Chapter 7
Green Network Design and Facility Location

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7.1 Introduction

Transportation emissions comprise a large share of the world's overall emissions, and freight transport is responsible for a relatively large share of these emissions. Transportation emissions can be reduced by making different choices in logistics, such as changing the mode of transport or changing the routing or loading of the vehicles in the network (see Chap. 5 by Blanco and Sheffi (2024) for more on green logistics). These logistics choices are influenced significantly by the inventory policies that have been deployed in a company (see Chap. 6 by Marklund and Berling (2024) for more on green inventory management). For instance, allowing for a more carbon-friendly slow mode of transportation would typically require increasing or repositioning the inventory in the supply network.

Apart from logistics choices and inventory policies, transportation performance in terms of costs and emissions is strongly determined by the design of the network. In distribution networks, this refers in particular to the location of distribution centers or other transport hubs such as factories or cross-docks. In this chapter, we address the issue of locating such a transport hub.

The logistics problem that determines the configuration of a company's delivery of goods is the facility location problem. The facility location problem is to locate a set of facilities (e.g., factories, cross-docks, distribution centers) in a physical space,

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such that all the demands of the customers are assigned to at least one facility and the total transport cost is minimized. While the literature on facility location is well established and large in size, in this chapter, we focus on a variant of this problem that specifically includes the transport carbon emissions in the formulation. We refer to location problems that aim at minimizing transportation CO_2 emissions as green facility location problems.

By limiting the scope to emissions from *mobile* sources (i.e., transport), we do not consider emissions from *stationary* sources that could be influenced by the location decision. Without being exhaustive, these may include:

– *Emissions at the distribution center*. These relate to the energy usage of the distribution center. In most cases, this would be electricity for light and/or automation and for refrigeration. Potentially, economies of scale could exist that would be related to the design of the network. Industry data suggest that in most distribution networks the emissions at the distribution center are less than 10% of the total logistics-related emissions.
– *Availability of local energy sources*. In particular, for energy-intensive operations, the availability of renewable local energy may significantly impact the supply chain emissions. For instance, locating an aluminum plant in an area where geothermal electricity is available could reduce a supply chain's overall carbon emissions while still increasing its transport emissions.

Excluding the emissions from stationary sources from the models discussed in this chapter implies that effectively we are limiting ourselves to distribution networks and the location choice of distribution centers and cross-docks. However, in our discussion, we use the more general term "facility."

Usually, companies designing their distribution channels select the locations of warehouses and distribution centers with the objective to serve the demand of the customers while minimizing distance (or transport costs). In this chapter, we review some models that include the transportation CO_2 emissions in the uncapacitated facility location. We then discuss the solutions we may obtain when the number of facilities to be located is fixed by using the p-Median problem. We present discussions and managerial implications for the green facility location. We are interested in learning whether location decisions obtained by cost minimization are different from those obtained by the green facility location model.

7.1.1 Facility Location and Carbon Emissions

Typically, facility location decisions are made by considering the associated costs that include transportation (from the facilities to the customers) and the operation of the facility (production and storage). As discussed above, we may split the main sources of CO_2 emissions associated with the location of facilities in a similar way: emissions from mobile sources (transportation) and emissions from stationary sources (production, storage, and handling). Having more facilities reduces the CO_2 emissions from mobile sources due to the fact that the distance from the facility to the customer destinations decreases. This increases emissions from stationary sources due to their larger number. Therefore, the challenge in green facility location is to define the proper number and position of the facilities that will serve a set of customers while minimizing the overall CO_2 emissions.

Many studies show that transportation and production may substantially contribute to CO_2 emissions. For example, the three main contributing sectors to emissions in the developed world are electricity production, energy-intensive manufacturing, and transportation (European Environmental Agency 2018). While production of electricity and energy-intensive manufacturing are considered within Scopes 1 and 2 of the GHG inventory, transportation by service providers is considered within Scope 3 emissions (see Chap. 3 by Boukherroub et al. (2024) for further details). Scope 3 emissions often represent the largest source of GHG emissions accounting for more than 90% of a company's carbon footprint (World Business Council for Sustainable Development 2021). In addition, when the facility location problem consists of locating distribution centers instead of manufacturing plants, typically, the CO_2 emissions from mobile sources are much higher than those of the stationary sources, as the latter then only include the emissions at the distribution center. Storage and handling emissions are substantially smaller than transportation emissions, by a factor of 10 for some products (Cholette and Venkat 2009). Therefore, in this chapter, we focus on studying the location of distribution centers with a main emphasis on transportation carbon emissions.

