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The impacts of congestion on time-definitive urban freight distribution networks CO_2 emission levels: Results from a case study in Portland, Oregon

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A B S T R A C T

Increased congestion during peak morning and afternoon periods in urban areas is increasing logistics costs. In addition, environmental, social, and political pressures to limit the impacts associated with CO_2 emissions are mounting rapidly. A key challenge for transportation agencies and businesses is to improve the efficiency of urban freight and commercial vehicle movements while ensuring environmental quality, livable communities, and economic growth. However, research and policy efforts to analyze and quantify the impacts of congestion and freight public policies on CO_2 emissions are hindered by the complexities of vehicle routing problems with time-dependent travel times and the lack of network-wide congestion data. This research focuses on the analysis of CO_2 emissions for different levels of congestion and time-definitive customer demands. Travel time data from an extensive archive of freeway sensors, time-dependent vehicle routing algorithms, and problems-instances with different types of binding constraints are used to analyze the impacts of congestion on commercial vehicle emissions. Results from the case study indicate that the impacts of congestion or speed limits on commercial vehicle emissions are significant but difficult to predict since it is shown that it is possible to construct instances where total route distance or duration increases but emissions decrease. Public agencies should carefully study the implications of policies that regulate depot locations and travel speeds as they may have unintended negative consequences in terms of CO_2 emissions.

1. Introduction

Urban freight is responsible for a large share, or in some cities the largest share, of unhealthy air pollution in terms of sulphur oxide, particulate matter, and nitrogen oxides in urban areas such as London, Prague, and Tokyo (OECD, 2003; Crainic et al., 2009). The fast rate of commercial vehicle activity growth over recent years and the higher impact of commercial vehicles (when compared to passenger vehicles) are increasing preexisting concerns over their cumulative effect in urban areas. In particular, environmental, social, and political pressures to limit the impacts associated with carbon dioxide (CO_2) emissions and fossil fuel dependence are mounting rapidly.

A key challenge for transportation agencies is to improve the efficiency of urban freight and commercial vehicle movements while ensuring environmental quality, livable communities, and economic growth. Research in the area of city logistics has long recognized the need for a balanced approach to reduce shippers' and carriers' logistics cost as well as community's traffic congestion and environmental problems (Taniguchi et al., 2003; Crainic et al., 2004).

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Although past and current research efforts into vehicle routing algorithms and scheduling are extensive (Cordeau et al., 2006) most research efforts have ignored freight-related environmental and social externalities. Furthermore, the body of research devoted to investigating the impacts of congestion on urban commercial vehicle operations and time-dependent travel times is relatively scant. In the existing literature, there are no published congestion case studies involving CO_2 emission levels, time-dependent vehicle routing problems, and a diverse set of customer constraints.

This research focuses on the analysis of CO_2 emissions for different levels of time-definitive customer demands using congestion data from an extensive archive of freeway and arterial streets and a time-dependent vehicle routing (TDVRP) solution method to design commercial vehicle routes. To the best of the author's knowledge, there is no published research on the impacts of congestion, land use, and travel speeds on CO_2 emissions for commercial vehicle routing in networks with time-dependent travel speeds, hard time windows, and real-world time/distance data.

This research is organized as follows: Section 2 provides the necessary background and a literature review. Section 3 presents the mathematical formulation of the time-dependent hard time windows routing problem as well as an expression to calculate CO_2 emissions. Section 4 describes the Portland case study, its data sources, and the solution approach. Section 5 presents and analyzes experimental results. Section 6 ends with conclusions.

2. Background and literature review

The literature review for this paper covers three main areas of research: (a) the effects of congestion and travel time variability on vehicle tours and logistics; (b) the impact of travel speeds on commercial vehicle emissions; and (c) time-dependent vehicle routing problems.

Direct and indirect costs of congestion on passenger travel time, shipper travel time and market access, production, and labor productivity have been widely studied and reported in the available literature. The work of Weisbrod and Donald (2001) provides a broad review of this literature. Survey results suggest that the type of freight operation has a significant influence on how congestion affects carriers' operations and costs. For example, results from a California survey indicate that congestion is perceived as a serious problem for companies specializing in less-than-truckload (LTL), refrigerated, and intermodal cargo (Golob and Regan, 2001). These results largely agree with reports analyzing the effects of traffic congestion in the Portland region (ERDG, 2005, 2007).

Congestion has a significant impact on routes where delivery times are heavily restricted by customer time windows and schedules. In addition, there may be a fairly inelastic relationship between delivery costs and customer's demand characteristics and levels. For example, Holguin-Veras et al. (2006) investigated the effects of New York City's congestion pricing on LTL deliveries and found little changes because delivery times were determined by customer time windows and schedules. Figliozzi (2007, 2009a) analyzes the effects of congestion on vehicle tour characteristics using continuous approximations to routing problems. Figliozzi (2007) analyzes how constraints and customer service time affect trip generation using a tour classification based on supply chain characteristics and route constraints. This work also reveals that changes in both vehicle kilometers traveled (VKT) and vehicle hours traveled (VHT) differ by type of tour and routing constraint. Hard time windows are the type of constraint that most severely increases VKT and VHT. Figliozzi (2009a) models the effects of congestion and travel time variability on vehicle tour characteristics; analytical and numerical results indicate that travel speed reductions and depot-customer travel distances are the key factors that exacerbate the impacts of travel time variability. Quak and De Koster (2009) utilized a fractional factorial design and regression analysis to quantify the impacts of delivery constraints and urban freight policies. Quak and De Koster (2009) findings confirm previous results. Vehicle restrictions that affected customers with time-window constraints did not have an impact on customer costs. However, vehicle restrictions are found to be costly when vehicle capacity is limited.

There is an extensive literature related to vehicle emissions and several laboratory and field methods are available to estimate vehicle emissions rates (Ropkins et al., 2009). Research results indicate that CO_2 is the predominant transportation greenhouse gas (GHG) and is emitted in direct proportion to fuel consumption, with a variation by type of fuel (ICF, 2006). For most vehicles, fuel consumption and the rate of CO_2 per mile traveled decreases as vehicle operating speed increases up to an optimal speed and then begins to increase again (ICF, 2006). Furthermore, the relationship between emission rates and travel speed is not linear.

