A Direct Route to Sustainability:

A Network Optimization Model to Reduce UNICEF Zimbabwe's Carbon Footprint

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A Direct Route to Sustainability:
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Abstract

As part of Agenda-2030, the United Nations developed the Sustainable Development Goals (SDGs) with the objective of achieving a better and more sustainable future. One of the key drivers for reaching this objective is to lower carbon emissions globally. In line with the carbon SDGs goals, the United Nations Children's Fund (UNICEF), a United Nations agency responsible for providing humanitarian and development aid to children worldwide, sponsors this capstone project to analyse the carbon emissions of its supply chain transportation network in Zimbabwe. Through this capstone project, we study the effects, in terms of carbon and costs, for utilizing direct routes between UNICEF's suppliers and end beneficiary. In this capstone project, we formulate a multi-objective optimization model that optimizes simultaneously the total costs and carbon emissions. Yet, in contrast with other green network design models that rely on aggregate methods for calculating carbon emissions (such as the Green House Gas protocol), in this study we not only use an equation that considers a more granular fuel consumption estimation of the vehicles (i.e. adapted from the Network for Transport Measures), but we also calculate the theoretical fuel consumption of the vehicle by using the comprehensive modal emissions model that also considers specific characteristics of the road, engine speed, engine displacement, velocity, total weight, road slope, and acceleration. To the best of our knowledge, this study is the first attempt to combine two of the most detailed estimation models of transport emissions. In addition, our proposed network design model includes the flow of multiple products within UNICEF Zimbabwe's supply chain network, as well as consolidation capabilities, that is, the output of the model provides the optimal combination of products to consolidate within each truck shipment. Our results are visualized using the Pareto Frontier that displays all optimal carbon and cost combinations for UNICEF's network. This Pareto Frontier serves as a tool that UNICEF's management can use to choose the desired levels of cost and carbon emission. Ultimately, we find that enabling direct routes in the model produces a win-win situation where both carbon emissions and costs are reduced.

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1 Introduction

1.1 Motivation

In between Energy, Agriculture, Transportation, Residential and Services, and other miscellaneous industries, the Transportation industry accounted for the highest carbon emissions from 1992 to 2014 (European Commission, 2022). In fact, Transportation accounts for approximately 25% of total CO_2 emissions per year globally (Wang 2019).

The European Commission also noted that Transportation has not seen the same gradual decline in emissions as other industries. Transportation emissions only started to decrease in 2007 yet they remain higher than 1990. (European Commission, 2022). Within the Transportation Industry, in 2014, road transport accounted for 72.8% of the total greenhouse gas emissions followed by 13.1 % for Civil aviation and 13.0% for Navigation (European Commission, 2022).

Transportation is also the stage of the Supply Chain that results in the most CO_2 emissions (International Transport Forum, 2016). In fact, within Supply Chain Management, supply chain network design (SCND) is the process for building and modelling the supply chain to understand the costs and time to bring goods and services to market within an organisation's available resources (CIPS, 2022).

SCND has become "a strategic issue for any company looking to meet targets in terms of economic competitiveness, time, and quality of service, especially in an economic environment characterized by the globalization of trade and the acceleration of industrial cycles" (Eskandarpour, 2015, p. 12).

Traditionally, the main objective of optimization models used in strategic network design focused on the economic aspect of supply chains (Goetschalcks and Fleischmann, 2008). However, more recently there has been a growing awareness about environmental issues (Chaabane and Ramudhin and Paquet, 2012).

A sustainable supply chain network design (SSCND) aims to model the finest supply chain network configuration that allows a firm to maximize its long-term benefits in all three pillars of sustainability, i.e., economic, environment and social aspects (Sidharath Joshi, 2021). SCND contains the determination of locations, numbers, and capacities of network facilities and the material flow between them (Pishvaee and Razmi, 2012).

Considering the importance of reducing total carbon emission within transportation, the goal of this capstone project is to conduct a sustainable supply chain network applied to the humanitarian sector. In this capstone project, the total carbon impact is not regarded distinctly from the total cost or the total social impact. The ultimate goal of this project is to provide the decision maker with a tool, Pareto Frontier, to aid him in taking an informative decision about the optimal trade-offs between total cost and total carbon. The Pareto Frontier would contain all optimal combinations of carbon and costs. The social impact would also be measured through scenario analysis on the optimal solution.

In the following chapters we first introduce the problem statement and the sponsoring company, UNICEF in chapter 1.2. Then we dive into analysing the various literature regarding sustainable supply chain network design in chapter 2. Later we detail the various methodologies we use to calculate the carbon footprint and the fuel consumption of the vehicle, in addition to a brief section on the mathematical optimization techniques used in chapter 3. In chapter 4we disclose the results received from the optimization model and conduct scenario analysis before finally closing with the general recommendations and conclusion.

1.2 Overview of UNICEF and Problem Statement

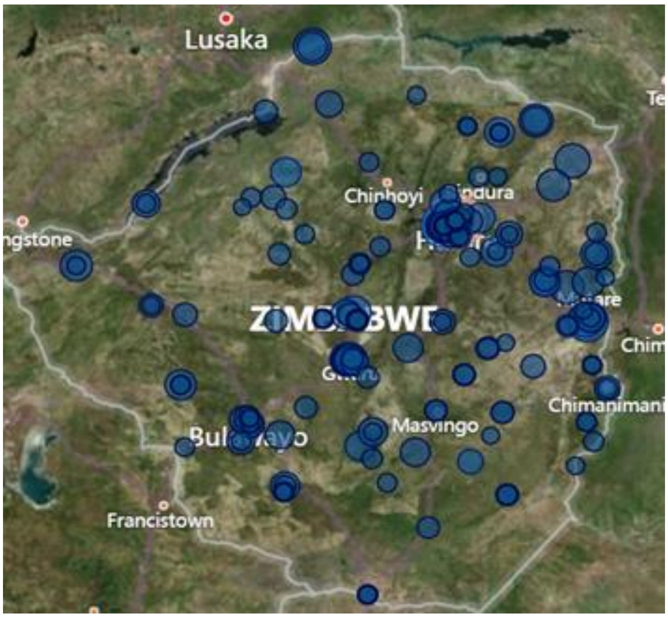
The United Nations Children's Fund (UNICEF) works in over 190 countries and territories to save children's lives, to defend their rights, and to help them fulfil their potential, from early childhood through adolescence UNICEF delivers sustainable access to lifesaving supplies where they are most needed, accelerating results for the most vulnerable children. (UNICEF, 2022). Therefore, UNICEF relies on complex supply chain networks to provide the commodities needed.

UNICEF procures hundreds of different products from more than 50 suppliers. Suppliers ship the products to UNICEF's central warehouse in the capital Harare, where it consolidates and repackages certain products. Ultimately, UNICEF distributes hundreds of products to over 200 destinations throughout Zimbabwe. The data that will be used in this capstone is sample data and does not represent the entire operations of UNICEF Zimbabwe.The various suppliers of UNICEF in Zimbabwe are shown in red circles Figure 1 where most suppliers are seen concentrated in Harare and Bulawayo expect for few and dispersed suppliers in small towns.

Figure 1
Supplier Location in Zimbabwe 2019-2021

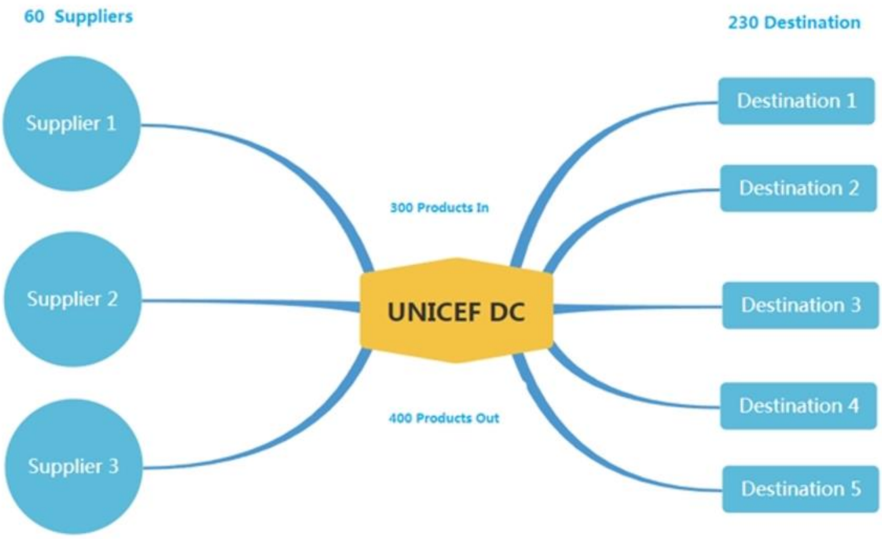
Unlike the distribution of UNICEF's suppliers which is concentrated in 2 major cities, UNICEF's beneficiaries are dispersed throughout Zimbabwe as shown in the blue circles on Figure 2 below.

Figure 2
Beneficiaries Locations in Zimbabwe 2019-2021



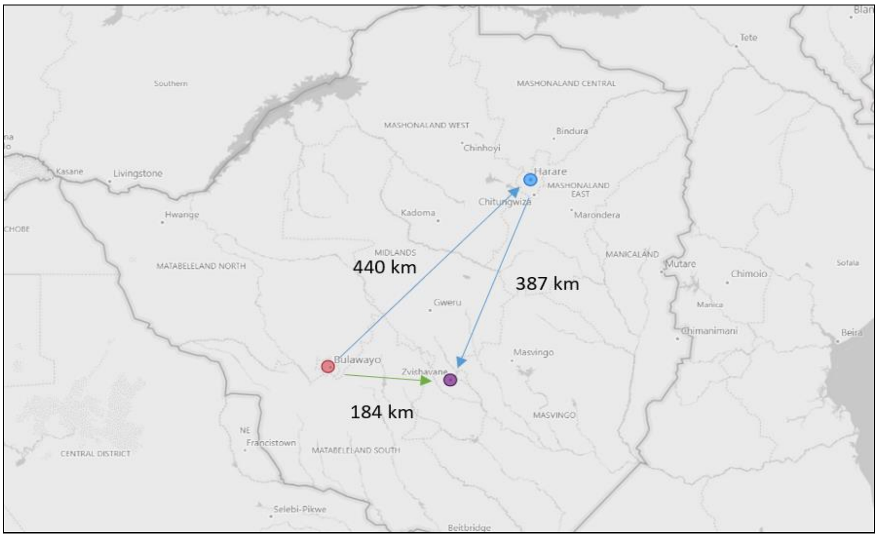
Most products flow through UNICEF’s central warehouse in Harare. Therefore, UNICEF’s current supply chain network can be illustrated by a transhipment model as shown in Figure 3 below.

Figure 3
UNICEF's Current Transshipment Model in Zimbabwe



While this model provides opportunity for consolidating the products in UNICEF’s warehouse, this model may not be optimal for the total cost and carbon. In Figure 4 below, we illustrate an example of a servicing a beneficiary located in Zvishanava.

