IMPACT OF CAP-AND-TRADE VS. CARBON TAX POLICY ON VEHICLE ROUTING

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Introduction

Global warming, a result of pollution and greenhouse gas (GHG) emissions, has become a major concern over the last decade. In Canada, GHG emission ns increased by 31% between 1990 and 2005 (Environment Canada, 2013). In 2011, transportation was responsible for 24% of the total GHGs (ibid.). Therefore, Ontario, along with other provinces, started setting GHG reduction targets to help fight climate change. Ontario, B.C., Quebec, and Manitoba are also members of the Western Climate Initiative (WCI), a collaboration that has the objective of tackling climate change at a regional level (WCI, 2014). Ontario’s target is to reduce its GHGs by 15% below 1990 levels by 2020 (Ministry of the Environment of Ontario, 2009). The government plans to achieve these goals through a set of programs affecting households and industries. Examples of previous and current land use and transportation related plans are: the Green Commercial Vehicle Program (GCVP), Metrolinx’s The Big Move, MoveOntario2020, and carbon pricing. As a result of the policies along with improvements in vehicle and fuel technologies, GHG emissions in Canada decreased to 5.1% between 2005 and 2012 (Environment Canada, 2013). However, it is estimated that in Ontario, current strategies can reduce GHGs to within 60% of the 2020 set targets (Miller, 2013; Ministry of the Environment of Ontario, 2013). Therefore, other strategies are still required to close this gap.

Transportation is the largest contributor to Ontario’s total GHG emissions, responsible for approximately one third of GHG emissions (Miller, 2013). GHG emissions in the transportation sector can be reduced through improvements in 1) vehicle engine and fuel efficiency 2) carbon content of the fuel; 3) using alternative modes of transportation; 4) system operations (e.g. assigning traffic in a way to ensure smoother traffic flow and educating drivers to drive more efficiently). This paper focuses on the last component for the case of fleet vehicle routing.

Until recently, most vehicle routing problems (VRP) were solved to find routes that would generally minimize distance, or time. However, increasing concerns about the external costs of transportation (such as emissions) from governments and customers are forcing companies to consider "greening" their operations by considering their fleet GHG emissions and thus attempting to solve the routing problem with more complex objectives. In this paper, the green vehicle routing problem (GVRP), a relatively new extension of the VRP, will be utilized for this purpose. The problem will be formulated for a firm that is assumed to have rich information about the emissions costs through the use of simulated driving cycles obtained from previous research (Amirjamshidi and Roorda, 2015). The objective of this paper is to investigate the differences and assert their statistical meaningfulness when routing vehicles to optimize total distance, time and emissions. The paper compares the effects of carbon taxes and cap-and-trade, the most widely used policies in carbon pricing.

The paper is organized as follows. The next section introduces the study area, link-specific emission factors, and range of demand for customers in the network. The problem formulation incorporating time, distance, and emissions is then presented, followed by the formulation under the cap and trade policy. Results of the study for single optimization scenarios, the carbon taxing and the cap and trade policy are then reported, followed by conclusions and recommendations for future research.

Toronto Case Study

The study area (Figure 1) includes the Toronto financial district and the eastern part of the Toronto Waterfront. The routing was solved for a hypothetical case of beverage trucks, assuming one depot and random customers with random demands. Initial assumptions of the problem are: 1) node 0 is the depot for all cases (shown with a star in Figure 1); and 2) ten nodes are randomly selected as customer nodes in each run (representing 20% of possible customer nodes).

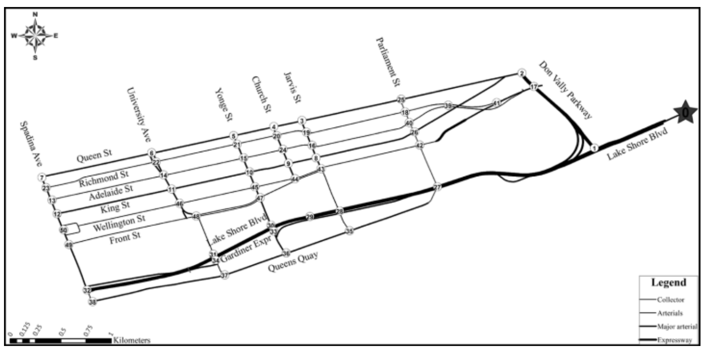

Figure 1- Study Area Network used for the Vehicle Routing Problem

Emission factors vary across cities due to each city's unique topography and road driving behaviour and they have been shown to vary by vehicle type, time of day and type of road (Saleh et al., 2009; Wang et al., 2008). For this reason, the links in the study area were categorized into the following five groups based on their speed limits and driving behaviours: Freeway, Lake Shore Blvd., University Avenue, major arterial, and major arterial with streetcars.

