Research article

Evaluating CO2 emissions, cost, and service quality trade-offs in an urban delivery system case study

Erica Wygonik a,*, Anne Goodchild b,1

a Department of Civil and Environmental Engineering, 135 More Hall Box 352700, University of Washington, Seattle, WA 98195–2700, United States of America
b Department of Civil and Environmental Engineering, 121E More Hall Box 352700, University of Washington, Seattle, WA 98195–2700, United States of America

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A B S T R A C T

Growing pressure to limit greenhouse gas emissions is changing the way businesses operate. This paper presents the trade-offs between cost, service quality (represented by time window guarantees), and emissions of an urban pickup and delivery system under these changing pressures. A model, developed by the authors in ArcGIS, is used to evaluate these trade-offs for a specific case study involving a real fleet with specific operational characteristics. The problem is modeled as an emissions minimization vehicle routing problem with time windows. Analyses of different external policies and internal operational changes provide insight into the impact of these changes on cost, service quality, and emissions. Specific consideration of the influence of time windows, customer density, and vehicle choice are included. The results show a stable relationship between monetary cost and kilograms of CO2, with each kilogram of CO2 associated with a $3.50 increase in cost, illustrating the influence of fuel use on both cost and emissions. In addition, customer density and time window length are strongly correlated with monetary cost and kilograms of CO2 per order. The addition of 80 customers or extending the time window 100 minutes would save approximately $3.50 and 1 kilogram of CO2 per order. Lastly, the evaluation of four different fleets illustrates significant environmental and monetary gains can be achieved through the use of hybrid vehicles.

The results demonstrate there is not a trade-off between CO2 emissions and cost, but that these two metrics trend together. This suggests the most effective way to encourage fleet operators to limit emissions is to increase the cost of fuel or CO2 production, as this is consistent with current incentives that exist to reduce cost, and therefore emissions.

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1. Introduction

The 2010 Inventory of U.S. Greenhouse Gas Emissions and Sinks (covering years 1990 through 2008) indicates the transportation sector produces the largest percentage of emissions from fossil fuel combustion by end-use sector, producing more than 1800 teragrams (Tg) of CO2 equivalents in 2008 and representing nearly one-third of emissions from fossil fuel combustion [1].

As demand on the world’s resources continues to increase, cities, regions, and states find themselves needing to foster economic growth and development while minimizing impacts to the environment. More than one thousand mayors in the United States have signed the Kyoto Protocol, committing to reduce greenhouse gas emissions by 7 percent over 1990 levels by 2012 [2]. Often viewed as a competing interest, those very mayors are struggling to protect their residents’ economic and social well-being without compromising the environmental goals they have established. Unfortunately, current business practices and land use patterns often create situations in which these goals do conflict—economic well-being requires extensive use of energy and travel.

This research offers one approach for including emissions into fleet assignment and vehicle routing to consider the trade-offs between monetary costs, emissions impacts, and service quality in residential urban pickup and delivery systems. While emissions from transportation activities are understood at a broad level and between modes, this research looks carefully at emissions for an individual fleet. This approach enables evaluation of the impact of a variety of internal changes and external policies on fleet performance metrics such as time window size, spatial restrictions to target or avoid dense areas, and vehicle size or type restrictions.

2. Theory

While few researchers have developed routing tools that optimize emissions, a number of researchers have considered emissions within routing problems and their work can provide insight into the
expected relationships between cost, service quality, and emissions. A few of those relevant relationships are mentioned here.

Siikavirta et al., Quak and de Koster, Allen et al., and van Rooijen et al. [3–7] adjusted output vehicle miles (or kilometers) traveled from delivery routing evaluations by emissions factors, finding more restrictive time windows have higher emissions than scenarios without time windows or with wider time windows. Given the significant contribution of fuel use to both costs and CO₂ emissions, any parameter that restricts the VRP optimization, including restrictive time windows, will likely yield higher costs and emissions.

