there are two graphs representing Baseline Model and Future Models for each of the trade-offs being observed: carbon emissions vs. transportation cost, and carbon emissions vs. On-The-Road (OTR) delivery time. The Baseline Model's trend and value of carbon emissions is much higher than the Future Models' carbon emissions as its extreme bounds per Figure 10 are much larger. At a glance, this significant difference is caused primarily by its limitation on transportation options.

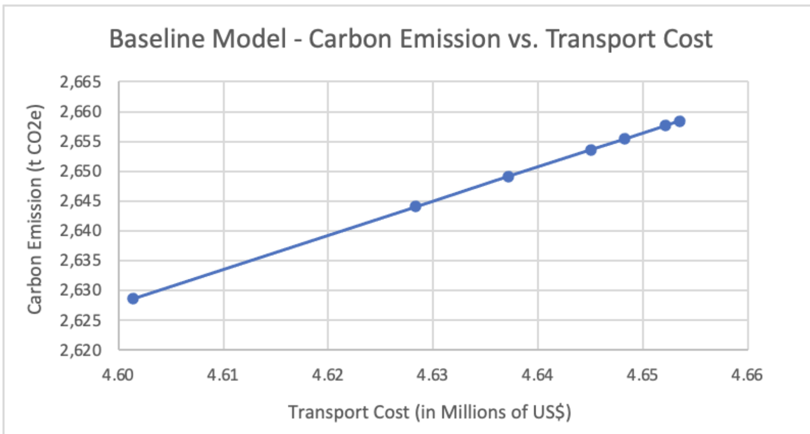
4.3.1 Carbon Emissions vs. Transportation Cost

For the Baseline Model, the Pareto frontier (Figure 12) shows an upward trend. This is because airplanes and Class 8 trucks are the only transport mode options in the Baseline Model. To minimize both objectives, Class 8 trucks are chosen automatically as the only transportation mode. Figure 12 shows the linear positive trend of carbon emissions to transport cost: as emissions increase, longer routes are taken using the Class 8 truck, increasing cost. The two carbon emissions extreme boundaries are 2,629 tCO_2e and 2,659

tCO_2e corresponding to the min carbon and min cost scenarios on Figure 10. In between these two extreme bounds, 6 observations were plotted to create the Pareto frontier.

Figure 12

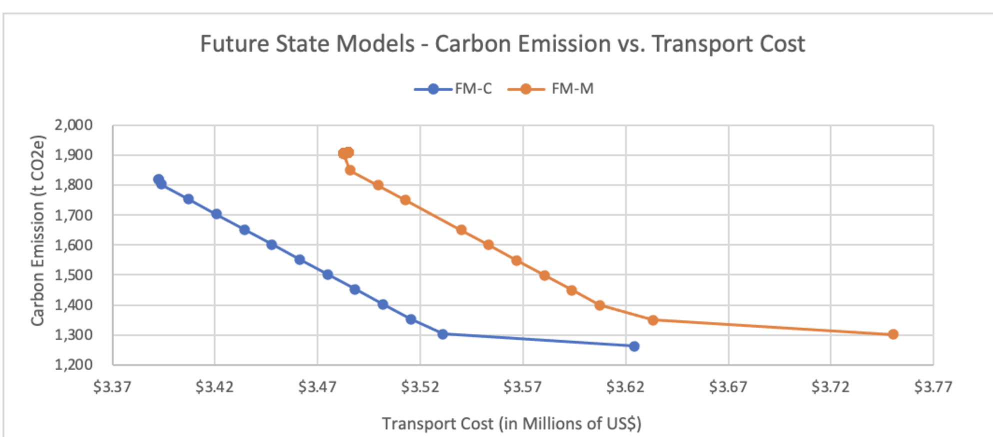
Pareto Frontier for Baseline Model on Carbon Emissions vs. Transport Cost



The Future State Model Pareto frontiers in Figure 13 illustrate negative slopes where the cost of transportation increases as the scenarios have less carbon emissions. Due to the decrease in costs for electricity powered vehicles, the FM-C's overall costs per carbon emissions scenario is lower compared to the FM-M. The two carbon emissions extreme boundaries were 1,301 tCO_2e and 1,907 tCO_2e for the FM-M and 1,262 tCO_2e and 1,818 tCO_2e for the FM-C. In between these two extreme bounds, 14 observations for FM-M and 13 observations for FM-C were plotted to create the Pareto frontier.

Figure 13

Pareto Frontier for Future Models on Carbon Emissions vs. Transport Cost

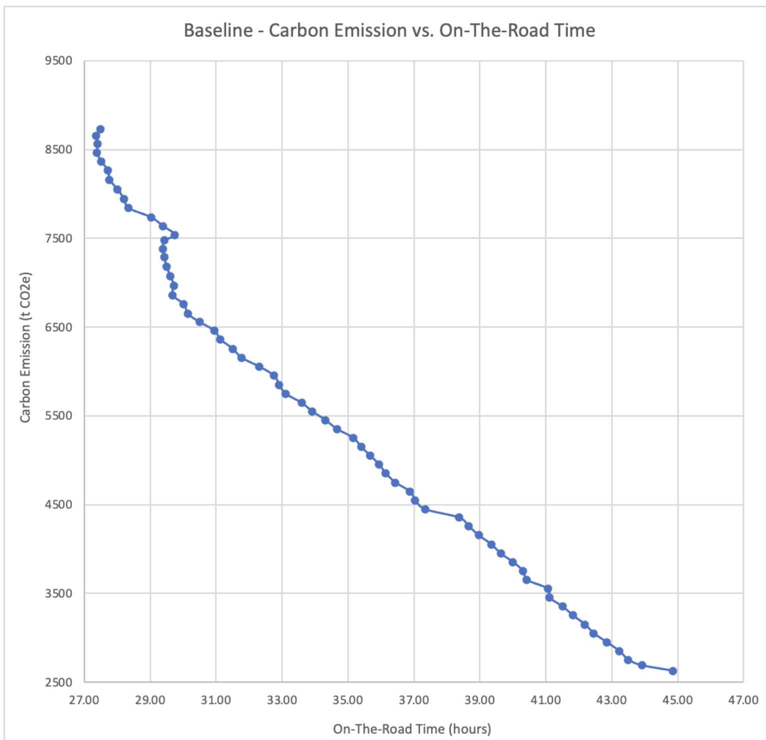


4.3.2 Carbon Emissions vs. On-The-Road Delivery Time

The Pareto frontiers for carbon emissions vs. OTR delivery time have negative slopes. The Baseline Model's carbon emissions extreme boundaries are 2,659 tCO_2e and 8,911 tCO_2e corresponding to the min carbon and min cost scenarios in Figure 14. In between these two extreme bounds, 63 observations were plotted to create the Pareto frontier.

