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ORIGINAL PAPER

An analytical model for vehicle miles traveled and carbon emissions for goods delivery scenarios

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Abstract

Introduction This paper presents an analytical model to contrast the carbon emissions from a number of goods delivery methods. This includes individuals travelling to the store by car, and delivery trucks delivering to homes. While the impact of growing home delivery services has been studied with combinatorial approaches, those approaches do not allow for systematic conclusions regarding when the service provides net benefit. The use of the analytical approach presented here, allows for more systematic relationships to be established between problem parameters, and therefore broader conclusions regarding when delivery services may provide a CO_2 benefit over personal travel.
Methods Analytical mathematical models are developed to approximate total vehicle miles traveled (VMT) and carbon emissions for a personal vehicle travel scenario, a local depot vehicle travel scenario, and a regional warehouse travel scenario. A graphical heuristic is developed to compare the carbon emissions of a personal vehicle travel scenario and local depot delivery scenario.
Results The analytical approach developed and presented in the paper demonstrates that two key variables drive whether a delivery service or personal travel will provide a lower CO_2 solution. These are the emissions ratio, and customer density. The emissions ratio represents the relative emissions impact of the delivery vehicle when compared to the personal vehicle. The results show that with a small number of customers, and low emissions ratio, personal travel is preferred. In contrast, with a high number of customers and low emissions ratio, delivery service is preferred.
Conclusions While other research into the impact of delivery services on CO_2 emissions has generally used a combinatorial approach, this paper considers the problem using an analytical model. A detailed simulation can provide locational specificity, but provides less insight into the fundamental drivers of system behavior. The analytical approach exposes the problem's basic relationships that are independent of local geography and infrastructure. The result is a simple method for identifying context when personal travel, or delivery service, is more CO2 efficient.

Keywords Freight transportation · Delivery services · CO_2 emissions

This article is part of Topical Collection on The role of planning towards sustainable urban mobility

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1 Introduction

Reducing carbon emissions from transportation is an important strategy for addressing global climate change. As a reflection of this, in December 2016, 196 countries approved a monumental climate change accord in Paris that aims to reduce greenhouse gas emissions, with the goal of limiting the rise in global temperatures to no more than 2 degrees Celsius [31]. If this is to be achieved, strategic rethinking of economic activity must be undertaken at many levels. This includes addressing the transportation of goods, and evaluating strategies for reducing carbon emission from goods movement activity.

The environmental implications of goods delivery scenario decisions cannot be intuitively understood. Instead, they can be understood with quantitative tools and analysis. In practice, firms who choose to pursue a business strategy involving goods delivery do so because of the possibility of greater expected profit margins. Any positive (or negative) environmental impacts of goods delivery are collateral to the decisions dictated by business logic, and understandably so when considering the perspective of the firms making those decisions.

From a policy maker's perspective, decisions must be made by identifying and analyzing all important considerations. For logistics and transportation systems, this analysis can be quite complex. With the explosion of delivery services in recent years, it is important for models and tools to be developed to help firms and policy makers alike to better understand environmental implications of these rising distribution services.

The purpose of our research is to develop models to understand the marginal impacts on emissions and vehicle miles traveled for goods delivery under various logistics scenarios. Generalized models and heuristics help develop the intuition to understand the interactions between goods delivery strategy decisions and the environmental impacts within the constraints of the transportation system. These types of models have some benefits over traditional analysis techniques, including high level indications of the most important factors to consider when vehicle miles travelled (VMT) and emissions reduction are of concern.

2 Literature review

Previous research has noted that urban policies designed to address local concerns including air quality impacts and noise pollution – like time and size restrictions – have a tendency to increase global impacts, by increasing the number of vehicles on the road, by increasing the total VMT required, or by increasing the amount of CO_2 generated [1, 14, 20, 21, 23, 27, 33, 36]. The work presented here is designed to use a simple analytical model to evaluate, using an approach not specific to one place, whether, and under what conditions, replacing passenger vehicle travel with delivery service can address both concerns simultaneously.

A sizable body of research has indicated replacement of personal travel to grocery stores with grocery delivery services has significant potential to reduce VMT. Using simple extrapolations from customer surveys, Cairns [5–7] estimates reductions in vehicle miles travelled (VMT) between 60 and 80% when delivery systems replaced personal travel. Using a simple simulation, the Punakivi team found reductions in VMT as high as 50 to 93% [17–19, 23]. Wygonik and Goodchild [34], using a simulation approach that modeled logistics directly,saw reductions of 70–95%.