Cairns published a number of papers in the late 1990s illustrating significant VMT reductions associated with grocery delivery. Her work was based in the UK and focused on the density of customers and their distribution, finding that increasing VMT savings were possible with increasing customer density [8]. Quak and de Koster and Allen et al. [4–6] also found restrictions on vehicle types negatively impacted environmental performance. The influence of vehicle type was dependent on the characteristics of the deliveries in question – delivery providers with a single large quantity of goods had the most negative environmental impacts under policies that limit vehicle size.

Most of this work has applied flat emissions factors to VRP distance outputs, treating emissions as a post-processing output, not as an input or influencing factor. Other work has aimed to explicitly reduce emissions but achieves this goal by reducing overall miles travelled or changing route start times to avoid congested times. In sum, while the literature discussing the relationships between time windows, customer density, vehicle fleet, and emissions do not solve the problem presented in this paper, they do indicate emissions can be reduced by providing wide time windows, serving high customer density, and carefully matching vehicles to necessary capacity.

Overall, the literature supports the theory that in general the goals of the private market (to reduce costs) are frequently aligned with the goals of society (to reduce emissions) and any external restriction on private behavior will limit the effectiveness of those societal goals (see the work of Holguín-Veras [9] for a more thorough discussion of this relationship). This paper continues to test that theory and quantify the magnitude of the effect of external policies on societal goals.

3. Methods

Optimizing the routing of urban pickup and delivery systems generally relies on solutions to the Vehicle Routing Problem (VRP). The VRP is an extension of the traveling salesman problem (TSP), a problem designed to find the shortest route between a number of destinations. The TSP theory originated with actual traveling salesmen needing to optimize their route for visiting a number of destinations before returning to their origin. The VRP extends the TSP to consider multiple routes over a fleet of vehicles, and the vehicle routing problem with time windows (VRPTW) extends the VRP to consider the influence of permitted time windows for stops on the routing solution. Solutions to this problem can improve any service that relies on routing and scheduling including garbage collection, third party logistics providers (UPS, FedEx), and airport shuttles. In general, this class of problems minimizes a particular cost for a fleet of vehicles picking-up or delivering goods. Traditionally, the costs these tools utilize include monetary, distance, and time costs [10]. Other costs of these services, for example noise and air pollution costs, are not currently paid by the fleet and are rarely reflected in VRP solutions.

Few researchers have developed tools for solving the VRP optimizing on emissions. The following research examines different ways to include emissions within a VRP optimization, though each falls short of solving the problem presented in this paper.

Figliozzi [11] has developed an emissions minimization vehicle routing problem (EVRP) solution which explicitly includes emissions in the cost minimization of a traditional vehicle routing problem with time windows. In this model, emissions are directly related to travel speed. To apply his model, Figliozzi modifies the Solomon [12] benchmark problems for vehicle routing problems with hard time windows to reflect the impact of congestion. His evaluation focuses on the impact of congestion on emissions using a simulated data set and does not apply that evaluation to a sample from an existing delivery provider.

Dessouky, Rahimi and Weidner [13] consider trade-offs between cost, service, and environmental performance for a demand-responsive transit operation. Simulating transit operations with a scheduling heuristic and considering life-cycle impacts to the environment, they found significant environmental improvements are possible with minimal additional costs for heterogeneous fleets optimized for emissions. These same benefits were not observed for homogenous fleets. This research looks at a number of measures of environmental performance and considers the life-cycle environmental impacts of each solution; it does not focus on or minimize the CO₂ emissions associated with routing.

Palmer [14] modified a vehicle routing problem solution to account for CO₂ emissions by a grocery delivery service. This model has the capability of minimizing on emissions or calculating emissions for optimizations on time or distance. He found reductions in emissions of 4.8% when optimizing for emissions instead of time, and reductions in emissions of 1.2% when optimizing for emissions instead of distance. His model focuses on estimating emissions based on speed and vehicle performance, and he estimates speed based on congestion. Palmer’s model is the closest to date at providing a useful model to consider the trade-offs between emissions and service. Because his model requires as an input the cost of CO₂ it does not allow for insight into the appropriate cost of CO₂ to modify behavior.

