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Estimating Emissions from Regional Freight Delivery under Different Urban Development Scenarios

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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

1. Introduction

Freight-shipment activities within large urban areas are critical because emissions from the freight-delivery trucks comprise a large share of toxic air pollutants and greenhouse gases in most metropolitan areas worldwide [1]. Due to a rapid increase in freight demand and significant growth in delivery activities, concerns about air-quality problems in urban areas have become more serious [2,3]. The residents in metropolitan areas are more likely to be affected by air pollution and greenhouse gas emission problems than those in rural areas since most of them live very close to the emission sources (e.g., commercial vehicles operated by diesel engines). However, only a few studies have investigated the development of urban freight-shipment models and their application due to a lack of data [4]. This motivates us to develop freight-shipment modeling and logistics planning at the regional level to estimate greenhouse gas emissions from freight trucks. Besides, various urban development scenarios are incorporated in this analysis since freight-shipment activities will be directly affected by different urban forms.

In this paper, a freight-delivery problem to (and from) a large number of freight demand (and supply) points within major freight zones in the United States (U.S.) is investigated. This problem can be defined as a large-scale vehicle routing problem (VRP) and a ring-sweep algorithm [5] is adopted and modified to estimate the total shipment cost in an urban transportation network. A case study is conducted to estimate not only future regional freight activities, but also the related CO_2 emissions from 2010 to 2050 in 30 freight zones which cover 22 major metropolitan areas in the U.S. The modeling framework presented in this study can be used to infer CO_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 [5] 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_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].

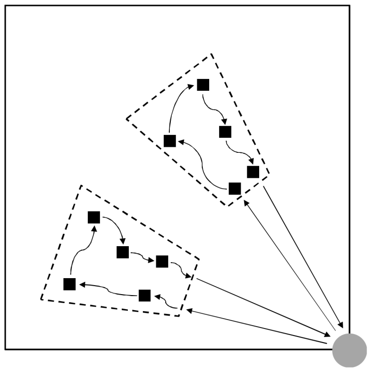


Figure 1. Delivery zone construction and shipment activity example.

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 λ 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):

$$L_1 = \frac{2\sum_{j=1}^{J} o_j}{Q} \tag{1}$$

$$L_2 = \sqrt{\frac{2}{3\lambda}} \tag{2}$$

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 α_1 and α_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:

$$L_{f1}^{k} = \frac{2\alpha_1 D_1 \sum_{i=1}^{I_k} E_{1i} d_{ki}}{C\sum_{i=1}^{I} E_{1i}} \tag{3}$$

$$L_{f2}^{k} = \frac{0.57 N_f^k}{\sqrt{\delta_f^k}}, \text{ where } N_f^k = \frac{\alpha_1}{a_1}\sum_{i=1}^{I_k} E_{1i} \text{ and } \delta_f^k = \frac{N_f^k}{A_k} \tag{4}$$

$$L_{p1}^{k} = \frac{2\alpha_2 D_2 \sum_{i=1}^{I_k} E_{2i} d_{ki}}{C\sum_{i=1}^{I_k} E_{2i}} \tag{5}$$

$$L_{p2}^{k} = \frac{0.57N_{p}^{k}}{\sqrt{\delta_{p}^{k}}}, \text{ where } N_{p}^{k} = \frac{\alpha_2}{a_2}\sum_{i=1}^{I_k} E_{i3} \text{ and } \delta_{p}^{k} = \frac{N_{p}^{k}}{A_k} \tag{6}$$

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:

$$G_T = \sum_{k=1}^{K}\left(L_{f1}^{k} + L_{f2}^{k} + L_{p1}^{k} + L_{p2}^{k}\right) \tag{7}$$

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).