Table 1 shows the estimated CO_2-eq of the three major GHGs for heavy duty diesel trucks on the five road categories in the network using MOVES2010b. The emission factors were based on simulated driving cycles for the AM peak (8:00 -9:00 am) developed for each road category using data from a calibrated traffic microsimulation model. Detailed information about the calibration and development of the driving cycles can be found in Amirjamshidi (2015). Average speed calculated from the microsimulation to reflect road conditions in the morning peak are also presented in this table.

Table 1- Average Speed, and Emission Factor by Road Type

	CO_2-eq EF (gr/km)	Average speed (kph)
Freeway	1189.70	41.0
Lake Shore Blvd.	1676.03	28.5
University Ave.	2404.95	12.4
Major arterial	2112.23	16.6
Major arterial with transit	1972.07	16.9

Customer Demands

Customer demands are generated randomly using a discrete uniform distribution. To gather information, a Metro store, a Loblaws store and a Mac's Milk store were visited to determine reasonable minimum and maximum demands for customers. Based on the gathered information, the following assumptions are made in the GVRP problem.

- Weight of 1 unit of demand is set to 4.7 kg (weight of a box);
- Capacity of the truck is set to 4335 units (maximum number of boxes that can fit in a standard 20 ft. container);
- The minimum and maximum values of demand per customer was set to:
    - Minimum demand = 1 box
    - Maximum demand = 1000 boxes (double the maximum demand reported by the stores).

Problem Formulation Incorporating Time, Distance, Emissions, and the Effect of Load on Emission

This paper focuses on the green vehicle routing problem (GVRP), a relatively new extension of the basic capacitated vehicle routing problem (CVRP). However, the formulation is extensible and may be modified to incorporate other extensions of the VRP, such as time windows, dynamic travel times, and heterogeneous fleets. The formulation assumes one depot, multiple vehicles of the same class, and a set of customers with known demands.

Let G= (V, A) be a graph where V={V_0 ,V_1 ,…,V_{n-1} ,V_n} is the vertex set and the set of arcs A={(i,j)|V_i,$V_j \in$ V, i≠j}. Vertex V_0 is the depot, and V_1 to V_n are customer nodes. q_i is the demand for customer (i); and d_{ij}, t_{ij}, and e_{ij} represent the distance, time, and emission of travelling from customer i to j, respectively. The formulation assumes that there are K identical vehicles available at the depot that can be used to deliver goods to customers, each with capacity Q (Q and q_i are of the same unit).
The basic VRP formulation for a drop-off CVRP is shown below.

$$\text{Min} \sum_i \sum_j [C_d d_{ij} x_{ij} + C_t t_{ij} x_{ij} + C_e e_{ij} x_{ij} + 0.017173 C_e e_{ij} (f_{ij} - P_{avg} x_{ij})] \quad (1)$$

s.t.

$$\sum_{V_i \in V} x_{ij} = 1 \qquad \forall V_j \in V \backslash \{V_0\} \quad (2)$$

$$\sum_{V_j \in V} x_{ij} = 1 \qquad \forall V_i \in V \backslash \{V_0\} \quad (3)$$

$$q_j x_{ij} \le f_{ij} \le (Q - q_i) x_{ij} \qquad \forall (i,j) \epsilon A \quad (4)$$

$$\sum_{V_j \epsilon V} f_{ji} - \sum_{V_j \epsilon V} f_{ij} = q_i \qquad \forall V_i \epsilon V \backslash \{V_0\} \quad (5)$$

$$\sum_{V_j \epsilon V} x_{0j} = \sum_{V_i \epsilon V} x_{i0} \le \text{K} \quad (6)$$