Both Siikavirta et al. [23] and Wygonik and Goodchild [34] examined the impact on CO_2 emissions from replacing passenger travel with a delivery service for grocery shopping. Wygonik and Goodchild observed reductions in CO_2 emissions between 20 and 75% when delivery systems served randomly selected customers and 80–90% reductions when delivery systems served clustered customers. These are comparable to the results observed by Siikavirta et al. [23]. Wygonik and Goodchild [33] found the cost and environmental impact per delivery order to be less in denser areas.

While some research has indicated replacement of personal travel to grocery stores with grocery delivery services has significant potential to reduce VMT, these articles have not addressed criteria pollutants, which are associated with significant health impacts [29, 30].

Gonzalez-Feliu [12] conducts simulations of four urban delivery scenarios to evaluate the total kilometer private car units (km.PCUs, a type of road occupancy measure) and CO_2 emissions for four scenarios. Gonalez-Feliu et al. [13] uses similar simulation techniques to predict the km.PCUs and CO_2 emissions for five probable goods movement scenarios concluding that a “mixed scenario” with the “best combination” of commercial planning, retail supply organization, and household supply organization could reduce km.PCUs and CO_2 emissions by the year 2050. Wygonik and Goodchild [33] evaluate trade-offs between cost and CO_2 emissions for different scenarios using different time windows, finding that cost and emissions generally trend together.

Other papers examine impacts of different commercial vehicles, but do not directly contrast commercial vehicles with personal vehicle use. For example, Stefan et al. [24] and Hunt and Stefan [15] use simulation models to evaluate impacts of urban vehicle trips on emissions and other factors. Gebresenbet et al. [11] evaluates the positive environmental impacts of an optimized food distribution system in a city in Sweden.

A number of papers explore the Pollution-Routing Problem (PRP), an extension of the Vehicle Routing Problem that accounts for greenhouse gas emissions and cost implications. Bektas and Laporte [2] propose mathematical models for the PRP that consider tradeoffs between “vehicle load, speed and total cost”. The authors suggest solving this problem optimally is more difficult that solving the VRP, but the results suggest strategies for overall savings. Jabali et al. [16] use a tabu search procedure to solve a time-dependent VRP with CO_2 cost considerations. Fraceschetti et al. [10] propose a model for the time-dependent version of PRP that considers traffic congestion. There are many other papers that expound upon these to determine optimal speeds and routes to minimize overall costs including emissions implications. These papers focus on the routing details of the PRP but do not compare results to delivery scenarios void of the VRP, such as personal vehicle travel.

Some papers link goods delivery supply chain design to emissions impacts. Cachon [4] investigates the relationship between retail store density and greenhouse gas emissions while considering cost implications. Stoopen [25] evaluates three scenarios in terms of routing and cost, determining that results depend heavily on "several factors, such as order volumes, vehicle size, distance, fees, and government regulations".

In Wygonik and Goodchild [35], a detailed analysis of vehicle miles traveled and three types of emissions is conducted for three goods delivery scenarios – personal vehicles, local depot delivery, and regional warehouse delivery. The three scenarios are evaluated for three regions in the greater Seattle area. The emissions evaluated include CO_2 and two criteria pollutants: PM_x and NO_{10}. The local depot scenario gives the most favorable results in terms of vehicle miles traveled, while the personal vehicles scenario minimizes PM_x and NO_{10} emissions. The results indicate that the appropriate strategy to reduce CO_2 emissions is highly sensitive to the logistical model employed, and the region within which the system is implemented.

Brown and Guiffrida [3] evaluate expected distances and CO_2 emissions for two simple scenarios: last mile delivery versus customer pickup for a circular delivery region. The implications of multiple stages of the supply chain and alternate geometries are not considered. The statistically fitted model equations are very similar in form to the equations we derive in this paper, although they are derived differently. The similarities support conclusions that are developed in this paper, focusing on the macro factors (geometry and scenario selection) that influence VMT and emissions outcomes rather than case specifics.