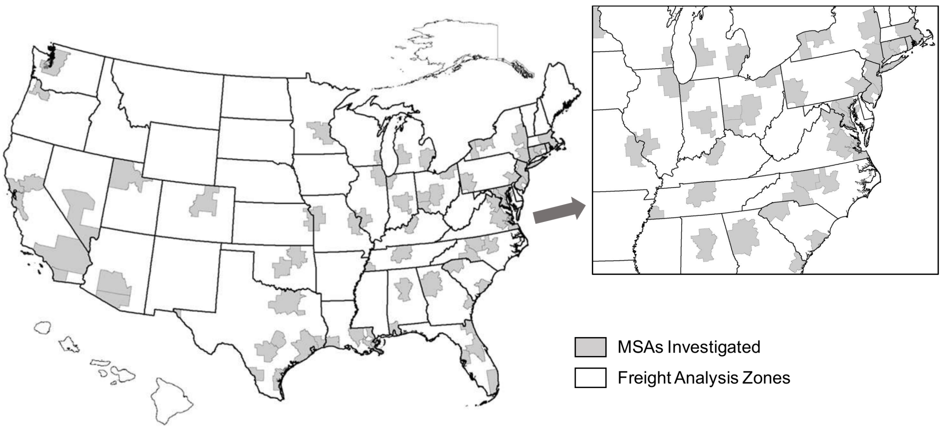


Figure 2. Domestic freight analysis zones (FAZs) in the U.S.

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	(c) DCBD	(d) Total Number of Employers					(e) Employment Density (# emp/sqml)				
			2010	2020	2030	2040	2050	2010	2020	2030	2040	2050
Atlanta	1	3	328,300	349,474	362,889	374,372	383,460	11,617	12,366	12,841	13,247	13,569
		6	538,336	583,925	613,019	638,024	657,878	4762	5166	5423	5644	5820
		9	810,257	887,933	937,660	980,462	1,014,494	3186	3491	3687	3855	3989
	2	3	367,829	444,817	496,818	542,820	580,137	13,016	15,740	17,580	19,208	20,529
		6	588,253	705,080	783,944	853,721	910,339	5204	6237	6935	7552	8053
		9	865,562	1,021,932	1,126,477	1,218,513	1,292,924	3403	4018	4429	4791	5083
	3	3	426,352	589,958	658,156	678,477	646,046	15,087	20,876	23,289	24,008	22,861
		6	686,339	973,424	1,188,407	1,388,267	1,556,274	6072	8611	10,513	12,281	13,767
		9	951,096	1,256,260	1,480,259	1,686,834	1,859,622	3739	4939	5820	6632	7312
Boston	1	3	544,170	548,477	522,083	498,015	470,746	19,256	19,408	18,474	17,623	16,658
		6	733,460	739,884	704,952	673,070	636,919	6488	6545	6236	5954	5634
		9	936,928	945,527	901,301	860,921	815,120	3684	3718	3544	3385	3205
	2	3	572,925	589,092	571,391	555,019	536,215	20,273	20,845	20,219	19,640	18,974
		6	761,858	779,962	753,680	729,447	701,699	6740	6900	6667	6453	6208
		9	963,439	982,925	946,938	913,842	876,030	3788	3865	3723	3593	3444
	3	3	593,708	618,720	604,880	592,045	577,281	21,009	21,894	21,404	20,950	20,427
		6	781,009	807,273	784,553	763,592	739,589	6909	7141	6940	6755	6543
		9	981,404	1,008,558	976,057	946,144	911,983	3859	3965	3838	3720	3586
Cleveland	1	3	188,218	186,454	182,791	179,558	176,260	6660	6598	6468	6354	6237
		6	308,921	306,123	300,295	295,153	289,907	2733	2708	2657	2611	2565
		9	459,488	455,381	446,826	439,273	431,570	1807	1790	1757	1727	1697
	2	3	188,403	187,052	184,232	181,727	179,170	6667	6619	6519	6431	6340
		6	309,149	306,846	302,045	297,779	293,428	2735	2714	2672	2634	2596
		9	459,697	456,095	448,600	441,948	435,167	1807	1793	1764	1738	1711
	3	3	188,568	187,422	185,035	182,913	180,747	6673	6632	6548	6473	6396
		6	309,269	307,102	302,609	298,616	294,537	2736	2717	2677	2642	2606
		9	459,803	456,323	449,094	442,678	436,137	1808	1794	1766	1740	1715
Dallas	1	3	221,022	232,142	239,793	246,398	251,647	7821	8215	8485	8719	8905
		6	468,259	504,205	529,136	550,761	568,007	4142	4460	4681	4872	5025
		9	740,872	810,539	859,366	901,988	936,176	2913	3187	3379	3546	3681
	2	3	223,109	256,603	280,606	301,836	319,024	7895	9080	9929	10,681	11,289
		6	471,382	540,858	590,444	634,164	669,472	4170	4785	5223	5610	5922
		9	745,615	866,639	955,805	1,036,285	1,102,671	2932	3407	3758	4074	4335
	3	3	231,068	306,652	368,326	403,977	402,803	8177	10,851	13,033	14,295	14,253
		6	483,298	685,995	863,376	1,038,421	1,191,599	4275	6069	7638	9186	10,541
		9	756,542	999,235	1,201,957	1,397,199	1,565,329	2975	3929	4726	5493	6154