$$\sum_{V_i \in S} \sum_{V_j \in S} x_{ij} \le |S| - 1 \qquad \forall S \subseteq V \backslash \{V_0\}, |S| \ge 2 \quad (7)$$

$$x_{ij} = 0,1 \quad f_{ij} \ge 0 \ \ \forall i,j \quad (8)$$

Where:
x_{ij}= binary variable equal to 1 if vehicle leaving node i, will visit node j next and 0 otherwise

f_{ij}= load of the vehicle travelling from customer i to customer j
P_{avg}= average payload for class 8 trucks (approximately 9 tons based on data reported by the USEPA SmartWay program, and the 2002 US Census bureau Vehicle Inventory Use Survey (VIUS)
S= any subset of customers not including the depot

The objective function (1) represents the generalized cost of the fleet, which is the sum of the total distance, time, and emissions (incorporating the effect of the truck's load) multiplied by their unit costs (C_d, C_t and C_e). Values for these coefficients used in this research are based on available literature and shown in Table 2. Constraints (2) and (3) assure that each customer is visited only once, and that a vehicle arriving at a node leaves that node, unless it is the depot. Constraint (4) guarantees that customers i and j can only be serviced by the same vehicle if the required load for the vehicle does not exceed its capacity. Constraint (4) also guarantees that if customers i and j are not visited by the same vehicle (x_{ij}=0), then f_{ij}=0. Constraint (5) enforces the conservation of flow on each node. Constraint (6) assures that any vehicle leaving the depot will return to the depot, and that the total number of vehicles should be equal to or less than the maximum number of available vehicles, K. The basic formulation does not include a fleet optimization component. Therefore, K is assumed to be unlimited. Finally, constraint (7) is the sub-tour elimination constraint. This constraint requires that, for any subset of customers S, the number of links travelled between the nodes in S (represented by $\sum\sum x_{ij}$) be less than or equal to the number of customers in S minus 1. This guarantees that no tours will be generated that do not include the depot.

Table 2- Monetary Costs

Monetary Cost	Value
C_d	0.71 \$/km
C_t	20.0 \$/hr
C_e	between 10-350 \$/tonCO_2-eq

Formulation of the VRP with Cap-and-Trade

Cap and trade policies are those that seek to impose limits on the total emission that is generated within a sector (Ministry of the Environment of Ontario, 2009; WCI, 2008). The legislative entity – usually the government – defines a limit for emissions. The licence to emit greenhouse gasses is then auctioned or otherwise allocated to the companies within a sector. The companies can then trade their unused emission capacity with each other. The fundamental ideology driving this policy is that it encourages research towards better technologies as a result of competition (WCI, 2014). The companies emitting larger amounts of greenhouse gasses as a result of older technologies would have to pay more to buy the unused capacity of those with better technologies, making their products less competitive (ibid). From the policymakers' perspective, the advantage of cap and trade is that the limit of emissions can be directly controlled. In taxing emissions, the control is indirect and it may be difficult to ascertain what the total amount of emissions will be.

In this section, the GVRP model presented in section 3 will be augmented to incorporate the effects of a cap and trade policy. As mentioned above, the cap and trade policy would result in a market (that may or may not be regulated by the policymaker) with variable pricing for emission capacity over time. The main focus of this research is on better analysis and optimization of emissions. Analysis of the cap and trade market dynamics is beyond the scope of this work and would require additional business insight. As a result, several simplifying assumptions have been made in constructing the model:

1- The initial selling price of the emission capacity is assumed to be somewhere within the range of values in Table 2. This assumption is justifiable as values outside this range would affect the entire transportation market to the point that existing business models would no longer be viable.
2- The price of the licence for emitting a tonne equivalent of CO_2 of greenhouses is assumed to be in the range of 0.1 to 10 times the

initial purchase price. Changes in price beyond this range would signify an unstable market and it has been suggested that in such cases the policymaker would introduce spare capacity to regulate the market (WCI, 2014). Similar to Kown et al (2013), it is further assumed that the trading price of carbon remains constant and is known in advance during the modelling horizon because dynamic price models would require intimate knowledge of the market.

The actions of a company in the cap and trade scenario can be considered under two circumstances: when the company has initially bought excess allowance and will sell this excess in the market – henceforth called the selling scenario – and when the company has not bought sufficient allowance and would require to top-up by buying excess allowance from another company – henceforth called the buying scenario.