All of the approaches mentioned above use modeled data-driven approaches such as simulation or optimization to evaluate and contrast the scenarios. This limits their conclusions to specific instances, in specific locations. It is clear, however, that the problem has essential geometric characteristics, and that key variables such as customer density, will strongly influence outcomes. The paper presented here presents a simple approximation model, which can divide the entire solution space into cases where passenger vehicles produce less CO_2, or delivery vehicles produce less CO_2, a few other papers incorporate approximation techniques into logistics models. Smilowitz and Daganzo [26] incorporate the continuum approximation into a model that optimizes costs for a distribution system design problem. Figliozzi [9] introduces a model to minimize emissions for the emissions vehicle routing problem with time windows, while Saberi and Verbas [22] complement his model with one that incorporates the continuum approximation and drops the time windows. Although these models include approximation techniques, they only evaluate one goods delivery scenario at a time without considering scenario selection. Like these papers, the paper presented here presents an analytical approximation model to evaluate and compare delivery systems. In doing so, general conclusions can be drawn about the comparison, that have not previously been made.

As urban goods delivery services become more popular, generalized approximation models to characterize VMT and emissions may aid private and public policy makers in determining under what conditions last mile logistics strategies that are best for society as a whole from an environmental perspective, as well as the key drivers that should be evaluated to make those strategy decisions. The model formulation presented below is general enough to give the modeler the flexibility to obtain VMT and emissions approximations for varying levels of available data detail.

3 Model development

This model measures distance between two points not on a road network, but using either the Manhattan or the Euclidean distance. This allows the problem to be generalized absent of a specific road network, which is specific to place. The Manhattan distance represents something of an upper bound on the expected travel distance between two points, and the Euclidean distance represents the lower bound, or shortest possible distance between two points. Distance between points is assumed to be representative of travel cost, and as such congestion is not a travel feature captured by the model. Our approach includes approximating discrete points and distances with continuous functions, as suggested by Daganzo in his seminal text "Logistics Systems Analysis" [8]. By approximating discrete functions with continuous ones, we can solve the problem analytically, rather than combinatorially, and more readily examine the structural properties.

The two environmental considerations within the scope of this paper are total vehicle miles traveled and total carbon emissions. The EPA MOVES model [28] suggests that for a particular vehicle type, emissions can be estimated using knowledge of the speed of the vehicle and distance traveled. The EPA MOVES model provides emissions coefficients for CO_2 with units of kg per mile. This suggests that there is a predictable relationship between distance traveled and emissions for a particular vehicle type, and therefore distance traveled for each vehicle type is considered of paramount importance when considering aggregate modeling of total emissions. We therefore begin with seeking to understand vehicle miles traveled using aggregated approximation models before moving on to understanding carbon emissions in terms of vehicle miles traveled. We begin by describing the approach used for estimating vehicle miles travelled (VMT) and CO_2 emissions for a scenario.

3.1 Estimating vehicle miles traveled for a generic goods delivery scenario

A goods delivery scenario, as defined here, is any circumstance involving any number of vehicles traveling to specific locations via routes to deliver and/or pickup goods. Our generic definition here allows, but does not require, multiple stages of a goods supply chain to be considered as part of the scenario.

Where there are vehicles on routes, the aggregate form of an equation to represent total VMT (vehicle miles traveled) is shown here:

Equation 1: Total VMT for generic scenario

$$VMT = \sum_{i=1}^{n} N_i \overline{t_i} \tag{1}$$

The variables in the generic scenario are defined here (Table 1).

In practice, the number of vehicle trips N_i is dependent on the total count of facility type at level i (we denote as D_i) and the effective vehicle capacity (v_i). The effective vehicle capacity (as opposed to the actual vehicle capacity) considers service level constraints and other policy implications that reduce the demand fulfilled per vehicle from the maximum possible.

Assuming a consistent effective vehicle capacity (average number of facilities fulfilled per vehicle trip can be observed and calculated), an approximation of the aggregate VMT function is the following:

Equation 2: Total VMT for generic scenario with capacity consideration

$$VMT = \sum_{i=1}^{n} N_i \overline{t_i} \approx \sum_{i=1}^{n} \frac{D_i}{v_i} \overline{t_i} \tag{2}$$

Where the two additional variables included are (Table 2):

Intuitively, the ratio $\frac{D_i}{v_i}$ is a simple indicator for how effectively a fleet of vehicles is aggregating shipments. For each scenario, the relationships between this ratio, vehicle emissions coefficients, and delivery region geometry may be able to give insights and provide approximations regarding carbon emissions performance. This paper investigates some of these relationships.