Congestion has a great impact on CO_2 vehicle emissions and fuel efficiency. In real driving conditions, there is a rapid non-linear growth in emissions and fuel consumption as travel speeds fall below 30 mph (Barth and Boriboonsomsin, 2008). CO_2 emissions double on a per mile basis when speed drops from 30 mph to 12.5 mph or when speed drops from 12.5 mph to 5 mph. These results were obtained using an emission model and freeway sensor data in California and weighted on the basis of a typical light-duty fleet mix in 2005. Frequent changes in speed, i.e. stop-and-go traffic conditions, increases emission rates because fuel consumption is a function of not only speed but also acceleration rates (Frey et al., 2008).

Some researchers have conducted surveys that indicate that substantial emission reductions can be obtained if companies improve the efficiency of routing operations (Léonardi and Baumgartner, 2004; Baumgartner et al., 2008). Other researchers using queuing theory, Woensel et al. (2001) modeled the impact of traffic congestion on emissions and recommend that private and public decision makers take into account the high impact of congestion on emissions. From an operational perspective, carriers cannot take into account the impact of congestion on emissions unless time-dependent travel times are considered when designing distribution or service routes. While classic versions of the VRP, specifically the capacitated VRP (CVRP) or VRP with time windows (VRPTW), have been widely studied in the available literature (Cordeau et al., 2006), time-dependent problems have received considerably less attention. The time-dependent vehicle routing problem (TDVRP) takes into account that links in a network have different costs or speeds during the day. Typically, this time-dependency is used to represent varying traffic conditions. The TDVRP was originally formulated by Malandraki and Daskin (1992). Time dependent models are significantly more complex and computationally demanding than static VRP models. Approaches to solve the TDVRP can be found in the work of several authors (Malandraki, 1989; Ahn and Shin, 1991; Jung and Haghani, 2001; Ichoua et al., 2003; Fleischmann et al., 2004; Haghani and Jung, 2005; Donati et al., 2008; Figliozzi, 2009b). The reader is referred to Figliozzi (2009b) for an up-to-date and extensive TDVRP literature review and the description of benchmark problems.

TDVRP instances are considerably more demanding than static VRP instances in terms of data requirements and computational time. However, solving more realistic TDVRP instances may indirectly achieve environmental benefits in congested areas because total route durations and distances can be reduced even though emissions are not part of the objective function (Sbihi and Eglese, 2007). Though the emissions problem is complex; as shown in Section 5, it is possible to construct instances where distance or duration increases but emissions decrease. Palmer (2008) studied the minimization of CO_2 emissions utilizing real network data, multi-stop routes averaging almost 10 deliveries per route, and shortest paths of Surrey county in the UK. However, Palmer's methodology does not allow for time-dependent speeds or multi-stop routes. Figliozzi (2010b) formulated the emissions vehicle routing problem (EVRP) with time-dependent travel times, hard time windows, and capacity constraints. In addition to the usual binary variables for assigning vehicles to customers, this is the first VRP with time windows formulation to include speed and departure time as decision variables and also present conditions and algorithms to determine efficient departure times and travel speeds. Figliozzi (2010b) showed that a routing formulation and solution algorithm that takes into account congestion and aims to minimize CO_2 emissions can produce significant reductions in emission levels with relatively small increases in distance traveled or fleet size.

To the best of the author's knowledge, there is no published work simultaneously integrating in a case study problems with time-dependent speeds, distinct depot locations, hard time windows, real-world network and congestion data, and commercial vehicles emissions.

3. Notation and problem formulation

Unlike the formulation presented by Figliozzi (2010b), in this research travel speeds are not optimized to reduce emissions but introduced as decision variables to represent restrictions due to freight policy measures, congestion, or time windows. Hence, carriers in this research continue "business as usual" without internalizing the costs of emissions.

Using a traditional flow-arc formulation (Desrochers et al., 1988) and building upon a formulation of the TDVRP with time windows (Figliozzi, 2010a), the vehicle routing problem studied in this research can be described as follows. Let $G = (V, A)$ be a graph where $A = \{(v_i, v_j): i \neq j \wedge i, j \in V\}$ is an arc set and the vertex set is $V = (v_0, \ldots, v_{n+1})$. Vertices v_0 and v_{n+1} denote the depot at which vehicles of capacity $q_{\max}$ are based. Each vertex in V has an associated demand $q_i \geqslant 0$, a service time $g_i \geqslant 0$, and a service time window $[e_i, l_i]$; in particular the depot has $g_0 = 0$ and $q_0 = 0$. The set of vertices $C = \{v_1, \ldots, v_n\}$ specifies a set of n customers. The arrival time of a vehicle at customer i, $i \in C$ is denoted a_i and its departure time b_i. Each arc (v_i, v_j) has an associated constant distance $d_{ij} \geqslant 0$ and a travel time $t_{ij}(b_i) \geqslant 0$ which is a function of the departure time from customer i. The set of available vehicles is denoted K. The cost per unit distance traveled is denoted c_d. A binary decision variable x_{ij}^k indicates whether vehicle k travels between customers i and j. A real decision variable y_i^k indicates service start time if customer i is served by vehicle k; hence the departure time is given by the customer service start time plus service time $b_i = y_i^k + g_i$. In the capacitated vehicle routing problem with time windows (VRPTW) it is traditionally assumed that carriers minimize the number of vehicles as a primary objective and distance traveled as a secondary objective without violating time windows, route durations, or capacity constraints. The problem analyzed in this research follows this traditional approach; however, CO_2 emissions are also computed to analyze emissions tradeoffs due to policy restrictions, time windows, or congestion levels.

3.1. Problem formulation

The primary objective is fleet size minimization as defined by (1) and the secondary objective is the minimization of distance traveled and route duration costs.