The goal of the optimization model would be to minimise the total cost. The cost in the selling scenario can be modelled as

$$C_t = C_{distance} + C_{time} + C_{allowance} - R_{selling} \quad (9)$$

Where $C_{distance}$ is the total cost associated with the distance that the vehicles travel, C_{time} the total cost that is associated with the time that the vehicles travel, $C_{allowance}$ the money that the company spends initially on buying the allowance and $R_{selling}$ the revenue that the company generates by selling excess allowance. If the unit cost of carbon in the trading market is C_e, then the revenue would be:

$$R_{selling} = C_e(EL - TE) \quad (10)$$

Where TE is the total emissions and EL the emission allowance that the company initially purchases. For the buying scenario the total cost is

$$\mathrm{C_t} = C_{distance} + C_{time} + C_{allowance} + C_{buying} \quad (11)$$

where C_{buying} is the cost of buying the necessary top up carbon emission allowance. This cost is

$$C_{buying} = C_e(TE - EL) \quad (12)$$

As $C_{buying} = -R_{selling}$ the overall objective of the optimization would be

$$\mathrm{C_t} = C_{distance} + C_{time} + C_{allowance} + C_e(TE - EL) \quad (13)$$

The cost associated with distance and time is the same as the previous model and the cost of initial allowance is

$$C_{allowance} = kEL \qquad (14)$$

where k is the initial cost of unit of carbon. The total cost can thus be written as

$$\mathrm{C_t} = C_{distance} + C_{time} + C_e TE + (k - C_e)EL \qquad (15)$$

Assuming that there is a limit to the allowance that the company can initially purchase (L), the following constraint should be added to the model:

$$0 \leq EL \leq L \qquad (16)$$

The first three elements of the objective function are identical to carbon taxing, albeit with a different C_e. The behaviour of the final element of the objective function in relation with constraint (16) is trivial: if $(k > C_e)$ then 0 will be chosen for EL as the minimum value and if $(k < C_e)$ then the maximum allowable value for EL will be chosen (L).

From this formulation it is evident that from an optimization point of view, the route selection will be identical to the case of carbon taxing. The important difference is that due to the fact that the price of carbon is determined in the trading market and does not have to be explicitly set by the legislators, there would be a potential for much wider range of prices.

Results

IBM ILOG CPLEX Optimization Studio was selected for solving the GVRP since it provides exact solution methods and is considered to be among the state-of-the-art efficient optimization toolkits widely used in the literature. Demand preparation for all runs involves generating the demand matrix for each simulation (each optimization criteria is simulated 1000 times). For each run 20% of the nodes are selected randomly as customers. Each customer is then assigned a random demand value using Monte Carlo simulation with a discrete uniform distribution on the interval [1, 1000].

Results: Distance vs. Time vs. Emission Optimal

The optimization problem with the objective function presented in equation (1) was initially solved for the following 3 optimization criteria:

1. Distance-optimal: where coefficients C_d, C_t, and C_e are (1,0,0) respectively,
2. Time-optimal: where the coefficient vector is (0,1,0),
3. Emission-optimal: where the coefficient vector is (0,0,1).

Table 3 summarizes the results for the case where the objective is to minimize distance, time, or emissions. Statistical analysis confirmed that the percent differences in total distance travelled, driving time, and CO_2-eq emitted are the result of different minimization criteria is statistically significant with 95% confidence. In other words, these values are not just the result of random simulations.

Table 3 shows that compared to the distance-optimal solution, the emission-optimal solution produced an average emissions reduction of 12.8%, with an average increase of 2.1% in total distance. A similar analysis between the emission-optimal and time-optimal problem shows an average emission reduction of 1.8% with an increase of 0.9% in total driving time.

