Vehicle Routing Problem for Emissions Minimization

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Environmental, social, and political pressures to limit the effects associated with greenhouse gas emissions are mounting. Little research has been done on reducing emissions as the primary objective of a routing problem despite the growth in use and impact of commercial vehicles. In the capacitated vehicle routing problem (VRP) with time windows, 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. New research focuses on a different problem: the minimization of emissions and fuel consumption as the primary or secondary objective. This creates the emissions VRP (EVRP). A formulation and solution approaches for the EVRP are presented. Decision variables and properties are stated and discussed. Results obtained with a proposed EVRP solution approach for different levels of congestion are compared and analyzed.

The fast rate of growth and the greater impact of commercial vehicle activity in recent years both further concerns about the cumulative effect of commercial vehicles in urban areas. Environmental, social, and political pressures to limit the effects associated with greenhouse gas (GHG) emissions and dependence on fossil fuels are mounting. A key challenge for public transportation agencies is to improve the efficiency of urban freight and commercial vehicle movements while ensuring environmental quality, livable communities, and economic growth.

Private companies are interested in reducing GHG emissions not only for marketing purposes, that is, for the favorable social perception of companies that are "greening" their operations, but also for economic reasons. The level of GHG emissions is a proxy for fuel consumption in diesel engines, and it is likely that in the near future GHG emissions will have a monetary cost. Under cap-and-trade system initiatives proposed by the U.S. government (and several state governments), emission costs will have a clear economic value, for example, carbon dioxide (CO_2) emissions in dollars per kilogram.

This research formulates, studies, and solves a new vehicle routing problem (VRP) in which the minimization of emissions and fuel consumption is the primary objective or is part of a generalized cost function. Departure times and travel speeds become decision variables. To the author's knowledge, there is no other research or formulation that minimizes vehicle emissions during design of routes in congested environments with time-dependent travel speeds, hard time windows, and capacity constraints. This creates a new type of VRP, the emissions vehicle routing problem (EVRP).

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BACKGROUND AND LITERATURE REVIEW

There is extensive literature related to vehicle emissions, and several laboratory and field methods are available for estimating vehicle emissions rates (*1*). Research indicates that CO_2 is the predominant transportation GHG and is emitted in direct proportion to fuel consumption, with a variation by type of fuel (*2*). For most vehicles, fuel consumption and the rate of CO_2 per mile traveled decrease as vehicle operating speed reaches approximately 55 or 65 mph and then begins to increase again (*2*); hence, the relationship between emission rates and travel speed is not linear.

Congestion has a great impact on vehicle emissions and fuel efficiency. In real driving conditions, there is a rapid nonlinear growth in emissions and fuel consumption as travel speeds fall below 30 mph (*3*). 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. Frequent changes in speed, as in stop-and-go traffic conditions, increase emission rates because fuel consumption is a function of not only speed but also acceleration rates (*4*). These results were obtained with an emission model and freeway sensor data in California and weighted on the basis of a typical light-duty fleet mix in 2005. The volume of emissions per mile is a function of the speed profile from the departure time until reaching destination.

In congested urban areas with significant speed changes due to recurrent congestion, such as predictable low speeds due to capacity constraints at peak hours, departure time must be considered in the design of EVRP routes. The time-dependent VRP (TDVRP) takes into account that links in a network have different costs or speeds during the day. Typically this is used to represent varying traffic conditions. The TDVRP was formulated by Malandraki and Daskin (*5*). Time-dependent models are significantly more complex and computationally demanding than are static VRP models; recent approaches to solving the TDVRP are reviewed elsewhere (*6–8*). An up-to-date and extensive TDVRP literature review is presented in another paper (*8*).