Primary objective

$$\text{minimize} \quad \sum_{k \in K} \sum_{j \in C} x_{0j}^k \tag{1}$$

Secondary objective

$$\text{minimize} \quad c_d \sum_{k \in K} \sum_{(i,j) \in V} d_{ij} x_{ij}^k \tag{2}$$

Constraints

$$\sum_{i\in C} q_i \sum_{j\in V} x_{ij}^k \leqslant q_{\max}, \quad \forall\, k \in K \tag{3}$$

$$\sum_{k\in K}\sum_{j\in V} x_{ij}^k = 1, \quad \forall\, i \in C \tag{4}$$

$$\sum_{i\in V} x_{il}^k - \sum_{i\in V} x_{lj}^k = 0, \quad \forall\, l \in C, \quad \forall\, k \in K \tag{5}$$

$$x_{i0}^k = 0, x_{n+1,i}^k = 0, \quad \forall\, i \in V, \quad \forall\, k \in K \tag{6}$$

$$\sum_{j\in V} x_{0j}^k = 1, \quad \forall\, k \in K \tag{7}$$

$$\sum_{j\in V} x_{j,n+1}^k = 1, \quad \forall\, k \in K \tag{8}$$

$$e_i \sum_{j\in V} x_{ij}^k \leqslant y_i^k, \quad \forall\, i \in V, \quad \forall\, k \in K \tag{9}$$

$$l_i \sum_{j\in V} x_{ij}^k \geqslant y_i^k, \quad \forall\, i \in V, \quad \forall\, k \in K \tag{10}$$

$$x_{i,j}^k (y_i^k + g_i + t_{i,j}(y_i^k + g_i)) \leqslant y_j^k, \quad \forall\, (i,j) \in A, \quad \forall\, k \in K \tag{11}$$

$$x_{ij}^k \in \{0, 1\}, \quad \forall\, (i,j) \in A, \quad \forall\, k \in K \tag{12}$$

$$y_i^k \in \Re, \quad \forall\, i \in V, \quad \forall\, k \in K \tag{13}$$

The constraints are defined as follows: vehicle capacity cannot be exceeded (3); all customers must be served (4); if a vehicle arrives at a customer it must also depart from that customer (5); routes must start and end at the depot (6); each vehicle leaves from and returns to the depot exactly once, (7) and (8) respectively; service times must satisfy time window start (9) and ending (10) times; and service start time must allow for travel time between customers (11). Decision variables type and domain are indicated in (12) and (13).

3.2. Emissions modeling

CO_2 emissions are proportional to the amount of fuel consumed which is a function of travel speed and distance traveled among other factors. In this research it is assumed that the weight of the products loaded does not significantly affect CO_2 emission levels in relation to the impacts of travel speeds. To incorporate recurrent congestion impacts and following a standard practice in TDVRP models, the depot working time $[e_0, l_0]$ is partitioned into M time periods $T = T^1, T^1, \ldots, T^M$; each period T^m has an associated constant travel speed $0 \leqslant s^m$ in the time interval $T^m = [\underline{t}^m, \bar{t}^m]$.

For each departure time b_i and each pair of customers i and j, a vehicle travels a non-empty set of speed intervals $S_{ij}(b_i) = \left\{ s_{ij}^m(b_i), s_{ij}^{m+1}(b_i), \ldots, s_{ij}^{m+p}(b_i) \right\}$ where $s_{ij}^m(b_i)$ denotes the speed at departure time, $s_{ij}^{m+p}(b_i)$ denotes the speed at arrival time, and $p + 1$ is the number of time intervals utilized. The departure time at speed $s_{ij}^m(b_i)$ takes place in period T^m, the arrival time at speed $s_{ij}^m(b_i)$ takes place in period T^{m+p}, and $1 \leqslant m \leqslant m + p \leqslant M$.

For the sake of notational simplicity the departure time will be dropped even though speed intervals and distance intervals are a function of departure time b_i. The corresponding set of distances and times traveled in each time period are denoted $D_{ij}(b_i) = \left\{ d_{ij}^m, d_{ij}^{m+1}, \ldots, d_{ij}^{m+p} \right\}$ and $T_{ij}(b_i) = \left\{ t_{ij}^m, t_{ij}^{m+1}, \ldots, t_{ij}^{m+p} \right\}$ respectively.

For heavy duty vehicles, the Transport Research Laboratory has developed a function that links emissions, distance traveled, and travel speeds for heavy duty trucks (TRL, 1999):

$$\left[\alpha_0 + \alpha_1 s_{ij}^l + \alpha_2 \left(s_{ij}^l \right)^3 + \alpha_3 \left(\frac{1}{\left(s_{ij}^l \right)^2} \right) \right] d_{ij}^l \tag{14}$$

With a the appropriate conversion factor the output from (14) can be converted from CO_2 tons per unit of distance (kilometers or miles) to fuel efficiency (diesel consumed per kilometer or mile) since fuel consumption and CO_2 emissions are closely correlated (ICF, 2006). The coefficients $\{\alpha_0, \alpha_1, \alpha_2, \alpha_3\} = \{1576.0;\ -17.6;\ 0.00117;\ 36067.0\}$ are parameters for the

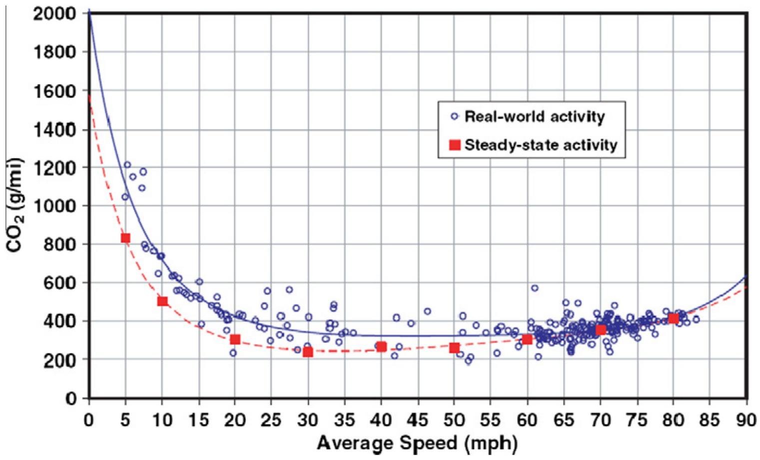

Fig. 1. CO_2 emissions as a function of average speed – Barth and Boriboonsomsin (2008).