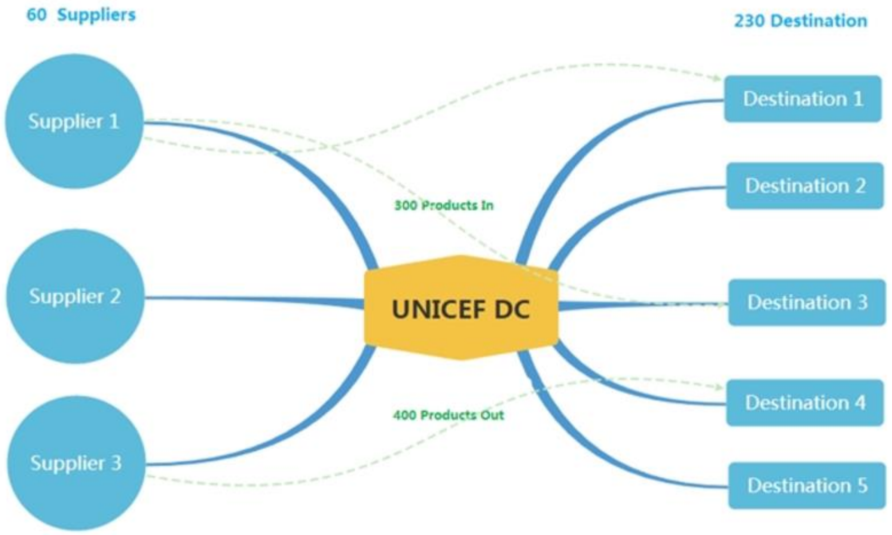
Figure 4
Example on Inefficiencies of Current Network Design



If a beneficiary is located in Zvishanava (purple) and has to be serviced from Bulawayo (red), with the current network design, the product would travel first from Bulawayo to the Warehouse in Harare (blue) for 440km, then it will travel back to Zvishanava for 387 km, for a total of 827 km.

Such setting may not be ideal in terms of total cost and carbon emissions. In an alternative network design, UNICEF can ship the product directly from Bulawayo to Zvishanva for a total 184 km, which represents a 77% reduction in total distance and has approximately 80% reduction in total time, from 10 hours to 2 hours. Such network design would require enabling direct routes between suppliers and beneficiaries as illustrated in Figure 5.

Figure 5
Proposed Network Design for UNICEF with Direct Routes



In this capstone project, we seek to quantify the optimal cost and carbon emissions of UNICEF's network in Zimbabwe and compare different scenarios where direct routes are enabled or disabled. Ultimately, we also seek to provide recommendation to UNICEF on the supply chain network design with the highest social impact.

Before formulating our models, in the following sections, we cover the various relevant literature on carbon measurement and green supply chain network design, and then taken cover the different methodologies we use for modelling UNICEF's network.

2 Literature Review

In the first Section 2.1 of the literature review we cover the different gases and metrics used to measure carbon emission in the literature. After covering the metrics for measurement, in Section 2.2 we then detail the various methods used to calculate the carbon emissions in the transportation industry; such methods be the basis of our mathematical modelling. In Section 2.3 we cover different carbon optimization models that have been used in the literature. In the last Section 2.4, we cover common techniques used to solve multi-objective functions. We use the techniques covered in Section 2.4 to minimize concurrently our objective functions for cost and carbon.

2.1 Carbon Footprint Emissions

According to Waltho, Elhedhli and Gzara (2019), Global warming occurs when certain gases in the earth's atmosphere are more prevalent than others, causing increased levels of radiation to be trapped near the earth's surface.

The United Nations Framework Convention on Climate Change (UNFCCC) describes the greenhouse gases (GHG) as the atmospheric gases responsible for causing global warming and climate change. According to the UNFCCC, the major GHG are carbon dioxide (CO_2), methane (CH4) and nitrous oxide (N20), and the less prevalent GHG are hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulphur hexafluoride (SF6), (UNFCCC, 2021).

In addition, the United Nations Intergovernmental Panel on Climate Change (IPCC, 2007) report coins the term "CO_2- equivalent emission" under which it aggregates all GHG emissions. The IPCC 2007 report defines CO_2-equivalent emission to be the amount of CO_2 emission that would cause the same time-integrated radiative forcing, over a given time horizon, as an emitted amount of a long-lived GHG or a mixture of GHGs. (IPCC, 2007).

"Carbon" (CO_2) gas is therefore used as a shorthand for GHG, as carbon dioxide is the main GHG released by human activities. (Boukherroub, et al., 2017). Hence all GHG emissions are converted and aggregated under a single metric "Carbon Dioxide Equivalent" (CO_2eq), which serves as a proxy for the carbon footprint emissions.

The CO_2-equivalent emission is obtained by multiplying the emission of a GHG by its Global Warming Potential (GWP) for the given time horizon. For a mix of GHGs it is obtained by summing the equivalent CO_2 emissions of each gas. CO_2-equivalent is a standard and useful metric for comparing emissions of different GHGs but does not imply the same climate change responses. (IPCC, 2007). In accordance with the above, going forward we use Carbon Dioxide Equivalent " (CO_2eq) that serves as a proxy for the carbon footprint emissions in UNICEF' model.

2.2 Carbon Footprint Calculation

The GHG Protocol, developed in partnership with the World Resources Institute and the World Business Council for Sustainable Development, specified three "scopes" of GHG emissions (Carbon Trust, 2013).

- Scope 1 emissions are a result of all company operations, production processes, waste streams, "fugitive" emissions, facilities, and employees.

- Scope 2 is emissions from purchased electricity, and
- Scope 3 is emissions associated with downstream distribution, use and end of life management of the product services (Carbon Trust 2013).

The Carbon Trust further note that Scope 3 emissions often represent the largest source of GHG emissions, and in some cases can account for up to 90% of the total carbon impact (Carbon Trust 2013).

Considering that UNICEF’s supply chain network does not include production processes associated with Scope 1, that UNICEF operate only one warehouse in Harare with related Scope 2 emissions, also considering that Scope 3 represent the largest source of GHG emissions in accordance the Carbon Trust, going forward we focus on the Scope 3 GHG emissions resulting from transportation.

Within transportation, carbon emission levels depend on various aspects such as engine type, terrain driven, driver tendencies, vehicle speed and vehicle weight (Elhedhli & Merrick, 2012). Elhedhli & Merrick also chart the relationship between vehicle weight and CO_2 emissions, and for various vehicle speeds and weights.

In fact, for estimating the overall carbon footprint emissions, Velázquez-Martínez and Fransoo (2017) noted that two of the most common activities-based methods are the GHG Protocol and the methodology developed by the Network for Transport and Environment (NTMCalc Basic 4.0., 2021) (Velázquez-Martínez & Fransoo, 2017).

In assessing the differences between the GHG Protocol and the Network for Transport and Environment methods, Velázquez-Martínez and Fransoo noted that the GHG Protocol methodology typically uses an emission factor that is independent of the type of the vehicle or type of road (Green House Gas Protocol, 2021), while the NTM methodology (NTMCalc Basic 4.0., 2021) requires more detailed parameters such as fuel consumption, distance travelled and weight per shipment.

Due to the foregoing, Velázquez-Martínez and Fransoo (2017), noted that a facility location model utilizing the GHG protocol would provide optimal locations that are identical to cost-minimization solutions.

UNICEF’s objective is to analyse the dependencies between carbon and cost and develop a model that would optimize both metrics concurrently. As such, considering that the GHG protocol provides optimal solutions identical to cost-minimization solutions, the GHG protocol is not considered in this capstone. Instead we focus on the NTM methodology which is more granular, and takes various metrics other than distance into account, such as weight, terrain slope, engine speed and others.

2.3 Network for Transport and Environment Methodology

The Network for Transport Measures, NTM is a non-profit organisation, initiated in 1993 aiming at establishing a common base of values on how to calculate the environmental performance for all various modes of traffic, including goods transport and passenger travel (NTM, 2022).

The Network for Transport and Environment, lists on its website the framework to calculate the environmental performance, measured as energy usage and emissions to air, of a cargo transport with a road vehicle. The NTM notes that result of the calculation will be expressed as kilo grams emission to air [kg] and use of energy [MJ] per shipment of X tonnes. The main steps are below (NTM,2022):

1. Collect information about the shipment

The shipment weight, volume and used cargo holders

2. Selection of relevant vehicle type and load capacity utilisation

NTM presents 10 different vehicle concepts. The environmental performance improves significantly as the load capacity increases with larger vehicles.

3. Vehicle operation distance and road types

Find the relevant distance the vehicle travels related to the transport of the investigated cargo shipment. Calculate the distance each vehicle travels on different road types.

4. Set fuel type and fuel consumption (FC)

The calculation depends on the fuel type due to its content of carbon, sulphur and aromatic hydrocarbons. The exhaust emissions are calculated from the fuel consumption of the selected vehicle. Average default values [l/km] are given for full and empty vehicles on urban roads, rural roads and motorways. The user should seek to obtain fuel consumption data for the specific transport in order to increase accuracy in the result.

5. Set emission factors and energy content of the fuel

6. Calculate vehicle environmental performance data (energy use and emissions to air) for the operation of the vehicle

For HGVs and LGVs – emission values are given for relevant engine types in the unit [g/l] fuel.

7. Compensate for the effect of applicable exhaust gas abatement techniques

Reduction potentials for filters and catalyst are presented.

8. Allocation to investigated cargo

> Calculate the share of the environmental performance data (energy use and emissions to air) that is related to the investigated shipment/cargo. Data for load capacity and default capacity utilisation is given.

The NTM further provides a framework to calculate the fuel consumption of the vehicle depending on the load carried. NTM's equation for fuel consumption is shown below (NTM, 2022):

$$FC_{LCU} = FC_{empty} + \left(FC_{full} - FC_{empty}\right) * LCU_{weight(phys)}$$

Where:

> LCU weight(phys) = Load Capacity Utilisation, defined as [cargo physical weight/mac weight capacity]
>
> FCLCU= Fuel consumption at load capacity utilisation LCU.