TDVRP instances are more data intensive than are static VRP instances, but their solution is likely to achieve environmental benefits in congested areas, albeit in an indirect way because emissions are not directly optimized (*9*). Other researchers conducted surveys indicating that emissions can be substantially reduced if companies improve the efficiency of routing operations (*10, 11*). Woensel et al. used queuing theory to model the impact of traffic congestion on emissions and recommended that private and public decision makers take into account the high impact of congestion on emissions (*12*). Goodchild and Sandoval discussed the factors that affect emissions in urban areas and potential solution methods, case studies, and public policy applications (*13*). However, no formulation, solution methods, or results are provided. To the author's knowledge, no published research deals with the formulation, properties, or solution approaches for the EVRP. The EVRP considered in this paper has time windows and capacity constraints as well as time-dependent travel times. The paper deals with a static problem, and the dispatcher is assumed to know the impact of recurrent congestion on travel speeds, that is, during morning and evening peak periods. For example, in a practical case, the dispatcher or carrier designs the routes the night before the route is serviced; the carrier is committed to visiting a specific set of costumers within a predetermined and hard time window.

NOTATION

By using a traditional flow-arc formulation (*14*), the EVRP with hard time windows and time-dependent speeds 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 $V = (v_0, \dots, v_{n+1})$. 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 $q_i \geq 0$, a service time $g_i \geq 0$, 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 $C = \{v_1, \dots, v_n\}$ 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 $d_{ij} \geq 0$ and a travel time $t_{ij}(b_i) \geq 0$, which is a function of the departure time from customer i. The set of available vehicles is denoted K. The cost per unit of route duration is denoted c_t, the cost per unit distance traveled is denoted c_d, the cost per unit of emission generated is denoted c_e, and the cost per vehicle is denoted c_k. The unit costs are finite and nonnegative real numbers.

EMISSION COSTS

Emission costs are proportional to the amount of GHG emitted, which is a function of travel speed and distance traveled. This research assumes a market value for 1 ton of CO_2; however, this approach may have limitations because it is difficult to estimate social, health, and environmental costs accurately (*15*).

To incorporate recurrent congestion effects and per standard practice in TDVRP models, the depot working time $[e_0, l_0]$ is partitioned into M time periods $\mathbf{T} = T^1, T^1, \dots, T^M$; each period T^m that belongs to the set T has an associated constant travel speed $0 \leq s^m$ in the time interval $T^m = [\underline{t}^m, \overline{t}^m]$. For each departure time b_i and each pair of customers i and j, a vehicle travels a nonempty set of speed intervals $S_{ij}(b_i) = \{s_{ij}^m(b_i), s_{ij}^{m+1}(b_i), \dots, s_{ij}^{m+p}(b_i)\}$, 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 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 $1 \leq m \leq m + p \leq M$.

For the sake of notational simplicity, the departure time will be dropped although 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 $D_{ij}(b_i) = \{d_{ij}^m, d_{ij}^{m+1}, \dots, d_{ij}^{m+p}\}$ and $T_{ij}(b_i) = \{t_{ij}^m, t_{ij}^{m+1}, \dots, t_{ij}^{m+p}\}$, respectively. The following conditions are necessary:

$$t_{ij}(b_i) = \sum_{l=0}^{l=p} t_{ij}^{m+l}$$

$$d_{ij} = \sum_{l=0}^{l=p} d_{ij}^{m+l}$$

$$d_{ij}^{m+l} = t_{ij}^{m+l} * s_{ij}^{m+l} \qquad \forall l \in \{0, 1, \dots, p\}$$

$$\underline{t}^m \leq t_{ij}^m = b_i \leq \overline{t}^m$$

$$\underline{t}^{m+p} \leq t_{ij}^{m+p} = a_j \leq \overline{t}^{m+p}$$

For heavy-duty vehicles, the U.K. Transport Research Laboratory has developed a function that links emissions and travel speeds (*16*):