Many practices exist in industry to reduce carbon emissions by implementing more efficient and sustainable practices into their logistics operations (e.g., Heineken Sustainability Report 2013; Groupe Danone 2014; MIT-EDF 2013). However, only a few have considered the location of distribution centers as a relevant alternative to reduce transport CO_2 emissions. For example, Unilever increased the number of regional hubs and located these hubs closer to the customers (Unilever Press Release 2013).

The location of facilities is critical to the efficient and effective operation of a supply chain; poorly placed plants can result in excessive costs and low service level no matter how well tactical decisions (e.g., vehicle routing, inventory management) are optimized (Daskin et al. 2005). In this chapter, we demonstrate that facility location choice may significantly impact mobile CO_2 emissions in the supply chain. Note that the main drivers of transportation carbon emissions are distance, vehicle load (Greenhouse Gas Protocol Standard 2015; Smart Freight Centre 2016), and the number of trips required to deliver a demand to each customer (Network for Transport Measures 2022). Changing the number and location of the facilities in the distribution network impacts all of these drivers.

7.1.2 Trade-Off Between Cost and Carbon Emissions in the Facility Location

Transportation costs (TC) in facility location problems typically take demand (w) and distance (d) into account. These costs are usually modeled as an objective function using the demand-weighted total distance ($TC = \alpha wd$) and assuming an α constant cost per distance per unit (Revelle et al. 2008). Notice that this formulation finds optimal solutions where the facilities are closer to regions with high demand. However, for minimizing transportation CO_2 emissions, good solutions may require a different analysis.

Transportation CO_2 emissions are affected by a variety of conditions related to the type of vehicle (e.g., engine power, torque, fuel-type, aerodynamic drag coefficient) and the characteristics of the delivery operation (e.g., road, slope, vehicle speed, load) (Akçelik and Besley 2003). Due to the lack of detailed information about the delivery operation (specific slopes, speed, aerodynamics, etc.) during the decision-making process, companies typically use more aggregate activity-based methods to estimate CO_2 emissions (see Chap. 3 by Boukherroub et al. (2024) for more background on carbon footprinting). Some of the most common activity-based methods are the GHG Protocol, the Global Logistics Emissions Council (GLEC) Framework (Greene and Lewis 2016), and the methodology developed by the Network for Transport Measures (NTM).

We notice that a facility location model based on the GHG Protocol or GLEC methodologies would provide optimal locations that are identical to cost minimization model solutions, i.e., optimal locations would tend to be closer to regions with high demand. This is because these estimation models multiply distance and cargo times a carbon intensity factor that assumes vehicle utilization, that is, it does not consider explicitly the number of trips required to deliver the specific cargo. This is not always the case, though, when a method like the NTM methodology is employed.

The NTM methodology requires more detailed parameters: fuel consumption efficiencies, distance traveled, and weight per shipment (NTM Road 2010). The fuel consumption efficiencies are a function of the type of truck, the load factor, and the type of road. NTM uses the European Assessment and Reliability of Transport Emission Models and Inventory Systems' database which developed a detailed emission model for all transport modes to provide consistent emission estimates at the national, international, and regional level (TRL 2010). The NTM estimation model is