Benedek and Rilett [15] developed a traditional passenger assignment model using user equilibrium and system optimal cost functions to optimize on CO₂ finding minimal change in time (0.5%) or emissions (0.15%) between scenarios optimized on one or the other. Their model did not consider routes with multiple stops, time windows, or vehicle capacity, and did not include the resulting costs for various routes.

While each of these researchers have made significant progress toward accounting for the environmental impacts of vehicle routing, none accounts for the trade-offs between cost, service, and emissions while allowing optimization of each.

ArcGIS software allows solving routing and scheduling problems. This software includes a complete road network with address data and link cost functions, but it does not estimate emissions from vehicle activity. This research extended the ArcGIS VRP tool to account for emissions enabling least-cost, least-time, and least-emissions routing for an urban pickup and delivery system with time windows. This tool enables analysis of different policies regarding changes in road network conditions, time window constraints, and fleet composition to consider the changes in cost and emissions for different scenarios.

ArcGIS can solve the VRP for urban pickup and delivery systems with capacity-constraints, multiple vehicles, and time windows. This tool can consider hard or soft time windows and is extended here to account for emissions when the problem involves shorter than one-hour stops. Based on EPA standards, an engine with catalytic converter in hot state will pass to a cold state after this amount of time and will require accounting for hot and cold start emissions, which is beyond the limits of this tool. However, stops in most residential urban pickup and delivery systems do not exceed this one-hour threshold.

While the exact details of the heuristic used in the ArcGIS software is proprietary, their help manual [16] indicates shortest paths are identified with Dijkstra’s algorithm [17] and order sequencing is completed with a tabu search heuristic [18]. These solutions are well-regarded for quickly producing reasonable results.

ArcGIS is used to minimize emissions and consider the trade-offs between emissions, cost, and service quality, for a specific case study fleet. This case study is based on a real pickup and delivery system, its
customers, order quantities, and delivery time windows. Some details of the operator, including its name, are omitted to protect confidentiality.

3.1. Model structure

The model used in this evaluation is a modified version of the standard ArcGIS vehicle routing problem tool, extended to incorporate CO₂ emissions. Two key extensions are necessary.

First, the ArcGIS VRP tool is designed to minimize one of two variables: time or distance. It also allows for a weighted combination of these two variables. While other tools in ArcGIS’s Network Analyst package allow the user to minimize on any available data element, the VRP tool is restricted to one time and one distance variable. Additional variables are not possible, thus limiting the ability of modeling all three variables of interest (time and distance [to determine cost], and emissions) within one system. In addition, due to the necessity of adhering to time windows, the time variable cannot be altered. The distance variable, however, can represent any numerical field labeled as such. By adding emissions information to the network before it was built, emissions could take the role of a distance in the optimization.

Financial cost is minimized by using the distance- and time-based cost parameters to combine distance and time into one cost objective. Second, because only two variables can be modeled at once, additional processing was required to track the third variable. To gather this data, the VRP output allowed simplification of the problem into a TSP and the output ordered and route-assigned stops could be run through the traditional Network Analyst Routing tool, recording the remaining variable.

3.2. Assumptions

Because this delivery service provider places a premium on service quality, all optimizations used hard time windows, guaranteeing that promised delivery times would be met.

Service times were developed based on the delivery type, delivery time (PreDawn or other), and the order size. The service time length directly affects how many customers can be served by one truck within the allowable window. Service times have fixed and variable components. The fixed component is lower during the PreDawn service window, and the variable component, which is associated with the number of bins in an order, is lower for Delivery Type A. The values used in this analysis are used by the case study service in their planning and are based on observed delivery times.