Figure 14

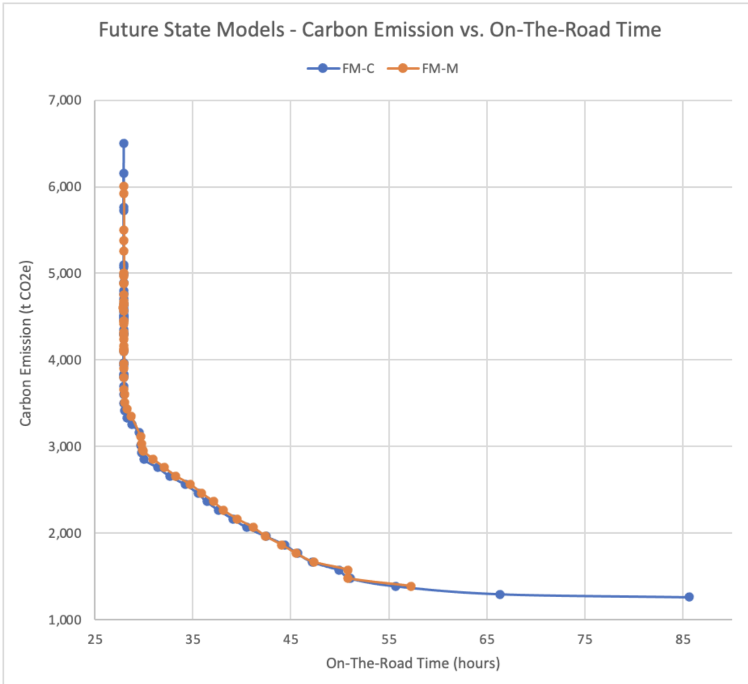
Pareto Frontier for Baseline Model on Carbon Emissions vs. OTR Delivery Time



Unlike the Pareto frontiers for carbon emissions vs. transportation cost, both Future models' Pareto frontiers for carbon emissions vs. OTR have nearly identical observations (see Figure 15). This similarity occurred because the only difference between the models is the carbon intensity of the electric vehicles as transportation selections in both models have the same average speed. The two carbon emissions extreme boundaries for these Pareto frontiers were 1,301 tCO_2e and 6,583 tCO_2e for the FM-M and 1,262 tCO_2e and 6,497 tCO_2e for the FM-C. In between these two extreme bounds, 53 observations for FM-M and 56 observations for FM-C were plotted to create the Pareto frontiers.

Figure 15

Pareto Frontier for Future Model on Carbon Emissions vs. OTR Delivery Time



4.4 MMTN's Science-Based Emissions Targets

The total emissions and carbon intensity targets set by SBTi's target setting tools, as described in Section 3.7, were derived using the Baseline minimum carbon emissions (min carbon) objective scenario's activity and total emissions output. The Baseline min carbon objective scenario is a proxy for MMTN's current middle-mile Baseline as it provides the current optimal network design scenario. This Baseline min carbon objective scenario is referred to as the Baseline scenario for the remainder of this report.

The scenarios (observation points) that fulfill the Science-Based Targets of 1.5°C, 2°C and WB2°C were identified from the Future State models' Paretos. However, since the Baseline Model's carbon emissions were much higher than the upper bound of Science-Based Targets (2°C), the Baseline Model's Pareto frontiers do not have any observation points that meet the Science-Based Targets.

4.4.1 Targets Generated

Inputting the Baseline scenario's total emissions of 2,629 tonnes as the base year (2020) emissions, the SBTi's Target Setting's Scope 3 tool generated the target year (2030) total emissions targets for the 2ºC, WB2ºC and 1.5ºC scenarios (Table 5). These targets were not based on any future activity increases and thus, the target numbers are based on the assumption that activity levels (tkm) do not increase from 2020 levels. Appendix E, Table 18 provides an approximation of the future carbon emissions and intensity targets generated by the increase in activity levels using the Science-Based Transport Specific Tool. Due to the transportation mode limitations of the Transport Specific tool, these approximations will not be used to inform this research.

Table 5

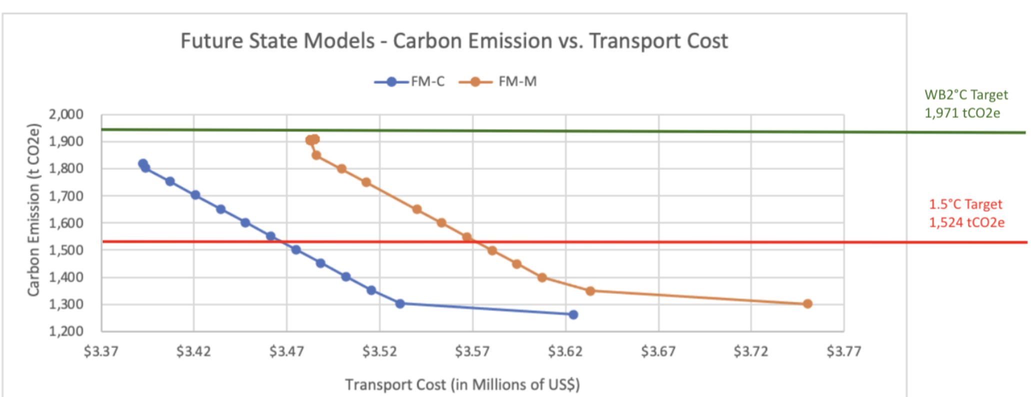
Science-Based Target Setting Tool - Scope 3 Targets Generated

	Base year (2020)	Target year (2030)	% Reduction
Company | Scope 3 emissions - 2C (tCO2e)	2,628.6	2,305.3	12.3%
Company | Scope 3 emissions - WB2C (tCO2e)	2,628.6	1,971.5	25.0%
Company | Scope 3 emissions - 1.5C (tCO2e)	2,628.6	1,524.6	42.0%

Once the target total emissions were derived, the scenarios that match these target numbers were identified on the Pareto frontiers for the Future State Models (see Figure 16). Since the optimal scenarios plotted on the Pareto frontiers for carbon emissions vs. transportation cost do not exceed 1,980 tonnes of CO_2e for the Future State Model's Market rate model (FM-M), only the WB2ºC and 1.5ºC target scenarios were identified. Thus, a 2ºC scenario is not considered optimal and not on the Pareto frontier. Moreover, only the 1.5ºC target scenario was identified to be optimal in the Future State's Company model (FM-C).