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

The coefficients $\{\alpha_0, \alpha_1, \alpha_2, \alpha_3\} = \{1{,}576 ; -17.6 ; 0.00117 ; 36{,}067\}$ are constant parameters for each vehicle type, and for other vehicle types there may be other polynomial terms or their inverse (*16*). The optimal travel speed that minimizes emissions is assumed to be the speed s^*, which for Expression 1 has the value $s^* \approx 44$ mph or 71 km/h. Expression 1 outputs CO_2 emissions in kilograms per kilometer when the speed is expressed in kilometers per hour. As congestion increases, the amount and cost of emissions increase dramatically (*3*). Figure 1 reflects light utility vehicles in real-world conditions on California highways. The volume of emissions generated by traveling from customer i to customer j and departing at time b_i is denoted $v_{ij}(b_i)$:

$$v_{ij}(b_i) = \sum_{l=0}^{l=p} \left(\alpha_0 + \alpha_1 s_{ij}^l + \alpha_3 \left(s_{ij}^l\right)^3 + \alpha_4 \frac{1}{\left(s_{ij}^l\right)^2} \right) d_{ij}^l \tag{2}$$

Total emission costs for a departure time b_i is the product $c_e\, v_{ij}(b_i)$. Expression 2 provides a simple yet good approximation for real-world CO_2 emissions versus travel speed profiles. Finally, in the EVRP, the emission function can be tailored to the travel or path characteristics between any two customers i and j.

PROBLEM FORMULATION

Two formulations are presented. The first assumes a multiobjective function that includes the costs of vehicles, distance traveled, route durations, and emissions. The second formulation follows the more traditional hierarchical approach.

Formulations of the VRP have only one type of decision variable, x_{ij}^k. There are two decision variables in the EVRP formulation; x_{ij}^k is a binary decision variable that indicates whether vehicle k travels between customers i and j. The 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 $b_i = y_i^k + g_i$. The real variable y_i^k allows for waiting at customer i; service start time may not necessarily be the same as arrival time, formally:

$$\alpha_i + g_i \leq b_i = \sum_{j \in V} \sum_{k \in K} \left(y_i^k + g_i\right) x_{ij}^k \tag{3}$$

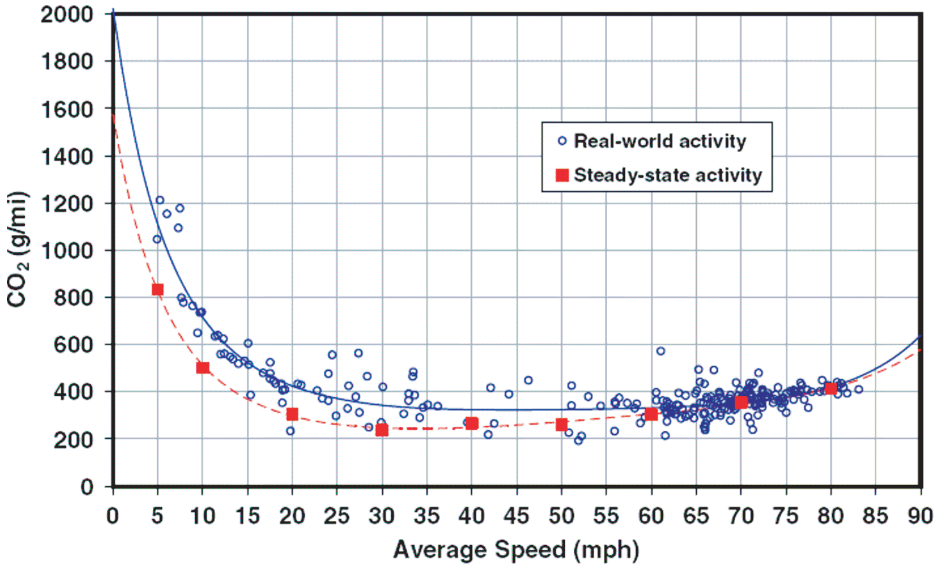

FIGURE 1 CO_2 emissions as function of average speed (*3*).

In addition, travel speed is a decision variable because the amount of emissions is a function of travel speed. However, under some mild assumptions, the EVRP problem can be simplified as analyzed in the section on solution approaches. It is assumed that vehicle engines are turned off while a customer is being served (service times are 0.5 h or longer); the emissions generated by a stop do not change because the total number of stops (customers) is constant. In this research, stopping after leaving a customer is not allowed.