Customer orders are delivered in stackable plastic bins. These bins are picked up on subsequent orders. Because the bins nest when empty, they take up little space and are not considered in the capacity limits of the trucks. In addition, because the bins are returned by customers during their next order, no additional stops occur for pickup bins. This problem is therefore simplified to an urban delivery system, disregarding pickup.

The model does not consider real-time routing changes. It is a planning tool and is not intended to provide dynamic routing information. In addition, this model currently assumes uncongested conditions.

3.3. Data

3.3.1. Fleet information

The delivery service provider has a homogenous fleet, in terms of capacity and engine technology, of 17 vehicles. All of their trucks are less than three years old, all are diesel, and all are approximately 16' single-unit vehicles. The vehicles can carry 90 bins, approximately 30 customer orders, and spend 5 to 15 minutes servicing each customer. The customers are residences spread throughout the urban area and are served by one warehouse also located in the urban area.

3.3.2. Cost data

Actual costs associated with this delivery system are proprietary, therefore costs were developed using industry data. Costs were developed for each link in the network assuming average hourly wages of $26.55 for van, light duty, and heavy duty truck drivers in the Seattle metropolitan area according to Salary.com [19] and typical truck operating costs of $1.13 per mile (not including driver wages and benefits which are included above) provided by Trego and Murray [20]. These values were converted to costs per second and costs per foot for analysis.

3.3.3. Emissions factors

Emissions factors were obtained from the 2010 MOVES model [21]. This analysis assumed uncongested conditions, so speed limit data from the StreetMap North America data set was used as the default flow speed for each road segment. Since the trucks work with hot engines due to their short stopping time, only running exhaust emissions are tracked.

The base assumption in the model reflects the provider fleet and uses emissions factors for single-unit short haul trucks with diesel fuel. Emissions factors were also developed for three scenarios: hybrid vehicles, larger trucks, and smaller trucks. To develop emissions factors for hybrid trucks, the base emissions factors were reduced by 40% as suggested by an EPA white paper [22]. Emissions factors for large trucks were represented with factors for combination short-haul trucks with diesel fuel, and emissions factors for smaller trucks were represented with factors from light commercial trucks with diesel fuel.

Emission factors were selected for an analysis year of 2010. Hourly kilograms of CO₂ equivalents per mile were extracted and averaged over each hour of the day, for weekdays, throughout the year for the King County, Washington region. Roadways with speeds of 5, 20, 25, and 35 miles per hour used urban unrestricted roadway emissions factors, and roadways with speeds of 45 and 55 miles per hour used urban restricted roadway emissions factors. Since the case study fleet is comprised of modern vehicles of varying age, emissions factors for 2007–2010 model years were averaged.

3.3.4. Network data set

The base network is pulled from the ESRI StreetMap North America data set [23]. These files include geographically-accurate representations of the road network for North America, and include information regarding speed limit, functional class, street name, and street number range.

This data set was modified in a number of ways for this evaluation. First, the data set was trimmed to only include road segments in the study area to reduce processing time. Next, the length in feet of each road segment was calculated and appended to the data table. Finally, information regarding the CO₂ emissions associated with each road segment for each vehicle type was also appended to the data table, based on the MOVES emissions factors, the roadway speed limit, the roadway functional class, the roadway length, and the vehicle type.

3.3.5. Customer sample

A one-day customer sample was gathered from the case study delivery service. The data set reflects three service windows (PreDawn, Breakfast, and Lunch/Dinner) and includes 576 customers. The PreDawn sample includes 283 customers all served within one 3.5 hour time window between 2:30 AM and 6:00 AM. The Breakfast sample includes 140 customers and time windows from 7:00 AM until 1:00 PM, and the Lunch/Dinner sample includes 153 customers and time windows from 3:00 PM until 9:00 PM. The Breakfast service window includes one 3-hour time window, in which one third of its customers are served, and five 1-hour time windows. The Lunch/ Dinner service window includes two 3-hour time windows, in which...
60 percent of its customers are served; six 1-hour time windows; and one 2-hour time window.