Using the above NTM model for estimating the fuel consumption, Velázquez-Martínez and Fransoo (2014) formulated the below multi-objective optimization equations which are applied to a supply chain network. Equation OF1 below is models the total costs in the transportation network while the equation OF2 below models the total carbon emissions.

$$Min \rightarrow OF1 = \sum_{i \in J} \sum_{i \in I} (A_{ij} \ \lceil \frac{h_i}{W_i} \rceil + v_{ij} d_{ij} \ \lceil \frac{h_i}{W_i} \rceil) Y_{ij}$$

$$Min \rightarrow OF2 = l \sum_{i \in J} \sum_{i \in I} d_{ij} \ \left\lceil \frac{h_i}{W_i} \right\rceil f^{e}_{i} Y_{ij} + \ l \sum_{i \in J} \sum_{i \in I} d_{ij} \frac{h_i}{W_i} (f_i^{f} - f_i^{e}) Y_{ij}$$

Subject to:

$$\sum_{j \in J} Y_{ij} = 1 \qquad \forall i \ \in I \qquad (1)$$

$$\sum_{j \in J} X_j = p \qquad (2)$$

$$Y_{ij} - X_j \leq 0 \qquad \forall i \in I \quad \forall j \in J \qquad (3)$$

$$X_j \in \{0,1) \qquad \forall j \in J \qquad (4)$$

$$Y_{ij} \geq 0 \qquad \forall i \in I \quad \forall j \in J \qquad (5)$$

Where:

h_i= Demand at node i ∈ I

d_{ij}= Distance between candidate facility site j ∈ J*, and customer location I* ∈ I

A_{ij}= Fixed cost per trip between candidate facility site j ∈ J*, and customer location I* ∈ I

v_{ij} = Cost per distance travelled between candidate facility site j ∈ J*, and customer location I* ∈ I

Wi= Truck capacity per trip restricted to customer location i ∈ I

n_{ij}= $\frac{h_i Y_{ij}}{W_i}$*= Number of trips per period required to serve the customer location I* ∈ I *from facility site j* ∈ J

k= Constance emission factor (2,621 grams of CO_2/liter of fuel)

f_i^e*= Fuel consumption of the empty vehicle used to serve at customer location* $i \in I$ *(liters/km)*

f_i^f*= Fuel consumption of the fully loaded vehicle used to serve at customer location I* ∈ I *(liters/km)*

In contrast with GHG protocol, the above OF2 objective functions calculates the total carbon emission depending on the fuel consumption of the vehicle which itself depends on the load carried. Ideally, the fuel consumption of the vehicle should be taken from field empirical observations.

In the absence of empirical data on the fuel consumption, the below comprehensive modal emissions model (Barth et al. 2005) is used:

$$F\left(\propto_{(\theta)}, l, v, d\right) = \frac{\lambda d}{v}\{kNV + \gamma\left[(w+l)\alpha_{(\theta)}v + \beta v^3\right]\}$$

Where:

λ= Conversion factor (l/kj)

k= Engine friction factor (kJ/rev/l)

N=Engine speed (rev/s)

v= Engine displacement (l)

w= Curb-weight (kg)

$\propto_{(\theta)}$= *Vehicle specific arc constant* $\propto_{(\theta)}= \tau + gsin\theta + gC_r cos\theta$

τ= *Acceleration (m/s2)*

g= Gravitational acceleration (m/s2)

C_r= *Coefficient of rolling resistance*

θ=*Road angle*

β= *Vehicle specific arc constant* $\beta = 0.5C_r cos\theta$

C_d= *Coefficient of aerodynamic drag*

ρ= *Air density (kg/m3)*

A= Frontal surface area (m2)

Therefore, in addition to using the NTM model that takes the consumption of empty loaded vehicle and the consumption of the fully loaded vehicle into account, in this capstone we take into consideration all the granular factors of Barth et al. (2005) formula.

2.4 Solving Sustainable Supply Chain Network Design Models

Several different approaches are available in the literature to minimize carbon emissions across a supply chain network. Such solve either single optimization models with one objective function or multi-objective optimization models with two objective functions. There are a few exceptions such as Erkut et al. (2008), who developed a mixed-integer linear program consisting of five objective functions, four to do with emissions, and one related to cost.

2.4.1 Single Objective Model Approach

In the literature, single-objective sustainable supply chain models are solved in three various forms. The first form has two different objective functions that relate to emissions and costs respectively. In such form each objective function is optimized separately and the solutions are compared. Mallidis et al. (2012) use this approach when examining environmental issues related to the shared use of transportation operations in Southeast Europe. This approach seems limited in its ability to simultaneously optimize on cost and carbon and converge on a global optimal solution.

The second form has one objective function inserted as a soft constraint in the model. Papapostolou et al. (2011) applied this form in their research on biofuel supply chains. The economic factor was the main component of the model in the objective function and various emissions and environmental factors as constraints. This approach is limited by the computation resources it requires.

The third form internalizes the CO2 emissions in the objective function. This approach is referred to as a preference-based/cooperative method (Deb 2002). Janic (2003) and Chang et al. (2008) in their respective papers both converted the carbon footprint emissions into their monetary equivalence using a conversion factor. The emissions were then expressed as an external cost, added to the economic objective, and solved as a single objective function. In this method however, it is very difficult to estimate CO2 costs as the research community has not agreed on the conversion factor to be used (Kim et al.2009).

In UNICEF's network model, the objective is to minimize concurrently the total carbon emissions and the total cost. The first form for solving single-objective models does not provide a global optimal solution and hence the model does not guarantee optimality. The second form for solving single optimal is computationally expensive and, considering the size of UNICEF's optimization model, this form is not suitable to be utilized. The third form for solving the single optimization problem is also not suitable as it presents fundamentals flaws for estimating the cost of the carbon emissions. Therefore, after analysing the main literature on single-objective optimization, we decide (due to the limitations mentioned above) that this single optimization approach was not sufficient to answer our research question.

2.4.2 Multi-Objective Model Approach

Eskandarpour and Dejax (2015) and Seuring (2013) both undertook a literature review of modelling approaches for sustainable supply chain networks. Table 1 highlights the different methods used to solve environmental and economic optimization problems. The most popular method to solve such multi-objective models in the literature is ε-constraint method followed by Metaheuristics and Weighted Sum methods. In this section we discuss the pros and cons of each of these methods.

Table 1
Solution for multi-objective models. Adapted from Eskandapour & Dejax (2015)

Type of Method	Number of Articles
ε-constraint method	25
Metaheuristics	11
Weighed sum of objectives	8
Cumulative Others	18

2.3.2.1 The ε-constraint method

The ε-constraint method is a mathematical programming technique, which transforms a multi-objective optimization problem into several constrained single objective problems (Becerra and Coello, 2006). This method has not been used too often in evolutionary computation, due to the fact that it does not generates a set of nondominated solutions in a single run, as most evolutionary algorithms do (Becerra and Coello, 2006). Becerra and Coello further noted that this method makes use of a single-objective optimizer which handles constraints, to generate one point of the Pareto front at a time; for transforming the multi-objective problem into several single-objective problems with constraints it uses the following procedure:

$$Minimize: \quad f_1(x)$$

$$subject\ to: \ f_j(x) \leq \varepsilon_j \ for\ all\ j = 1,2,\ldots,m \qquad j \neq l, x \in S$$

It has been found that this method is relatively expensive when solving “easy” multi-objective problems, because of the several single-objective optimizations executed (Becerra and Coello, 2006).

2.3.2.2 Metaheuristics Methods

As in single-objective optimization, the techniques to solve a multi-objective optimization problem (MOP) can be classified into exact and approximate (also called heuristic) algorithms (Talbi, Vassur, Nebro and Alba, 2011). Exact methods are effective for problems of small sizes, when problems become harder, usually because of their NP-hard complexity, approximate algorithms are mandatory (Talbi, Vassur, Nebro and Alba, 2011) . Talbi, Vassur, Nebro and Alba also added that, in general, with very large problems and/or multi-objective problems, the efficiency of single metaheuristics may be compromised.

2.3.2.3 Weighted-Sum Method

The weighted sum method is one of the most widely used due to its simplicity (Science Direct, 2022). The weighted sum method converts multiple objectives into an aggregated scalar objective function by first assigning each objective function with a weighting factor and later summing up all the contributors to obtain the overall objective function. By using the weighted sum method, each objective is given a weight to differentiate their relative importance during the aggregation of the overall objective function (Science Direct, 2022). According to Science Direct. The composite objective function using the weighted sum is:

$$F(x) = w_1 f(x)_1 + w_2 f(x)_2 + \cdots + w_m f(x)_m$$

Where:

$$\sum_{i=1}^{M} w_i = 1$$

The weighted sum method for multi-objective optimization (MOO) continues to be used extensively not only to provide multiple solution points by varying the weights consistently, but also to provide a single solution point that reflects preferences presumably incorporated in the selection of a single set of weights (Marler & Arora, 2009).

As detailed above, the ε-constraint method is computationally expensive hence it is not suitable for models with large data sets as UNICEF’s. In addition, the metaheuristic model provide an approximate solution to the optimal values and is an alternative to NP-hard models which is not the case. For UNICEF we opt to proceed with the weighted-sum method as it is the best fit method considering UNICEF’s data set discussed in the following section.

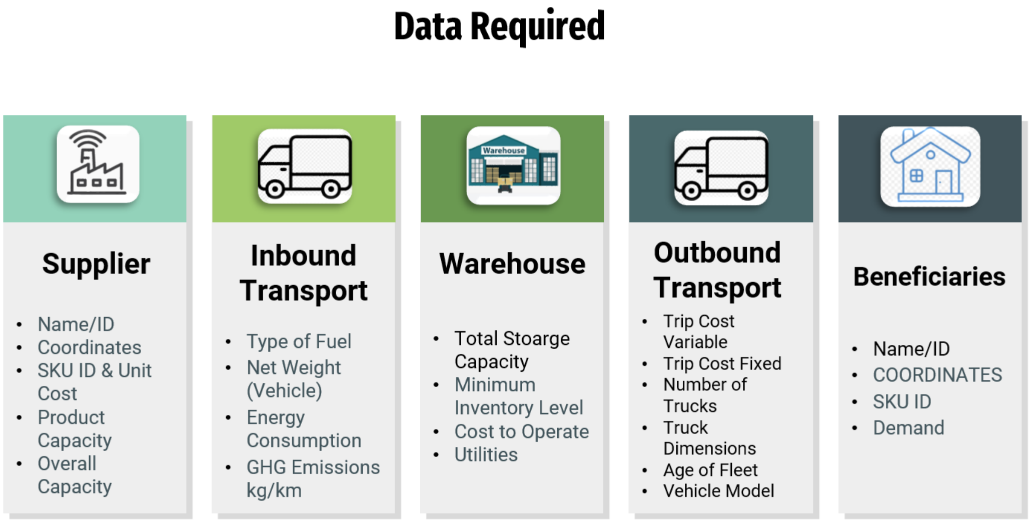
3 Data and Methodology

In this section we first cover the various data cleaning and segmentation to UNICEF's data set, then we detail the mathematical formulation and related methodologies that were used to obtain the optimal values for total carbon emissions and total cost for UNICEF's supply chain network.

3.1 Data Processing

To collect the data needed for the modelling, a data collection spreadsheet was developed. If information was not available, UNICEF noted it in this spreadsheet. Data was required for five distinct parts of the supply chain network, the suppliers, the inbound transporters, the warehouse operations, the outbound transporter, and the end beneficiaries as shown on Figure 6 below.