Figure 16

Science Based Target Scenarios Identified on Carbon Emissions vs. Transport Cost Pareto Frontier

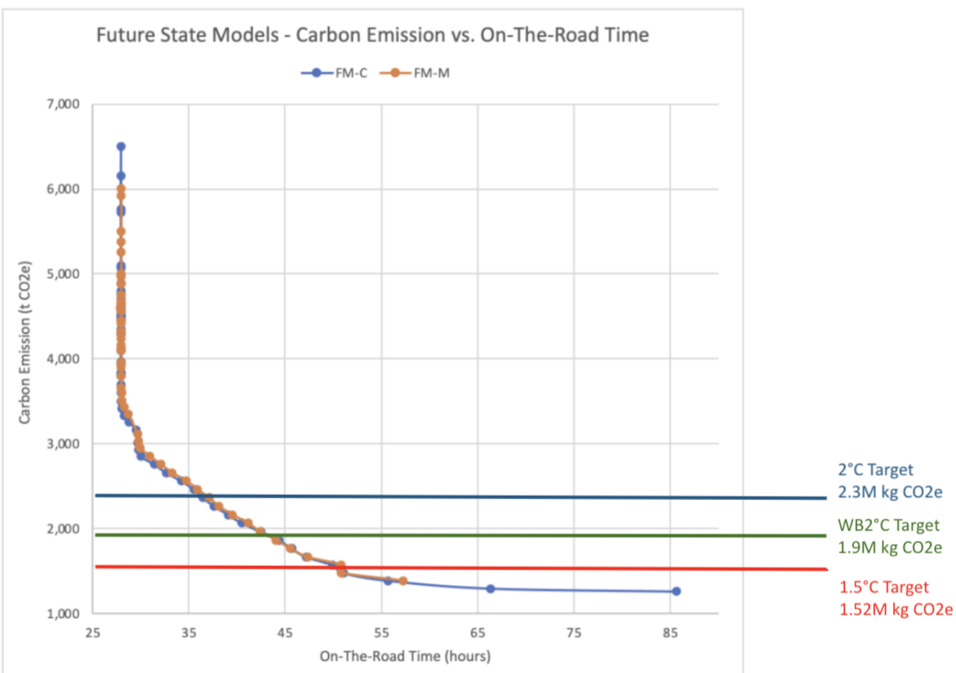


The Future models prove that the Science-Based Targets can be achieved with additional transport choices, such as electric-powered vehicles, that are more carbon efficient. Figure 16 above illustrates the FM-C compared side by side with the FM-M. Both models have utilized the same vehicle modes for most of their lanes, but the FM-C's overall costs in each scenario is lower compared to the FM-M due to the decrease in variable cost for electric vehicles. For instance, at the 1.5°C target scenario (or 1,524 tCO_2e), FM-C's costs are $105,608 less than FM-M's values.

On the other hand, optimal scenarios considering both the objectives of minimizing carbon emissions and OTR delivery time can satisfy the Science-Based Targets generated by the Target Setting Tool - Scope 3. Figure 17 illustrates the observation points that match these Science-Based Targets.

Figure 17

Science-Based Target Scenarios Identified on Carbon Emissions vs. Delivery Time Pareto Frontier



4.4.2 Science-Based Target Scenarios

The optimal scenarios on the Pareto frontiers for the Future State Models only matched the Science-Based Targets of 1.5°C and WB2°C. Taking a deeper dive into these target scenarios, the following nodes were opened for both scenarios: 16 IXD, 78 FC, and 82 SC facilities. This configuration presents almost no material change compared to the Baseline Model's facilities configuration of the network. Table 6 below lists the vehicle mix selected for these scenarios, illustrating that only alternative fuel transport modes were selected. In addition, Class 8 tractor trailers are still the dominant mode of transportation due to its relative speed and variable cost compared to other vehicle types. Appendix D Figure 18 provides a detailed map of the network design including the modes of transportation used.

Table 6

Vehicle Utilization for Carbon Emissions Level at 1.5^{o}C and Well Below 2^{o}C

Modes	Future State - Market Rate		Future State - MMTN Rate	
	at 1.5ºC	at WB2ºC	at 1.5ºC	at WB2ºC
Class 8 Tractor (Electric)	83.61%	63.71%	83.11%	77.77%
Rail (Electric)	16.04%	7.92%	16.54%	8.64%
Vessel (Biofuel)	0.20%	0.20%	0.20%	0.20%
Small Air Cargo, Medium Haul (Biofuel)	0.11%	15.19%	0.11%	6.75%
Large Air Cargo, Short Haul (Biofuel)	0.04%	0.04%	0.04%	0.04%
Large Air Cargo, Medium Haul (Biofuel)	0%	12.94%	0%	6.60%

Moreover, the carbon intensity can be calculated for each of the scenarios by finding the ratio of total activity (tkm) to total carbon emissions. Table 7 shows calculated carbon intensity by scenario. The WB2^{o}C and 1.5^{o}C scenarios provide a lower carbon intensity than the Baseline value. The 2^{o}C scenario that is not optimal and not found on the Pareto frontier graph illustrates a higher carbon intensity compared to the Baseline. More striking is the difference between the carbon intensities generated from target scenarios and the default carbon intensity values used to estimate total carbon emissions for different vehicle types (see Appendix B, Table 11 and 12) as explained in Section 3.3.1. For example, the diesel-powered Class 8 tractor trailer's carbon intensity value used, per the GLEC framework, is 150 gCO_2/tkm. This value is over 789 times more than the 2^{o}C scenario's carbon intensity and over 1,667 times more than that of the 1.5^{o}C scenario.

Table 7

Carbon Intensity for Science-Based Target Scenarios

Scenarios	Total 2020 Activity (tkm)	CO_2 Emissions (t)	Carbon Intensity (gCO_2/tkm)
Baseline – Min Carbon	20,549,174,855	2,629	0.13
2ºC	12,380,800,978	2,305	0.19
WB2ºC	20,274,027,049	1,971	0.10
1.5ºC	16,171,222,283	1524	0.09

5. Discussions & Recommendations

The results derived from this research provided some key learnings that inform the considerations for redesigning a middle-mile distribution network that optimizes for the objectives of minimum carbon emission, transportation cost and on-the-road time. The key model results, when optimizing for these objectives, illustrated that the trade-offs between on-the-road time and carbon emissions or transportation cost was significant compared to the trade-off between carbon emissions and transportation cost. This was primarily because faster transportation vehicles were far less carbon-efficient (i.e., airplanes). However, the Future State Models proved that alternative transportation, including intermodal transportation and alternative-fuel vehicles, provide opportunities to minimize the trade-offs between transport cost as well as delivery time and total carbon emissions in the network. In addition, the two Future State Models revealed that MMTN's transportation variable costs and carbon emissions can decrease if it were to generate its own electricity from renewable energy sources.