Two types of deliveries occur (Delivery Type A and B), and service times vary according to this delivery type and the order size. Each customer’s address, time window, order size in bins, and delivery type was recorded.

3.4. Analysis scenarios

The delivery provider considered in this case study offers different delivery time windows to its customers. Given the constraints the different time windows impose on routing and scheduling, a primary focus of this evaluation is the potential emission reductions from changing the length of time windows. In addition, the model is used to examine the influence of customer density on emissions as well as the potential emissions reductions from modifying the fleet either to a newer fleet of cleaner trucks or by utilization of trucks with different capacity. Twelve scenarios in addition to the baseline were considered. Table 1 below illustrates the differences between the various scenarios. For each scenario, two different objective functions were minimized; cost (dollars) and emissions (kilograms of CO2). Currently, this provider assigns delivery vehicles in three shifts: PreDawn, Breakfast, and Lunch/Dinner. To replicate that baseline, initial optimizations were run for each of the three delivery shifts. An additional baseline (Scenario 1) was developed with the three shifts merged into one main file, to determine potential gains from redistribution of the time windows within the service windows. Scenarios 2–5 examine the impact of time windows; Scenarios 6–9 examine the impact of destination density; and Scenarios 10, 11, and 12 examine the impact of fleet modification.

The first analysis considers the influence of time windows on cost and emissions. Scenarios 2–5 consider the impact of time windows, and all orders were reassigned into 90-minute, 60-minute, 30-minute, and 15-minute time windows, respectively. Shorter time windows are more convenient for customers, therefore represent higher service quality, but are associated with higher costs and potentially higher emissions for the service provider. If service windows are extended, businesses have greater flexibility on route choice and delivery ordering (which can reduce vehicle miles traveled). The first scenario set enables agencies to consider timing restrictions for freight/delivery vehicles, and provides agencies insight about the costs to businesses of these policies. Some governmental agencies trying to balance delivery needs with quality of life issues and congestion concerns use prohibitions on the time of day certain size or classes of vehicles can access roadways or urban centers. By evaluating the impacts of limiting or extended permissible time windows, the first scenario set provides insight into the potential environmental and cost impacts of these types of restrictions.

A second set of scenarios examines the influence of service area on cost and emissions levels. Scenarios 6–9 considered the impact of density and included 50 percent, 33 percent, 25 percent, and 12.5 percent of the original number of orders, respectively. In these scenarios, the customers who are served continued to be provided with excellent service, but the potential customer base is reduced. Only providing service to dense neighborhoods may allow businesses to provide service at a reduced cost and emission level but may hamper their long-term growth potential. The second scenario set provides information about the residential densities that can support delivery service from cost and environmental perspectives. Similar to the Boston metro impositions on bike share, where the chosen vendor is required to serve the high-value and riskier communities, this evaluation can inform policies using delivery service to address food deserts by requiring complete city coverage.

Finally, a third evaluation compares the benefits from these earlier analyses with gains achieved by vehicle fleet modification. Scenarios 10, 11, and 12 consider the impact of alternative vehicles by adjusting the capacity, cost, and emissions factors representing hybrid, larger, and smaller vehicles. The hybrid vehicles were assumed to have the same capacity as the current fleet, but with more efficient engine technology. The larger vehicles were assumed to be two-thirds larger and carry 150 bins, while the smaller vehicles were assumed to be half the size of the existing fleet and carry 45 bins. Cleaner vehicles will likely be associated with reduced emissions, but at a higher cost. Larger vehicles may provide more efficient service, but require a capital investment and have higher externalities per vehicle. Smaller vehicles have less impact per vehicle but may require additional routes. The final scenario set allows evaluation of clean vehicle policies and policies that restrict the size or type of vehicle. Another way some governmental agencies balance