Figure 6
List of Data requested from UNICEF



Data Required

Supplier
- Name/ID
- Coordinates
- SKU ID & Unit Cost
- Product Capacity
- Overall Capacity

Inbound Transport
- Type of Fuel
- Net Weight (Vehicle)
- Energy Consumption
- GHG Emissions kg/km

Warehouse
- Total Stoarge Capacity
- Minimum Inventory Level
- Cost to Operate
- Utilities

Outbound Transport
- Trip Cost Variable
- Trip Cost Fixed
- Number of Trucks
- Truck Dimensions
- Age of Fleet
- Vehicle Model

Beneficiaries
- Name/ID
- COORDINATES
- SKU ID
- Demand

3.1.1 UNICEF Data

The data received from UNICEF are sample data which do not represent the entire figures. It consists of sample shipment data covering the calendar years of 2019 to 2021, inclusive. The sample data include approximately 3000 incoming orders from the suppliers, as well as roughly 20,000outgoing orders to UNICEF’s beneficiaries. A first analysis on the data shows that the data contains information on around 500 different products which are distributed to over 200 different destinations across Zimbabwe. These products are supplier from over 50 suppliers. Table 2 below summarizes UNICEF’s data before cleaning or segmentation:

Table 2
Summary of UNICEF Data before Cleaning and Segmentation

Incoming Orders	3,155
Outgoing Orders	16,988
Number of Incoming Parts	32,161,134
Number of outgoing Parts	23,297,765
Number of Products	521
Number of Destinations	140
Number of Suppliers	50

3.1.2 Data Cleaning

The sample data of UNICEF contains a considerable amount of missing values. For the incoming orders, some line items are missing either the destination address, the name of supplier, or the number of parts orders. For the outgoing orders some line items are missing destination address.

The line items with missing values are impossible to include in the model therefore we proceed to impute such data. Table 3 below summarizes the resulting data set after imputing for the missing values:

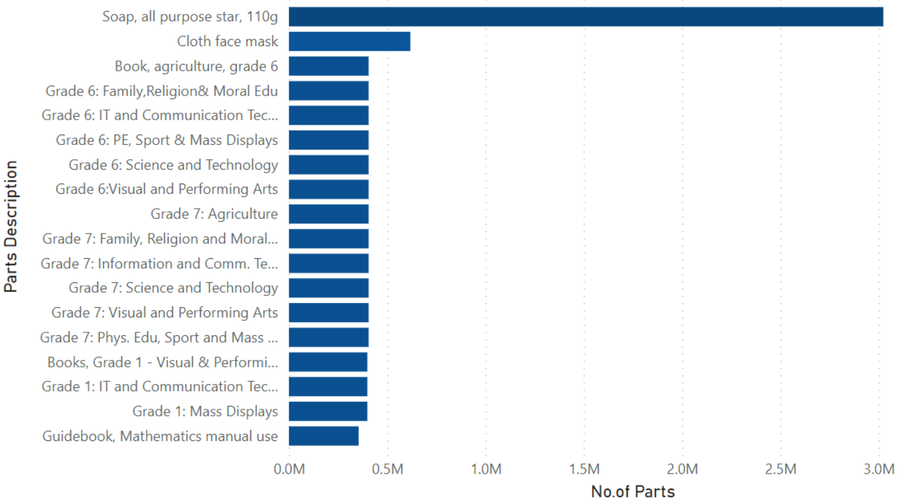
Table 3
Summary of UNICEF Sample Data after Cleaning before Segmentation

Incoming Orders	2,332
Outgoing Orders	14,678
Number of Incoming Parts	21,211,613
Number of outgoing Parts	19,866,220
Number of Products	488
Number of Destinations	139
Number of Suppliers	50

3.1.3 Data Segmentation

After we clean the data, we proceed into segmentation. As the aim of this project is to provide insights to UNICEF on a strategic level, we decide to segment the data to include only the product that constitute 80% of the total demand (by number of items). Therefore, we proceed to remove the items that were rarely ordered (less than 20 % of total demand). This also allows us to reduce the data size and ensure that the optimization model runs faster. Figure 6 illustrates the number of outgoing items from the UNICEF warehouse. .

Figure 7
Outgoing a Parts from UNICEF Warehouse



We have also analysed the distribution of the demand by month of the year. The distribution is shown on Figure 8 below:

Figure 8

Distribution of Demand by Month

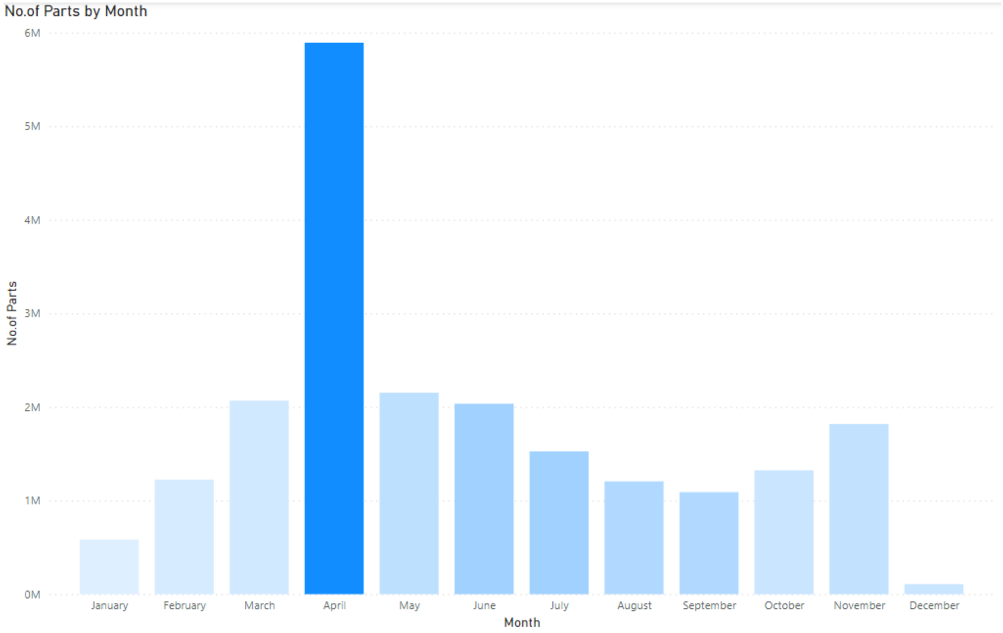


Table 4 below summarizes the resulting data after segmenting for the highest 80% in number of items ordered:

Table 4

Summary of UNICEF Data after Segmenting for highest 80% in Number of Demand

Incoming Orders	584
Outgoing Orders	6,416
Number of Incoming Parts	8,777,319
Number of outgoing Parts	18,018,699
Number of Products	97
Number of Destinations	138
Number of Suppliers	20

UNICEF provided the sample data for the incoming and the outgoing orders in separate spreadsheets. These spreadsheets are distinct and are not linked. Therefore, in some instances, we have demand data for which we do not have information about the related supplier. In the optimization model we formulated (for which we provide further detail in the following section), we assumed the capacity of the suppliers to be the actual supply that the suppliers provided in total for year 2019 to 2021. We therefore impute the outgoing demand data that do not have corresponding incoming supply data. Table 5 below summarizes the resulting data after imputing for inconsistencies between outgoing and incoming data; this is the final data set we use in the multi-objective optimization model.

Table 5
Summary of UNICEF Data after Segmenting for Consistent Demand and Supply

Number of outgoing Parts	7,604,750
Number of Products	43
Number of Destinations	138
Number of Suppliers	20

3.2 Methodology

Conducting supply chain network design is achieved in several steps as illustrated in Figure 9 below. The initial steps include gathering and analysing the data as well as conducting a literature review. Analysing the data contributes to understanding the different characteristics of the network, and the literature review aids with identifying important metrics as well as modelling technique relevant to the case at hand.

Figure 9
Methodology Process Steps

After the data and literature review steps, we proceed into devising a mathematical formulation for the specific supply chain network design. In this step, the objective functions and the constraints of the model are identified. The mathematical formulation for UNICEF's supply chain network is covered in the next section.

Further to the mathematical formulation, we execute the mathematical programming of the model. In this capstone we use python programming with Gurobi library for modelling. Using the math program, we then conduct several scenario and sensitivity analysis to test the robustness of the model and to extract valuable insights. A detailed list of the methodology steps is listed below:

1. Prepare the data:
    - Design and send a data collection template to UNICEF.
    - Clean the data (duplications, irrelevant observations, structural errors, unwanted outliers, missing data) in conjunction with UNICEF.
    - Segment data for feasibility and replicability.
    - Structure the data for use in Python/Gurobi solver.

2. Develop metrics:
    - Decide how the carbon emissions are measured and captured.
    - Identify the costs associated with the network design.
    - Incorporate a social benefit metric that can be measured as a result of the minimization of the cost and environmental metrics.
3. Build network design models:
    - Formulate the multi-objective function mathematically that minimizes the carbon emissions and cost.
    - Incorporate the hard and soft constraints associated with the network design.
    - Build the current baseline model and the alternative model with direct shipment.
    - Transfer the mathematical formulation for use in Python and Gurobi solver.
4. Analysis:
    - Plot Pareto frontiers using the weighed sum approach and identify the extreme boundaries of each Pareto frontier from objective function.
    - Develop different network structure scenarios that mimic real-life scenarios.
    - Conduct sensitivity analysis to test the robustness of the results.

3.3 Mathematical Formulation

The mathematical formula of UNICEF’s supply chain network is based on model of Velázquez-Martínez and Fransoo (2014) that is detailed in the literature review section. The model contains two distinct objective functions, one modelling the total cost of the network, and the other modelling the total carbon. The two objective functions are listed below:

1. *Min → OF1:* $\sum_i A_{iw}y_{iw} + \sum_i v_{iw}d_{iw}y_{iw} + \sum_j A_{wj}y_{wj} + \sum_j v_{wj}d_{wj}y_{wj} + \sum_i \sum_j A_{ij}y_{ij} + \sum_i \sum_j v_{ij}d_{ij}y_{ij}$
2. *Min → OF2 =* $l(\sum_i d_{iw}f_i^e y_{iw} + \sum_i d_{iw}(f_i^f - f_i^e)\frac{x_{iw}}{C_{iw}}) + l(\sum_j d_{wj}f_w^e y_{wj} + \sum_j d_{wj}(f_w^f - f_w^e)\frac{x_{wj}}{C_{wj}}) + l(\sum_i \sum_j d_{ij}f_i^e y_{ij} + \sum_i \sum_j d_{ij}(f_i^f - f_i^e)\frac{x_{ij}}{C_{ij}})$

Objective function OF1 models the total cost of UNICEF's supply chain network and is dependent on the fixed costs 'A' for each truck, as well as the variable costs 'v' of the trucks per kilometre. Objective function OF2 is dependant on the fuel consumption of the vehicle $'f_i^e'$ for the empty vehicle and 'f_i^f' for the fully loaded vehicle.

The above objective functions consider all possible arcs in the model, namely the arcs from each supplier 'i' to the warehouse 'w', the arcs from the warehouse 'w' to each destination 'j' , and the direct arcs from each suppliers 'i' to each destination 'j'.