Finally, the Science-Based Targets provided insights into the optimal scenarios on the Pareto frontiers that will meet the global carbon emissions reduction targets. First, it was determined that if business continues as usual (per the Baseline Model's Pareto frontier), MMTN will not be able to comply with any of the targets recommended by climate science research and global regulatory bodies and adopted by a growing number of corporate climate leaders. Second, only the WB2^{o}C and 1.5^{o}C Science-Based Targets were considered optimal for all Pareto frontiers, narrowing the key scenarios that will meet both the business objectives as well as global carbon emissions reduction objectives.

5.1 SBTi 1.5^{o}C Carbon Emissions Target

Following the Paris Agreement to the agreed upon limit of global warming by 1.5^{o}C above pre-industrial levels, in 2019, the Intergovernmental Panel on Climate Change (IPCC) reported the necessity to maintain the global temperature increase below 1.5^{o}C to avoid irreversible damage to our world (IPCC, 2020). In response, a global coalition of UN agencies, business and industry have created the Business Ambition for 1.5^{o}C call to action, urging organizations to commit to setting ambitious Science-Based Targets. The SBT Setting Tool utilized in this research provided the 1.5^{o}C target carbon emissions for our models, helping identify the specific observation (scenario) on the Pareto graphs that matched this target. This target scenario therefore, lays out the guidelines for the optimal carbon-efficient network design scenario for middle-mile distribution.

5.2 Key Trade-offs at 1.5°C Target

The 1.5°C target scenario's vehicle mix, node locations and decisions as well as carbon intensity results were captured in detail in Section 4.4.2. By comparing the target scenario with the Baseline min emissions objective scenario (Baseline scenario), key trade-offs were realized. The following sections will discuss these trade-offs in detail.

5.2.1 Cost Trade-off Calculation

Per the results in Section 4.4.2, since there is almost no difference in the physical network configuration (i.e., facilities) between the Baseline Model and the 1.5°C target scenario, the cost trade-off between the Baseline scenario versus the 1.5°C scenario can be represented by the increase in variable transportation cost per ton carbon emission reduced. The Baseline scenario's variable cost per ton carbon emissions (CO_2e) produced is $1,750 t/$CO_2e$ produced. Table 8 below provides the variables used to calculate this cost: ratio of total transportation variable cost to total carbon emissions (CO_2e) emitted.

Table 8

Variable Cost Per Ton Carbon Emissions Produced on Baseline Scenario model

Transport Variable Cost	CO_2e Emissions (tonnes)	Variable Cost/ tCO_2e Produced
$4,600,341	2,629	$1,750

Since there were two Future State models and corresponding Pareto Frontiers (Figure 16 and 17), two separate scenarios that meet the target carbon emissions at the 1.5°C were identified: Future State model - Company Rate (FM-C), and Future State model - Market Rate (FM-M). Table 9 below provides the corresponding ratios of total transportation variable cost to total carbon emissions (CO_2e) emitted for each 1.5°C scenario.

The variable cost per ton carbon emissions (CO_2e) produced at the 1.5°C scenario is $69 (11%) less for the FM-C model compared to the FM-M model. This difference indicates that variable costs per carbon emissions produced decrease when the company can procure its electricity from its own renewable energy sources.

The increase in variable cost per ton decrease in CO_2e is computed by taking the difference of the variable cost per ton CO_2e produced between the Baseline scenario and the 1.5°C scenarios. This difference captures the variable cost trade-off of adopting a network design scenario that complies with the 1.5°C global warming target. The variable cost for each additional ton of carbon emissions reduced is estimated to be either \$520 or \$589. In other words, if MMTN produces its own electricity, its variable transportation cost will increase by \$520 per CO_2e reduced. If MMTN procures market rate electricity, the transportation variable cost will be \$589 per ton CO_2e decrease.

Table 9

Increase in Variable Cost Per Ton Carbon Emissions Decrease at 1.5°C Scenario

1.5°C Scenarios	Transport Variable Cost	CO_2e Emissions (tonnes)	Variable Cost/ tCO_2e Produced	Increase in Variable Cost/ tCO_2e decrease
Future State Model - MMTN Rate	\$3,461,000	1,524.6	\$2,270	2,270-1,750= **\$520**
Future State Model - Market Rate	\$3,566,000	1,524.6	\$2,339	2,339-1,750=**\$589**

5.2.2 On-The-Road Time Trade-off Calculation

The On-The-Road (OTR) time trade-off between the Baseline scenario and 1.5°C scenario can be represented by the increase in OTR time. Table 10 below provides a summary of the average OTR time (in hours) for the Baseline, 2°C, WB2°C and 1.5°C scenarios as well as the corresponding total carbon emissions reduced compared to Baseline emissions.

The results indicate that in order for MMTN to adopt a 1.5°C emissions target scenario (a 42% decrease in emissions), its current Baseline average OTR time will have to increase by an average of 4 hours (9%). In addition, the 2°C and WB2°C target scenarios prove that there would not be a trade-off in average OTR time, rather, it would be the opposite. The carbon-efficient vehicle types such as biofuel airplanes could improve Baseline average OTR time by 4-10 hours (9%-22%), while still decreasing total carbon emissions in the network.

Table 10

Average On-The-Road Delivery Time and CO_2e Difference by Target Scenarios

Scenario	Average OTR time (hours)	Difference from Baseline (hours)	CO_2e Decrease from Baseline Scenario (ton)
Baseline	46 hours	Not Applicable	
2°C	36 hours	-10 hours	324 tonnes
WB2°C	42 hours	-4 hours	657 tonnes
1.5°C	50 hours	+4 hours	1,105 tonnes

5.3 Limitations and Future Research

Although the methodology developed in this research attempts to solve for the optimal scenarios that minimize carbon emissions while quantifying cost and time trade-offs for the middle-mile distribution network, there are some limitations to the approach used in this research. The key limitations are as follows:

- Data availability:
    - Vehicle Data: Did not use actual carbon emissions intensity factors, fuel burn, load factor and speed per transportation types
    - Cost Data: Did not use actual fuel and electricity costs
- Assumptions around:
    - Availability and scalability of alternative fuel technologies
    - Carbon emissions scope within the forward-flow transportation
    - Static demand volume and locations
- Exclusion of other transportation costs such as capital expenditure and labor
- Inclusion of a proxy last mile in network optimization

First, due to the unavailability of primary data, when accounting for carbon emissions the research used Scope 3 (subcontracted) methodology and relied on publicly available generalized data for carbon emissions intensity factors. Specifically, the general averages for carbon emissions intensity factors potentially underestimated total carbon emissions of the network. This is because GLEC intensity factors assume an average fill rate of vehicles but MMTN's vehicles typically have lower fill rates than industry averages. As this is a modeling exercise, the values presented here are merely suggestions of potential future emissions. In practice, emissions will vary depending on the exact types of vehicles used, the load factor, as well as on-the-ground conditions like traffic, topography, or weather and road conditions. By capturing these key data points, carbon emissions estimates can be better refined in future research, providing a more realistic result, especially for low fill rate vehicles or lanes in the middle-mile.