<table>
<thead>
<tr>
<th>Description</th>
<th>Service windows</th>
<th>Time windows</th>
<th>Density</th>
<th>Capacity (bins)</th>
<th>Cost</th>
<th>Emissions factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Baseline – predawn</td>
<td>Base Base</td>
<td>Base 90</td>
<td>Base</td>
<td>Moves: single unit short-haul truck</td>
<td></td>
</tr>
<tr>
<td>Scenario 1</td>
<td>New baseline</td>
<td>1</td>
<td>Base</td>
<td>Base 90</td>
<td>Base</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>1.5 h time windows</td>
<td>3</td>
<td>90 min</td>
<td>Base</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>1 h time windows</td>
<td>3</td>
<td>60 min</td>
<td>Base</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>30 min time windows</td>
<td>3</td>
<td>30 min</td>
<td>Base</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>15 min time windows</td>
<td>3</td>
<td>15 min</td>
<td>Base</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 6</td>
<td>50% customer density</td>
<td>3</td>
<td>Base</td>
<td>50%</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 7</td>
<td>33% customer density</td>
<td>3</td>
<td>Base</td>
<td>33%</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 8</td>
<td>25% customer density</td>
<td>3</td>
<td>Base</td>
<td>25%</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 9</td>
<td>12.5% customer density</td>
<td>3</td>
<td>Base</td>
<td>12.50%</td>
<td>90</td>
<td>Base</td>
</tr>
<tr>
<td>Scenario 10</td>
<td>Hybrid vehicle</td>
<td>3</td>
<td>Base</td>
<td>80% of Base</td>
<td>60% of Base</td>
<td>Moves: combo short-haul truck</td>
</tr>
<tr>
<td>Scenario 11</td>
<td>Larger vehicle</td>
<td>3</td>
<td>Base</td>
<td>150</td>
<td>Base</td>
<td>Moves: light commercial truck</td>
</tr>
<tr>
<td>Scenario 12</td>
<td>Smaller vehicle</td>
<td>3</td>
<td>Base</td>
<td>45</td>
<td>Base</td>
<td>Base</td>
</tr>
</tbody>
</table>
delivery needs with quality of life issues and congestion concerns use
prohibitions on the size or classes of vehicles can access roadways or
urban centers. This scenario set considers the cost and environmental
impacts of clean vehicle use or restrictions on vehicle size.

In addition to the policies targeted by each scenario, the baseline
evaluation (examining the sensitivity of cost and emissions as direct
trade-offs) informs the effectiveness of roadway tolling and carbon
taxes as incentives to change behavior. While the results of this type of
analysis are not presented here, these policies can be evaluated by
modifying the assumed costs for each link by time of day. Given the
close association between cost and CO2 emissions observed in the
results, roadway tolling and carbon taxes will further incent both
lower cost and lower emissions routing and scheduling choices.

The hourly costs were kept consistent for all scenarios, since they
reflect driver wages and benefits. The mileage costs were kept consistent
for all scenarios except the one that considers implementation of a
hybrid fleet. For this scenario, the ATRI fuel/oil costs and fuel tax costs
were reduced to reflect the 70% improvement in fuel economy reported
by the EPA[22] and leasing and maintenance costs were increased by
25% to reflect additional costs of owning and repairing hybrid vehicles. In
the end, the hybrid scenario assumed each mile of travel cost $0.91, a
reduction of approximately 20% over standard vehicles.

The scenarios included constraints to ensure work hour regulations
were not violated (8 hour limits on each truck), and the truck capacities
were not violated (90 bins using current vehicles). The provider
currently operates 17 trucks, and this limit was considered the upper
bound of the number of allowable vehicles. Table 2 illustrates the
number of orders and given or weighted average (denoted with an [a])
time windows for all scenarios. The weighted average time window is
given for all Breakfast and Lunch/Dinner scenarios that use the base time
window distribution and thus have a mixed set of time windows.