The decision variables of the model are listed below:

x_{iw} , x_{wj} , x_{ij} = *Overall products flow on arcs ,* $\forall i,w$,$\forall w,j$, $\forall i,j$
y_{iw}, y_{wj} , y_{ij} = *Number of Trucks on arcs* $\forall i,w$,$\forall w,j$, $\forall i,j$
z_{iwk},, z_{wjk}, z_{ijk} = *Flow of single product k on arcs,* $\forall i,w$,$\forall w,j$, $\forall i,j$

Other indices of the model are defined below:

h_{jk} = *Demand for product k by Customer j* $\in J$ *(kg/product)*
S_{ik} = *Available supply of product k at Supplier* $i \in I$ *(kg/product)*
I_k = *Required level of Inventory for Product k at Warehouse w* $\in W$ *(kg/product)*
d_{ij} , d_{wj}, d_{ij} = *Distance between arcs (km)*
C_{iw}, C_{wj}, C_{ij} = *Truck capacity per arc (kg)*

l = *Constant emission factor (2,621 grams of CO2/liter of fuel)*

Decision variables z_{iwk},, z_{wjk}, z_{ijk} represent the individual flow of each product on each arcs. These decision variables are not included in the objective functions but are introduced in the constraints. The model has a total of 12 constraints, representing demand constraints, supply constraint, conservation of flow within the warehouse, as well as linking constraints between the integer number of of the trucks 'y' and the overall product flow on each arc. The constraints are listed below:

Linking constraints of y with x- direct route:

$$y_{ij} \geq \frac{x_{ij}}{C_{ij}} \qquad \forall i \in S, \forall j \in J \qquad (1)$$

Linking constraints of y with x from suppliers to warehouse

$$y_{iw} \geq \frac{x_{iw}}{C_{iw}} \qquad \forall i \in S \qquad (2)$$

Linking constraints of y with x from warehouse to customers:

$$y_{wj} \geq \frac{x_{wj}}{C_{wj}} \qquad \forall j \in J \qquad (3)$$

Linking constraints of y with x- direct route:

$$y_{ij} \leq \frac{x_{ij}}{C_{ij}} + 1 \qquad \forall i \in S, \forall j \in J \qquad (4)$$

Linking constraints of y with x from suppliers to warehouse:

$$y_{iw} \leq \frac{x_{iw}}{C_{iw}} + 1 \qquad \forall i \in S \qquad (5)$$

Linking constraints of y with x from warehouse to customers:

$$y_{wj} \leq \frac{x_{wj}}{C_{wj}} + 1 \qquad \forall j \ \in J \qquad (6)$$

Demand – Truck constraint Direct shipment:

$$y_{ij}C_{ij} \geq \sum_{k} z_{ijk} \qquad \forall i \ \in S, \forall j \in J \qquad (7)$$

Demand – Truck constraint Transhipment 1 :

$$y_{iw}C_{iw} \geq \sum_{k} z_{iwk} \qquad \forall i \ \in S \qquad (8)$$

Demand – Truck constraint Transhipment 2 :

$$y_{wj}C_{wj} \geq \sum_{k} z_{wjk} \qquad \forall j \ \in J \qquad (9)$$

Supply Constraint- Product specific:

$$\sum_{w} z_{iwk} + \sum_{j} z_{ijk} \leq S_{ik} \qquad \forall i \in S, k \in K \qquad (10)$$

Conservation of Flow:

$$\sum_i \sum_w z_{iwk} - \sum_j \sum_w z_{wjk} \geq I_k \qquad \forall j \not\subset D, \ \not\subset S, k \in K \qquad (11)$$

Demand Constraint:

$$\sum_{w} z_{wjk} + \sum_{i} z_{ijk} \geq h_{jk} \qquad \forall j \ \in h, \ \ k \in K \qquad (12)$$

Positive flows:

$$x_{iw}, x_{wj}, x_{ij} \ \ Integer \geq 0 \ \ \forall i, w, k$$

$$z_{iwk}, z_{wjk}, z_{ijk} iInteger \geq 0 \ \ \forall i, w, k$$

$y_{iw}, y_{wj}, y_{ij}\ Integer \geq 0\ \ \forall i, w, k$

The mathematical model above was programmed using python with Gurobi package and was loaded with the cleaned and segmented UNICEF’s data. The code of the mathematical programme can be found in appendix. The results of the model are discussed in the following section.

4 Results

Before conducting the multi-objective optimization, we first run standalone optimizations for each of the carbon and cost. Such optimizations indicate the minimum levels possible when disregarding the effect of the other metric. In the standalone optimization we also analysed the effect of enabling or disabling direct routes, we, therefore, run the following two scenarios:

1. Transhipment scenario: where direct routes between suppliers ‘i’ and destination ‘j’ are disabled
2. Transhipment and Direct route scenario: where direct routes between suppliers ‘i’ and destination ‘j’ are enabled.

After the separate optimizations, we optimize the cost and carbon simultaneously and draw a Pareto frontier showing the different trade-offs between the two metrics.

4.1 Standalone Transhipment Optimization

4.1.1 Carbon Minimization

To conduct this standalone carbon optimization, we set the alpha value (weight) on the carbon objective function to be 1 and the alpha value on the cost objective function to be 0. In addition, we disable the direct routes by assigning a high distance value to the corresponding arcs. Ultimately our model constitutes a transhipment model only.

For confidentiality reasons we cannot release the exact results of the model. For the purpose of this capstone the change in carbon emissions will be expressed as a percent change when compared to the original transhipment model. Therefore, the total carbon (CO_2) for the Transhipment model is considered the baseline scenario which is **benchmarked at 100%.**

The model generates the optimal flow of all products on each arc. However, for illustration purposes and for ease of comparison we list in Table 6 below the optimal flow for 1 product only (5 Keys to Safer Food, A2 poster, Ndebele).

Table 6
Optimal flow for 5 Keys to Safer Food, A2 Poster – Carbon Model Transshipment

Source	Destination	Flow
Supplier 1	Warehouse	1126
Supplier 2	Warehouse	400
Warehouse	Destination 1	80
	Destination 2	56
	Destination 3	260
	Destination 4	240
	Destination 5	40
	Destination 6	160
	Destination 7	80
	Destination 8	380
	Destination 9	80
	Destination 10	150

4.1.2 Cost Minimization

To conduct the standalone carbon optimization for, we set the alpha value (weight) on the cost objective function to be 1 and the alpha value on the carbon objective function to be 0. In addition, we disable the direct routes by assigning a high distance value to the corresponding arcs. Ultimately our model constitutes a transhipment model only.

For the purpose of this capstone the change in costs will be expressed as a percent change when compared to the original transhipment model. Therefore, the cost for the Transhipment model is considered the baseline scenario which is **benchmarked at 100%.** The model generates the optimal flow of all products on each arc. However, for illustration purposes and for ease of comparison we list in Table 7 below the optimal flow for 1 product only (5 Keys to Safer Food, A2 poster, Ndebele).

Table 7
Optimal flow for 5 Keys to Safer Food, A2 Poster – Cost Model Transshipment

Source	**Destination**	**Flow**
Supplier 1	Warehouse	1860
Supplier 2	Warehouse	186
Warehouse	Destination 1	80
	Destination 2	56
	Destination 4	520
	Destination 3	260
	Destination 6	240
	Destination 7	40
	Destination 9	160
	Destination 10	80
	Destination 12	380
	Destination 5	80
	Destination 4	150

4.2 Direct and Transhipment Optimization

4.2.1 Carbon Minimization

To conduct this standalone carbon optimization, we set the alpha value (weight) on the carbon objective function to be 1 and the alpha value on the cost objective function to be 0. In this model we enable direct routes between suppliers ‘i’ and destinations ‘j’. Ultimately our model includes transhipment and direct routes.

The resulting minimum total carbon (CO_2) for the Transhipment and direct model is reduced by 12% when compared to the baseline scenario (transhipment model).

The model generates the optimal flow of all products on each arc. However, for illustration purposes and for ease of comparison we list in Table 8 below the optimal flow for 1 product only (5 Keys to Safer Food, A2 poster, Ndebele).

Table 8
"5 Keys to Safer Food, A2 Poster" flow, Carbon Model Transshipment & Direct

Source	Destination	Flow
Supplier 1	Warehouse	506
Supplier 2	Warehouse	170
Warehouse	Destination 1	56
	Destination 2	260
	Destination 4	40
	Destination 3	160
	Destination 6	80
	Destination 7	80
Supplier 1	Destination 9	520
	Destination 10	240
	Destination 12	380
Supplier 2	Destination 5	80
	Destination 4	150

4.2.2 Cost Minimization

To conduct the standalone carbon optimization for, we set the alpha value (weight) on the cost objective function to be 1 and the alpha value on the carbon objective function to be 0. In this model we enable direct routes between suppliers 'i' and destinations 'j'. Ultimately our model includes transhipment and direct routes.

The resulting minimum cost for the Transhipment with direct model is reduced by 8% when compared to the baseline scenario (transhipment model).

The model generates the optimal flow of all products on each arc. However, for illustration purposes and for ease of comparison, we list in Table 7 below the optimal flow for 1 product only (5 Keys to Safer Food, A2 poster, Ndebele).

Table 9

"5 Keys to Safer Food, A2 Poster" flow, Cost Model Transshipment and Direct

Source	Destination	Flow
Supplier 1	Warehouse	1646
Supplier 2	Warehouse	250
Warehouse Supplier 9	Destination 1	80
	Destination 2	56
	Destination 4	520
	Destination 3	260
	Destination 6	240
	Destination 7	40
	Destination 9	160
	Destination 10	80
	Destination 12	380
	Destination 5	80
Supplier 3	Destination 4	150

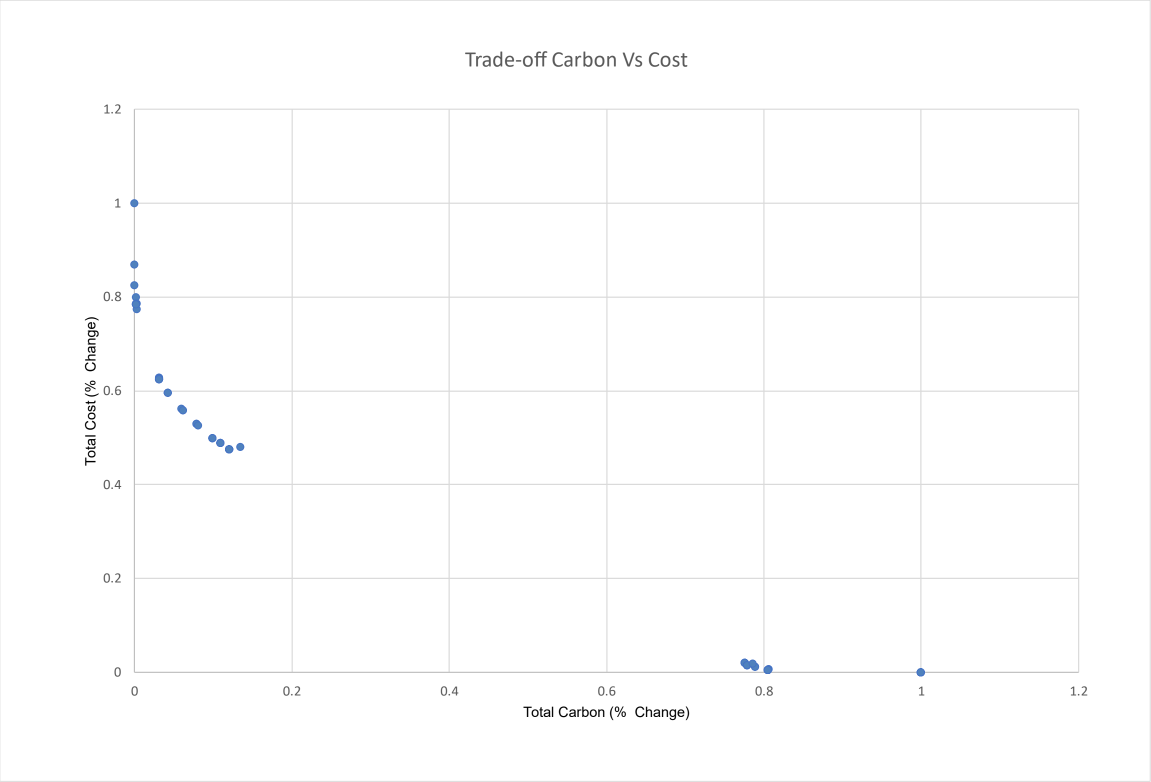
4.3 Multi-Objective Transhipment Optimization

To decide on a trade-off between total carbon emissions and total costs, we conduct a multi-objective optimization and draw a Pareto frontier. We run the multi-objective optimization using the weighted-sum method with a step function to iterate on several values of alpha. The step value used is 0.001 iterating for alpha between 0 and 1.