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.

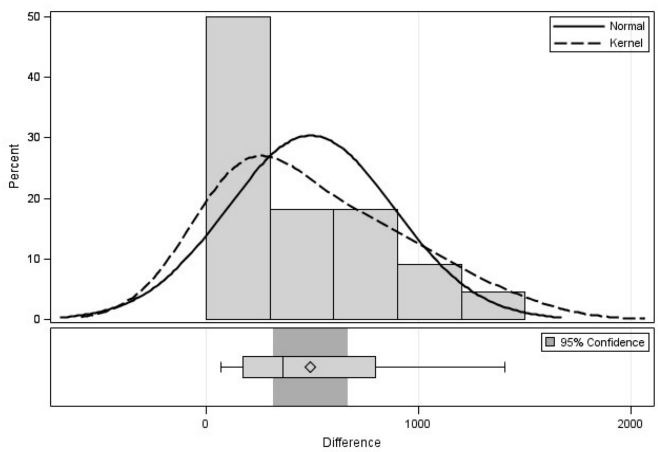
Table 2. Total regional freight-delivery cost in 22 MSAs.

(a) MSA	**(b)**	**(c) Total Travel Distance (10^3 m Per Day)**					**(d) Freight Shipment (10^3 ton-mile Per Day)**									
	Scenario	**2010**	**2020**	**2030**	**2040**	**2050**	**2010**	**%**	**2020**	**%**	**2030**	**%**	**2040**	**%**	**2050**	**%**
Atlanta	1	1818	2579	3417	4390	5488	3636	7.3	5157	38.4	6834	47.0	8780	53.7	10,976	57.8
	2	1723	2063	2641	3312	4082	3445	1.6	4126	10.7	5282	13.7	6624	16.0	8164	17.4
	3	1695	1863	2324	2856	3478	3390		3726		4648		5712		6955	
Boston	1	551	664	780	909	1053	1102	4.5	1328	11.3	1560	12.3	1819	13.4	2106	14.4
	2	535	622	727	844	972	1069	1.4	1244	4.2	1454	4.7	1687	5.2	1944	5.6
	3	527	597	695	802	920	1054		1193		1389		1604		1841	
Cleveland	1	554	661	781	916	1072	1109	5.8	1,323	7.8	1,562	8.3	1,832	8.6	2,143	8.7
	2	529	624	734	860	1005	1058	1.0	1,247	1.6	1,469	1.8	1,719	1.9	2,009	1.9
	3	524	614	721	844	986	1048		1,227		1,443		1,687		1,971	
Dallas	1	949	1414	1897	2462	3112	1897	2.9	2828	28.5	3793	35.5	4924	40.3	6223	43.2
	2	925	1142	1471	1861	2318	1850	0.3	2283	3.8	2942	5.1	3722	6.1	4635	6.7
	3	922	1100	1400	1754	2173	1844		2200		2799		3509		4346	
Denver	1	603	825	1070	1359	1696	1206	1.1	1649	14.4	2141	16.6	2718	18.4	3392	20.1
	2	598	763	979	1231	1523	1197	0.3	1525	5.8	1958	6.6	2462	7.3	3047	7.9
	3	597	721	918	1147	1412	1193		1442		1837		2295		2825	
Detroit	1	1249	1500	1781	2084	2409	2498	5.7	3000	7.4	3563	8.2	4168	9.0	4819	10.1
	2	1196	1413	1665	1931	2211	2391	1.2	2826	1.2	3330	1.1	3862	1.0	4422	1.0
	3	1182	1397	1647	1911	2189	2363		2793		3294		3822		4378	
Houston	1	1793	2452	3067	3776	4591	3586	1.4	4904	28.3	6135	28.6	7553	29.5	9182	31.2
	2	1776	2174	2715	3330	4020	3552	0.4	4349	13.8	5430	13.8	6660	14.1	8041	14.9
	3	1768	1911	2385	2917	3500	3537		3821		4771		5834		7000	
Los Angeles	1	1707	2240	2762	3364	4042	3414	3.9	4480	14.9	5525	16.3	6729	18.0	8085	19.7
	2	1658	2030	2483	2996	3567	3317	1.0	4060	4.2	4966	4.6	5993	5.1	7134	5.6
	3	1642	1949	2374	2851	3377	3284		3898		4749		5702		6754	
Miami	1	1622	2448	3321	4359	5554	3243	0.9	4896	3.0	6642	3.6	8718	4.0	11,108	4.3
	2	1616	2386	3216	4197	5326	3231	0.5	4772	0.4	6432	0.3	8394	0.1	10,653	0.0
	3	1608	2376	3207	4192	5324	3215		4752		6414		8383		10,648	
Minneapolis	1	1412	1874	2307	2786	3295	2824	2.7	3747	26.0	4614	29.4	5573	33.1	6589	37.0
	2	1379	1518	1826	2152	2481	2757	0.2	3036	2.1	3652	2.5	4305	2.8	4962	3.1
	3	1375	1487	1782	2093	2406	2751		2973		3564		4187		4812	
