Abstract: This study aims to develop a regional freight-shipment model to forecast freight movement within freight-delivery regions and examine the relationship between regional freight-shipment activities and the related environmental problems such as greenhouse gas emissions. A methodology for freight distribution and collection within geographical regions is proposed, in which a significantly large number of freight demand or supply points needs to be served. This problem can be considered as a large-scale vehicle routing problem and solved by an asymptotic approximation method. A set of closed-form formulas is constructed to obtain a near-optimal total travel distance of a fleet of trucks from multiple distribution centers. A case study is conducted to forecast regional freight-delivery cost in the selected metropolitan areas in the United States. Numerical results under three urban development scenarios show that the proposed methodology can be used to estimate the total cost and related vehicle CO$_2$ emissions effectively.

Keywords: urban freight delivery; vehicle CO$_2$ emission; sustainable urban development; large-scale vehicle routing problem; asymptotic approximation method
presented in this study can be used to infer CO\textsubscript{2} emission distributions and eventually estimate human exposures to the various emissions from the freight-delivery activities in large urban areas.

The exposition of this paper is as follows. Section 2 reviews the related literature. The proposed methodology including brief review of the ring-sweep algorithm is presented in Section 3. Section 4 conducts a case study where detailed data preparation and assumptions made in this study are provided. Finally, Section 5 concludes the study and discusses related future work.

2. Literature Review

The VRP is one of the combinatorial optimization problems closely related to our logistics system model where a fleet of vehicles that start and end their delivery service at a central terminal need to serve spatially distributed customers. Since Dantzig and Ramser [6] introduced the VRP, numerous studies have been presented to solve the problem. For example, Solomon [7] and Potvin and Rousseau [8] proposed constructive heuristics, and Thompson and Psaraftis [9], Potvin and Rousseau [10], and Taillard et al. [11] studied local search algorithms to solve the VRP. The VRP with time windows is an extension of the traditional VRP in which each customer needs to be visited within a certain time interval that is called as a time-window constraint [7,12,13]. Another variation of the VRP is a VRP with pickup and delivery in which each customer has two types of demand including a pickup and delivery service [14–16]. Although extensive studies have been conducted on the VRP and its variations and numerous solution algorithms have been proposed by many researchers, they are practically hard to implement in our problem which is based on a large-scale demand distribution logistics system.

Various heuristics and meta-heuristics approaches have been developed and implemented to solve the large-scale VRP [17]. Among them, a cluster-first route-second algorithm is one of the comprehensible methods, in which the total delivery region is partitioned into many vehicle-routing zones (VRZs) such that each zone contains a given number of delivery demand points and the VRP is conducted within each zone. Daganzo [18,19] presented an easy manual recipe to construct the tour zones and a near-optimal travel cost was obtained from simple formulae provided in the literature. Newell and Daganzo [5,20] developed guidelines for constructing the VRZ in a large-scale network assuming stochastic delivery points can be represented by a continuous customer demand density function. Since it is an asymptotic approximation method for large-scale problems, better results can be obtained as more delivery points are included in the delivery area. Recently, Ouyang [21] suggested methodologies to automatically design the VRZ and obtain near-optimal solutions for the large-scale problems. A set of zoning techniques including a disk model from Ouyang and Daganzo [22] was used.

A comprehensive overview of various urban freight tour models has been provided in Holguín-Veras et al. [23] and a system of models able to simulate urban freight-shipment tours to estimate freight vehicle origin–destination flows is presented in Nuzzolo and Comi [24]. Among those previous studies, a ring-sweep algorithm [3] is adopted in this research to estimate the total freight-delivery cost within various freight regions in the U.S. since we consider a large number of supply or demand points in delivery regions. Then, the amount of CO\textsubscript{2} emission production in the study regions caused by freight-delivery activities can be computed by applying appropriate emission factor [25]. Since the ring-sweep algorithm assumes freight demand points are homogeneous, the same amount of identical freight is required to be delivered from a single terminal in a freight region. However, this assumption might not be true in real-world situations, since customers in different industries comprise each freight demand point. Besides, multiple distribution centers can be observed in most real-world freight regions. Thus, in this study, the ring-sweep algorithm is modified to address these issues. We consider employees in wholesale trade, retail trade, and manufacturing industries to represent each freight demand point. Also, large numbers of truck and railroad terminals are included in the proposed model. To obtain the total cost for collecting the freight, we can assume the large number of supply points at an origin region (instead of demand points at a destination region) need to be served and the same approach can be applied.
3. Model Formulation

The ring-sweep algorithm is briefly introduced to explain the basic concept of the methodology in this study. Then, the original ring-sweep algorithm is modified to be applied to the regional freight-delivery problem.