heavy duty truck type. For other vehicle types, e.g. medium or light duty trucks, there may be other polynomial terms (TRL, 1999). These parameters are likely to change over time as technology and engines evolve; however, the CO_2 percentage changes and tradeoffs analysis presented in Section 5 are likely to remain valid unless there are dramatic changes in the shape of the speed-emissions curve. The optimal travel speed that minimizes emissions per mile is assumed to be the speed s^*, which for expression (14) the value is $s^* \approx 44$ mph or 71 kmh. Expression (14) outputs CO_2 emissions in kg/km when the speed is expressed in km/h. As congestion increases, the amount and cost of emissions increases dramatically. In addition, below free-flow travel speeds, real-world stop-and-go conditions further increase emissions (Barth and Boriboonsomsin, 2008). Fig. 1 depicts the change in emissions between steady-state and real-world congested conditions. CO_2 emission rates under real-world congested conditions can be up to 40% higher than emission rates under steady-state conditions.

The volume of emissions generated by traveling from customer i to customer j and departing at time b_i is denoted $\upsilon_{ij}(b_i)$:

$$\upsilon_{ij}(b_i) = \sum_{l=0}^{l=p} \left[\alpha_0(s_{ij}^l) + \alpha_1 s_{ij}^l + \alpha_2 (s_{ij}^l)^3 + \alpha_3 \frac{1}{(s_{ij}^l)^2} d_{ij}^l \right] \tag{15}$$

Expression (15) provides a simple yet good approximation for real-world CO_2 emissions vs. travel speed profiles. Acceleration impacts are not considered because detailed speed profiles will be required; however, to account for the emission rate increases in stop-and-go traffic conditions, the term $\alpha_0(s_{ij}^l)$ could be adjusted.

3.3. Speed constraints

Travel speeds are limited by speed limits or congestion. As indicated by constraint (16), a vehicle traveling between two costumers i, j cannot exceed the travel speed for that link in period of time l.

$$\underline{s}_{ij}^l \leqslant s_{ij}^l \leqslant \overline{s}_{ij}^l \tag{16}$$

In addition, travel speeds are also limited by road characteristics. To represent different road characteristics between two customers i, j the segment of distance d_{ij} is partitioned into a set of $R(i,j)$ segments that for the partial distance set:

$$\left\{ r_{ij}^1, r_{ij}^2, \ldots, r_{ij}^{R(i,j)} \right\}$$

such that $d_{ij} = \sum_{l'=1}^{l'=R(i,j)} r_{ij}^{l'}$

Each segment $r_{ij}^{l'}$ has an upper and lower speed bounds. Combining speed constraints due to time of the day and road section we obtain the more general constraint expression (17) for time of day l and section l' between customers i, j:

$$\underline{s}_{ij}^{l,l'} \leqslant s_{ij}^{l,l'} \leqslant \overline{s}_{ij}^{l,l'} \tag{17}$$

4. Portland case study

Considered a gateway to international sea and air freight transport, the city of Portland has established itself both in name and trade as an important component of both international and domestic freight movements. Its favorable geography to both international ocean and domestic river freight via the Columbia River is also complimented by its connection to Interstate-5 (I-5), providing good connectivity to southern California ports and international freight traffic from Mexico and Canada

(EDRG, 2007). Recent increases in regional congestion, however, have hindered considerably freight operations and brought about a substantial increase in delivery costs (Conrad and Figliozzi, 2010).

The I-5 freeway corridor provides the main north–south freight corridor and is used by most carriers delivering in downtown Portland, regional through traffic, and many commuters. Land use patterns are used to locate two carrier's depots in warehousing/industrial areas that are located in relatively central and suburban locations respectively. The I-5 freeway corridor, even under congested conditions, provides the shortest distance and time path between the urban and suburban depot and downtown Portland. Freeway, arterial, and local segments are established for each path as required by expression (17).

Fig. 2 also shows the relative location of downtown Portland, the I-5 corridor, the central depot, and the suburban depot. Experimental results described in Section 5 utilize the central and suburban depot locations shown in Fig. 2 as well as an intermediate depot location (not shown in shown in Fig. 2) located between the central customers and the suburban depot. The intermediate depot is located on I-5 at a distance that is approximately 1/3 of the distance between the central customers and the suburban depot. The central, intermediate, and suburban depots are located in areas with warehousing or related land uses or commercial activities.

4.1. Travel speed data

Time-dependent travel speed data comes from 436 inductive loop detectors along interstate freeways in the Portland metropolitan area. Traffic data is systematically archived in the Portland Oregon Transportation Archived Listing (PORTAL). A complete description of this data source is given by Bertini et al. (2005). The travel speeds used in this research are calculated from 15 min archived travel time data averaged over the year 2007 along the I-5 freeway corridor spanning from