The resulting Pareto frontier is shown in Figure 10 below. The decision maker in UNICEF can use this Pareto Frontier to decide on the desired level of optimal carbon and costs. This Pareto Frontier is built using transhipment network and Direct route network; the direct routes were enabled.

Figure 10

Pareto Frontier - Trade-Off of Cost and Carbon



The above Pareto Frontier enables the decision maker to make an informed decision on the trade-offs between the optimal values of total carbon and total cost.

5 Scenario Analysis

In this section, we analyse and compare different scenarios on the multi-objective model. For a fixed value of alpha within the model, we initially compare the difference in cost and carbon in between a Transhipment model, a Transhipment model with direct routes, and a model with only direct routes. Subsequently, we analyse the effect of unifying the truck sizes within the mode. Lastly, we conduct a scenario to study the social impact of UNICEF's network, and the trade-off between carbon, cost and social.

5.1 Scenario 1: Transhipment Model

Considering a transhipment model with the direct routes disabled, for an alpha value of 0.76, the resulting network yields the following optimal values. For confidentiality reasons we cannot release the exact results of the model. For the purpose of this capstone the change in costs and carbon for the multi-objective optimization will be expressed in percentage form. Therefore, the total cost and carbon for the Transhipment model is the baseline scenario which is **benchmarked at 100%.**

Table 10
Results of Transshipment Optimization Model

Total Carbon Emissions (%)	100%
Total Cost (%)	100%
Total Suppliers Used (No.)	15
Total Lanes Utilized in Network (No.)	152
Total Trucks in Network (No.)	465
Total Distance Covered (Km)	48,711.4

The resulting network is shown in Figure 11, where red lines represent incoming flows and green lines represent outgoing flows.

Figure 11
Optimal Transshipment Network

5.2 Scenario 2: Direct and Transhipment model

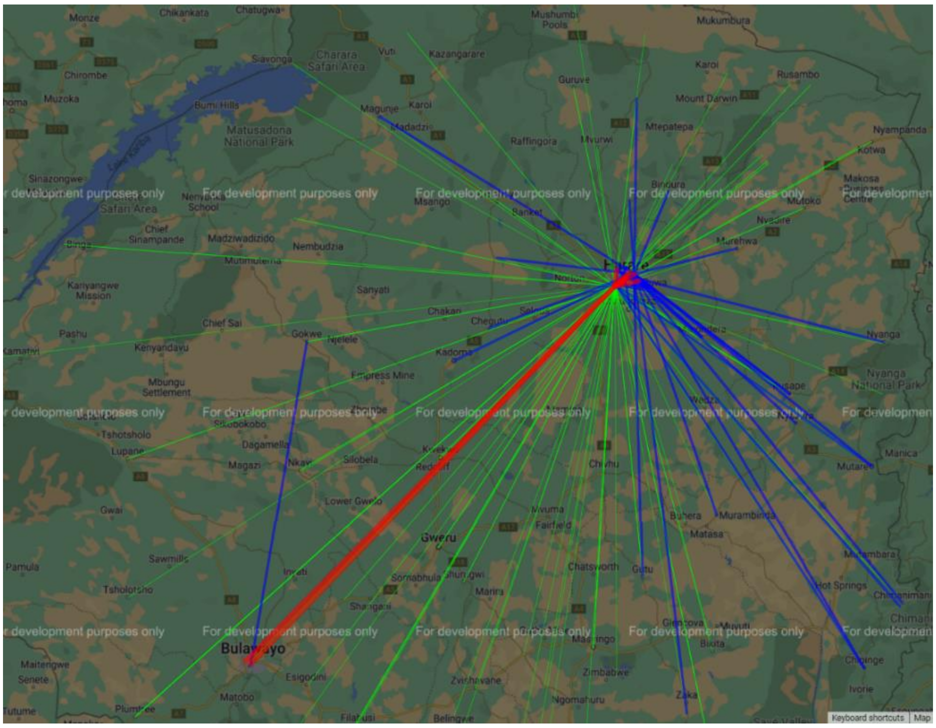
Considering a model with direct and transhipment routes (direct routes enabled), for an alpha value of 0.76, the resulting network yields the following optimal values:

Table 11
Results of Direct and Transshipment Optimization Model

Total Carbon Emissions (%)	-10%
Total Cost (%)	-7%
Total Suppliers Used (No.)	15
Total Lanes Utilized in Network (No.)	202
Total Trucks in Network (No.)	374
Total Distance Covered (Km)	46,219.4

The resulting network design is shown in Figure 33, where red lines represent incoming flows, green lines represent outgoing flows, and blue lines represent direct flow from supplier to destination

Figure 12
Optimal Direct and Transshipment Network



5.3 Scenario 3: Network with Direct Routes Only

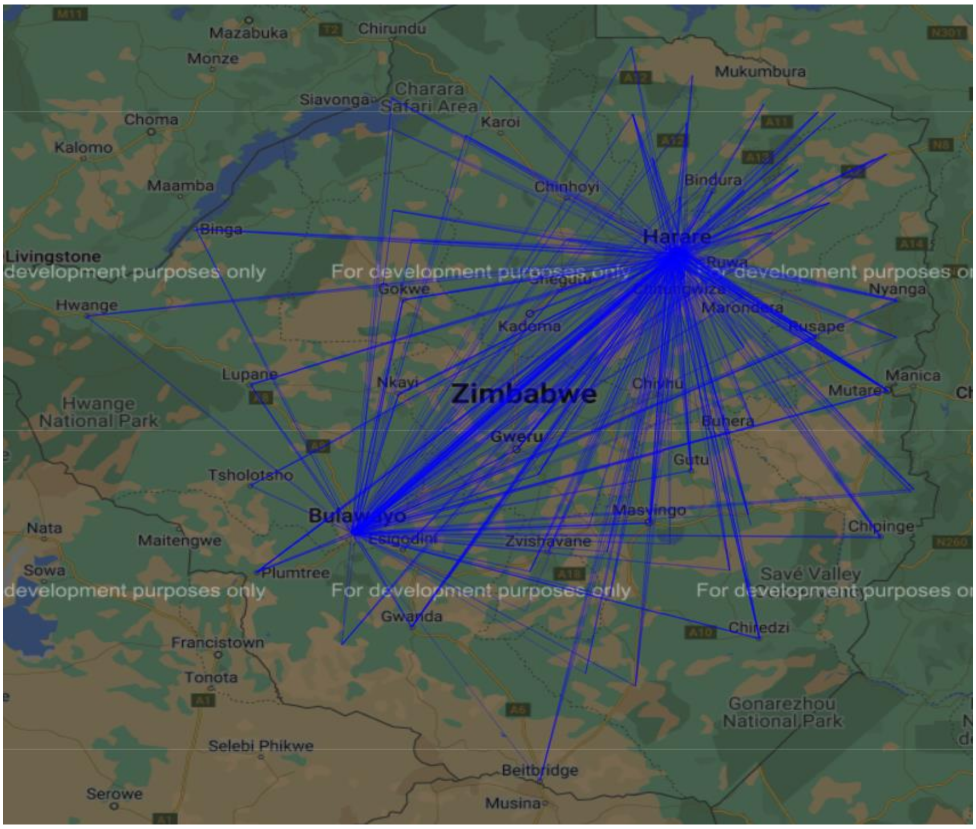
Considering a model with direct and transhipment routes (direct routes enabled), for an alpha value of 0.76, the resulting network yields the following optimal values.

Table 12
Results of Direct Only Optimization Model

Total Carbon Emissions (%)	+320%
Total Cost (%)	+270%
Total Suppliers Used (No.)	19
Total Lanes Utilized in Network (No.)	746
Total Trucks in Network (No.)	782
Total Distance Covered (Km)	210,439

The resulting Network is shown in the below figure where the blue lines represent the direct flows between suppliers and end destinations.

Figure 13
Optimal Network Design with Direct Shipments Only



5.4 Scenario 4: Unifying Truck Sizes to 5 Tons

UNICEF assigns truck sizes on a case-by-case basis depending on the load and weights of the shipment required to be transported. Designated personnel at UNICEF's warehouse are responsible to allocate truck sizes for each shipment. The supply chain network models in this capstone do not optimize on the size of the trucks; rather in the models we assumed the truck size to be dependent on the distance transported. Specifically, we assumed a truck size of 5 tons if the distance is less than or equal to 100 km, a truck size of 12 tons if the distance is between 100km and 200km, and a truck size of 20 tons for distances greater than 200km. In addition to the capacity of the truck, the truck size impacts the fixed cost and variable costs of the trucks.

In this scenario, we study the effects of unifying all truck sizes to the smallest truck size of 5 tons. The resulting model yields the following optimal values.

Table 13
Results of Network Design - 5 Ton Trucks Only

Total Carbon Emissions (%)	+90%
Total Cost (%)	+30%
Total Suppliers Used (No.)	17
Total Lanes Utilized in Network (No.)	297
Total Trucks in Network (No.)	474
Total Distance Covered (Km)	98,856.5

5.5 Scenario 5: Unifying Truck Sizes to 12 Tons

Similar to Scenario 4, Scenario 5 involves unifying truck sizes. However instead of the 5 tons trucks we study the effects of unifying the truck sizing to 12 tons trucks. The resulting model yields the following optimal values.

Table 14
Results of Network Design - 12 Ton Trucks Only

Total Carbon Emissions (%)	+8%
Total Cost (%)	-7%
Total Suppliers Used (No.)	15
Total Lanes Utilized in Network (No.)	211
Total Trucks in Network (No.)	276
Total Distance Covered (Km)	54,892.1

5.6 Scenario 6: Unifying Truck Sizes to 20 Tons

Like Scenario 4 and 5, in Scenario 6 we study the effects of unifying the truck sizes. In this scenario we assume the largest truck size of 20 tons. The resulting model yields the following optimal values.