$$E = l\left[d\left(f^e + \left(f^f - f^e\right)\frac{w}{W}\right)\right],$$

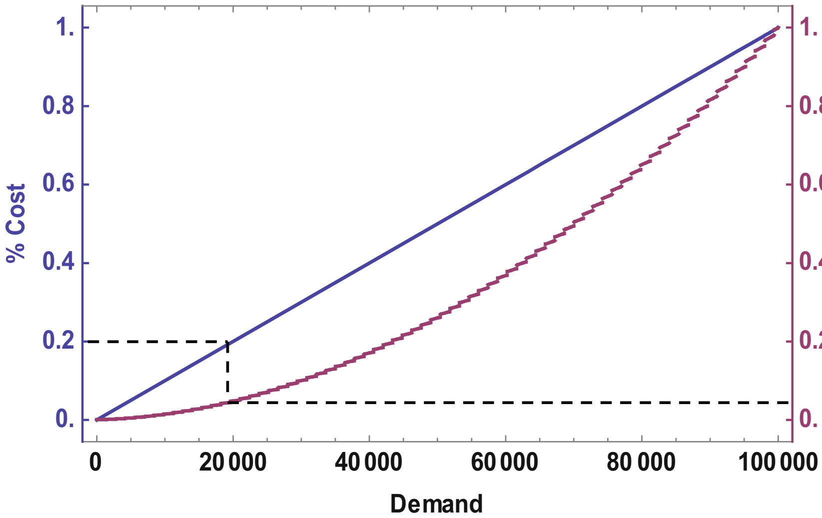

Fig. 7.1 Transport costs and CO_2 emissions over different demand levels

where

E total emissions in grams of CO_2
l constant emission factor (2621 grams of CO_2/liter)
f^e fuel efficiency consumption of the empty vehicle (liters/km)
f^f fuel efficiency consumption of the fully loaded vehicle (liters/km)
W truck capacity

Comparing transport cost and CO_2 emissions, notice that the effect of distance is linear in both expressions. Demand and truck capacity, however, affect transportation costs differently than they affect CO_2 emissions. Figure 7.1 shows the comparison of transport costs and CO_2 emissions for different demand levels. For this example, we use a 14-ton truck for urban road type, and we set 100 demand units equivalent to 1 ton.

Note that the growth in demand does not translate into a linear increase in CO_2 emissions, as it is in cost. For example, a demand of 20,000 units increases the cost up to 20%, while the increase in CO_2 is approximate of 5%. The chart also shows that an increase in demand has an impact on CO_2 emissions, mainly when this growth implies more trips.

Because of these differences in the transport cost and CO_2 emission structures, intuitively, we may conclude that facility location models with either one or the other objective function may have different optimal solutions. While cost minimization models find optimal locations closer to high-demand nodes, CO_2 minimization models may also consider optimal locations closer to demand nodes where a larger number of trips are required to serve the customer's demand. This characteristic of CO_2 minimization models may be observed in both the high-demand nodes and for restricted truck accessibility constraints in the nodes. Therefore, in facility location problems, solutions obtained by minimizing transportation costs are not necessarily equivalent to solutions obtained by minimizing transportation CO_2 emissions.

7.2 Green Facility Location Models

In this section, we present some general facility location models that are commonly studied in the logistics literature, including both continuous and discrete models. We later discuss some extensions of these models that study CO_2 emissions in location decisions.

7.2.1 Traditional Facility Location Models

The facility location problem has a very long history. It was first introduced by Weber (1909), and a large number of extensions and applications can be found in the literature. For a basic explanation of the facility location problems, we refer to Daskin (2008) and Daskin et al. (2005), and for recent reviews, we refer to Melo et al. (2009) and Revelle et al. (2008). Typically, facility location problems are classified based on their solution space as *continuous* if the candidate locations can be located anywhere within the area or *discrete* if the candidate facilities are restricted to a finite set of locations (Daskin 2008). In addition, when continuous models assume that demands are distributed continuously across a service region, this approach is known as *analytical* location models.

The continuous and analytical approaches provide a general overview of the optimal locations and are commonly used for researchers to provide guidelines or insights (Geofrion 1976). A variety of applications can be found in the literature related to extensions of location models, such as the hub location problem (Saberi and Mahmassani 2013), freight transport network (Campbell 2013), and hub-and-spoke network design (Carlsson and Jia 2013). For analytical models, solution methods are derived by using mathematical analysis, while for continuous location models that are not analytically solvable, iterative numerical procedures ensure their convergence to optimal solutions, for example, the Weiszfeld (1936) algorithm for the Weber problem.

For practical applications, discrete formulations are more realistic to provide feasible and optimal locations but are more difficult to solve. For this type of model, candidate locations are pre-screened based on complementary information such as supplier's proximity, labor proximity, local regulations, and available physical space, among others. The basic model that locates the optimal facility among a set of candidate locations in a discrete space is known as the p-Median problem. The p-Median problem is defined as follows (ReVelle and Swain 1970):

Let I be a set of demand nodes and J be a set of candidate locations.