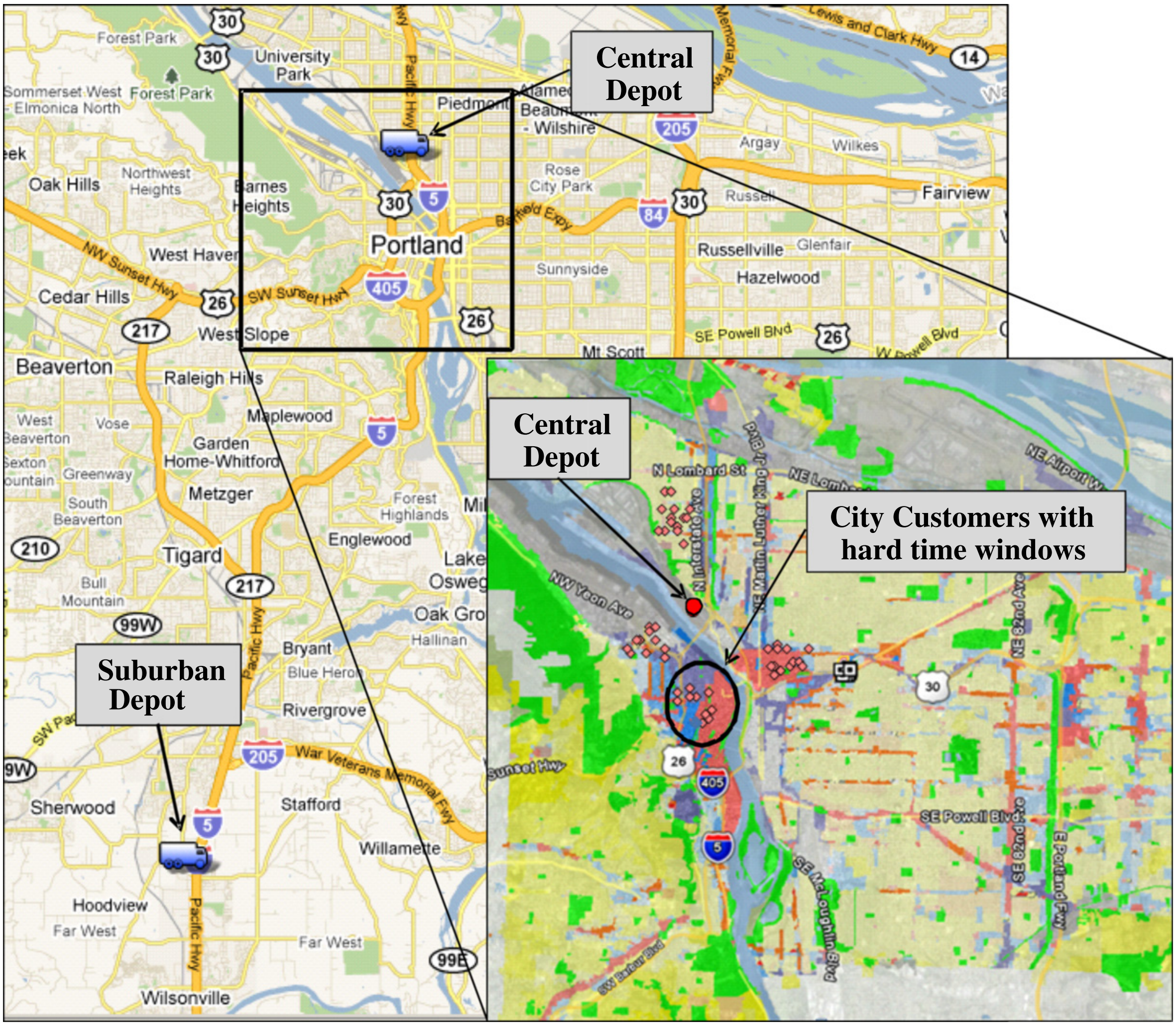

Fig. 2. Depots and customer locations (base map sourced from Google maps. Google Maps at http://maps.google.com).

the Portland suburb of Wilsonville to Vancouver, Washington. In addition, Portland State University had access to truck GPS location and time data that can be used to calculate travel speeds (Wheeler and Figliozzi, 2011). Fig. 3 compares a typical week of average time-dependent travel time data using sensor data from PORTAL and GPS base data for a section of Interstate 5; historical travel time speeds based on sensor data are a good proxy for truck travel speeds.

Fig. 3 also shows that free-flow travel speeds, around 60 mph, take place at night – mostly between 9 pm and 6 am. Some commercial vehicles travel at speeds as high as 70 or 75 mph. This research assumes that travel speeds between 6 am and 9 pm are a function of time of the day. The base scenario, uncongested travel times, assumes a constant time dependent speed of 65 mph in the freeways and 30 mph in the arterial network. Travel speed on arterials is based on speed limits during uncongested hours and estimating congested travel times based on patterns observed in the Portland area (Wolfe et al., 2007). The percentage of local street travel is relatively small and mostly limited to connections between customers and freeways/arterials. Local speed is assumed to have a constant value of 10 mph.

4.2. Customer data

A primary goal of this research is to quantify the impact of congestion on emissions for typical customer constraints in the Portland Metropolitan area. It is assumed that delivery hours correspond to normal business hours between 8 am and 4 pm. Since delivery times are heavily dictated by customer time windows and schedules (Holguin-Veras et al., 2006), it is assumed that vehicles depart from each depot so that they serve the first customer after 8 am.

The distribution of customers' requests is assumed to take place in Portland downtown as shown in Fig. 2. The literature indicates that congestion impacts on route characteristics are highly dependent on the type of binding constraint. To study a diverse set of binding constraints and customer distributions, the experimental design is based on the classical instances of the VRP with time windows proposed by Solomon (1987). The Solomon instances include distinct spatial customer distributions, vehicles' capacities, customer demands, and customer time windows. These problems have not only been widely studied in the operations research literature but the datasets are readily available.

The well-known 56 Solomon benchmark problems for vehicle routing problems with hard time windows are based on six groups of problem instances with 100 customers. The six problem classes are named C1, C2, R1, R2, RC1, and RC2. Customer locations were randomly generated (problem sets R1 and R2), clustered (problem sets C1 and C2), or mixed with randomly generated and clustered customer locations (problem sets RC1 and RC2). Problem sets R1, C1, and RC1 have a shorter scheduling horizon, tighter time windows, and fewer customers per route than problem sets R2, C2, and RC2 respectively. Demand constraints are binding for C1 and C2 problems whereas time-window constraints are binding for R1, R2, RC1, and RC2 problems. In this research the Solomon customer time windows are made proportional to the assumed normal business hours between 8 am and 4 pm so the original demand and time-window constraints are maintained. Customer locations have been scaled to fit Portland downtown area but the relative spatial distribution among customers has been preserved.

4.3. Solution algorithm

The time-dependent vehicle routing problems are solved using the route construction and improvement algorithm described in detail in Figliozzi (2009b). This approach, also denoted IRCI for *Iterated Route Construction and Improvement* has also been successfully applied to VRP problems with soft time windows (Figliozzi, 2010a). As in previous research efforts with a exploratory and policy motivation (Quak and de Koster, 2007), the focus of this research is not on finding optimal routes for simpler problems (i.e. constant travel times problems) but on approximating carriers' route planning as well as possible and capturing the trade-off between congestion, depot locations, customer characteristics, and CO_2 emissions in the case study area.