3.2 Estimating carbon emissions for a generic goods delivery scenario

A way of estimating carbon emissions mass for a particular vehicle type is by multiplying its distance traveled by its expected emissions coefficient, C (units kg per mile). If we assume the vehicle type segmentation is analogous to facility type segmentation for a particular vehicle goods scenario, the total expected carbon emissions can be expressed with the following:

Equation 3: Total emissions for generic scenario

$$E = \sum_{i=1}^{n} C_i N_i \overline{t_i} \approx \sum_{i=1}^{n} C_i \frac{D_i}{v_i} \overline{t_i} \tag{3}$$

Where C_i is carbon emissions coefficient for the primary vehicle type used to transport goods from facility level i to facility level $i+1$. Some examples of emissions coefficients by vehicle type that will be referenced later in this paper are the following (Table 3):

Although the aggregate form of the equations for total VMT and total carbon emissions are intuitive and less than useful themselves, we will expound on their simplicity to explore the theoretical implications of delivery region geometry on aggregate VMT and carbon emissions when comparing scenarios.

3.3 Personal vehicle travel scenario

We now apply these approaches to each of the three scenarios. The first scenario explored is inspired by the work of Wygonik [32]. A personal vehicle travel scenario is defined as a scenario where a combination truck delivers goods from a regional warehouse to local depots while customers use personal vehicles to drive from their homes to pickup goods from local depots. The graphical and variable definitions for the personal vehicle travel scenario are shown below (Fig. 1 and Table 4).

Table 1 Generic scenario variables

Variable	Tree terminology	Logistics terminology	Example(s)
i	Level number i	Facility type	Regional warehouse, local depot, customer homes
n	Total count of levels	Total count of facility types	$n=3$ for a scenario including regional warehouse, local depots, and customer homes
N_i	Count of descendants at level i	Count of vehicle trips from facility type i to facility type $i+1$	Number of vehicle trips from local depots to customer homes
t_i	Mean distance from parent vertices in level i to the children in level $i+1$	Mean route distance for vehicle trips from facility type i to facility type $i+1$	Mean round trip distance from customer home to local depot

Table 2 Additional generic scenario variables

Variable	Logistics terminology	Example(s)
D_i	Count of facility type i	Number of customer homes
v_i	Effective vehicle capacity	Maximum number of deliveries per shared-use vehicle trip route

Applying the generic goods delivery scenario equations to the personal vehicles delivery scenario yields the following equations.

Equation 4: Total VMT for personal vehicle travel scenario

$$VMT_{PV} = \sum_{i=1}^{n} N_i \overline{t_i} \approx \sum_{i=1}^{n} \frac{D_i}{v_i} \overline{t_i} \tag{4}$$

Equation 5: Total emissions for personal vehicle travel scenario

$$E_{PV} = \sum_{i=1}^{n} C_i N_i \overline{t_i} \approx \sum_{i=1}^{n} C_i \frac{D_i}{v_i} \overline{t_i} \tag{5}$$

Geometric considerations are taken into account when calculating an approximation for t_i. For a delivery region with constant customer density, the Euclidian mean distance or Manhattan mean distance or over the delivery region to the depot can be used to estimate the mean homes to depot route distance, t_2.

Although the Euclidian distance is convenient for derivation purposes, it does not represent realized travel distance on a road network. Euclidian distance is straight line distance and does not take roadway constraints into consideration. Another way to approximate mean personal vehicle route distance to the depot is by calculating the mean Manhattan distance to the depot over the delivery region. This approximation is likely closer to the true travel distance when considering the grid layout of most streets. Figure 2 shows a visual comparison of the difference between the Euclidian distance and Manhattan distance for the personal vehicle travel scenario.

The Manhattan metric for all scenarios in this paper because of its more relevant applicability to urban delivery scenarios. An equation to derive the Manhattan mean distance to the center of a delivery region is shown below:

Equation 6: Mean Manhattan distance derivation

$$MMD \approx \frac{1}{A} \iint_{0}^{A} (|x| + |y|) dxdy \tag{6}$$

Where:

MMD	*Mean Manhattan distance to the center of the delivery region (in miles)*
A	*Area of delivery region (in miles^2)*
(x,y)	*domain of all points in delivery region assuming center is located at (0,0)*

If the center of the delivery region is offset from the depot of the delivery region, an estimate of the distance between the two (d_2) must be used in the approximation of mean homes to depot route distance, t_2. The complete approximation for the one-way route distance is show below.