Parameters:

h_i demand at node $i \in I$
d_{ij} distance between candidate facility site $j \in J$ and customer location $i \in I$

Decision variables:

X_j 1 if we locate at site $j \in J$, 0 otherwise
Y_{ij} fraction of demand at customer location $i \in I$ that is served by facility at site $j \in J$

The p-Median problem is then formulated as follows (P1):

$$\text{Min} \rightarrow \sum_{j \in J} \sum_{i \in I} h_i d_{ij} Y_{ij}$$

Subject to

$$\sum_{j \in J} Y_{ij} = 1 \; \forall i \in I \tag{1}$$

$$\sum_{j \in J} X_j = p \tag{2}$$

$$Y_{ij} - X_j \leq 0 \; \forall i \in I \forall j \in J \tag{3}$$

$$X_j \in \{0, 1\} \; \forall j \in J \tag{4}$$

$$Y_{ij} \geq 0 \; \forall i \in I, \forall j \in J \tag{5}$$

The objective function minimizes the demand-weighted total distance. Constraint (1) states that each demand node is covered. Constraint (2) establishes that p facilities are located. Constraint (3) states that the facility is opened when a demand node is assigned. Constraints (4) are the integrality constraints and (5) are the nonnegative constraints. When applied to a general network, the p-Median problem can be difficult to solve. However, since the single-sourcing condition holds in this formulation (i.e., Y_{ij} will naturally take values of zero or one), the property limits the potential facility locations to the network nodes, and therefore it reduces the number of possible location configurations to $n\,!\,/(n-p)\,!\,p!$, where n is the number of nodes (Owen and Daskin 1998). However, a total enumeration of all possible solutions may be computationally prohibited. Kariv and Hakimi (1979) showed that the p-Median problem is NP-hard.

The p-Median problem has been the basis of multiple extensions such as the fixed charge facility location problem, both uncapacitated and capacitated, and in other problems such as multi-item and multi-echelon (Geoffrion and Graves 1974) (Pirkul and Jayaraman 1996). It also has multiple real-world applications such as plant location-allocation (Daskin and Dean 2005), network design (Kalpakis et al. 2001; Ruffolo et al. 2007; Stephens et al. 1994), sensor deployment (Greco et al. 2010), and data mining (Christou 2011). Other applications are presented in ReVelle et al. (2008). The p-Median problem has also attracted much research attention in combinatorial optimization, and many solution methods have been proposed to solve the problem. For instance, variable neighborhood search (Hansen and Mladenovi 1997), genetic algorithm (Hosage and Goodchild 1986), tabu search (Rolland et al. 1997), scatter search (García-López et al. 2003), ant colony optimization (Kochetov et al. 2005), and simulated annealing (Murray and Church 1996). Pullan (2008) finally presents a population-based hybrid search that was tested again multiple instances from literature, and the results show that the algorithm finds the optimal solutions for many problems, and for others, it was capable of finding improvements on the best-known solutions from the literature.

A natural extension of the p-Median problem is to relax the number of facilities to be opened p and include a fixed location cost f_j. This problem is called the fixed charge facility location problem ($P2$) (Balinski 1965):

$$\text{Min} \rightarrow \sum_{j \in J} \sum_{i \in I} f_j X_j + \alpha \sum_{j \in J} \sum_{i \in I} h_i d_{ij} Y_{ij}$$

Subject to (1)–(5)

When we also include a constraint (6) $\sum_{i \in I} h_i Y_{ij} - b_j X_j \leq 0, \forall j \in J$, that limits the assigned demand at facility $j \in J$ to a maximum of b_j, the resulting model (P3) is known as the capacitated facility location problem. Similar to the p-Median problem, the fixed charge facility location is also NP-hard. Previous approaches used to solve the p-Median problem may also be applicable in this case. Other solution heuristics methods are tabu search (Glover 1989; Glover and Laguna 1997) and the dual ascendant algorithm (Erlenkotter 1978), among others.

7.2.2 Carbon Emissions in Facility Location Models

We now discuss some models that include the estimation of CO_2 emissions in the facility location problem. As mentioned in Sect. 1, transportation CO_2 emissions in facility location models should be considered carefully, specifically because cost and CO_2 emission structures do not typically share the same structures. However, some studies demonstrate that even when taking into account the same structure, solutions obtained by minimizing transport costs are not always equivalent to solutions obtained by minimizing CO_2 emissions in more complex logistics networks (e.g., intermodal).

7.2.2.1 Analytical and Continuous Models

We start by discussing the study of Bouchery and Fransoo (2015) on intermodal hinterland network design. The authors present an analytical model that aims at finding the optimal location of one facility (in their example, an inland container terminal) with respect to cost, carbon emissions, and modal shift objectives. The demand is assumed to be uniform over a rectangular region representing the hinterland of the port under consideration. The density of the demand is equal to ρ containers per square kilometer, and the origin of the flows (the port) is located at the coordinates $(0, 0)$.