4. Results

4.1. Cost and emissions

The method described above allows an analysis of the relationship
between cost and emissions. Fig. 1 illustrates the relationship be-
 tween cost in dollars per order and kilograms of CO2 per order,
considering Scenario 2 through Scenario 9, along with the Baseline,
 grouped by scenario type (base, time window, density). As illustrated,
the cost per order increases between $3.15 and $3.77 for each addi-
tional kilogram of CO2 for each scenario type, with high r² values
(0.85 to 0.91). This relationship is very consistent within all of these
scenarios and illustrates the close relationship between monetary cost
and CO2 emissions.

This relationship is examined in comparison to the number of
orders and the time window length for each case in Fig. 2. Most of the
cases have dollars per kilogram of CO2 values between 0 and 5, with
no discernable relationship to the number of orders or the time
window size. Two outliers are observed, each with notably high
values of dollars per kilogram of CO2.

These two figures indicate a stable relationship between monetary
cost and CO2 emissions, with an average value of approximately $3.50
per kilogram of CO2. This value is a function of the fuel cost included in
the operating costs of trucks. As the cost of fuel increases or taxes are
added to carbon this value will also increase, but without significant
to the technology there will continue to be a linear
relationship between monetary cost and kilograms of CO2 produced.

4.2. Monetary and environmental costs of improved service

To quantify the relationship between service quality and monetary
and environmental cost, a multiple linear regression analysis was
performed and regression equations were developed considering time
window size, number of customers, and monetary cost or CO2 emissions.

Equation 1 illustrates how monetary cost depends on time windows
and number of orders for cases when the routes are designed to
minimize monetary cost. Equation 2 illustrates how monetary cost
depends on time windows and number of orders for cases when the

Table 2
Number of Orders and Weighted Average or Given Time Window Size.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of Orders</th>
<th>Time Window (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>283</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 1</td>
<td>283</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>283</td>
<td>90</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>283</td>
<td>60</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>283</td>
<td>30</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>283</td>
<td>15</td>
</tr>
<tr>
<td>Scenario 6</td>
<td>142</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 7</td>
<td>94</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 8</td>
<td>70</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 9</td>
<td>35</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 10</td>
<td>283</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 11</td>
<td>283</td>
<td>210</td>
</tr>
<tr>
<td>Scenario 12</td>
<td>283</td>
<td>210</td>
</tr>
</tbody>
</table>
routes are designed to minimize emissions. Equation 3 illustrates how emissions depend on time windows and number of orders for cases when the routes are designed to minimize emissions. Multiple linear regression indicates the coefficients for time window size and number of customers are significant at the 0.01 level with either dollars or emissions as the dependent variable for either of the two routing methods. The statistics for each analysis are shown below in Table 3 through Table 6.

Examining the coefficients and elasticities for the four equations indicate the number of orders is always slightly more in Table 3 through Table 6. 

Elasticity t value Pr (|t|) $r^2$ F N

| Estimate | St. Error | Elasticity | t value | Pr (|t|) | $r^2$ | F | N |
|----------|-----------|------------|---------|---------|-------|---|---|
| Intercept | 21.480 | 1.028 | 20.086 | 0.000 *** | 0.834 | 52.9 | 24 |
| Time Windows | -0.035 | 0.005 | -1.43 | -7.119 | 0.000 *** | |
| Number of Orders | -0.045 | 0.004 | -1.45 | -10.25 | 0.000 *** | |

Equation 1 Optimize Dollars, Calculate Dollars per order

$\delta = -0.035 \times (\tau) - 0.045 \times (\eta) + 21.48$

Equation 2 Optimize Emissions, Calculate Dollars per order

$\delta = -0.040 \times (\tau) - 0.050 \times (\eta) + 23.33$

Equation 3 Optimize Dollars, Calculate Emissions per order

$\xi = -0.010 \times (\tau) - 0.015 \times (\eta) + 7.11$

Equation 4 Optimize Emissions, Calculate Emissions per order

$\xi = -0.007 \times (\tau) - 0.013 \times (\eta) + 6.23$

with

$\tau$ time window in minutes,

$\eta$ number of orders,

$\delta$ dollars per order,

$\xi$ kg of CO$_2$ per order

Using these equations, the influence of customer density and time window length can be quantified. For example, the addition of 80

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Using these equations, the influence of customer density and time window length can be quantified. For example, the addition of 80
customers in this service area or extending the time window 100 minutes would save approximately $3.50 and 1 kilogram of CO2 per order.