Equation 7: One-way average personal vehicle route distance

$$\frac{\overline{t_2}}{2} \approx d_2 + MMD \approx d_2 + \frac{1}{\pi r^2/4} \int_{0}^{r} \int_{0}^{\sqrt{r^2-y^2}} (x+y) dxdy = d_2 + \frac{8}{3\pi} r \tag{7}$$

Where:

t_2	*Mean route distance for all personal vehicles (in miles)*
d_2	*Distance from depot to center of delivery region*
MMD	*Mean Manhattan distance to the center of the delivery region (in miles)*
r	*radius of delivery region (in miles)*
(x,y)	*domain of all points in delivery region assuming center is located at (0,0)*

Using these assumptions to obtain an estimate of t_2, the approximations of VMT and total carbon emissions for the personal vehicle travel scenario are shown below.

Equation 8: VMT for personal vehicles assuming circular region

$$VMT_{PV} = \sum_{i=1}^{n} N_i \overline{t_i} \approx \sum_{i=1}^{n} \frac{D_i}{v_i} \overline{t_i} \approx N_1 t_1 + \frac{D_2}{1} 2\left(d_2 + \frac{8}{3\pi} r\right) \tag{8}$$

Table 3 Emissions coefficient variables

Variable	Definition
C_{ct}	Expected carbon emissions coefficient of combination truck (in kg/mi)
C_{su}	Expected carbon emissions coefficient of shared-use vehicle (in kg/mi)
C_{pv}	Expected carbon emissions coefficient of personal vehicles (in kg/mi)

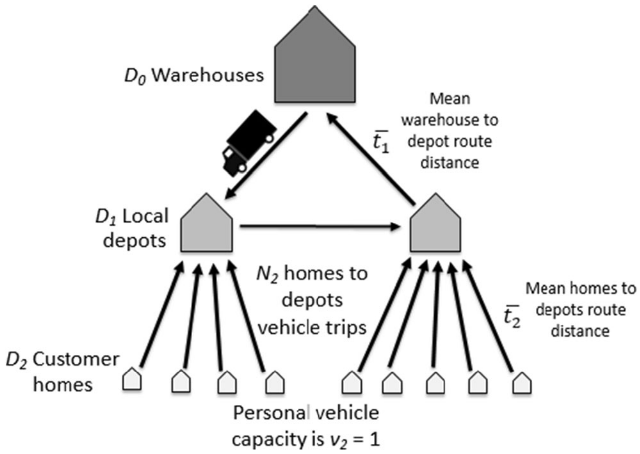

Fig. 1 Personal vehicle travel scenario

And

Equation 9: Emissions for personal vehicles assuming circular region

$$E_{PV} = \sum_{i=1}^{n} C_i N_i \overline{t_i} \approx \sum_{i=1}^{n} C_i \frac{D_i}{v_i} \overline{t_i} \approx C_{ct} N_1 t_1 + C_{pv} \frac{D_2}{1} 2 \left(d_2 + \frac{8}{3\pi} r \right) \quad (9)$$

3.4 Local depot travel scenario

We now move to deriving VMT and emissions for the second scenario; local depot travel. The graphical and variable definitions for local depot delivery scenario are shown below. Note that the only variable differences between this scenario and the previous are N_2, v_2 and t_2 (the variables that differentiate shared-use vehicle use from passenger vehicle use) (Fig. 3 and Table 5).

Applying the equations above to this scenario yields the following expression to evaluate total VMT and carbon emissions for the local depot delivery scenario.

Table 4 Personal vehicle travel scenario variables

Variable	Definition
D_0	Number of regional warehouses
D_1	Number of local depots
D_2	Number of customer homes
N_1	Number of warehouse to depot trips
$N_{2,\ PV}$	Number of home to local depot trips
v_1	Warehouse to depot vehicle capacity
$v_{2,\ PV}$	Home to depot vehicle capacity
t_1	Mean warehouse to depot route distance
$t_{2,\ PV}$	Mean homes to depot route distance

Equation 10: Total VMT for local depot delivery

$$VMT_{LD} = \sum_{i=1}^{n} N_i \overline{t_i} \approx \sum_{i=1}^{n} \frac{D_i}{v_i} \overline{t_i} \quad (10)$$

Equation 11: Total VMT for local depot delivery

$$E_{LD} = \sum_{i=1}^{n} C_i N_i \overline{t_i} \approx \sum_{i=1}^{n} C_i \frac{D_i}{v_i} \overline{t_i} \quad (11)$$

The $N_2 t_2\ \overline{d}_2$ term describes the optimal distance for the vehicle routing problem (VRP) from each depot to customer homes in the depot's delivery region. To understand how the geometry of the delivery region affects this total VMT, we incorporate the Daganzo [8] approximation for the vehicle routing problem.