Table 15
Results of Network Design - 20 Ton Trucks Only

Total Carbon Emissions (%)	-12%
Total Cost (%)	-16%
Total Suppliers Used (No.)	15
Total Lanes Utilized in Network (No.)	170
Total Trucks in Network (No.)	217
Total Distance Covered (Km)	43,327.5

5.7 Scenario 7: Increasing Demand by 10%

In order to stress-test our model we also create various scenarios where the demand is increased. In this scenario we consider that the base demand increased by 10 %. At first the model was unfeasible as we had exceeded the supply constraint.

Assuming an equal 10% increase in the supply constraints, the resulting model yields the optimal values in the table below. Note that all routes were enabled in this scenario.

Table 16
Robustness Test of Model- Demand 10% Increase

Total Carbon Emissions (%)	-7%
Total Cost (%)	-3%
Total Suppliers Used (No.)	17
Total Lanes Utilized in Network (No.)	219
Total Trucks in Network (No.)	407
Total Distance Covered (Km)	48,253

5.8 Scenario 8: Increasing Demand by 30%

In this scenario we consider that the base demand increased by 30%. At first the model was unfeasible as we had exceeded the supply constraint.

Assuming an equal increase in the supply constraints, the resulting model yields the optimal values as seen in table below. All routes were enabled in this scenario.

Table 17
Robustness Test of Model - Demand 30% Increase

Total Carbon Emissions (%)	+11%
Total Cost (%)	+5%
Total Suppliers Used (No.)	17
Total Lanes Utilized in Network (No.)	219
Total Trucks in Network (No.)	407
Total Distance Covered (Km)	48,253

5.9 Scenario 9: Decreasing Demand by 20%

We also test our model for a decrease in total demand by 20%. The resulting model yields the optimal values in the table below. All routes were enabled in this scenario:

Table 18

Robustness Test of Model - Demand 20% Increase

Total Carbon Emissions (%)	-17%
Total Cost (%)	-13%
Total Suppliers Used (No.)	16
Total Lanes Utilized in Network (No.)	194

Total Trucks in Network (No.)	330
Total Distance Covered (Km)	43,872

5.10 Scenario 10: Increase Supply by 10% Outside Harare

In this scenario we test the model for an increase in supply of 10 % from locations that are outside Harare (>50 km) . The resulting model yields the optimal values in the below table. Note that all routes were enabled in this scenario:

Table 19
Social Test - 10% Supply Increase for Locations Outside Harare

Total Carbon Emissions (%)	-8%
Total Cost (%)	-4%
Total Suppliers Used (No.)	15
Total Lanes Utilized in Network (No.)	210
Total Trucks in Network (No.)	393
Total Distance Covered (Km)	47,786

5.11 Scenario 11: Increase Supply by 20% Outside Harare

In this scenario we test the model for an increase in supply of 20 % from locations that are outside Harare (>50 km). The resulting model yields the optimal values in the below table. Note that all routes were enabled in this scenario:

Table 20
Social Test - 20% Supply Increase for Locations Outside Harare

Total Carbon Emissions (%)	-5%
Total Cost (%)	-1%
Total Suppliers Used (No.)	16
Total Lanes Utilized in Network (No.)	217
Total Trucks in Network (No.)	413
Total Distance Covered (Km)	49,712

5.12 Scenario 12: Increase Supply by 30% Outside Harare

In this scenario we test the model for an increase in supply of 30 % for locations that are outside Harare (>50 km). The resulting model yields the optimal values in the below table. Note that all routes were enabled in this scenario:

Table 21
Social Test - 30% Supply Increase for Locations Outside Harare

Total Carbon Emissions (Tons)	-1%
Total Cost (USD)	+2%
Total Suppliers Used (No.)	16
Total Lanes Utilized in Network (No.)	220
Total Trucks in Network (No.)	425
Total Distance Covered (Km)	51,721.5

6 Discussion and Recommendations

In this section we compare and analyse the results of the scenarios detailed in section 5. We adopt a conservative approach by utilizing the optimal transhipment model as a baseline. Therefore the gains of the various scenarios are at least equal or greater than UNICEF’s current mode of operations.

6.1 Assessment of Direct Routes Option

With respect to the option for enabling direct routes within UNICEF’s network, scenarios 1 to 3 provide the main insights. The differences (in percentages) for the resulting optimal values are given in the table below.

Table 22

Comparison Transshipment and Transshipment & Direct Routes

	Transhipment	% Difference	Transhipment + Direct Routes	% Difference	Direct Routes
Total Carbon Emissions (Tons)	CBI	-11%	CBI	+79%	CBI
Total Cost (USD)	CBI	-8%	CBI	+76%	CBI
Total Suppliers Used (No.)	15	0%	15	+21%	19
Total Lanes Utilized in Network (No.)	152	33%	202	+73%	746
Total Trucks in Network (No.)	465	-20%	374	+52%	782
Total Distance Covered (Km)	48,711.4	-5%	46,219.4	+78%	210,439

As seen in in the table above, the transhipment and direct routes model has the least amounts of carbon emissions and total costs. The amounts are 11 % and 8 % lower respectively than those of the second-best model which is the Transhipment model. Due to a confidentiality agreement with UNICEF we cannot include the exact figures can not be disclosed and in the table are replaced with CBI (confidential business information).

While opening direct routes seem to be beneficial for the total carbon footprint and total cost, such amounts for the direct routes model are very high. In comparison with the transhipment, and direct route model, the direct routes model has 79% additional carbon emissions and 76% additional costs.

This is likely due to the fact that the transhipment and direct routes model provides an opportunity for the goods to be consolidated in the warehouse. In the direct route model, the suppliers can only consolidate products which they are selling, and different product from different suppliers are shipped separately. This yields a higher number of trucks in the overall network which is 52% higher than the transhipment and direct route model and which results in higher costs and higher carbon emissions.

As such, a key recommendation to UNICEF is to use a model with all direct and transhipment routes enabled.

6.2 Assessment of Truck Size

In additional to assessing the direct routes option we also assessed the difference in total carbon and total costs resulting from using varying truck sizes. In scenarios 4,5 and 6 above we unified the truck sizes to 5 ton, 12 tons and 20 tons respectively. The associated models had the following differences in optimal values:

Table 23

Differences between Truck Sizes using Transshipment & Direct Routes

	5 Tons Trucks	% Difference	12 Tons Trucks	% Difference	20 Tons Trucks
Total Carbon (tons)	CBI	-45%	CBI	-19%	CBI
Total Cost (USD)	CBI	-33%	CBI	-9%	CBI
Total Suppliers Used (No.)	17	-12%	15	0%	15
Total Lanes Utilized in Network (No.)	297	-29%	211	-19%	170
Total Trucks in Network (No.)	474	-42%	276	-21%	217
Total Distance Covered (Km)	98,856.50	-44%	54892	-21%	43327.5

Due to a confidentiality agreement with UNICEF we cannot include the exact figures cannot be disclosed and in the table are replaced with CBI (confidential business information).

The results highlighted in the above table indicate that using higher sized trucks contributed to the reduction of both carbon footprint and costs. Compared with the model with 5 tons trucks, a model with 20 tons trucks uses approximately 64 % less carbon emissions and 42% less costs. This is likely attributed to the fact that such models are fully optimized and hence the models are consolidating the products within the trucks and using 20 tons trucks results in a lower number of trucks in the system.

Compared with the 5 tons truck model that has 474 total trucks deployed in the network, the 20 tons trucks utilize 217 trucks to transport the same quantity of goods. Hence, even though the 20 tons trucks are carrying more weight (and therefore generating more carbon emission per truck and are costlier) the reduction in the total number of trucks offsets the additional carbon and costs resulting from using the 20 tons trucks.

As such, a key recommendation to UNICEF is to consolidate products within the trucks and use higher sized trucks.

6.3 Assessment of Social Impact

To assess the social impact of UNICEF's network, we ran scenarios 10, 11 and 12 where we increased the supply from regions that are outside Harare (>50 km). The aim is to analyse the effects on carbon and cost from sourcing more products further away from Harare. The models had the following differences in values:

Table 24
Values for Increased Supply outside Harare

	Increase Supply (10%)	% Difference	Increase Supply (20 %)	% Difference	Increase Supply (30 %)	%
Total Carbon (tons)	CBI	-8.24%	CBI	-5.01	CBI	-0.33%
Total Cost (USD)	CBI	-4.73%	CBI	-0.75%	CBI	2.89%
Total Suppliers Used (No.)	15	0.00%	16	6.67%	16	6.67%

Total Lanes Utilized in Network (No.)	210	38.16%	217	42.76%	220	44.74%
Total Trucks in Network (No.)	393	-15.48%	413	-11.18%	425	-8.60%
Total Distance Covered (Km)	47,786	-1.90%	49,712	2.05%	51,721.50	6.18%

Due to a confidentiality agreement with UNICEF we cannot include the exact figures cannot be disclosed and in the table are replaced with CBI (confidential business information).

Increasing supply from regions outside of Harare results in lower cost and carbon emissions when compared to the current transhipment policy at UNICEF. An increase in supply of 10% from suppliers outside of Harare results in an 8.24% cost reduction and 4.73% less carbon emissions. The results above indicate that increasing supply from regions outside Harare is not linearly proportional to the effects of cost and carbon. When increasing supply for such regions from 10 % to 20 % above baseline, the total carbon increases by 3.23% and the total cost by 3.98%. Similarly, when increasing supply from 20 % to 30 % above baseline, the total carbon increase by 4.92 % and the total cost by 3.67%.

As such, a key recommendation for UNICEF is to source more from suppliers outside Harare, to increase the social impact of the supply chain while also reducing total carbon emissions and cost.

7 Assumptions and Limitations

7.1 Assumptions

The models and analysis discussed above were based on several assumptions most importantly the following:

1. The model included the data for the full 3 years period (2019 to 2021).
2. The model segmented the data for 80% of the total demand.
3. The previous supply data of the suppliers were assumed to be equal to their capacities.
4. Inventory was assumed to be equal to zero at the warehouse, yet the model can easily incorporate inventory assumptions.
5. The model calculated the fuel consumptions for the empty and full trucks, it did not utilize real consumption data.
6. The model did not optimize on the truck size. It assumed a certain truck size depending on the distance covered.
7. The slopes in the model were calculated based on the elevations of the sources and destination. More aggregate slopes have to be implemented.
8. For the calculation of the fuel consumptions, the engineer friction, engine speeds, engine displacement and vehicle speeds were assumed to be constants.

To counter-effect the above assumptions, it is recommended that UNICEF acquire data for more than 3 years and analyse the trends. After the latter is done and the outliers removed (specially outliers relating to Covid-19), UNICEF can then forecast the demand for a shorter period (monthly or quarterly) and re-run the model with the forecasted numbers. Accordingly, UNICEF would use the model to optimize its tactical operation network.