3.1. Ring-Sweep Algorithm Review

The ring-sweep algorithm proposed by Newell and Daganzo [5] is based on an asymptotic approximation method, which assumes customer demand follows a continuous density function that may vary slowly over space. This algorithm is suitable for problems that involve a significantly large number of demand or supply points in the VRP. The fundamental idea of the algorithm is demonstrated in Figure 1, adapted from Ouyang [21].

![Figure 1. Delivery zone construction and shipment activity example.](image)

In Figure 1, a freight-delivery region is described by a square with solid lines, and a grey circle at the right-hand corner represents a distribution center. A large number of freight demands (i.e., customers) are assumed to be randomly distributed within the solid-line square. Trucks from the distribution center need to deliver the products to the customers, some of which are represented by small black squares in this figure. The objective of this problem is to minimize the total cost, the total truck-shipment distance, in order to satisfy the freight demand of the large number of customers. The ring-sweep algorithm assumes identical customers comprise each freight demand point, and the same products are distributed from a single distribution center to each demand point. The freight-delivery region represented by a square with solid lines splits into many delivery zones such as small trapezoids with broken lines. Freight demand in one trapezoid need to be satisfied by one freight truck, i.e., the total demand in one delivery zone is the same as the capacity of one freight truck. Then, a set of trucks needs to travel back and forth between the distribution center and the border of their assigned delivery zones, which is generally described as the line-haul movement. Also, each truck has to visit every demand point within a zone to serve the customer, which is generally described as the local travel. A near-optimal solution to this problem can be computed by summing the line-haul movement distance and the local travel distance across all the divided freight zones in a given region without actual vehicle movement tracking. A set of equations to obtain the near-optimal total vehicle-distance with proof are provided in Newell and Daganzo [5]. To compute the total cost for collecting the freight, the same methodology can be applied assuming that significantly large number of supply points (i.e., producers), instead of demand points, need to be served in a freight region, i.e., an origin of the freight shipment. Note that this study can be considered as the routing problem at the second level in a two-echelon distribution system [26,27] since the distribution centers in this study correspond to the intermediate depots in two-echelon VRP and the location of each distribution center is assumed to be given.
3.2. Regional Freight Distribution and Collection Modeling

In an arbitrary freight-delivery region, let \( J \) be the total number of randomly distributed freight demand points. Define \( o_j \) as distance from a distribution center to the demand point \( j \). Also, let \( Q \) be a capacity of the delivery truck and \( \lambda \) be the demand point density in a given region. Then, the total line-haul movement distance (\( L_1 \)) and the total local travel distance (\( L_2 \)) are proposed as follows in Newell and Daganzo [5], and the near-optimal total vehicle travel distance in a region is sum of Equations (1) and (2):

\[
L_1 = \frac{2\sum_{j=1}^{J} o_j}{Q} \\
L_2 = \sqrt{\frac{2}{3\lambda}}
\]  

The ring-sweep algorithm assumes the demand points in a freight region are homogeneous, which means that the amount of freight required for each demand point is identical. This assumption might not be true in practice since customers in different industries comprise freight demand points. Besides, multiple distribution centers can be observed in most freight-delivery regions. In this study, the original ring-sweep algorithm is modified to resolve these issues and to be applied to real-world freight distribution and collection modeling, in which numbers of truck and railroad terminals are included. Employees in wholesale and retail trade industry as well as manufacturing industry are considered separately, which cover most of the employees across all business sectors in the U.S. For conciseness of presentation, procedures only related to freight distribution from truck terminals are explained.