Equation 12: Daganzo's [8] approximation for the Vehicle Routing Problem

$$L_{vrp} \leq L_{tsp} + \frac{2D}{v_m} d \quad (12)$$

Where:

L_{vrp}	*travel length for vehicle routing problem (our $N_2\ \overline{d}_2$)*
L_{tsp}	*travel length for traveling salesman problem*
D	*Total demand (our D_2)*
v_m	*Vehicle capacity (our v_2)*
d	*Distance from depot to center of tour area*

The VRP approximation also requires the traveling salesman problem (TSP) approximation.

Equation 13: Daganzo's [8] approximation for the traveling salesman problem

$$L_{tsp} \approx k \sqrt{A N_h} \quad (13)$$

Where:

L_{tsp}	*Travel distance (in miles)*
k	*Network constant (0.72 for Euclidian and 0.92 for Manhattan)*
A	*Service area (in miles^2)*
N_h	*Number of customers on route (our D_3)*

When all terms are combined, the resulting expression evaluates total VMT.

Equation 14: Total VMT for local depot delivery scenario, upper bound

$$VMT_{LD} \leq N_1 \overline{t}_1 + k \sqrt{A D_2} + \frac{2 D_2}{v_2} d \quad (14)$$

The final term in the above expression accounts for the nonzero distance from the depot to the center of the tour area,

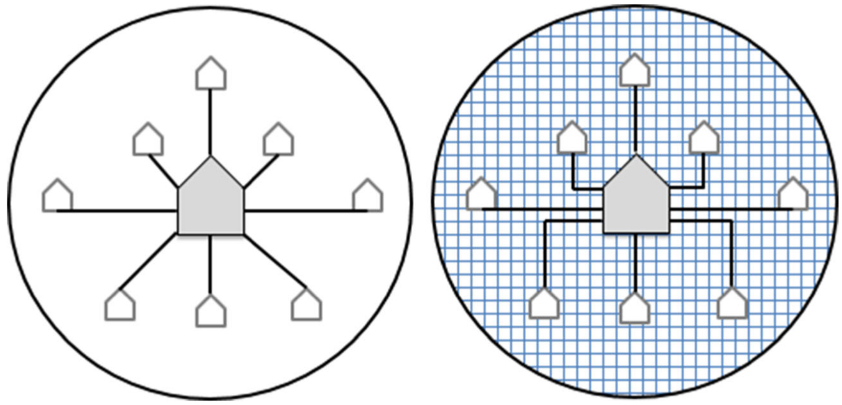

Fig. 2 Euclidian distance vs. Manhattan distance for personal vehicle scenario

along with delivery vehicle capacity. We may also use the above expression without the final term as an approximation that assumes a distance of zero from the depot to the center of the tour area, which can be considered a lower bound.

Equation 15: Total VMT for local depot delivery scenario, lower bound

$$VMT_{LD} \leq N_1 \bar{t}_1 + k\sqrt{AD_2} \tag{15}$$

To evaluate total emissions, incorporate the emissions coefficients. The ranges for approximating total VMT and total carbon emissions for the local depot delivery scenario are below.

Equation 16: Bounded approximation for total VMT for local depot delivery scenario

$$N_1 \bar{t}_1 + k\sqrt{AD_2} \leq VMT_{LD} \leq N_1 \bar{t}_1 + k\sqrt{AD_2} + \frac{2D_2}{v_2} d \tag{16}$$

And

Equation 17: Bounded approximation for total carbon emissions for local depot delivery scenario

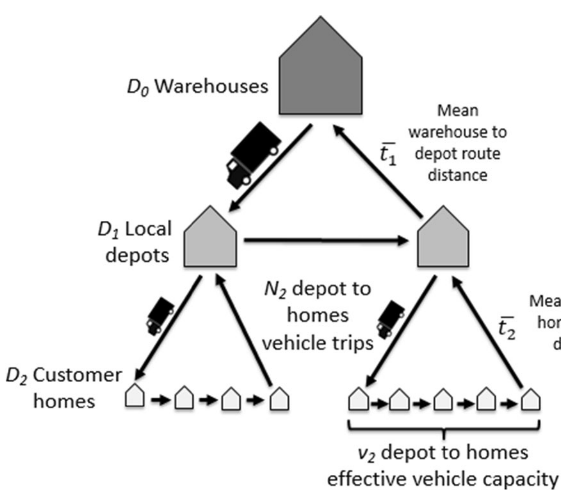

Fig. 3 Local depot vehicle delivery scenario

$$C_{ct} N_1 \bar{t}_1 + C_{su} k\sqrt{AD_2} \leq E_{LD} \leq C_{ct} N_1 \bar{t}_1 + C_{su}\left(k\sqrt{AD_2} + \frac{2D_2}{v_2} d\right) \tag{17}$$

It should not come as a surprise that the upper bound proves to be a much better predictor of VMT and emissions than does the lower bound. It is included here to give the structure to allow the exploration of the importance of the final term.