On the other hand, the current methodology only accounts for carbon emissions from forward-flow transportation of the middle-mile distribution network. Carbon emissions from other sources, including but not limited to transshipment facilities, reverse logistics or the manufacture of the vehicle components such as lithium batteries are not considered. Moreover, since one of MMTN's value propositions is focused on the speed of delivery, increased delivery time may decrease customer volume. This volume can transfer to more customers making physical trips to the store instead of online delivery, increasing overall carbon emissions. Although these sources of carbon emissions were out of scope for this research project, the current approach helped determine a high-level picture of the strategies and nuances in optimizing the middle-mile network operations for carbon efficiency. Future research incorporating all the relevant sources in the middle-mile network could provide a more detailed view of carbon emissions reduction opportunities from non-mobile sources.

Second, the Future State Models assumed the availability and scalability of alternative fuel technologies and vehicles such as electric-powered rail, biofuel-run airplanes and electric heavy-duty trucks. In reality, such transportation technologies are not readily available to scale in the U.S. In the U.S. currently, there aren't any electric railroads for freight, so the future models are not replicable in the immediate future. In addition, although electric-powered heavy-duty trucks are becoming more prevalent in the market, the battery range (ability to hold a charge) is a challenge for long haul delivery as this relies heavily on increased road infrastructure that supports battery charging. For airplanes, the uptake of Sustainable Aviation Fuels (SAF) is highly dependent on the availability and cost of such fuels. Currently, SAF production is only 1% of total jet fuel needs (IATA, 2020). There is also a high-cost differential between SAF and conventional jet fuel, which is estimated to be about a 100% to 200% higher price premium for SAF compared to the average pre-covid oil prices (World Economic Forum and Energy Transition Commission, 2020). Further research only incorporating diesel-powered vehicles is worth analyzing as the addition of intermodal transportation such as rail and vessels can provide a more realistic picture of short-term carbon emissions reduction opportunities.

In addition, the significant upfront investment and ongoing maintenance costs of alternative transportation are not part of the model's cost objective. Besides the capital costs for obtaining alternative fuel technology, the ongoing costs such as sourcing batteries and implementing renewable-powered charging stations can be significant. However, a more advanced analysis considering the potential total costs for adopting alternative fuels and vehicles in the transportation network could provide the net trade-off between total costs and minimizing emissions.

Another limitation is that the methodology assumed static demand volume and location as well as one product type for a single time period. Service constraints for each of the demand nodes were also not considered. The approach may be improved with more detailed information on the variability of demand of different products across multiple time periods with customer-specific service constraints.

Finally, the model optimization is based on a network that includes the middle-mile plus a proxy last mile (SC-Customer). This was because the model needed to make the open/close decisions required for SC candidate locations. This approach falls short of fully optimizing for just the middle-mile as the model minimizes the key objectives of cost, time and carbon emissions based on the entire network of four nodes (IXD, FC, SC and Customers). To optimize for just the middle-mile, the SC locations will have to be predetermined.

5.4 Recommendations Summary

The research has provided some clear insights into the path for achieving the optimal middle-mile network design scenarios that meet MMTN's carbon reduction goals.

A key learning was that MMTN will not reach any of the Science-Based Targets, per the Paris Agreement goal of keeping global temperature rise below to well below 2^{o}C or preferably to 1.5^{o}C, if business were to continue as usual. The Baseline Model's Pareto frontiers (Figure 12 and Figure 13) illustrated that the optimal scenarios for the Baseline did not meet these Science-Based Targets. In other words, all the Baseline optimal solutions, when accounting for the objectives of cost, carbon emissions and time, fell short of meeting even the upper bound of the Science-Based Targets (2^{o}C).

Moreover, the results illustrated that per Liljestrand et al.'s (2015) hypothesis that intermodal transportation has a large potential to reduce carbon emissions, the addition of intermodal transportation in our Future State Models did in fact, help reduce carbon emissions in the middle-mile distribution network. The research also proved that procuring electricity generated by company-owned renewable energy does decrease variable costs and carbon emissions slightly as well as decrease costs to reduce emissions.

However, rail and vessels were not the most utilized for any of the optimal scenarios because of the intermodal transportations' limitations in speed and need for drayage between nodes. In addition, comparing the future models in our research, such electricity procurement practices reduce carbon emissions by a mere 1-4%. Thus, even though developing renewable energy sources for electricity, and adding intermodal transportation to the current network helps reduce carbon emissions, these measures do not provide the most opportunity for carbon emissions reduction in MMTN's middle mile distribution network.

The research found that to achieve significant reduction in carbon emissions that meet the 1.5°C and the well below 2°C targets, the middle-mile distribution network needs to transition 100% of its transportation activity to alternative fuel transportation modes. All the vehicle mode types that were selected for the optimal scenarios that meet the Science-Based Targets were alternative-fuel transportation (Table 6, Section 4.4.2). Therefore, significant innovation and investment in alternative fuel transportation modes is required from MMTN for this transition.

The investment in infrastructure to support long distance electric trucks as well as electric rail is imperative for the actual adoption of these modes on the scale that is required for the middle-mile distribution network. From the two modes, electric-powered Class 8 trucks were the most utilized transportation mode in the optimal network scenarios at 60-80%, while electric rails were at 8-16% of total vehicle mix. Infrastructure that supports the battery charging of long-haul trucks and the construction of electric railroads is necessary for its utilization in MMTN's middle-mile network.