To construct the regional freight-delivery model from truck terminals, we assume a set of truck terminals \( K \) is given, which is composed of arbitrary located multiple terminals in the given freight region. Then, each freight demand point is assigned to the closest terminal. We let \( I_k \) be the total number of demand points assigned to the truck terminal \( k \in K \), \( d_{ki} \) be the distance (miles) from the terminal \( k \in K \) to the demand point \( i \). Also, the number of employees in a wholesale and retail trade industry and a manufacturing industry in the demand point \( i \) are respectively denoted by \( E_{1i} \) and \( E_{2i} \). The truck capacity is represented by \( C \) (tons). Additionally, the total daily freight demand of wholesale and retail trade industry and manufacturing industry in the freight-delivery region are denoted by \( D_1 \) and \( D_2 \) (tons per day). Parameters \( a_1 \) and \( a_2 \) represent percentage of employees in wholesale and retail trade industry and manufacturing industry that are served from the truck terminals, respectively. The average number of employees per firm in the wholesale and retail trade industry is represented by \( a_1 \) and that in the manufacturing industry is denoted by \( a_2 \) to show how many employees are served on average by one delivery across different industries. The sum of the total area assigned to the terminal \( k \) is represented by \( A_k \) (square miles).

Considering previous Equations (1) and (2), the total line-haul movement distance and the total local travel distance can be constructed for a specific truck terminal \( k \) in the form of (3) and (4) for commodities related to the wholesale and retail trade industry, and (5) and (6) for commodities related to the manufacturing industry; Equations (3) and (5) are related to the line-haul movement and Equations (4) and (6) are for the local travel distance:

\[
L_{k1}^{f1} = \frac{2\alpha_1 D_1 \sum_{i=1}^{I_k} E_{1i} d_{ki}}{C \sum_{i=1}^{I_k} E_{1i}} \tag{3}
\]

\[
L_{k2}^{f2} = \frac{0.57 N_k^f}{\sqrt{\delta_k^f}}, \text{ where } N_k^f = \frac{\alpha_1}{a_1} \sum_{i=1}^{I_k} E_{1i} \text{ and } \delta_k^f = \frac{N_k^f}{A_k} \tag{4}
\]

\[
L_{p1}^{k} = \frac{2\alpha_2 D_2 \sum_{i=1}^{I_k} E_{2i} d_{ki}}{C \sum_{i=1}^{I_k} E_{2i}} \tag{5}
\]
Finally, summing Equations (3)–(6) across all terminals, \( k \in K \) yields the total freight-delivery cost \( (G_T) \) from truck terminals in the given freight-delivery region as follows:

\[
G_T = \sum_{k=1}^{K} \left( L_{f1}^k + L_{f2}^k + L_{p1}^k + L_{p2}^k \right)
\]  

(7)

Note that above procedures are only for the total cost of the truck terminals. A significant share of regional freight demand is also distributed from railroad terminals. Delivery trucks start their travel from several railroad terminals in a region, and each demand point is assigned to the closest railroad terminal. The total freight demand will be combined into two industry groups as well (i.e., wholesale and retail trade industry and manufacturing industry). A set of equations similar to (3)–(7) can be formulated to compute the total freight-delivery cost from railroad terminals in the freight-delivery region. Finally, the atmospheric impact levels caused by freight movement from both truck and railroad terminals can be estimated for each study region using appropriate emission factor.

In this study, other transportation modes such as an intermodal system [28], waterway, coastal shipping, or pipeline are excluded due to the lack of freight-flow data [29]. This paper assumes the haulage networks are operated based on the form of common ownership. When the freight transportation networks are dominated by single private company or shared by multiple operators, the freight demand zones need to be categorized considering which haulage networks they are mostly assigned on. Then, the proposed modeling framework can be applied to each group of freight zones to obtain the freight-delivery cost.

4. Case Study

A case study is conducted to estimate regional freight-delivery activities under different urban development scenarios and the related vehicle CO\(_2\) emissions from 2010 to 2050 in 30 freight-delivery regions in the U.S. which cover 22 major metropolitan areas.

4.1. Data Preparation and Assumptions

The concept of the freight analysis zone (FAZ), originally defined in Freight Analysis Framework version 3 (FAF3) [27], is adopted to represent geographical regions with regard to freight activities (i.e., origins and destinations of freight shipment). Figure 2, adapted from FAF3 [29], shows a map of the 123 domestic FAZs. Note that the regions in grey represent the study sites investigated in this paper. Also, the East Coast areas are magnified to improve recognition accuracy.