Table 3- Percentage Difference in the Total Distance, Time, and Emissions Compared to the Optimal Case

Optimization Criteria	Total Distance	Total time	Total CO_2-Eq
Distance-optimal		5.3%	12.8%
Time-optimal	2.5%		1.8%
Emission-optimal	2.1%	0.9%	

Results with the Carbon Tax Policy

This section summarizes the results of the objective function incorporating the monetary costs of distance, time, and emissions presented in Table 2, henceforth referred to as the cost-optimal problem. In other words, the cost-optimal problem analyzes the case where the objective is to reduce the total cost of operating a fleet under the carbon tax policy.
The following observations can be made:

- The maximum emission reduction possible is 1.2% which occurs at the maximum value for C_e;
- With the maximum emissions reduction, total travel distance and time increase by only 0.1% ;
- If C_e is set to \$30 (which is approximately what the Government of Canada and most of the studies have recommended), emissions would decrease by 0.5% with almost no change in total distance and time;
- If C_e is set to \$150 (which is used by the European Union Emissions Trading System), emissions would decrease by 0.90% with an increase of 0.06% and 0.01% in total travel distance and time, respectively.

The results of this section for implementing a carbon tax on GHG emissions show that this policy, alone, has potential to slightly help provinces reach their targets on the assumption that commercial vehicle operators will act to reduce total costs.

Results with the Cap-and-Trade Policy

In order to assess the effect of the market price on the total emissions, the model presented in section 3 is optimized with the wider cost range from \$10 to \$3500 per tonne. The results are shown in Figure 2. As observed in the graph, beyond the initial low prices, the sensitivity of emissions to the unit cost of carbon in the market is very low when the total cost is optimized. This shows that the initial assumption of the known price of carbon is valid as changes in the price beyond

$350 decrease emissions by less than 0.6% signifying that the majority of the routes remain consistent.

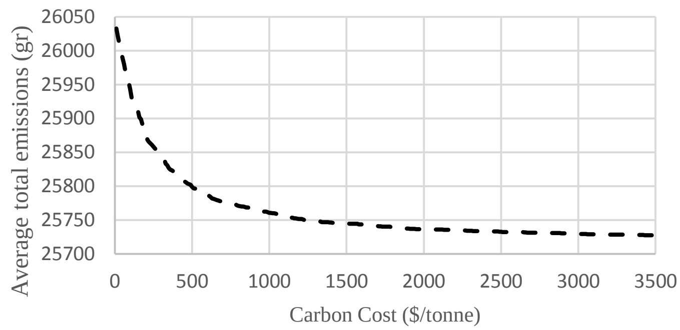

Figure 2- The Effect of Market Price of Carbon on Emissions in the Cap-and-Trade Policy

The low sensitivity shows that the higher emission costs that could result from the cap and trade scenario would not affect route choices. As a result, whilst the costs increase, the emissions do not decrease substantially. Considering commercial vehicle routing alone, cap and trade would not further reduce transportation carbon emissions when compared to carbon tax.

Conclusions

In this paper a green vehicle routing problem was formulated and solved for a hypothetical beverage delivery company to optimize their costs under cap and trade and carbon tax policies to assess their effects on emissions and costs incurred by the companies.

In compiling the simplified test case, the following limitations resulted from limited availability of data:

- The ranges for demands, truck capacities and the product dimensions are selected according to approximations based on limited data. In a real delivery scenario these figures could deviate from the assumed numbers.
- The location of the depot was assumed to be on a corner of the network were logistics facilities are located. Selecting an alternative location could affect the output of the optimization

The effect of implementing the carbon tax or cap-and-trade policy for reducing carbon emissions in transportation was also discussed. Within the scope of this research, the behaviour of transportation fleets would be the same under carbon taxing and cap-and-trade with respect to route selection if the cost of carbon was equivalent. The difference would be in the effective cost of carbon where in one scenario it is directly controlled by the government and in the other results from the economic equilibrium in the carbon trading market. Considering the challenges in implementing cap and trade in the transportation sector, i.e. specifying robust reporting standards, incorporating sufficient market control, implementing legal devices for dealing with excess emissions, etc. it is less likely to be a preferable option for reducing carbon emissions in this sector.

In order to get a more thorough understanding of the cap-and-trade policy, it is recommended that a dynamic model of the carbon trading market be established. Such a model would allow assessment of the effect of the policy without assuming that each has prior knowledge of prices.

Another potential extension to the test case VRP model in this paper would be to assess scenarios where particular deliveries could be cancelled due to high emissions associated with that specific delivery (or additional charges levied against the customer).

Furthermore, studying a heterogeneous fleet would allow fleet operators to better evaluate the use of vehicles of different sizes or fuel types in their fleet.

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