Total Cost Minimization EVRP

minimize

$$\sum_{k\in K}\sum_{j\in C} c_k x^k_{0j} + c_d \sum_{k\in K}\sum_{(i,j)\in V} d_{ij} x^k_{ij} + c_t \sum_{k\in K}\sum_{j\in C}\left(y^k_{n+1} - y^k_0\right) x^k_{0j} + \sum_{k\in K}\sum_{(i,j)\in V} x^k_{ij} c_e v_{ij}\left(y^k_i + g_i\right) \quad (4)$$

subject to

$$\sum_{i\in C} q_i \sum_{j\in V} x^k_{ij} \le q_{\max} \qquad \forall k \in K \quad (5)$$

$$\sum_{k\in K}\sum_{j\in V} x^k_{ij} = 1 \qquad \forall i \in C \quad (6)$$

$$\sum_{i\in V} x^k_{il} - \sum_{i\in V} x^k_{lj} = 0 \qquad \forall l \in C, \forall k \in K \quad (7)$$

$$x^k_{i0} = 0, x^k_{n+1,i} = 0 \qquad \forall i \in V, \forall k \in K \quad (8)$$

$$\sum_{j\in V} x^k_{0j} = 1 \qquad \forall k \in K \quad (9)$$

$$\sum_{j\in V} x^k_{j,n+1} = 1 \qquad \forall k \in K \quad (10)$$

$$e_i \sum_{j\in V} x^k_{ij} \le y^k_i \qquad \forall i \in V, \forall k \in K \quad (11)$$

$$l_i \sum_{j\in V} x^k_{ij} \ge y^k_i \qquad \forall i \in V, \forall k \in K \quad (12)$$

$$x^k_{i,j}\left(y^k_i + g_i + t_{i,j}\left(y^k_i + g_i\right)\right) \le y^k_j \qquad \forall (i,j) \in A, \forall k \in K \quad (13)$$

$$x^k_{ij} \in \{0,1\} \qquad \forall (i,j) \in A, \forall k \in K \quad (14)$$

$$y^k_i \in \Re \qquad \forall i \in V, \forall k \in K \quad (15)$$

The constraints are defined as follows. Vehicle capacity cannot be exceeded (Constraint 5). All customers must be served (Constraint 6). If a vehicle arrives at a customer, it must also depart from that customer (Constraint 7). Routes must start and end at the depot (Constraint 8). Each vehicle leaves from and returns to the depot exactly once (Constraints 9 and 10, respectively). Service times must satisfy time window start (Constraint 11) and ending (Constraint 12) times. Service start time must allow for travel time between customers (Constraint 13). Decision variables type and domain are indicated in Constraints 14 and 15.

Partial Cost Minimization EVRP

In the capacitated VRP 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. This second formulation follows the traditional approach and allows for a partial reduction of potential emissions. The primary and secondary objectives are defined by Constraints 16 and 17, respectively. The tertiary objective is the minimization of distance traveled and route duration costs.

$$\text{minimize} \sum_{k\in K}\sum_{j\in C} x^k_{0j} \quad (16)$$

$$\text{minimize} \sum_{k\in K}\sum_{(i,j)\in V} x_{ij}^k c_e v_{ij}\left(y_i^k + g_i\right) \tag{17}$$

$$\text{minimize } c_d \sum_{k\in K}\sum_{(i,j)\in V} d_{ij}x_{ij}^k + c_t \sum_{k\in K}\sum_{j\in C}\left(y_{n+1}^k - y_0^k\right)x_{0j}^k \tag{18}$$

The same constraints, Constraints 5 through 15, apply to this hierarchical objective function.