The model assumes that transport cost and carbon emissions have the same structure and considers two transport mode options: direct shipment (shipment via truck directly from the origin to the customer) and intermodal transportation (shipment via rail to an intermodal terminal and subsequently from the terminal via truck to the customer). The cost and CO_2 emissions of serving a demand region i of size A_i by using direct shipment are expressed as follows: $Z_{0,i}^{DS} = \delta_{0,i}\rho A_i Z_1$ and $E_{0,i}^{DS} = \delta_{0,i}\rho A_i E_1$, respectively, where

$\delta_{o,\,i}$ distance from the port to the gravity center of demand zone i (km)
Z_1 truck transportation cost per container-kilometer
E_1 carbon emissions from truck transportation (kg of CO_2 per container-km)

The cost and CO_2 emissions when using intermodal transportation are expressed as follows: $Z_{0,j}^{IT} = \delta_{0,T}\,(ZF_2 + \rho A_i Z_2) + \delta_{T,i}\rho A_i Z_1$ and $E_{0,i}^{IT} = \delta_{o,T}\,(EF_2 + \rho A_i E_2) + \delta_{T,i}\rho A_i E_1$, where

$\delta_{0,\,T}$ distance from the port to the inland terminal (km)
$\delta_{T,\,i}$ distance from the terminal to the gravity center of demand zone i (km)
ZF_2 fixed train transportation cost per km
Z_2 linear train transportation cost per container-km
EF_2 fixed emissions associated with train transportation (kg of CO_2 per km)
E_2 linear train transportation emissions (kg of CO_2 per container-km)

The authors identify optimal solutions based on European data. Their results show that the terminal is located closer to the port when optimizing cost and is located further away from the port when optimizing carbon emissions. This result shows that even when cost and CO_2 emissions have the same structure, there are significant differences in the optimal solutions for both formulations. This effect is clearly explained by the differences in the fixed train parameters, which are also consistent with the fact that train transportation under high utilization is more efficient from an emission perspective than road transportation, but it is more expensive in terms of cost. For more details, we refer to the full study (Bouchery and Fransoo 2015).

Although some other articles on continuous green facility location models can be found in the literature, the area is still very scarce. Buyuksaatci and Esnaf (2014) present a carbon emission-based facility location problem that considers the minimization of CO_2 emissions by using the gravitational center method. The study uses a formulation based on the GHG protocol, but it does not discuss any managerial insight or implication derived from the proposed formulation.

7.2.2.2 Discrete Models

We now discuss the studies on green facility location models with discrete formulations. Diabat and Simchi-Levi (2010) present a two-level multi-commodity facility location problem with a carbon constraint. Their problem is to decide the optimal location of plants and distribution centers and the assignment, in such a way that the total costs are minimized and the carbon emissions do not exceed a specific carbon cap. The model assumes carbon emissions from distributions by using a distance emission factor (tons of CO_2 per km) and thus neglecting the impact of the load on CO_2 emissions (see Chap. 5 by Blanco and Sheffi (2024)). Despite this rather coarse assumption, the general conclusion seems in line with intuition: if carbon emission allowance decreases, supply chain cost increases.

Elhedhli and Merrick (2012) study a supply chain network design problem that takes CO_2 emissions into account. The objective of the study is to simultaneously minimize logistics costs and the environmental costs of CO_2 emissions by strategically locating warehouses within the distribution network. This model considers the GHG Protocol estimation of CO_2 emissions and uses a scaling parameter to convert the CO_2 into cost. This approach allows the inclusion of the cost of carbon emissions into the supply chain network design. The experimental results show that the addition of carbon costs drives solutions with more distribution centers being opened to decrease CO_2 emissions in transportation.

Although the study provides interesting managerial insights, the model uses the most aggregate approaches to estimate CO_2 emissions in transportation (i.e., the GHG Protocol with EPA emission factors). Velázquez-Martínez et al. (2014a) address the effects of using different aggregation levels to measure transport carbon emissions, and they show that errors associated with aggregation could be substantial and systematic. This suggests that increasing the level of detail in the facility location problem is necessary.