In addition, collaborative partnerships with potential suppliers of alternative fuel vehicles are necessary for this transition. MMTN can support the innovation at companies that have already started heavily investing in creating technologies that run on alternative fuel. For example, Boeing announced that its entire airplane fleet will have the capabilities to fly on biofuel by 2030 (Johnson, 2021). MMTN is in a unique position to join forces with such firms to not only influence the design of the vehicle modes that cater to MMTN's business needs but also ensure sufficient supply for its network. In the same way, MMTN can support the development of low-carbon fuels by supporting initiatives to expand sustainable production and distribution of these fuels, as well as initiatives such as carbon insets (Smart Freight Centre and Deutsche Post DHL Group, 2020) to advance their uptake.

Since MMTN utilizes a mix of both owned and subcontracted fleet, a barrier to a full transition of all heavy-duty truck transportation to alternative fuel trucks is the capabilities of its subcontractors. MMTN can combat this barrier by providing incentives such as training and material support to transition all its heavy-duty truck subcontractors.

6. Conclusion

Increasing repercussions of climate change fueled by rising transportation carbon emissions, coupled with the global call to decarbonize by intergovernmental and corporate bodies, provides an opportunity to develop and implement carbon-efficient distribution networks that also meet business needs. By optimizing for the key business objectives of minimizing transportation cost and delivery time as well as the environmental objective of minimizing carbon emissions, this research found that optimal middle-mile network design scenarios on the Pareto frontier that meet global Science-Based Targets to keep emissions well below 2ºC and 1.5ºC exist. In addition, the trade-offs to meeting these carbon emissions reduction targets were derived. The research found that the trade-offs for implementing the 1.5ºC target scenario are an increase in variable cost by $589 (33%) for each additional ton of carbon emissions reduced as well as an increase of 4 hours (9%) to average on-the-road delivery time.

Although the research focus is directly contributing to the middle-mile distribution network, the findings from the research are applicable to re-imagining the carbon-efficient network design along the entire supply chain. The results suggest that there is no evidence that optimizing the existing baseline vehicles will eventually reduce the carbon emissions level. Instead, to realize these optimal network design scenarios that meet global carbon reduction targets, it is necessary to replace all fossil fuel -powered vehicles with alternative fuel-powered transportation and technology. This transition will require significant investment and innovation in infrastructure and technology for electric, biofuel and other alternative energy-powered transportation. Future studies can further explore the implications of the upfront capital costs and the limitations of transitioning subcontracted and owned fleets to alternative fuel powered vehicles.

7. Appendix

Appendix A: GLEC Framework Formulas

Equation 1: Scope 2 Conversion of Electricity to GHGs

$$\text{kg } CO_2\text{e emissions} = \sum_1^n \left(\text{electricity (kWh)} \times \text{electricity emission factor} \left(\frac{\text{kg } CO_2\text{e}}{\text{kWh electricity}}\right)\right)$$

Equation 2: Scope 3 Freight Transport Total Activity Calculation (in tkm)

$$\sum_{\text{trip}=1}^{n} \text{tkm} = \text{tonne}_{\text{trip 1}} \times \text{kilometer}_{\text{trip 1}} \ldots + \text{tonne} \times \text{kilometer} \ldots + \text{tonne}_{\text{trip n}} \times \text{kilometer}_{\text{trip n}}$$

Equation 3: Scope 3 Emissions calculation using fuel efficiency

$$\text{kg } CO_2\text{e emissions} = \sum_1^n \left(\textit{total} \text{ tkm} \times \text{fuel efficiency factor} \left(\frac{\text{kg fuel}}{\text{tonne-km}}\right) \times \textit{fuel emission factor} \left(\frac{\text{kg } CO_2\text{e}}{\text{kg fuel}}\right)\right)$$

Equation 4: Scope 3 Emissions Calculation using CO_2e intensity factors

$$\text{kg } CO_2\text{e emissions} = \sum_1^n \left(\textit{total} \text{ tkm} \times CO_2\text{e } \textit{intensity factor} \left(\frac{\text{kg } CO_2\text{e}}{\text{tonne-km}}\right)\right)$$

Source: Global Logistics Emissions Council Framework for Logistics Emissions Accounting and Reporting Version 2.0 (p. 16) by S. Greene & A. Lewis, 2019, Smart Freight Centre.

Appendix B: Transportation Modes

Table 11

Average fill rates and carbon intensity factors for current transportation types

Current Transportation Type	Vehicle Characteristics	Corresponding Vehicle Categorization in GLEC	Carbon Intensity Factors (g CO_2e/tkm)
Class 8 Tractor- Trailer (diesel)	>13 t	Rigid Truck (12-20 t GVW)	150
Class 6 Truck (diesel)	8.5t - 12t	Rigid Truck (7.5-12 t GVW)	240
Boeing 737 Cargo Aircraft (aviation fuel)	Air, freighter	Air, Medium Haul, freighter (1000-3700 km)	710
Boeing 737 Cargo Aircraft (aviation fuel)	Air, freighter	Air, Short haul, freighter (<1000km)	1390
Boeing 767 Cargo Aircraft (aviation fuel)	Air, freighter	Air, Medium Haul, freighter (1000-3700 km)	710
Boeing 767 Cargo Aircraft (aviation fuel)	Air, freighter	Air, Short haul, freighter (<1000km)	1390

Source: Table 35 and Table 42, GLEC Framework (Greene & Lewis, 2019)

Table 12

Average fill rates and carbon intensity factors for alternative transportation types

Alternative Transportation Types (Energy type)	Corresponding Vehicle Categorization in GLEC	Emission Intensity Factors (g CO_2e /tkm)
Vessel (Diesel)	Motor Vessels <80 m (<1000 t)	30
Rail (Diesel)	Average/mixed load diesel traction	28
Rail (Electric)	Average/mixed load electric traction	10
Class 6 (Electric)	Rigid Truck (7.5-12 t GVW)	168.5[1]
Class 8 (Electric)	Rigid Truck (12-20 t GVW)	105.3
Large Air Cargo Short-haul (Biofuel)	Air, Short Haul, freighter (1000-3700 km)	463.3[2]
Large Air Cargo Medium-haul (Biofuel)	Air, Medium Haul, freighter (1000-3700 km)	236.6[3]
Small Air Cargo Short-haul (Biofuel)	Air, Short Haul, freighter (1000-3700 km)	463.3[2]
Large Air Cargo Medium-haul (Biofuel)	Air, Medium Haul, freighter (1000-3700 km)	236.6[3]
Vessel (Biofuel)	Motor Vessels <80 m (<1000 t)	19.7[4]

Source: Table 35, 36, 38, 42, 44, 45, 46 GLEC Framework (Greene & Lewis, 2019)