3.5 Regional warehouse travel scenario

The final sceanario, regional warehouse travel, is similar to the local depot scenario in that it involves shared-use vehicles to deliver to customer homes. It is simpler in the sense that it bypasses use of local depots and involves deliveries directly to customer homes on routes from regional warehouses. The graphical and variable definitions for the regional warehouse travel scenario are shown below (Fig. 4 and Table 6).

Mathematically, the equations to approximate total VMT and total carbon emissions for the regional warehouse scenario are very similar to the local depot delivery scenario equations except for two major differences. Firstly, there are only

Table 5 Local depot vehicle delivery scenario variables

Variable	Definition
D_0	Number of regional warehouses
D_1	Number of local depots
D_2	Number of customer homes
N_1	Number of warehouse to depot trips
$N_{2,\,LD}$	Number of depot to home trips
v_1	Warehouse to depot vehicle capacity
$v_{2,\,LD}$	Depot to homes vehicle capacity
t_1	Mean warehouse to depot route distance
$t_{2,\,LD}$	Mean depot to homes route distance

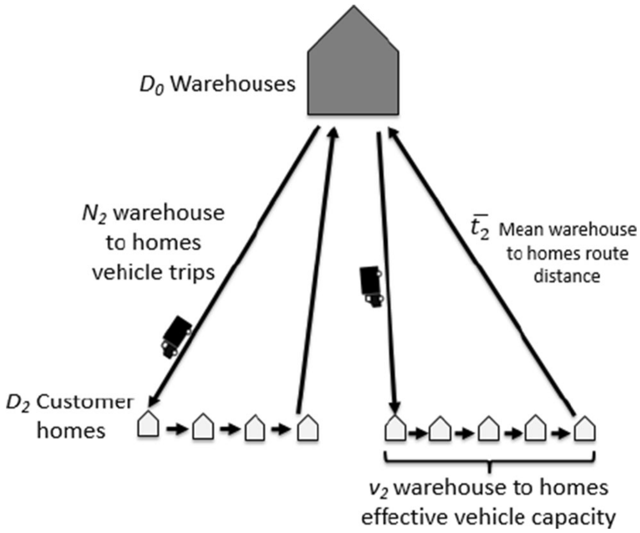

Fig. 4 Regional warehouse delivery scenario

two facility types (instead of three in the local depot scenario), so all terms in the equations involving combination truck routes are not present in the regional warehouse travel scenario. Secondly, the VRP is from the regional warehouse to the customer homes (instead of from local depots), so the mean distance from the warehouse to the center of the delivery regions d is greater in the regional warehouse scenario than in the local depot scenario. All other logic is identical to the local depot delivery scenario, so the approximations for total VMT and total carbon emissions are:

Equation 18: Total VMT for regional warehouse scenario

$$k\sqrt{AD_2} \le VMT_{RW} \le k\sqrt{AD_2} + \frac{2D_2}{v_2}d \tag{18}$$

And

Equation 19: Total emissions for regional warehouse scenario

$$C_{su}k\sqrt{AD_2} \le E_{RW} \le C_{su}\left(k\sqrt{AD_2} + \frac{2D_2}{v_2}d\right) \tag{19}$$

Note that d is the mean distance from the regional warehouse to the center of the delivery areas for the regional warehouse scenario.

Table 6 Regional warehouse delivery scenario variables

Variable	Definition
D_0	Number of regional warehouses
D_2	Number of customer homes
$N_{2,\ RW}$	Number of warehouse to home trips
$v_{2,\ RW}$	Warehouse to homes vehicle capacity
$t_{2,\ RW}$	Mean warehouse to homes route distance

4 Application

The form of the aggregate VMT and carbon emissions approximations lends itself to the development of heuristics to compare the sensitivity of total VMT and total carbon emissions to important factors that differentiate scenarios. Here is an example where scenarios are compared heuristically.

If the personal vehicle travel scenario carbon emissions is compared to the local depot delivery scenario carbon emissions, the comparison can be simplified into an emissions ratio like the one shown below.