Phoenix	1	440	598	750	976	1282	879	0.2	1197	19.8	1500	20.7	1953	21.6	2565	22.2
	2	439	521	649	841	1100	877	0.0	1042	4.3	1299	4.5	1681	4.7	2200	4.9
	3	439	500	621	803	1049	877		999		1243		1605		2098	
Pittsburgh	1	880	1019	1155	1317	1518	1760	3.1	2038	16.9	2310	18.2	2634	19.6	3035	21.0
	2	869	960	1082	1227	1406	1738	1.8	1919	10.1	2164	10.7	2453	11.4	2811	12.1
	3	854	872	977	1101	1254	1708		1743		1954		2203		2508	
Portland	1	528	699	853	1025	1222	1057	0.4	1398	18.4	1707	18.8	2051	19.5	2444	20.6
	2	527	627	763	915	1085	1055	0.2	1253	6.1	1527	6.3	1829	6.6	2170	7.1
	3	526	591	718	858	1013	1052		1181		1437		1716		2027	
San Diego	1	939	1263	1546	1878	2253	1878	3.3	2526	32.6	3093	35.2	3756	37.7	4506	40.1
	2	914	995	1196	1428	1685	1828	0.6	1991	4.5	2392	4.6	2855	4.7	3371	4.8
	3	909	952	1143	1363	1608	1818		1904		2287		2727		3216	
San Francisco	1	830	1014	1220	1468	1749	1661	4.3	2029	6.6	2439	7.2	2935	8.0	3498	8.8
	2	800	960	1147	1371	1622	1600	0.5	1919	0.8	2294	0.8	2742	0.9	3243	0.9
	3	796	952	1138	1359	1608	1593		1903		2275		2718		3215	
Seattle	1	516	731	934	1171	1454	1032	3.7	1462	27.3	1868	31.1	2343	34.1	2907	36.3
	2	500	614	768	948	1161	1000	0.4	1228	6.9	1537	7.8	1895	8.5	2322	8.9
	3	498	574	712	873	1066	995		1148		1425		1747		2133	
Tampa	1	1175	1581	2043	2609	3288	2351	6.1	3162	26.5	4086	37.2	5218	49.6	6576	62.0
	2	1137	1395	1727	2105	2531	2273	2.6	2789	11.5	3454	16.0	4210	20.7	5062	24.7
	3	1107	1250	1489	1744	2030	2215		2501		2978		3488		4059	
Chicago	1	2858	3594	4373	5261	6258	5715	6.0	7189	15.3	8746	16.9	10,522	18.4	12,516	19.5
	2	2708	3172	3817	4548	5369	5415	0.4	6344	1.8	7634	2.1	9096	2.3	10,738	2.5
	3	2696	3117	3739	4444	5237	5391		6234		7479		8888		10,474	
Philadelphia	1	2039	2563	3108	3741	4490	4079	3.2	5127	14.1	6216	14.6	7481	15.2	8980	15.7
	2	1993	2342	2831	3397	4066	3987	0.8	4684	4.2	5661	4.4	6793	4.6	8132	4.8
	3	1977	2247	2711	3247	3881	3954		4494		5423		6495		7762	
St. Louis	1	1151	1424	1664	1933	2231	2301	1.9	2848	11.5	3327	12.1	3865	12.7	4461	13.4
	2	1130	1287	1494	1723	1974	2261	0.1	2575	0.8	2988	0.7	3446	0.5	3947	0.4
	3	1129	1277	1484	1714	1967	2258		2554		2968		3428		3933	
New York	1	2807	3756	4727	5847	7151	5614	4.1	7513	17.0	9455	19.4	11,695	21.3	14,301	22.6
	2	2712	3278	4050	4933	5963	5424	0.5	6557	2.1	8101	2.3	9866	2.3	11,927	2.2
	3	2697	3210	3960	4821	5833	5395		6421		7920		9642		11,666	
Washington, D.C.	1	1626	2256	2832	3498	4256	3251	0.9	4512	24.0	5663	25.5	6996	26.9	8512	28.3
	2	1607	1773	2196	2678	3219	3214	−0.2	3546	−2.5	4392	−2.7	5356	−2.8	6439	−3.0
	3	1611	1819	2257	2756	3318	3222		3,639		4,514		5512		6635	