SOLUTION APPROACHES FOR PARTIAL EVRP

The solution approach for the partial EVRP can benefit from the application of existing algorithms for the TDVRP. After a solution is found for the TDVRP, there are at least two alternative approaches: (*a*) the values of the x_{ij}^k decision variables are fixed and the volume of emissions is reduced by an algorithm that can alter only the departure times $b_i = y_i^k + g_i$, and (*b*) the volume of emissions is reduced by an algorithm that can alter both departure times $b_i = y_i^k + g_i$ and assignment variables x_{ij}^k subject to Constraint 19:

$$\sum_{k\in K}\sum_{j\in C} x_{0j}^k \le K^* \tag{19}$$

where K^* is the best fleet size solution obtained with a TDVRP algorithm.

Given that approach *a* is clearly suboptimal, this research focuses on the development of an algorithm that follows approach *b*. This section discusses properties of Emission Functions 1 and 2. These properties are useful for reducing the computation effort required to evaluate emission levels for the partial EVRP.

PROPERTIES OF EMISSION FUNCTION

Waiting at a customer location may be necessary to reduce emission costs; for example, waiting at a customer location may be beneficial during periods of high congestion and reduced travel speeds. However, waiting may have an impact on future travel times and reduce the capacity to serve subsequent customers in the route. For any given route *k* defined by the sequence of customers (0,1,2, . . . , *i*, *j*, . . . , *q*, *q* + 1), where 0 and *q* + 1 denote the depot, it is possible to define $\underline{y}_i^k$ and $\overline{y}_i^k$ for customer *i* where $\underline{y}_i^k$ and $\overline{y}_i^k$ are the earliest and latest feasible service times, respectively.

Property 1 states that it may be better to wait at a customer location if travel speeds are lower that a certain speed threshold.

The proof of Property 1 is as follows. Because of the last component of Emissions Function 1, it always possible to find a speed $s^m \ge 0$ such that the cost of emissions is larger than the cost of waiting but departing before or at $\overline{y}_i^k$. Emissions per unit of distance traveled increases as travel speeds approach zero, and there is a speed at time $\underline{y}_i^k$ where costs are reduced only if the vehicle waits at a customer location.

Property 2 states that for speeds below the optimal level s^* and strictly decreasing travel speeds in the union of intervals defined by $S_{ij}(\underline{y}_i^k + g_i)$ and $S_{ij}(\overline{y}_i^k + g_i)$, the departure time that minimizes emissions is given by $b_i = \underline{y}_i^k + g_i$.

The proof of Property 2 is as follows. Travel speeds are below optimal and strictly decreasing if

$$s > s^m \ge s^{m+1} \qquad \forall m \in S_{ij}\left(\underline{y}_i^k + g_i\right) \cup S_{ij}\left(\overline{y}_i^k + g_i\right)$$

Emission levels increase as speeds decrease from the optimal value. Given that Emissions Function 2 has a unique global minimum at *s*, delaying the departure time will only increase emission costs.

Property 3 states that for speeds below the optimal level *s* and strictly increasing travel speeds in the union of intervals defined by $S_{ij}(\underline{y}_i^k + g_i)$ and $S_{ij}(\overline{y}_i^k + g_i)$, the departure time that minimizes emissions is given by $b_i = \overline{y}_i^k + g_i$.

The proof of Property 3 is as follows. Travel speeds are below optimal and strictly increasing if

$$s^m < s^{m+1} < s \qquad \forall m \in S_{ij}\left(\underline{y}_i^k + g_i\right) \cup S_{ij}\left(\overline{y}_i^k + g_i\right)$$

Given that Emissions Function 2 has a unique global minimum at s^*, delaying the departure time will only decrease emission costs.

Similar mirror properties can be derived for speeds above the optimal level and strictly decreasing or increasing travel speeds.

Property 4 states that for arbitrary travel speeds in the union of intervals defined by $S_{ij}(\underline{y}_i^k + g_i) \cup S_{ij}(\overline{y}_i^k + g_i)$ and no stops between customers *i*, *j*, the departure time that minimizes emissions can be found following a comparison of a finite number of departure times. The number of comparisons is less than or at most equal to two times the number of time intervals that define $S_{ij}(\underline{y}_i^k + g_i) \cup S_{ij}(\overline{y}_i^k + g_i)$.