Total freight-shipment distance in a delivery region will be significantly affected by different patterns of urban spatial structure, which will eventually determine the total vehicle-emission estimation in freight regions. In this regard, the urban spatial structure model [30] provided three urban development scenarios as follows: (1) “business as usual” in which the urban sprawl and the following employment decentralization in 1990s and 2000s continues in most U.S. metropolitan areas; (2) “polycentric development” in which the development of a central business district (CBD) follows the current decentralization trend, but sub-centers experience high-growth which induces population and employment concentration; and (3) “compact development” in which both CBD and sub-centers follow high growth. The urban spatial structure model is based on the employment density gradient model combined with a dynamic spatial method [31], which considers the locations of the CBD and sub-centers as independent variables to estimate the spatial autocorrelation and examine the durability of the built environment (i.e., time-series effect).
Figure 2. Domestic freight analysis zones (FAZs) in the U.S.

The urban spatial structure model provided a forecast of employment distributions at the census tract level for each scenario from 2010 to 2050 in 10-year increments in 30 major FAZs. The FAZs considered in this study cover 22 selected metropolitan statistical areas (MSAs) where the number of total populations are greater than or equal to 2,000,000 in the year 2000. In most cases, one FAZ includes one MSA. However, three MSAs at Chicago, Philadelphia and St. Louis are each associated with two FAZs; New York MSA is associated with three FAZs; and Washington, D.C. MSA is associated with four FAZs. Table 1 illustrates how the total number of employers and employment density change as the distance from the CBD increases in four example MSAs. Column (a) presents the MSAs investigated in this analysis and column (b) shows the three urban development scenarios such that scenario 1 is the “business as usual”, scenario 2 is “polycentric development” and scenario 3 is “compact development”. Column (c) describes the distance from the CBD (DCBD) in miles. Columns (d) and (e) represent the total number of employers and the employment density (i.e., total number of employees per square mile), respectively. The results show that the highest employment density is observed under the compact development scenario, while the lowest employment density can be found under the business as usual scenario across all radii around the CBD for all four example MSAs.

We assume truck terminals are located on the points near major highway junctions, and railroad terminals are assumed to be located near major railway junctions. Each FAZ is made up of mutually disjointed census tracts. Freight demand in every census tract is assumed to be centered on the centroid of the census tract. Distances from truck and railroad terminals to each census tract centroid, total number of census tract in the FAZs, and the areas of census tract assigned to each truck and railroad terminal are measured using a geographic information system (GIS) database. The four-step inter-regional freight demand forecasting model [32] composed of trip generation, trip distribution, mode split and traffic assignment procedures provides truck and rail freight attraction and production data for each FAZ from 2010 to 2050 using the FAF3 [29], database which contains information on the freight movement in terms of tonnage and value between all shipment origin-destination pairs in 2007. The database contains 43 kinds of commodities such as agriculture products, fish, grain, wood products, textile, leather, coal, petroleum products and so forth. The freight demands in different commodity types are assigned to two industry groups, i.e., wholesale and retail trade industry and manufacturing industry, using data from the multi-region and multi-sector computable general equilibrium model [33]. Results from the freight demand forecasting model include amount of freight flow between all shipment origin–destination pairs (i.e., FAZs) in the U.S., which are used to estimate various parameters as well as future truck and rail freight movement in the proposed model. We assume light and medium trucks at a speed of 30 miles per hour are used for freight delivery in urban areas and their capacity is 4 tons [34,35].
Table 1. Total number of employers and employment density in four example metropolitan statistical areas (MSAs).