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.

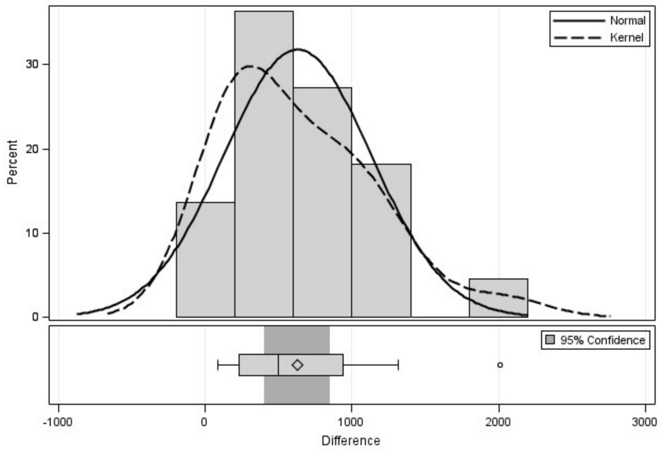
Table 3. Total distance to the assigned terminals in four example MSAs.

(a) MSA	(b) Scenario	(c) Total Distance to the Assigned Terminals (10^3 Mile)									
		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		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	

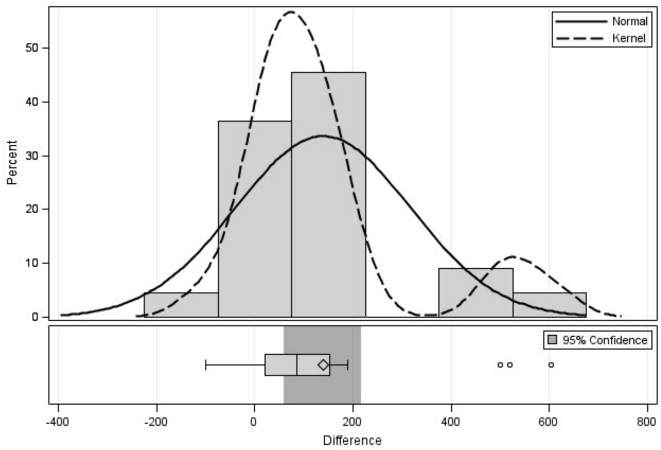


(a)

Figure 3. *Cont.*



(**b**)



(**c**)

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 CO_2 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 CO_2 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 CO_2 for each mile shipment at a speed of 30 miles per hour.

Table 4. CO_2 emission estimations related to regional freight activities in 22 MSAs.

(a) MSA	(b) Scenario	(c) CO_2 (10^3 kg per day) 2010	2020	2030	2040	2050	(a) MSA	(b) Scenario	(c) CO_2 (10^3 kg per day) 2010	2020	2030	2040	2050
Atlanta	1	1304	1849	2450	3148	3936	Pittsburgh	1	631	731	828	944	1088
	2	1235	1479	1894	2375	2927		2	623	688	776	880	1008
	3	1215	1336	1666	2048	2494		3	612	625	701	790	899
Boston	1	395	476	559	652	755	Portland	1	379	501	612	735	876
	2	383	446	521	605	697		2	378	449	547	656	778
	3	378	428	498	575	660		3	377	423	515	615	727
Cleveland	1	398	474	560	657	768	San Diego	1	673	906	1109	1347	1616
	2	379	447	527	616	720		2	656	714	858	1024	1209
	3	376	440	517	605	707		3	652	683	820	978	1153
Dallas	1	680	1014	1360	1765	2231	San Francisco	1	596	727	875	1052	1254
	2	663	819	1055	1335	1662		2	574	688	823	983	1163
	3	661	789	1004	1258	1558		3	571	682	816	975	1153