[1] Converted total kWh/t-km of 0.39 to g CO_2e/t-km using the 2018 U.S. electricity emissions factor of 0.9529lbs (or 432g) CO_2e/kWh from the U.S. Energy Information Administration (EIA)
[2,3] Assumed to be one-third of the emissions intensity factors from aviation fuel powered air freighters
[4] Calculated by multiplying its fuel consumption factor (0.0091 liters/t-km) by total kg carbon emissions/liter (2.6)

Table 13

Transportation Modes Summary

Vehicle Type	Short Haul (<500 km or <310 mi)	Medium Haul (500-1000 km or 310-621 mi)	Long Haul (>1000km or >621 mi)	Average # of Packages Per Trip or Capacity	Consumption factor (l/tm-km) or (kWh/tm-km)	Empty Weight of Vehicles (tonnes or tm)	Average Weight of Packages Per Trip (tonnes or tm)	Fuel Price using weight of vehicle and avg packages ($/mi)	Emission Intensity Factors (g CO2e /tm-km)	Average Speed (MPH)
Class 8 Tractor Trailer	Yes	Yes	Yes	1500	0.0480	7.5	1.021	0.431	150	40
Class 6 Box Truck	Yes			700	0.0740	6	0.476	0.505	240	40
Boeing 737, Medium Haul (AvF)			Yes	10000	0.2290	43.6	6.804	5.999	710	575
Boeing 767, Medium haul (AvF)			Yes	18000	0.2290	86.5	12.247	11.753	710	575
Boeing 737, Short Haul (AvF)		Yes		10000	0.4484	43.6	6.804	11.745	1390	575
Boeing 767, Short Haul (AvF)		Yes		18000	0.4484	86.5	12.247	23.009	1390	575
Rail (Diesel)	Yes	Yes	Yes	1500	0.0087	23	1.021	0.220	28	55
Inland Vessel (Diesel)	Yes	Yes	Yes	30000	0.0079	110	20.412	1.086	26	15
Class 8 Tractor (Electric)	Yes	Yes	Yes	1500	0.2530	7.5	1.021	0.451	105.3	40
Class 6 Truck (Electric)	Yes			700	0.3900	6	0.476	0.528	168.48	40
Small Air Cargo, Medium Haul (Biofuel)			Yes	10000	0.2290	43.6	6.804	15.458	236.667	575
Large Air Cargo, Medium Haul (Biofuel)			Yes	18000	0.2290	86.5	12.247	30.285	236.667	575
Small Air Cargo, Short Haul (Biofuel)		Yes		10000	0.4484	43.6	6.804	30.263	463.333	575
Large Air Cargo, Short Haul (Biofuel)		Yes		18000	0.4484	86.5	12.247	59.289	463.333	575
Rail (Electric)	Yes	Yes	Yes	1500	0.0322	23	1.021	0.162	10	55
Inland Vessel (Biofuel)	Yes	Yes	Yes	30000	0.0079	110	20.412	1.380	19.656	15

Table 14

Intermodal Transportation Considerations

Vehicle Type	Rail	Barge	Air	Vessel
# Terminals	167	142	74	171
# Combination	19334	1684	134561	5101
#Lines/Systems	7	10	-	-
Minimum Distance to Other Terminals	50	50	100	50
Maximum Distance to Nodes (facilities)	50	50	100	50
Source	BNSF, CSX, UP, etc	*worldportsource.com*, Top 10 River Systems	FAA List of Largest Cargo Airport, Google Maps	Top 30 Ports used for IXD Candidate Locations
Assumptions and Considerations	- Includes Class I Rail = ~70% of total track miles - All rail lines are connected - Electric Rail to utilize current rail tracks in US	-Includes 10 water systems in the US - Vessels can only travel within the same water systems	- Only long and medium haul - 8 modes of airplanes - Use top cargo airports and international airports	- Only long haul - Shipment can be from Ports in the West coast to East coast - Current West ports to East ports distance uses straight line approach

Appendix C: Fuel Price

Table 15

US National Average Fuel Price[2]

Fuel Type	Fuel Price (Per 08 / 2020)	Units of Measurement
Diesel	2.48	$/gal
Biodiesel (B20)	2.35	$/gal
Biodiesel (B99/B100)	3.15	$/gal
Jet Fuel[3]	51.35	$/bbl
Electricity (Market Rate)	0.13	$/kWh
Electricity (Company Rate)	0.10	$/kWh

[2] U.S. Department of Energy. (2020). Clean Cities Alternative Fuel Price Report, July 2020. https://afdc.energy.gov/fuels/prices.html
[3] IATA. (2020). Jet Fuel Price Monitor. https://www.iata.org/en/publications/economics/fuel-monitor/

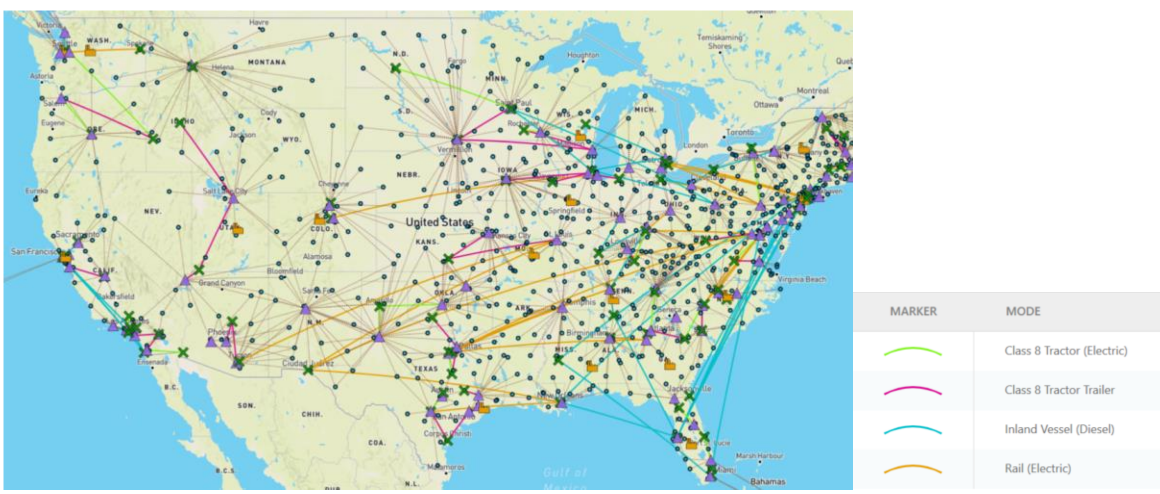
Appendix D: Network Design Maps

Figure 6

Ports and inland waterways in the US. Source: USACE - Institute of Water Resources, 2016

Figure 18

Network Design for the Targeted Carbon Emissions Scenario at 1.5°C



Note. Figure 17 visualizes the network between FC to SC to Customers. IXD to FC is excluded due to the large amount of cross country connections.