| (a) MSA | (b) Scenario DCBD | (c) 2010 | (d) 2020 | (e) 2030 | (f) 2040 | (g) 2050 | (h) Total Number of Employers | (i) Employment Density (# emp/sqmi) |
|---------|-------------------|---------|---------|---------|---------|---------|----------------|-------------------------------|
| Atlanta | 1 | 328,300 | 349,474 | 362,889 | 374,372 | 383,460 | 383,460 | 11,617 | 12,366 | 12,841 | 13,247 | 13,569 |
|         | 2 | 367,829 | 444,817 | 496,818 | 542,820 | 580,137 | 580,137 | 15,116 | 15,740 | 16,299 | 16,897 | 20,529 |
|         | 3 | 426,352 | 589,958 | 678,477 | 794,441 | 910,339 | 910,339 | 21,559 | 22,941 | 23,610 | 24,324 | 25,286 |
| Boston  | 1 | 544,170 | 548,477 | 522,883 | 498,015 | 470,746 | 470,746 | 19,256 | 19,408 | 18,474 | 17,623 | 16,658 |
|         | 2 | 572,925 | 599,092 | 571,391 | 555,019 | 536,215 | 536,215 | 20,273 | 20,845 | 20,219 | 19,640 | 18,974 |
|         | 3 | 593,708 | 618,720 | 604,880 | 592,055 | 569,040 | 569,040 | 21,009 | 21,894 | 21,099 | 19,209 | 19,404 |
| Cleveland | 1 | 188,218 | 186,454 | 182,791 | 179,558 | 176,260 | 176,260 | 6660 | 6598 | 6488 | 6354 | 6237 |
|         | 2 | 217,149 | 256,043 | 280,665 | 300,245 | 295,153 | 295,153 | 8197 | 8163 | 8080 | 7946 | 7813 |
|         | 3 | 231,040 | 287,052 | 318,232 | 339,793 | 346,948 | 346,948 | 11,727 | 11,519 | 11,349 | 11,120 | 10,926 |
| Dallas  | 1 | 221,022 | 232,142 | 239,793 | 246,398 | 251,647 | 251,647 | 179,727 | 176,260 | 176,260 | 176,260 | 176,260 |
|         | 2 | 468,259 | 504,205 | 550,761 | 568,007 | 544,620 | 544,620 | 11,797 | 11,797 | 11,797 | 11,797 | 11,797 |
|         | 3 | 740,872 | 810,539 | 901,988 | 936,176 | 913,570 | 913,570 | 1793 | 1793 | 1793 | 1793 | 1793 |

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4.2. Results and Discussion

Numerical results from the proposed model are described in Table 2. Columns (a) and (b) list the 22 MSAs and the three urban development scenarios considered in this study. Columns (c) and (d), respectively, describe the total regional freight-delivery cost in miles and ton-miles. Column (d) also includes percentage differences of the total freight-delivery ton-mile cost from the one associated with scenario 3 for each MSA. Note that mile and ton-mile costs in columns (c)–(d) are on a daily basis.
| Scenario | 2010 | 2020 | 2030 | 2040 | 2050 | 2010% | 2020% | 2030% | 2040% | 2050% |
|----------|-----|-----|-----|-----|-----|-------|-------|-------|-------|-------|
| Atlanta  | 1   | 181 | 257 | 341 | 439 | 548 | 1636  | 297  | 597  | 802  | 1054  | 1193  | 1389  | 1574  | 1782  | 2189 | 2363  | 2200  | 2799  | 3509  | 4346  |
| Boston   | 1   | 55  | 664 | 780 | 909 | 1053| 1102  | 45   | 1328 | 1156 | 1560 | 1823 | 1913 | 2106 | 2210 | 2306 | 2382 | 2432 | 2472 | 2512 | 2591 | 2711 |
| Cleveland| 1   | 554 | 661 | 781 | 916 | 1072| 1109  | 5.8  | 1323 | 7.6  | 1562 | 8.3  | 1832 | 6.6  | 2106 | 5.7  | 1944 | 5.6  | 1841 |
| Los Angeles | 1   | 949 | 1414| 1897| 2462| 3112| 1897  | 2.9  | 2828 | 28.5 | 3793 | 35.5 | 4924 | 40.3 | 6223 | 43.2 |
| Miami    | 1   | 1707| 2240| 2762| 3364| 4042| 3414  | 5.7  | 3000 | 7.4  | 3563 | 8.2  | 4169 | 9.0  | 4819 | 10.1 |
| Portland | 1   | 880 | 1019| 1155| 1317| 1518| 1760  | 3.1  | 2038 | 16.9 | 2310 | 18.2 | 2634 | 19.4 | 3053 | 21.0 |
| Philadelphia | 1   | 800 | 960 | 1082| 1227| 1406| 1738  | 1.8  | 1919 | 10.1 | 2164 | 10.7 | 2453 | 11.4 | 2811 | 12.1 |
| San Francisco | 1   | 516 | 731 | 934 | 1171| 1454| 1032  | 5.7  | 1462 | 27.3 | 1686 | 31.1 | 2343 | 34.1 | 2907 | 36.3 |
| Seattle  | 1   | 500 | 614 | 768 | 948 | 1161| 1000  | 0.4  | 1228 | 6.9  | 1537 | 7.8  | 1985 | 8.5  | 2232 | 8.9  |
| Tampa    | 1   | 1175| 1581| 2043| 2609| 3288| 2351  | 6.1  | 3162 | 26.5 | 4086 | 37.2 | 5218 | 49.6 | 6576 | 62.0 |
| Chicago  | 1   | 800 | 960 | 1147| 1371| 1622| 1600  | 0.5  | 1919 | 0.8  | 2294 | 0.8  | 2742 | 0.9  | 3243 | 0.9  |
| New York | 1   | 2039| 2563| 3108| 3741| 4490| 4079  | 3.2  | 5127 | 14.1 | 6216 | 14.6 | 7481 | 15.2 | 8980 | 15.7 |
| Washington, D.C. | 1   | 1626| 2256| 2832| 3498| 4256| 3251  | 0.9  | 4512 | 24.0 | 5635 | 25.5 | 6996 | 25.5 | 8512 | 28.3 |