The proof of Property 4 is as follows. Travel speeds and their intensity of emissions are constant during each time interval. Without stops, for any given departure time, the emissions function is a strictly increasing function of travel time duration, and the extremes can be found either for departures that coincide with the beginning of time intervals or for departures that result in arrivals at the end of time intervals. Hence, it is sufficient to check the level of emissions for departure times that coincide with the beginning of each time period or for departure times that bring customer *j* to the end of a time period.

ALGORITHM FOR PARTIAL EVRP

A strategy for solving the partial EVRP is first to minimize the number of vehicles by using a TDVRP algorithm and then to optimize emissions subject to a fleet size constraint. A description of the TDVRP algorithm used in this experiment along with a full problem statement is described in detail elsewhere (*8*). This iterated route construction and improvement (IRCI) approach has been successfully applied to VRP problems with soft time windows (*17*). The IRCI algorithm consists of a route construction phase and a route improvement phase, each utilizing two separate algorithms. During route construction, the auxiliary routing algorithm $\mathbf{H}_r$ determines feasible routes with the construction algorithm $\mathbf{H}_c$ assigning customers and sequencing the routes by using a greedy heuristic to approximate the cost of adding customers to a route. Route improvement is performed with the route improvement algorithm $\mathbf{H}_i$, which groups underutilized routes or routes with a low number of customers looking to consolidate customers into a set of improved routes.

Optimization of Departure Times

An algorithm was derived in the section on solution approaches to optimize the departure time between any given customers *i*, *j* and an initial condition, that is, a_i the arrival time at customer *i*. Let $\mathbf{H}_b(i, j, a_i)$ be the algorithm that optimizes the departure time for any pair of customer and initial condition.

Before $\mathbf{H}_b(i, j, a_i)$ is defined, it is necessary to define an auxiliary function with which to calculate backward travel time $\text{bt}(y_j^k)$:

Data:

$\mathbf{T}$ and S = time intervals and speed

v_i, v_j, y_j = two customers served in this order in route k, y_j^k is the current service time at customer j

START $\text{bt}\left(y_j^k\right)$

if $y_j^k < l_j \; \& \; y_j^k < \overline{y}_j^k$ **then**

$\qquad y_j^k \leftarrow \min\left(l_j, \overline{y}_j^k\right)$

end if

find $k, t_{\underline{k}} \le y_j^k \le t_{\overline{k}}$

$b_i \leftarrow y_j^k - d_{ji}/s_k$

$d \leftarrow d_{ji}, t \leftarrow y_j^k$

while $b_i < t_{\underline{k}}$ **do**

$\qquad d \leftarrow d - \left(t - t_{\underline{k}}\right)s_k$

$\qquad t \leftarrow t_{\underline{k}}$

$\qquad b_i \leftarrow t - d/s_{k+1}$

$\qquad k \leftarrow k+1$

end while

$\overline{y}_i^k \leftarrow \min\left(b_i - g_i, l\right)$

Output:

$y_j^k, \overline{y}_i^k$

END $\text{bt}\left(y_j^k\right)$

The algorithm $\mathbf{H}_b(i, j, a_i)$ is defined as follows:

1. For customer i in a route the earliest and latest feasible service times $\underline{y}_i^k$ and $\overline{y}_i^k$ are found using $\underline{y}_i^k = \min(e_i, a_i)$ and $\overline{y}_i^k = \text{bt}(y_j^k)$.
2. For customer i define the union of intervals defined by $S_{ij}(\underline{y}_i^k + g_i) \cup S_{ij}(\overline{y}_i^k)$ as the intervals of time needed to cover the periods of time between $(\underline{y}_i^k + g_i, \overline{y}_i^k)$. The times periods that cover the ordered pair of times $[x, y]$ is denoted $\{T(x, y)\}$ and is constructed as follows: for each $T^m \in \mathbf{T}$ add a time period to $\{T(x, y)\}$:
   - if $x \le \underline{t}^m, \overline{t}^m \le y$, then $T^m \in \{T(x, y)\}$, or
   - if $\underline{t}^m < x, y \le \overline{t}^m$, then $\{x, \overline{t}^m\} \in \{T(x, y)\}$, or
   - if $x \le \underline{t}^m, y < \overline{t}^m$, then $\{\underline{t}^m, y\} \in \{T(x, y)\}$.
3. Define: $\min \leftarrow v_{ij}(b_i = \underline{y}_i^k)$, $b_i^* = b_i$
   - For each period of time $T^m \in \{T(\underline{y}_i^k + g_i, \overline{y}_i^k)\}$ calculate $v_{ij}(b_i = \underline{t}^m)$
     – if $v_{ij}(b_i = \underline{t}^m) \le \min$
     then $\min \leftarrow v_{ij}(b_i = \underline{t}^m)$, $b_i^* = b_i$
   - For each period of time $T^m \in \{T(\underline{y}_i^k + g_i, \overline{y}_i^k)\}$ calculate $v_{ij}(b_i = \text{bf}(\overline{t}^m))$
     – if $v_{ij}(b_i = \text{bf}(\overline{t}^m)) \le \min$
     then $\min \leftarrow v_{ij}(b_i = \text{bf}(\overline{t}^m))$, $b_i^* = b_i$
4. Return best departure time b_i^* and emissions costs "min"

Hence, departure times can be optimized given any pair of feasible customers.

Improvement of Emissions Costs by Changing Routes

An algorithm has been derived to optimize the departure time between any given. Emissions are further reduced by adapting a heuristic approach developed by Kontoravdis and Bard using a greedy randomized adaptive search concept (GRASP) for the VRPTW (*18*). The improvement approach combines the construction phase proposed by Figliozzi with GRASP (*17*).

The pseudocode can be summarized as follows:

- Select any two routes and join the customers into a set C'.
  – Choose from C' two customers i_1 and i_2 that are the most time constrained.
  – $C' \leftarrow C'/\{i_1, i_2\}$
  – Initialize two routes r_1 and r_2 by selecting i_1 and i_2 as the first customers, respectively.
  – Do until no $i \in C'$ can be feasibly inserted into r_1 or r_2, for each $i \in C'$
  1. Find the best feasible insertion location into r_1 and r_2 [the feasible insertion with minimum emissions cost given by $\mathbf{H}_b(i, j, a_i)$].
  2. Insert the minimum emissions cost customers into r_1 or r_2.
  – Complete the routes using a greedy approach (minimizing emissions), calculate insertion costs using $\mathbf{H}_b(i, j, a_i)$.
  3. After a customer is inserted, try to insert any unrouted customer into r_1 or r_2.
  – Evaluate if there is an improvement in the total volume of emissions without exceeding the original number of routes.
  – Tabu the previously selected customers and pick a pair of not-yet-selected routes.
  – Continue until there are no more unselected pairs.

EXPERIMENTAL RESULTS

The experimental setting is based on the classical instances of the VRPTW proposed by Solomon (*19*). The Solomon instances include distinct spatial customer distributions, vehicle capacities, customer demands, and customer time windows. These problems have been widely studied in the operations research literature and the data sets 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: 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 do problem sets R2, C2, and RC2, respectively.