Appendix E: Science-Based Targets

Table 16

Data Required for Science-Based Target Setting Tools

Input Data Required	Science-Based Target Setting Tools	
	Scope 3 Tool	**Transport Sector**
Type of Transport Related Emissions	Not Available	Freight Transport Emissions
Transport Category	Not Available	Select from a list of several transportation types depending on the modes selected in the optimized Baseline Model scenario.
Base Year	2020	
Target Year	2030	
WTW Emissions for Base Year (tCO_2e)	Not Required	Use the total carbon emissions figure from the optimized Baseline Model
Activity in Base Year (tkm)	Not Required	Use the total activity (tkm) figure from the optimized Baseline Model
Expected Activity in Target Year	Not Required	Extrapolate total activity (tkm) in 2020 by increasing annual activity by 10% year over year (YoY) till 2030.

Table 17

Baseline Data Inputs for the Target Setting Tool - Transport Sector

Input Data Required	Data Inputted
Type of Transport Related Emissions	Freight Transport Emissions
Transport Category	Heavy Freight Trucks
Base Year	2020
Target Year	2030
WTW Emissions for Base Year (tCO_2e)	2,629
Activity in Base Year (tkm)	20,549,174,855
Expected Activity in Target Year (tkm)	53,299,267,341

Table 18

Targets Generated for Minimum Emissions Baseline by Science-Based Target Setting Tool - Transport Sector

Emissions Measure	Base Year (2020)	2ºC Target Year (2030)	WB2ºC Target Year (2030)
WTW Carbon Emissions (tonnes)	2,629	767,582.62	416,589.16
WTW Carbon Intensity (gCO_2e/tkm)	0.13	14.55	7.90

Note. The Transport Specific Tool, in contrast to the Scope 3 tool, provided Science-Based Targets carbon emissions and intensity target numbers that are based on an increase of activity level (tkm) by 10% YoY from 2020 activity levels. Per the methodology discussed in Section 3.7, and Table 17 in Appendix E, the Baseline scenario's outputs for total emissions (CO_2e) and activity (tkm) as well as the extrapolated activity levels for 2030 were inputted to the Transport Specific tool to derive the total emissions and total carbon intensity for 2ºC and WB2ºC targets for 2030. Since the Baseline scenario had only utilized Class 8 trucks, the Heavy Freight Trucks transport category was selected and the corresponding total WTW emissions of 2,629 tonnes of CO_2e and activity level of ~20.5 billion tkm were inputted into the Excel tool. Table 18 summarizes the resulting output from the tool.

Appendix F: Other Related Network Design Literature

Two of the basic FLPs are the center of gravity (COG) problem and the distance-based approach. Melo et al. (2007) provided a comprehensive review of the literature of FLP as it relates to the mentioned considerations. From their review, over 80% of the literature dealt with single-period and deterministic problems and referenced either one or two layers. Few studies consider uncertainty as a parameter due to the complexity of stochastic models (Rezaee et al., 2017).

The two most common within this spatial taxonomy are Continuous and Discrete Models (Daskin, 2008). Both models generally assume that demands arise only at discrete locations (Daskin, 2008). Continuous models assume that facilities (nodes) can be located anywhere in the area, vs. discrete models, which assume that the facilities are restricted to a finite set of locations. Discrete models are more common as they provide a more realistic and feasible optimal location compared to the continuous models (Melo et al., 2007). The most common among the variations of discrete models are the median-based models, most notably the p-median problem, which selects *p* facilities to minimize demand-weighted total distance (Daskin, 2008).

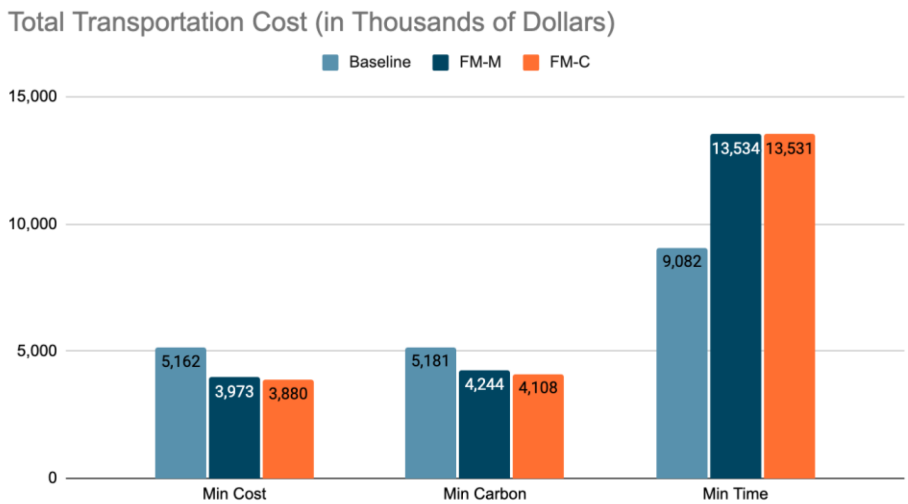
The Vehicle-Routing problem (VRP) is one other research area that is applied to the SCND problem. It was first introduced by Dantzig and Ramser (1959) through their research on the truck dispatching problem (Dantzig & Ramser, 1959). The VRP is an optimization problem to determine the routes that several fleets travel to achieve their goals while being limited by the model constraints (Widuch, 2019). The objective of the VRP can vary widely such as, to find the shortest route, to find the lowest transportation cost, to minimize the number of fleets, or to minimize the travel lead time. Some variants of VRP are Green VRP, Electric VRP, Unmanned VRP, and School Bus Routing Problem (Widuch, 2019). Commonly, VRP is constrained by vehicle capacity, number of vehicles, distance to travel, delivery time, and other promises to customers for service level (Laporte, 2007). Zhen et al. (2020), for instance, focuses on minimizing the total travel time of vehicles.

Moreover, since facility locations are interrelated with routes, Nagy and Salhi (2007) introduced the Location-Routing Problem (LRP). Instead of looking at the routes for the fleet, the LRP focuses on where the location of each node or facility should be placed. Each facility has its function and is subject to the capacity to fulfill the demand in the region. Adding more complexity to the location-routing problem, Liu and Lee (2003) extended the problem to include inventory and named it the Location-Routing-Inventory problem.

Appendix G: Entire Network Optimization Output

Figure 19

Total Transportation Costs at the Extreme Boundaries for IXD-FC-SC-Customer Node Network



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