Equation 20: Personal vehicles to local depot emissions ratio

$$e = \frac{E_{PV}}{E_{LD}} \approx \frac{C_{ct}N_1\bar{t_1} + C_{pv}D_2 2\left(d_2 + \frac{8}{3\pi}r\right)}{C_{ct}N_1\bar{t_1} + C_{su}\left(k\sqrt{AD_2} + \frac{2D_2}{v_2}d_2\right)} \tag{20}$$

Where:

e *Expected ratio of emissions for the personal vehicle scenario to the regional warehouse scenario*

While there are several variables included in the above ratio, it is worth mentioning that most of them are present in both the numerator and the denominator of the ratio. The inclusion of the variables in both scenario approximations can result in some interesting effects when comparing scenarios. When the ratio is greater than 1, the local depot delivery scenario is expected to have less carbon emissions. When the ratio is less than 1, the personal vehicle travel scenario is expected to have less total carbon emissions.

To show an example of some of these interesting effects, consider personal vehicle travel and local depot delivery scenario alternatives where the delivery region is circular, customer density is constant, combination truck considerations are not considered ($t_2 = 0$), and the depot is in the center of the delivery region ($d_2 = 0$). With all these assumptions, the ratio simplifies to:

Equation 21: Personal vehicles to local depot emissions ratio when $t = 0$ and $d = 0$

$$e = \frac{E_{PV}}{E_{LD}} \approx \frac{C_{pv}D_2\frac{16}{3\pi}r}{C_{su}k\sqrt{\pi r^2 D_2}} \approx \frac{C_{pv}}{C_{su}}1.041\sqrt{D_2} \tag{21}$$

The ratio can be represented graphically in terms of C_{pv}/C_{su} and D_2. For the assumptions listed above, the following view indicates when local depot delivery is expected to minimize emissions and when the personal vehicles travel scenario is expected to minimize emissions (Fig. 5).

The heuristic above does not consider all important factors that contribute to total carbon emissions for the two scenarios (including t_2 and d_2), but it helps frame the nature of the

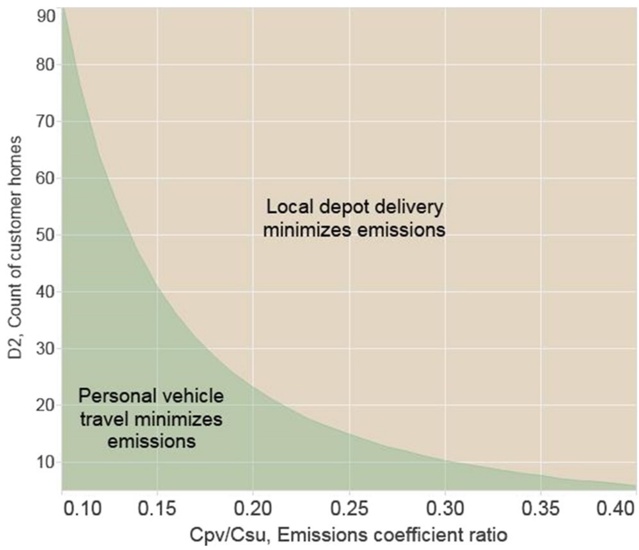

Fig. 5 Scenario selection to minimize emissions

interaction between the emissions coefficient ratio and count of customer homes within the constraints of the transportation system. Other variables of interest to decision makers can be considered heuristically as well.

5 Conclusions

The generalized form of the approximation models developed to evaluate total VMT and carbon emissions for the three delivery scenarios indicates that a simplified comparison of VMT and emissions between different goods delivery scenarios is feasible and provides conclusive insights. This simple approach allows us to see that the key variables are customer density and emissions ratio, and under which conditions passenger vehicles are expected to provide lower emissions than delivery vehicles. Delivery trucks are expected to provide emissions benefits where customer density is high (e.g. in an urban area), and where the emissions footprint of the truck is closer to the passenger car. This means that delivery should be considered as an emissions reduction strategy if customers can be clustered together in time and space, and that delivery companies should be encouraged to use the lowest emissions vehicle possible. The simplicity of the approach allows for quick identification of candidate areas, however, a more detailed analysis considering congestion, and local infrastructure details, should be conducted as a next step.

While an aggregate model cannot take into account unique geographic features or road networks, this is in fact the strength of the approach; the analysis provides insight into the geometric properties of the problem, and the role of density and emissions factors. The models presented above are an introduction to the use of heuristics to make high level VMT and emissions comparisons between scenarios, and can complement more detailed analyses that may be appropriate for more data driven applications.

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