The TDVRP solution algorithm consists of a route construction phase and a route improvement phase, each utilizing two separate algorithms (Fig. 4). During route construction, the auxiliary routing algorithm $\mathbf{H_r}$ repeatedly determines feasible

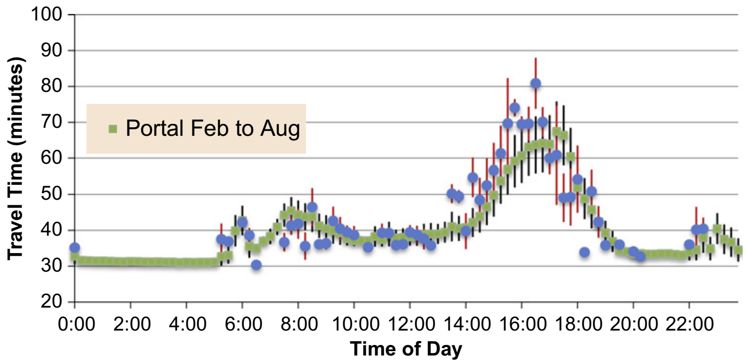

Fig. 3. Example of travel speed variations using sensor and GPS data.

routes using a greedy insertion approach with the construction algorithm $\mathbf{H_c}$ assigning customers and sequencing the routes. Route improvement is done first with the route improvement algorithm $\mathbf{H_i}$ which compares similar routes and consolidates customers into a set of improved routes. Lastly, the service time improvement algorithm $\mathbf{H_y}$ eliminates any time window violations, and then reduces the route duration without introducing additional early or late time window violations; these tasks are accomplished by using the arrival time and departure time algorithms $\mathbf{H_{yf}}$ and $\mathbf{H_{yb}}$, respectively, and re-sequencing customers as needed. It is with these algorithms that the travel time data are inserted into the solution algorithm.

Although the application of the TDVRP algorithm does not change, it is necessary to develop a travel speed and an emissions calculation sub-algorithm to estimate CO_2 levels as a function of the customer sequence, departure time, and road type. The speeds for each time period and path sections as well as the CO_2 emissions calculation are calculated as shown in Algorithm $\mathbf{H_e}$. After initializing the variables (line 1), the algorithm calculates a departure time that satisfies time-window constraints (lines 2–5). Line 6 introduces the loop condition that ensures that the distance between customers is reached. Lines 7 and 8 ensure that the correct section and time period are selected respectively. Line 9 sets the travel speed to the highest feasible value and line 10 calculates the arrival time after completing the current segment. Lines 11–14 calculate emissions if the current segment can be completed in the current interval of time. Otherwise new time periods are utilized until the segment is completed (lines 15–23) and emissions are accumulated in line 20. This process is repeated for all road segments between the two customers until all emissions are properly accounted for. According to $\mathbf{H_e}$ the vehicles travel at the fastest possible speed as permitted by congestion and road type.

Algorithm $\mathbf{H_e}$

Data:

T and S: time intervals and speeds

v_i, v_j, a_i, b_i: two customers v_i, v_j served in this order in route k, a_i is the current arrival time at customer i and b_i the proposed departure time

START

1 **initialize** $D \leftarrow 0,\ t \leftarrow 0,\ v_{ij}(b_i) \leftarrow 0$
2 **if** $b_i < \max(e_i, a_i) + g_i$ **then**
3 $b_i \leftarrow \max(e_i, a_i) + g_i,\ t \leftarrow b_i$
4 **else** $t \leftarrow b_i$
5 **end if**
6 **while** $D \leqslant d_{ij}$ **do**
7 **find** $\min(k')$ such that $D \leqslant \sum_1^{k'} r_{ij}^{k'}$
8 **find** k such that $t_{\underline{k}} \leqslant t \leqslant t_{\bar{k}}$
9 $s \leftarrow \bar{s}_{ij}^{k,k'}$
10 $a_{k'} \leftarrow t + r_{ij}^{k'}/s$
11 **if** $a_{k'} < t_{\bar{k}}$ **then**
12 $v_{ij}(b_i) \leftarrow v_{ij}(b_i)$ + formula (15) with speed $s_{kk'}$, distance $r_{ij}^{k'}$
13 $d \leftarrow r_{ij}^{k'}, t \leftarrow \max(b_i, t_{\underline{k}}), D \leftarrow D + r_{ij}^{k'}$
14 **end if**
15 **while** $a_{k'} > t_{\bar{k}}$ **do**
16 $d \leftarrow d - (t_{\bar{k}} - t)s_{kk'}$
17 $D \leftarrow D + (t_{\bar{k}} - t)s_{kk'}$
18 $t \leftarrow t_{\bar{k}}, s_{k+1,k'} \leftarrow \bar{s}_{ij}^{k+1,k'}$
19 $a_{k'} \leftarrow t + d/s_{k+1,k'}$
20 $v_{ij}(b_i) \leftarrow v_{ij}(b_i) +$ formula (15) with speed $s_{k+1,k'}$, distance
21 $(\min(a_{k'}, t_{\bar{k}+1}) - t)s_{k+1,k'}$
22 $k \leftarrow k + 1$
23 **end while**
24 **end while**

End

Output:

$a_{k'}$, arrival time at customer j

$v_{ij}(b_i)$ = CO_2 emissions between customers i, j for a departure time b_i

5. Experimental results

Three basic scenarios are developed: (1) "uncongested" or base case, (2) "congested" case, and (3) uncongested case but limiting travel speed to 44 mph in freeways – the most efficient travel speed in terms of vehicle CO_2 emissions – and 30 mph