Table 2. Total regional freight-delivery cost in 22 MSAs.
In most cases, scenario 1, business as usual, shows the largest and scenario 3, compact development, shows the least total freight-delivery cost in miles and ton-miles. Results from the paired t-test presented in Figure 3 statistically support mean differences among the three groups, each of which is composed of the total travel distances (miles) in 2050 from the given scenario. All pairs from the three groups are shown to be significantly different under the significance level of 0.01. Results from scenario 1 are significantly larger than those from scenarios 2 and 3 by 490 and 629 (10^3 m) on average, respectively. Results from scenario 2 are also significantly larger than those from scenario 3. The same trends are observed from 2010 to 2050; analysis using freight-shipment ton-mile cost generates the same trends as well. The results demonstrate significant advantage of compact as well as polycentric urban forms, which are known to lead to high-density and sustainable urban development by combining residential and commercial zones [36]. Note that the percentage differences in column (d) grow significantly faster over the years in Atlanta, Dallas, Denver, Houston, Minneapolis, Phoenix, Portland, Seattle, Tampa, and Washington. This is caused by a rapid increase in the number of employees located far from the truck or railroad terminals, which results in a prompt increase in the total long-haul movement distance. Table 3 shows the total distance from all employees to the assigned terminals in four example MSAs.

Table 3. Total distance to the assigned terminals in four example MSAs.

| (a) MSA | (b) | (c) Total Distance to the Assigned Terminals (10^3 Mile) |
|--------|-----|-------------------------------------------------------|
|        | Scenario | 2010 | 2020 | 2030 | 2040 | 2050 |
| Atlanta | 1 | 28,765 | 5.5 | 46,200 | 28.6 | 50,599 | 35.0 | 54,009 | 40.0 | 56,155 | 43.1 |
|         | 2 | 27,801 | 2.0 | 40,198 | 11.9 | 43,152 | 15.2 | 45,420 | 17.7 | 46,853 | 19.4 |
|         | 3 | 27,266 | 35,926 | 37,473 | 37,473 | 38,576 | 39,246 |
| Boston  | 1 | 20,670 | 5.1 | 24,131 | 12.8 | 23,929 | 14.1 | 23,660 | 15.5 | 23,127 | 16.8 |
|         | 2 | 20,221 | 2.8 | 23,032 | 7.7 | 22,759 | 8.5 | 22,412 | 9.4 | 21,831 | 10.2 |
|         | 3 | 19,665 | 21,390 | 20,978 | 20,481 | 19,804 |
| Cleveland | 1 | 13,461 | 3.7 | 13,896 | 5.0 | 13,866 | 5.4 | 13,810 | 5.6 | 13,719 | 5.8 |
|          | 2 | 13,225 | 1.9 | 13,589 | 2.7 | 13,542 | 3.0 | 13,475 | 3.1 | 13,380 | 3.2 |
|          | 3 | 12,979 | 13,228 | 13,153 | 13,071 | 12,971 |
| Dallas   | 1 | 25,625 | 1.8 | 39,375 | 17.2 | 42,971 | 21.6 | 45,471 | 24.8 | 46,780 | 26.9 |
|          | 2 | 25,266 | 0.4 | 34,892 | 3.9 | 37,265 | 5.5 | 38,910 | 6.8 | 39,734 | 7.8 |
|          | 3 | 25,168 | 33,595 | 35,326 | 36,426 | 36,872 |