Higher costs and higher emissions per order are associated with fewer orders and shorter time windows (see Figs. 3 and 4). These relationships between cost and emissions to order number and time window length parallel one another, resulting in the consistent cost per kilogram of CO2 noted above.

4.3. Influence of vehicle fleet

Finally, significant emissions and monetary cost reduction can be made by using hybrid vehicles. For all three service windows, the lowest emissions are observed in the cases with a hybrid fleet of the same capacity as the existing fleet. The routing for the fleet is the same in the base case and the hybrid case, but with the benefit of the

reduction in emissions and monetary costs associated with the hybrid vehicles. The more efficient routing enabled by larger trucks is more than offset by their higher emissions, resulting in net higher emissions than in the base case. The smaller vehicles yield improved emissions over the base case in some instances, but a 17-vehicle fleet of smaller trucks is not always able to serve the customer base. For the service windows with lower customer demand, smaller vehicles are more efficient than the existing fleet, but less efficient than the hybrid vehicles. For the service window with the largest demand (PreDawn) the smaller vehicles are only able to serve about 70% of the existing demand. A complete summary of the data is provided in Table 7.

5. Conclusion

This analysis has illustrated a number of key features of the emissions vehicle routing problem with time windows (EVRPTW).
First, the relationship between monetary cost and CO2 emissions is consistent between scenarios at approximately $3.50 per kilogram of CO2. These results indicate a direct relationship between monetary cost and emissions, and delivery providers who focus on low cost routing will generally also have low emissions. The results demonstrate there is not a trade-off between CO2 emissions and cost, but that these two metrics trend together. This suggests the most effective way to reduce cost, and therefore emissions.

The addition of 80 customers in this service area or extending the time window 100 minutes would save approximately $3.50 and 1 kilogram of CO2 per order. Strongly correlated with the monetary cost and emissions per order is not a trade-off between CO2 emissions and cost, but that these two metrics trend together. This suggests the most effective way to encourage fleet operators to limit emissions is to increase the cost of fuel or CO2 production, as this is consistent with current incentives that exist to reduce cost, and therefore emissions.

In addition, both customer density and time window length are strongly correlated with the monetary cost and emissions per order. The addition of 80 customers in this service area or extending the time window 100 minutes would save approximately $3.50 and 1 kilogram of CO2 per order.

Beyond providing insight into the trade-offs between costs, emissions, and service quality, these results can also inform delivery providers regarding the relative cost of various business decisions. The cost increases associated with a lower customer density can be offset through wider time windows. Delivery providers looking to expand their service area into less populated regions may be able to do so cost effectively by developing appropriately adjusted time windows. For example, a delivery provider with 90 minute time windows typically serving 100 customers, can serve 50 customers at the same cost if the time windows are increased to 155 minutes.

Lastly, the results from the evaluation of four different fleets illustrate significant environmental and monetary gains can be achieved through the use of hybrid vehicles. In addition, the optimal vehicle size for a given customer density and service quality is neither too big nor too small and must be carefully selected.

This analysis focused on modifications to the service parameters of one delivery provider. Greater differences between time windows and customer densities may illustrate more complexity in the relationships than observed here. In addition, this model currently assumes uncongested conditions. The addition of congestion will yield interesting results and is an important next extension. Despite these limitations, this evaluation provides a useful tool for establishing the trade-offs between cost, emissions, and service quality for an urban delivery system using the EVRPTW. This tool is suitable to evaluate the impact of spatial and temporal infrastructure restrictions, and the impact of time of day roadway tolls.

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**References**