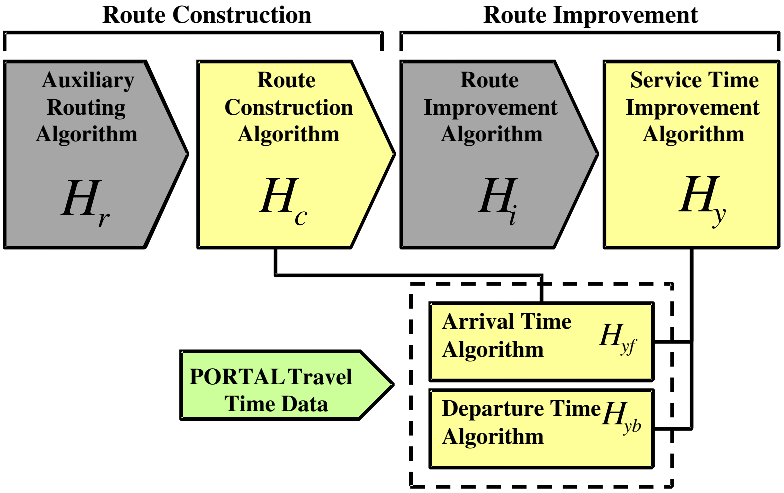

Fig. 4. Solution method of the iterative route construction and improvement (IRCI) algorithm.

in local networks. The latter case (3) is denoted "speed limit-uncongested" case. The average results, i.e. the averages per Solomon problem type, per routing class and for the central depot are presented in Tables 1 and 2. Table 1 compares the base "uncongested" case (1) against the "congested" case (2). In Tables 1–4 the percentage change shown takes the uncongested situation as a base. For example, a positive % in the row of routes (or emissions levels) indicates that the average number of required routes (or emissions levels) has increased.

In Table 1 route durations have an increase across the board due to congestion and longer travel times. Fleet size increases in instances R1, R2, RC1, and RC2 because time windows are the binding constraints. However, fleet size does not change for C1 and C2 problems because vehicle capacity is the binding constraint and the existing fleet of vehicles can serve the same number of customers even under congested conditions. The percentage increase in CO_2 emissions greatly varies across problem types. The highest CO_2 increase is found in R1 and RC1 problems where customers have tight time windows and larger fleet sizes.

Table 2 compares the "speed limit-uncongested" case against the "uncongested" case. In all cases, the percentage change utilizes the uncongested situation as a base. As expected, duration increases across the board because speed limits have been

Table 1
Central depot, uncongested vs. congested case.

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicles	14.9	22.2	0.0	0.0	13.8	17.4
Distance	10.0	−2.3	0.0	0.0	8.3	−1.0
Duration	43.9	42.6	40.4	27.3	40.1	43.9
Emissions	18.2	4.2	1.0	0.8	17.0	8.6

Table 2
Central depot, uncongested vs. speed limit-uncongested case.

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicle	7.4	0.7	0.0	0.0	0.0	1.1
Distance	−5.5	0.0	0.0	0.0	−0.8	−0.5
Duration	4.6	9.7	38.0	24.1	8.0	8.3
Emissions	−13.9	−4.5	−25.5	−17.3	−4.6	−4.3

Table 3
Suburban depot, uncongested vs. congested case.

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicles	15	21	0	0	14	17
Distance	14	15	0	−1	13	12
Duration	49	51	29	63	46	48
Emissions	23	28	8	9	21	23

Table 4
Suburban depot, uncongested vs. speed limit-uncongested case.

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicles	1	0	0	0	1	0
Distance	−1	0	0	0	1	0
Duration	12	10	13	25	14	11
Emissions	−4	−2	−1	−17	−3	−2

reduced along the freeway sections. However, it can be observed in Table 2 that emissions may decrease significantly when speed limits are imposed without significantly increasing fleet size, e.g. type R2. In other problems, a CO_2 emissions reduction is achieved with an increase in fleet size and a reduction in distance travel, e.g. type R1. The departure time from the depot is also affected by the speed limit. To reach the first customer within the time window, an earlier departure time may be needed if freeway speeds are reduced or if it is necessary to travel during a congested time period. Hence, traffic congestion or speed limits will have different impacts if customer time windows and depot location require the usage of congested time periods or time periods where speed limits are binding.

The average results per routing class and for the suburban depot are presented in Tables 3 and 4. Table 3 compares the base "uncongested" case (1) against the "congested" case (2). In all cases, the percentage change shown takes the uncongested situation as a base. As observed in the central depot results, route durations have an increase across the board and fleet size does not change for C1 and C2 problems because vehicle capacity is the binding constraint and the existing fleet of vehicles can serve the same number of customers even under congested conditions. The percentage increase in CO_2 emissions is in all cases greater than the increases in fleet size or distance traveled because more time is spent traveling on congested network links.

Table 4 compares the "speed limit-uncongested" case against the "uncongested" case for the suburban depot. In all cases, the percentage change shown is taking the uncongested situation as a base. As expected, duration increases across the board. It can be observed, again, in Table 4 that emissions may decrease significantly when speed limits are imposed without increasing distance traveled or fleet size, e.g. type C2. In other problems, an emissions reduction is achieved with a slight increase in fleet size or distance traveled, e.g., R1 and RC1 problems respectively. Comparing Tables 2 and 4 it seems that emissions percentage *decreases* are higher for the central depot; to explain this decrease is necessary to look at the type of road utilized by the vehicles and the timing of the depot departure in relation to the congested travel periods. Emissions reductions, keeping travel distance constant, can be explained by two factors: (a) the proportion of travel at the optimal speed on the freeway and (b) the proportion of travel on non-freeway segments. Customer time windows and depot locations can affect both factors.