This section proposes new test problems that capture the typical speed variations of congested urban settings. The problems are divided into three categories of study: uncongested, somewhat congested, and congested. The depot working time $[e_0, l_0]$ is divided into five time periods of equal duration: $[0, 0.2l_0]$, $[0.2l_0, 0.4l_0]$, $[0.4l_0, 0.6l_0]$, $[0.6l_0, 0.8l_0]$, and $[0.8l_0, l_0]$, and the corresponding travel speeds are in the three cases as follows:

$$\text{uncongested} = \left[2.00, 2.00, 2.00, 2.00, 2.00\right]$$

TABLE 1 Somewhat Congested Versus Uncongested: Travel Times

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicle	10	17	0	0	7	10
Distance	2	0	−7	−4	0	−2
Duration	28	25	18	23	25	24
Emissions	12	−4	−2	0	13	19

$$\text{somewhat congested} = [2.00, 1.25, 2.00, 1.25, 2.00]$$

$$\text{congested} = [2.00, 0.90, 1.20, 0.90, 2.00]$$

It is assumed that the optimal travel speed, that is, 44 mph, is equivalent to a speed of 2.0 in the Solomon problems. This assumption ensures that the properties stated in the section on solution approaches are valid and applicable. This is a mild assumption in congested urban areas with low travel speeds and low speed limits. For example, the commercial vehicle maximum travel speed on the urban Interstate freeways in Portland, Oregon, is only 55 mph.

The average results per routing class are presented in Tables 1 and 2. Table 1 compares the somewhat-congested and uncongested cases. In all cases, the percentage change assumes the uncongested situation as a base. For example, a positive percentage in the row of routes (or emissions levels) indicates that the average number of needed routes (or emissions levels) has increased.

Table 1 shows that emissions do not increase across the board. Types C1 and C2 are constrained by capacity and register a small change in emissions. In addition, the customers are clustered. Types RC1 and RC2 register the greatest changes in emissions levels as travel speed decreases. The greatest change in average fleet size takes place with the R1 and R2 types. As expected, duration or travel time increases across the board.

Table 2 compares the congested and uncongested cases. In all cases, the percentage change assumes the uncongested situation as a base. As expected, duration increases across the board. Table 2 shows that emissions do not increase across the board. Types C1 and C2 are constrained by capacity and register a small change in emissions. A similar pattern is observed but RC2 problems do not register an increase in emissions.

These results highlight that changes in emissions are a function of problem type. It is clear that uncongested travel speeds tend to reduce emissions on average; however, this is not always the case, and in some cases the opposite trend can be observed. Further research is needed into alternative algorithms for minimizing emissions in congested areas, because this research is limited to exploring changes for distinct levels of congestion.

TABLE 2 Percentage Change, Congested Versus Uncongested Travel Times

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicle	27	38	0	0	22	29
Distance	4	5	−11	−10	3	0
Duration	60	68	52	35	57	60
Emissions	26	25	6	0	30	0

TABLE 3 Unconstrained Number of Routes: Percentage Change, Congested Versus Uncongested Travel Times

	R1 (%)	R2 (%)	C1 (%)	C2 (%)	RC1 (%)	RC2 (%)
Vehicle	29	42	0	0	26	29
Distance	12	24	0	7	7	17
Duration	73	97	59	59	63	85
Emissions	22	−27	4	−7	28	−11

If the objective function is to minimize emissions and lift the constraint that restricts any increase in the number of routes, the results are encouraging. Table 3 shows that relatively small increases in fleet size lead to dramatic reductions in emissions levels, for example, R2 problems. Minor reductions are obtained for problems R1 and RC1. In some cases, the reductions take place even when the same number of vehicles on average is maintained, for example in C1, C2, and RC2 problems. These preliminary results indicate that there may be significant emissions savings if commercial vehicles are routed by taking emissions into consideration.

CONCLUSIONS

This research introduced a new kind of VRPTW, the EVRP. Two variants of the problem were formulated. Properties of the emissions formula and optimal departure times were given. A heuristic was proposed to reduce the level of emissions given a number of feasible routes for the time-dependent VRPTW.

These preliminary results indicate that there may be significant emissions savings if emissions are considered during routing of commercial vehicles. In congested areas, it may be possible to reduce unhealthy or GHG emissions with a minimal or null increase in routing costs. However, these benefits are not to be expected across the board. The results indicate that congestion effects on emission levels are not uniform. Route characteristics and dominant constraint type appear to play a significant role in emissions levels.

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