Cost may not necessarily be the only driver to reduce CO_2 emissions in transportation. For example, companies may be subject to a cap-and-trade system or may use carbon emission reductions as a driver for brand management, product differentiation, or employee motivation (CDP 2011a, b). This suggests that a practical formulation of green facility location models should potentially take simultaneously cost and CO_2 objectives into account.

A possible alternative to consider both objectives (cost and CO_2 emissions) is to model the green facility location problem using a multiobjective setting. Most real-world problems naturally involve multiple objectives (minimizing cost, maximizing service level, minimizing CO_2 emissions, etc.) A multiobjective approach allows to define a set of efficient solutions (or a Pareto frontier) which is defined as the set of solutions such that there is no other solution that dominates them, i.e., each

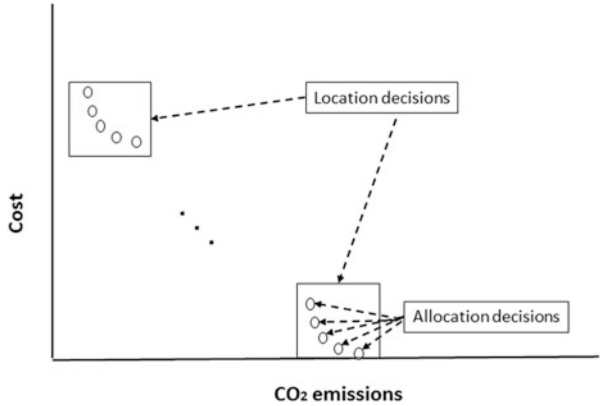

Fig. 7.2 Trade-off solutions for customer location-allocation decisions. Adapted from Harris et al. (2014)

solution of the set is strictly better than the rest of the solutions in at least one objective and is not worse than the rest of the solutions in all objectives (Coello 2009). These efficient solutions are often preferred to single solutions because they can be practical when considering real-life problems since the final solution of the decision-maker is always a trade-off (Konak et al. 2006).

In line with this stream of research, Harris et al. (2014) present a formulation of the fixed charge facility location model (*P3*) with two objective functions: costs and CO_2 emissions. Their facility location model considers individual depots with capacities b_j, where each customer is served directly by a single depot, thus forcing the "single-sourcing condition" to be held in the model. Therefore, it is possible to build a solution algorithm that first determines which facilities to open and then allocates the customers to the open facilities. The study proposes an expression to estimate transportation CO_2 emissions based on the GHG Protocol, i.e., transportation CO_2 emissions are linearly dependent on the distance traveled and demand.

The study discusses a multiobjective optimization solution method for the cost and CO_2 facility location model, in which a decision-maker can explore trade-off solutions for customer allocation based on the preselected facility location. Figure 7.2 (Harris et al. 2014) shows the different solutions of the location decision and, for each decision, the potential allocation assignment.

The article focuses on the solution methods and provides a framework to analyze trade-offs between cost and CO_2 emissions for location models.

Because we notice that all previous studies conclude that the increase in the number of open facilities implies a reduction in transportation CO_2 emissions (and typically more facilities also imply higher costs), we may argue that a practical approach to analyzing the trade-off between cost and CO_2 emissions in facility locations is to simplify the formulation by not including the fixed emission per open facility. Therefore, we are interested in studying the effect of transportation cost versus transportation CO_2 emissions with a fixed amount of facilities previously defined (i.e., p-Median problem).

Velázquez-Martínez et al. (2014b) study the trade-off between cost and CO_2 emissions by using a multiobjective approach for the facility location problem. The model corresponds to the p-Median problem with cost and CO_2 objective functions. The general assumptions of the p-Median problem apply to this model; that is, deterministic demand and the candidate locations are known in advance. In addition, the model also assumes that the company may manage multiple trucks with different capacities, and the trucks are assigned according to demand node constraints (or company policy). These assumptions allow the model to include the possibility that certain customers are reachable only by certain types of trucks, with distinct cost structures.