Travel speed changes can have unexpected consequences even if customer time windows are not included in the analysis. The following example illustrates potential unexpected changes in emissions when speed limits are imposed (see Table 5). Let us assume a freeway speed of 50 mph and a non-freeway (local streets) speed of 25 mph. For the sake of simplicity, let's also assume that the optimal emissions travel speed is 44 mph producing an emission level of 1.00 unit; at 40 or 50 mph the emissions level is 1.10 units (10% higher per mile traveled) and at 25 mph the emissions level is producing 1.30 units (30% higher per mile traveled). Let us assume that a route "A" visits all costumers traveling 20 miles on freeways and 10 miles on local streets. If freeway speeds were to increase above 50 mph, total emissions in route "A" would increase unless. If a speed limit on freeways is introduced, route "B", the total amount of emissions will drop to 33 units (5.7%). However, if there is a route duration constraint of 50 min route "B" is not feasible and the next best feasible option, route "C", has a longer duration and distance traveled than route "A". However, total emissions are reduced to 33.2 units (5.3%) because the proportion of freeway travel has increased. Furthermore, if the objective function is to reduce fleet and distance, a suboptimal choice from the emissions perspective will be made if route "D" (with longer travel distance) but less emissions is not chosen. If the reduction of freeway speed is more than it is required (congestion), the results are even worse than in the initial starting point (compare route "E" vs. route "A"). Hence, policies that aim to reduce CO_2 emission levels by reducing speed limits will be more successful if (a) freeway travel speeds are at the optimum emissions speed level, (b) the imposition of a speed limit does not increase the proportion of distance traveled in local roads, and (c) the overall distance traveled does not increase.

Table 5
Route comparisons when speed and duration constraints are introduced.

Route	Speed		Emission factors		Distance		Total		
	Freeway	Local	Freeway	Local	Freeway	Local	Distance	Duration	Emissions
A	50.0	25.0	1.1	1.3	20.0	10.0	30.0	48.0	35.0
B	44.0	25.0	1.0	1.3	20.0	10.0	30.0	51.3	33.0
C	44.0	25.0	1.0	1.3	26.0	5.5	31.5	48.7	33.2
D	44.0	25.0	1.0	1.3	27.1	4.5	31.6	47.8	33.0
E	40.0	25.0	1.1	1.3	28.5	3.0	31.5	50.0	35.3

Table 6
Urban vs. intermediate and suburban depot (uncongested conditions).

		R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Intermediate depot	Distance	137	105	136	111	137	110
	Duration	111	58	108	65	110	63
	Emissions	112	93	111	96	111	96
Suburban depot	Distance	555	425	550	450	554	445
	Duration	449	233	436	263	446	256
	Emissions	327	272	325	283	327	281

Table 7
Urban vs. intermediate and suburban depot (congested conditions).

		R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Intermediate depot	Distance	137	105	136	111	137	110
	Duration	98	53	95	59	97	58
	Emissions	141	108	140	114	141	113
Suburban depot	Distance	555	425	550	450	554	445
	Duration	371	202	361	227	368	221
	Emissions	464	356	459	376	463	372

When time windows are present, the analysis is more difficult because the departure time from the depot is also constrained by the speed limit or the timing of the congested period (to reach the first customer within the time window, an earlier departure time may be needed if freeway speeds are reduced or if it is necessary to travel during a congested time period).

Important emission reductions can be obtained by optimizing travel speeds. However, it should be clear that depot location has a significant role on total level of emissions. To better illustrate this point a new depot, the intermediate depot, is added approximately 1/3 of the way between the central area and the suburban depot. To simplify comparisons, there are no changes in vehicle fleet size and local distance in Tables 6 and 7 because vehicles in the intermediate and suburban depots are allowed to depart earlier and return later. In addition, depots time windows are relaxed so that the same routes are followed. In both Tables 6 and 7, the percentage changes utilize the central depot case (uncongested and congested respectively) as a reference point Vehicle percentage change is not shown as the fleet sizes are kept constant to facilitate comparisons.

As expected, distances and durations increase across the board if the depot is moved away from the customer service area. In all cases, distance increases more than duration because there is a higher proportion of faster freeway travel when the depot is located farther away. Emission percentage increases are smaller than distance percentages increases in the uncongested case because fast freeway travel produces fewer emissions than slow travel in local/arterial roads. However, in some congested cases emissions can grow faster than distance traveled (Table 7, intermediate depot). In this case, for the intermediate depot, the vehicles are forced to travel the freeway during the most congested time periods (to serve the early morning customers (around or before 8 am) or after serving the late afternoon customers (around or right after 4 pm). However, for the suburban depot the location is so far that even when vehicles are forced to travel the freeway during the most congested time periods part of the freeway travel takes place under uncongested conditions.

The results presented in this section highlight the fact that the impact of congestion on commercial vehicle emissions may be difficult to forecast. Easier to interpret results are obtained if time windows can be partially relaxed so that the same routes are compared. However, some general trends can be observed in all cases. It is clear that uncongested travel speeds tend to reduce emissions on average. Unfortunately, this is not always the case and in some cases the opposite trend could be observed if free flow speeds are increased beyond the optimal emissions travel speed.

6. Conclusions

This research focused on the analysis of CO_2 emissions for different levels of congestion and time-definitive customer demands. The case study used travel time data from an extensive archive of freeway sensors, time-dependent vehicle routing algorithms, and problems-instances with different customer characteristics. The results indicate that congestion impacts on commercial vehicle emissions are highly significant though difficult to predict, for example, it is shown in this researc that it is possible to construct instances where total route distance or duration increases but emissions decrease. Hence, public agencies and highway operators must carefully study the implications of policies that limit travel speeds or increase speed limits as they may have unintended negative consequences in terms of CO_2 emissions. If travel speeds are reduced to a speed that is ‘‘optimal'' from an emissions perspective, emissions can be reduced without a significant increase in fleet sizes or distance traveled if the utilization of arterials or local streets does not increase. In addition, the type of objective function (distance, duration, or emissions based) used may affect the results.

As a general finding, suburban depots and tight time windows tend to increase emissions on average though the emission increases are affected by several factors such as duration of the congested period, percentage of freeway travel time traveled under congested conditions, and the difference between free flow, optimal, and congested speeds. From a land use planning and policy perspective, reserving areas for warehousing and distribution activities close to distribution or service areas may significantly decrease commercial CO_2 emissions, especially as congestion levels increase. However, these benefits are not to be expected across the board and may heavily depend on depot locations as well as network and customer demand characteristics. Further research is needed to explore alternative policies to minimize emissions in congested areas without increasing logistics costs or decreasing customer service levels.

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