Figure 3. Cont.
Figure 3. Paired t-test results. (a) Paired t-test results of the total travel distance in 2050 between scenario 1 and scenario 2; (b) paired t-test results of the total travel distance in 2050 between scenario 1 and scenario 3; (c) paired t-test results of the total travel distance in 2050 between scenario 2 and scenario 3.

Column (c) of Table 3 presents the total distance in thousand miles and percentage differences of the total distance from that obtained from scenario 3. Note that the total distance for all employees to reach their assigned terminals rapidly increases in Atlanta and Dallas, indicating that the number of employees far from the terminals increases fast for those two MSAs.

Vehicle CO₂ emission estimations resulting from future freight activities in 22 MSAs are presented in Table 4. Column (a) shows the 22 MSAs under investigation and the three urban form scenarios are described in column (b). Column (c) in Table 4 presents CO₂ emission estimations associated with freight-delivery activities in each urban development scenario. Emission factor for light and medium trucks is obtained from research on vehicle emissions and energy consumption [37] and a stochastic urban freight-truck routing study [25] such that each truck produces 717.10 grams of CO₂ for each mile shipment at a speed of 30 miles per hour.
Table 4. CO₂ emission estimations related to regional freight activities in 22 MSAs.

| MSA           | Scenario | 2010 | 2020 | 2030 | 2040 | 2050 |
|---------------|----------|------|------|------|------|------|
| Atlanta       | 1        | 1304 | 1849 | 2450 | 3148 | 3936 |
|               | 2        | 1235 | 1794 | 2375 | 2972 | 3774 |
|               | 3        | 1215 | 1336 | 1666 | 2048 | 2494 |
| Pittsburgh    |          |      |      |      |      |      |
|               | 1        | 395  | 476  | 559  | 652  | 755  |
|               | 2        | 383  | 446  | 521  | 605  | 697  |
|               | 3        | 378  | 428  | 498  | 575  | 660  |
| Boston        |          |      |      |      |      |      |
|               | 1        | 398  | 474  | 560  | 657  | 768  |
|               | 2        | 379  | 447  | 527  | 616  | 720  |
|               | 3        | 376  | 440  | 517  | 605  | 707  |
| Cleveland     |          |      |      |      |      |      |
|               | 1        | 680  | 1014 | 1360 | 1765 | 2251 |
|               | 2        | 663  | 819  | 1055 | 1335 | 1662 |
|               | 3        | 661  | 789  | 1004 | 1258 | 1558 |
| Chicago       |          |      |      |      |      |      |
|               | 1        | 1286 | 1758 | 2200 | 2708 | 3292 |
|               | 2        | 1274 | 1559 | 1947 | 2388 | 2883 |
|               | 3        | 1268 | 1370 | 1711 | 2092 | 2510 |
| Denver        |          |      |      |      |      |      |
|               | 1        | 321  | 421  | 578  | 787  | 975  |
|               | 2        | 429  | 547  | 702  | 883  | 1092 |
|               | 3        | 428  | 517  | 658  | 823  | 1013 |
| Detroit       |          |      |      |      |      |      |
|               | 1        | 896  | 1076 | 1277 | 1494 | 1728 |
|               | 2        | 857  | 1013 | 1194 | 1385 | 1585 |
|               | 3        | 847  | 1001 | 1181 | 1371 | 1570 |
| Houston       |          |      |      |      |      |      |
|               | 1        | 1224 | 1606 | 1981 | 2413 | 2899 |
|               | 2        | 1189 | 1456 | 1781 | 2149 | 2558 |
|               | 3        | 1178 | 1398 | 1703 | 2044 | 2422 |
| Los Angeles   |          |      |      |      |      |      |
|               | 1        | 1163 | 1756 | 2381 | 3126 | 3983 |
|               | 2        | 1159 | 1711 | 2306 | 3010 | 3819 |
|               | 3        | 1153 | 1704 | 2300 | 3006 | 3818 |
| Miami         |          |      |      |      |      |      |
|               | 1        | 1012 | 1344 | 1654 | 1998 | 2363 |
|               | 2        | 989  | 1088 | 1311 | 1543 | 1779 |
|               | 3        | 986  | 1066 | 1278 | 1501 | 1725 |
| Phoenix       |          |      |      |      |      |      |
|               | 1        | 315  | 429  | 538  | 700  | 920  |
|               | 2        | 315  | 374  | 466  | 603  | 789  |
|               | 3        | 315  | 358  | 446  | 576  | 752  |