To formulate the carbon emission objective function, the authors include the NTM methodology in the objective function (Velázquez-Martínez et al. 2014b). Note that $\left\lceil \frac{h_i}{W_i} \right\rceil$ represents the number of trips that are required to serve customer $i \in I$ and, thus, affects the total distance traveled:

$$l \sum_{j \in J} \sum_{i \in I} d_{ij} \left[f_i{}^e \left\lceil \frac{h_i}{W_i} \right\rceil + \left(f_i{}^f - f_i{}^e \right) \frac{h_i}{W_i} \right] Y_{ij}$$

This formulation enables us to understand in more details the trade-off between distance (d_{ij}) and utilization (h_i/W_i) while deciding the location-allocation decisions. For example, when serving customers with a homogeneous fleet (i.e., $W_i = W$ for all $i \in I$), the location solutions are the same as those that are obtained by *P1*, i.e., facilities are located closer to customers with the highest demand, thus minimizing transport cost is equivalent to minimizing CO_2 emissions. However, when serving customers with a nonhomogeneous fleet (e.g., caused by truck constraints due to regulations or transport infrastructure), facilities may be located closer to customers served by small trucks. This may be explained due to the fact that multiple trips are required and, thus, more distance is traveled to serve these customers.

7.3 Practical Implications of the Green Location Models

Transportation is one of the main contributing factors to global carbon emissions, and thus, when dealing with facility location models in a distribution context, transportation emissions may be substantially higher than the emissions due to production or storage. In addition, because facility location models define the configuration of deliveries, green location models become an important alternative to reduce CO_2 emissions in logistics. Because transportation usually is included in Scope 3 of the GHG inventory and usually represents the highest source of emissions in a supply chain, companies may start focusing more on increasing the number of distribution centers while increasing the reachability to customers. We have seen this phenomenon at the biggest retailers, like Amazon, as a result of their fast-shipping business model and increased customer service speed (Dastin 2020).

While cost minimization solutions tend to locate facilities closer to high-demand customers, CO_2 emission minimization solutions tend to locate facilities closer to customers that have truck accessibility constraints. This is explained because truck constraints drive the number of trips required to serve customers, and this factor is larger than the increase in demand and/or utilization. This may be particularly important for companies managing nonhomogeneous vehicle fleets or for policymakers in large dense areas where demand is high (based on the high density of inhabitants and small stores), but heavy-duty vehicles are not allowed. New regulations may be needed to balance the accessibility of big trucks in certain periods to increase logistics efficiency and also reduce the number of small vehicles in those regions.

For some logistics problems, even when aggregate approaches are used to estimate transportation CO_2 emissions and thus this formulation shares the same structure with transportation cost, the location solutions may be substantially different. For companies that are interested in increasing modal shift or using more intermodal transport, these strategies may result in an increase in CO_2 emissions. Particularly when different modes are used like in intermodal networks, the difference in parameters for transportation cost and CO_2 emissions can lead to a completely different set of solutions for both objective functions.

A multiobjective setting for the green facility location models may provide decision-makers with a framework to analyze the trade-off between cost and CO_2 emissions. This approach may bring a new tool for companies to define better strategies to reduce CO_2 emissions. Because decision-makers likely seek alternatives that reduce emissions while keeping costs low, multiobjective modeling provides a set of trade-off solutions that were previously unknown in single-objective modeling. This may imply that new solutions may appear with a good offset between cost and CO_2 emissions. For example, locations with small increases in cost may imply high reductions of CO_2 emissions.

7.4 Directions for Future Work

The area of green facility location is still small in research. Because transportation costs and CO_2 emissions do not have the same structure, a specific formulation for the CO_2 emission minimization model for facility locations should be considered. Unfortunately, few studies consider the detailed expression to estimate transportation CO_2 emissions in location models, and most of them use GHG Protocol and GLEC framework; thus, the complete effect has not been studied and understood.

In addition, only a few companies have implemented strategies using facility locations to reduce their environmental impact. Thus, more applications of the models in practical cases are needed so more understanding of the models and trade-offs can be achieved and validated in practice. In addition, a few articles from prior literature include in their formulations the emissions generated by the facilities and usually only the production of electricity. The models are mainly focused on the emissions caused by transportation, specifically for last-mile delivery. However, no research has been conducted to analyze the impact of the transportation of raw materials in facility locations, and thus, more model formulations are needed to address this gap.

In this chapter, we have limited our discussion to the impact of carbon emissions from mobile sources. However, considering the different sources of energy for the facilities (wind, fuels, etc.), and including them in the future green facility location models to understand the impact of energy sources on planned locations, is a fruitful research avenue, specifically in connection with the electrification strategy of the transport sector. Facilities may play a key role to support electrified transportation and serve as onsite storage for electric batteries or other types of sources, as well as energy hubs to allow for plug load, and charging stations.

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