Denver	1	432	591	768	975	1216	Seattle	1	370	524	670	840	1042
	2	429	547	702	883	1092		2	358	440	551	680	833
	3	428	517	658	823	1013		3	357	412	511	626	765
Detroit	1	896	1076	1277	1494	1728	Tampa	1	843	1134	1465	1871	2358
	2	857	1013	1194	1385	1585		2	815	1000	1238	1509	1815
	3	847	1001	1181	1371	1570		3	794	897	1068	1251	1455
Houston	1	1286	1758	2200	2708	3292	Chicago	1	2049	2578	3136	3773	4488
	2	1274	1559	1947	2388	2883		2	1942	2275	2737	3261	3850
	3	1268	1370	1711	2092	2510		3	1933	2235	2682	3187	3756
Los Angeles	1	1224	1606	1981	2413	2899	Phila-delphia	1	1462	1838	2229	2682	3220
	2	1189	1456	1781	2149	2558		2	1429	1679	2030	2436	2916
	3	1178	1398	1703	2044	2422		3	1418	1611	1944	2329	2783
Miami	1	1163	1756	2381	3126	3983	St. Louis	1	825	1021	1193	1386	1600
	2	1159	1711	2306	3010	3819		2	811	923	1071	1236	1415
	3	1153	1704	2300	3006	3818		3	810	916	1064	1229	1410
Minnea-polis	1	1012	1344	1654	1998	2363	New York	1	2013	2694	3390	4193	5128
	2	989	1088	1310	1543	1779		2	1945	2351	2905	3537	4276
	3	986	1066	1278	1501	1725		3	1934	2302	2840	3457	4183
Phoenix	1	315	429	538	700	920	Washington, D.C.	1	1166	1618	2031	2509	3052
	2	315	374	466	603	789		2	1152	1272	1575	1920	2309
	3	315	358	446	576	752		3	1155	1305	1618	1976	2379

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 CO_2 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 CO_2 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 CO_2 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 CO_2 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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