Since the amount of emissions generated from vehicles at a constant mild speed are proportional to the freight-delivery activities, the largest and the least amount of CO₂ emissions are observed in scenario 1 and scenario 3 in general. In terms of freight-transport operations, a compact urban form enables freight-delivery companies to consolidate their products and maximize their truck-capacity utilization. As such, operating a full truck load typically leads to reducing empty mileage, which increases energy efficiency and decreases greenhouse gas emissions as well.

5. Conclusions

Freight transportation is well known as a major cause of environmental problems. A great number of small- or medium-size trucks have been used in last-mile delivery, especially in large urban areas, and they have contributed to large share of various emissions since most of them use diesel engines as a power supply. Residents in metropolitan areas can be affected easily by the air-pollution problems, and greenhouse gas emissions are often concentrated in urban areas, which motivated us to investigate the regional freight distribution and collection modeling problem in a large urban area. This problem is addressed by the large-scale VRP since the number of randomly distributed demand points in a freight-delivery region is assumed to be extremely large. The ring-sweep algorithm [5] is adopted and modified to incorporate inhomogeneity of demand points in a real-world situation; multiple distribution centers in a delivery region are also considered in the proposed model. A set of formulas is constructed to estimate large-scale freight-delivery efficiency, in which the total travel distance of a fleet
of trucks within each FAZ is obtained as a sum of the total line-haul movement distance and the total local travel distance; the obtained freight-delivery cost for each study region is used to estimate vehicle CO₂ emissions. Since it is an asymptotic approximation method and the number of demand points in our setting is significantly large, the output is expected to be quite accurate. A case study is conducted to forecast daily regional freight-delivery cost from 2010 to 2050 using employment distribution data under three urban form scenarios in 30 FAZs, which include 22 major MSAs in the U.S. The numerical results are found to estimate future regional freight-delivery cost and the related CO₂ emissions for each urban form scenario effectively. It was also found that the spatial distribution of freight demand impacts greatly on the freight-delivery efficiency and the following vehicle emissions; compact urban development leads to low vehicle delivery cost in ton and ton-mile, which will be able to reduce CO₂ emissions in large urban areas. This reduction in emissions would affect air pollutants as well. The results in this study will be useful for transportation planners and decision makers in public or private sectors when estimating human exposure to emissions from freight delivery in metropolitan areas, thereby eventually enhancing the public benefit and social welfare.

In future studies, freight movement or routing modeling among different metropolitan areas can be considered in order to complete the comprehensive modeling framework. The current study only addresses freight distribution and collection problems in freight destination or origin regions. This limitation could be resolved by incorporating long-distance freight movement into the proposed model, which will be able to provide more precise freight activities as well as following emission estimations. The results can also be combined with the business models in Perboli et al. [38] to further develop regional as well as continental sustainable freight-transportation systems. Second, the extension and application of the proposed methodology to the metropolitan areas in other countries will be possible. The final results from the proposed model include useful information such as predicted freight-shipment cost in mile and ton-miles, which can be used to estimate the related vehicle emissions. Such modeling framework eventually could be applied to address many environmental problems, for instance recent severe air-pollution and human health problems in Seoul, South Korea [39].

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