In addition to the above, it is also recommended that UNICEF incorporates more granular data on the supplier's capacities, on the demand of each customer, on the inventory requirement in the warehouse, on the actual fuel consumptions of the vehicles.

7.2 Limitations

7.2.1 Segmentation

A limitation of the capstone was the necessity to use segmentation as part of the methodological approach. Due to the scope of the project, it was not possible to include all products, suppliers, or end destinations. There were several reasons why all the information was not included. First, there was missing data in the datasheets provided for the research. Second, some data did not pertain to the problem we were trying to solve. Third, for the model 80% of the data was selected. If a different percentage point was taken it is possible that the results could be different. Finally, the data was segmented based on volume demanded over three years. It is also possible to segment the data by other means such as cost, importance, dimensions etc.

7.2.2 Baseline comparison

As no granular data was provided on the trucks and the routes that were utilized over the three years, it was difficult to create a baseline scenario to compare our model to. Datapoints such as truck size, average speed, fill rate etc. would have been needed to accurately calculate the actual CO2 emission rate and cost over this timeframe. This information was unavailable. For the baseline the optimized transhipment network design was used.

7.2.3 Method of Data Collection

The characteristics of the products were vital to the functionality of the model and its representation of reality. Particularly the weight and volume played a critical role in truck allocation and route selection. Assumptions had to be made on the weight and volume of certain products as the information was not available. This was done by conducting online analysis of similar products. No on the ground observations were conducted to control the authenticity of the data that was provided.

7.2.4 Time Period

The model looked at the data over the entire three-year period (2019-2021). It might be the case that if each year is examined individually the results of the model could produce different optimal outcomes. This aggregation of data, while necessary for a strategic overview, simplifies the complexity of the distribution network. In the model, full truckloads are used as the basis for the flow of goods on the arcs. UNICEF allow employs a full truck load method. However, due to the timeless nature of the model which is only limited by the bounds of the three-year period, products can be mixed from different weeks, months or even years. UNICEF would not wait months for a supplier to have enough products to fill a truck. The operational reality on the ground is that the products are shipped also if they are not full truckload.

7.2.5 COVID Pandemic

From the analysis of the data, it could be seen that the COVID pandemic seems to have had an impact on the flow of products in the distribution network. Certain products made up most of the volume in the years 2020 and 2021 but had very little volume in the year 2019. An example of these produce are soap and face masks. As these two products are closely related to the COVID pandemic it is possible that the inclusion of these products could affect the optimized network design. To check the validity of the results of the modelling process data from previous years should be analysed. Unfortunately, this was outside the scope of the capstone project.

7.2.6 Computational Limitation

As the multi-objective model computation is complex. Due to this there was a time limit placed on the calculation process. This has the effect of creating a slight difference between the optimal pareto frontier and the results of our model, which we consider near optimal. To calculate the difference with the inclusion of a time limit a comparison was made between a sample of time constrained and unconstrained optimization. The difference was 0.0001% and 99. 97% of the optimal solutions.

8 Conclusions

In this capstone project, we modelled UNICEF’s supply chain network in Zimbabwe and provided a Pareto frontier that illustrates the optimal combinations of total carbon emissions and total costs. We also analysed the effects of enabling or disabling direct routes between suppliers and end beneficiaries and the effects on cost and carbon emissions associated with increasing UNICEF’s reach and social impact. Our proposed network model formulation not only utilized the granular NTM approach that takes into account the fuel consumption of the vehicles, but it also calculates the theoretical fuel consumption of the vehicles by using the Barth et al. (2005) equation which takes into account other variables specific to the characteristics of the road and vehicles such as engine speed, engine displacement, speed, weight, road slope, acceleration.

The three primary recommendations from the capstone are as follows:

- Using a transhipment model with selected direct routes enabled reduced the overall total cost and carbon emissions.
- Consolidating the products within the trucks and using a higher sized trucks entailed lower total cost and carbon emissions.
- UNICEF to consider expanding its supplier base in remote regions beyond Harare to increase its social impact and benefit from the diminishing effects on total cost and carbon emissions.

8.1 Future Research

To improve upon the model and enhance the supply chain design, the next step would be to include facilities in the optimization process. This could include two components that are independent of each other but are complementary. First, is the question of optimal facility location. In the case of UNICEF Zimbabwe this implies their distribution centre. Our capstone focused on the flow of products, the arcs they move on, and the transportation modes that carry them. However, we did not focus on where the warehouse/warehouses should be located. Maybe Harare is not the optimal location. It is also possible that multiple locations would create a more optimal network design. Our model could be the foundation upon which such a facility location model could be built. Second, the operations at the warehouse could also be included in the modelling process. The costs and carbon emissions associated with the warehouse and the functions that take place there could be included. For example, the costs associated with labour, rent, utilities, and equipment or the emissions associated with heating and electricity could be included in the model. This granular level of detail would make the model more robust and representative of reality.

As we alluded to in capstone, this capstone has given UNICEF a strategic overview that demonstrates that including direct shipments alongside their current transhipment model is optimal. This is a major insight that can help UNICEF create a more efficient supply chain that can simultaneously reduce costs and carbon emissions. However, a problem remains, how can these key insights be operationalized. A productive approach for further research, which can also be applied in a real setting with UNICEF, would be to amend our model so that it can optimize on monthly or quarterly basis. This would allow product and truck flows to be optimized at a tactical level, which would have the benefit of reducing costs and carbon emissions as demonstrated in this capstone.

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APPENDIX

```
#Python Code for Multi-Objective optimization:
import gurobipy as gp
from gurobipy import GRB
import pandas as pd
import pylab as plt

# Defining functions to import data into python
def make_dict(file):
    data=pd.read_excel(file)
    c=data.columns
    d={}
    for k in range(len(data)):
        d[(data[c[0]][k],data[c[1]][k])]=data[c[2]][k]
    return d
def make_simpledict(file):
    data=pd.read_excel(file)
    c=data.columns
    d={}
    for k in range(len(data)):
        d[data[c[0]][k]]=data[c[1]][k]
    return d
def make_arc(file):
    data=pd.read_excel(file)
    c=data.columns
    d=[]
    for k in range(len(data)):
        d.append((data[c[0]][k],data[c[1]][k]))
    return d
def make_triplet(file):
    data=pd.read_excel(file)
    c=data.columns
    d={}
    for k in range(len(data)):
        d[(data[c[0]][k],data[c[1]][k],data[c[2]][k])]=data[c[3]][k]
    return d
def make_list(file):
    data=pd.read_excel(file)
    c=data.columns
    d=[]
    for k in range(len(data)):
        d.append(data[c[0]][k])
    return d

# Import Excel sheet into python
Products = make_list('Products.xlsx')
nodes = make_list('Nodes.xlsx')
Suppliers = make_list('Suppliers.xlsx')
```

```
Customers = make_list('Customers.xlsx')
Warehouse=['WILLOWVALE MOTOR INDUSTRIES COMPLEX, CORNER
DAGENHAM/GLENEAGLES ROAD, HARARE']
arcs=make_arc('Arcs.xlsx')
Demand=make_dict('Demand.xlsx')
Supply=make_dict('Supply.xlsx')
Inventory=make_dict('Inventory.xlsx')
TruckCapacity=make_dict('TruckCapacity.xlsx')
Distance=make_dict('Distance.xlsx')
FE=make_dict('FE.xlsx')
FF=make_dict('FF.xlsx')
FixedCost=make_dict('FixedCost.xlsx')
VariableCost=make_dict('VariableCost.xlsx')

# Define the Optimization Model
def Model(alpha):
    m = gp.Model('netflow')
    m.Params.TimeLimit=30
    flow = m.addVars(Products,arcs,vtype=GRB.INTEGER,name="flow")
    truck = m.addVars(arcs,vtype=GRB.INTEGER,name="truck")
    totalflow = m.addVars(arcs,name="totalflow")
    l=2.621*1.5
    l2=2.621
    m.setObjectiveN((gp.quicksum(truck[a[0],a[1]]*FixedCost[a] for a in arcs )+
                    gp.quicksum(truck[a[0],a[1]]*Distance[a]*VariableCost[a] for a in arcs
)),2,weight=alpha)

    m.setObjectiveN(l*(gp.quicksum(truck[a[0],a[1]]*Distance[a]*FE[a] for a in arcs )+
                  gp.quicksum((totalflow[a[0],a[1]]/TruckCapacity[a])*(FF[a]-FE[a])*Distance[a] for
a in arcs )),1,weight=1-alpha)

    # link constraint - demand individual flow - Truck constraint
    m.addConstrs(truck[a[0],a[1]]*TruckCapacity[a] >= sum(flow[p,a[0],a[1]] for p in Products)
for a in arcs)

    #linking constraint truck - overall flow
    m.addConstrs(truck[a[0],a[1]]*TruckCapacity[a] >= totalflow[a[0],a[1]]  for a in arcs)

    #linking constraint truck - overall flow
    m.addConstrs(TruckCapacity[a]*(truck[a[0],a[1]]-1) <= totalflow[a[0],a[1]] for a in arcs)

    #Demand Constraint
    m.addConstrs(sum(flow[product, supplier , customer] for supplier in Suppliers)+
             sum(flow[product, warehouse , customer] for warehouse in Warehouse)
             >= Demand[product,customer]  for product in Products for customer in
Customers)


    #Supply Constraint - Product specific
    m.addConstrs(sum(flow[product, supplier , warehouse] for warehouse in Warehouse)+
```

```
             sum(flow[product, supplier , customer] for customer in Customers)
             <= Supply[product,supplier]  for product in Products for supplier in Suppliers)
    #Conservation of flow
    m.addConstrs(sum(flow[product, supplier , warehouse] for supplier in Suppliers)-
             sum(flow[product, warehouse , customer] for customer in Customers)
             >= Inventory[(warehouse,product)] for warehouse in Warehouse for product in
Products)
    # Compute optimal solution
    m.optimize()
    k=m.getAttr('x',truck)
    f=m.getAttr('x',totalflow)
    Cost=round((sum(k[a[0],a[1]]*FixedCost[a]  for a in arcs )+
            sum(k[a[0],a[1]]*Distance[a]*VariableCost[a] for a in arcs )),1)

    Carbon=round(l2*(sum(k[a[0],a[1]]*Distance[a]*FE[a] for a in arcs )+
                sum((f[a[0],a[1]]/TruckCapacity[a])*(FF[a]-FE[a])*Distance[a] for a in arcs)),1)
    return (Carbon,Cost)
# implementing step function to draw Pareto Frontier
results={}
Carbon=[]
Cost=[]
i=0
step=0.01
while i<0.99:
    a=Model(i)
    Carbon.append(a[0])
    Cost.append(a[1])
    results[i,a[0]]=a[1]
    i=i+step

df = pd.DataFrame(data=results, index=[0])
df = (df.T)
df.to_excel('CarbonandCostvsAlpha.xlsx')
# plotting Pareto Frontier
plt.figure('plot')
plt.plot(Carbon,Cost)
plt.title('Trade-off Carbon vs Cost')
plt.xlabel("Total Carbon")
plt.ylabel("Total Cost")
```