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CO_2 Emission using Road Gradient and Real-Time Traffic Monitoring in Vehicle Routing Problems

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Abstract
The upsurge in atmospheric CO_2 levels has come to humankind's attention during the last couple of decades, mainly because of the rise in the global temperature, ice sheets melting, and more frequent and intense natural disasters. Hereby, the focus of this study is to develop a robust routing model that minimizes CO_2 transportation emissions so that this can be used worldwide to minimize global warming issues. The empirical study in this work proves that the advantages of our proposed method for CO_2 reduction in regions with a growing economy, especially in Latin America and the Caribbean, where GDP growth disassociates from fossil fuel consumption and the topography can seriously affect the air pollution generated by vehicles, is an efficient solution as a short-term mitigation strategy. The main contribution of this study is to penalize very steep or slow roads from the fleet route map. The application of this method is vastly relevant in areas where elevation above sea level of towns is very high. Therefore, how the routes are made plays a huge role in the carbon footprint of vehicle fleets. The problem considered in this paper is to produce routes for a fleet of delivery vehicles that minimizes fuel emissions, considering the load of the vehicle, the time traveled, the distance traveled, and the road gradient of a road network using the information extracted from Google Earth. The study investigates a dynamic capacitated vehicle routing problem as an NP-hard problem and generates a linear model that efficiently can capture CO_2 emissions. Numerical results using ant colony optimization (ACO) validate the proposed strategy. Key findings highlight -2.62% of CO_2 emissions changes within a short computational time.

Keywords: CO_2 emission, vehicle routing problems, road gradient, real-time traffic monitoring, ant colony optimization

I. Introduction

Efforts for sustainable urban design based on requirements for developing and managing smart cities, so-called Society 5.0, have been received particular attention in recent years (Velásquez-Bermúdez et al., 2019; Fathi et al., 2019). Research in this domain includes performance development evaluation for green supply chain (Santoso et al., 2019) and eco-efficiency design of vehicle routing problem (VRP) (Fathi et al., 2009). To respond to the increasing social environmental awareness and to decrease the CO_2 emissions that vehicle routing causes, an efficient solution method is required. Our methodology describes the use of the route required information to build delivery sequences using a modified ant colony optimization algorithm. Results of the optimization are compared with to traditional approaches. Finally, the main conclusions and future research work are presented.

II. Methodology

The problem in this paper is considered to recommend routes for a fleet of delivery vehicles that minimizes fuel emissions based on the vehicle load, travel time, travel distance, and road gradient. For measuring the road elevation/gradient, Google Earth information is used every time that the vehicle changes the road or makes a turn. According to the Google Earth information, the gradient is calculated as a difference between altitude at the point i (beginning of a road) and point j (end of the road) and shown by e_{ij}. The travel time (t_{ij}) is obtained by calculating the time of the trip when the vehicle is departed from point i and arrived at point j. A controlled variable is considered as the ratio of general t_{ij} over the travel time when traffic is at its lowest. By measuring the control variable, the extra time in each route caused by the traffic conditions at the desired time can be estimated. The travel distance (d_{ij}) between point i and j is extracted from the Google map API key.

To estimate the CO_2 emissions for a heavy-duty vehicle (HDV) with a range of 32-40 tons capacity for general merchandise, a linear function of d_{ij}, e_{ij}, t_{ij}, and truckload (q) between points i and j is considered as follow:

$$CO_2(q_{ij}, d_{ij}) = d_{ij}\left(\frac{f_1 - f_2}{C} q_{ij} + f_2\right) t_{ij} e_{ij} \tag{1}$$

where f_1 and f_2 are constant values of CO_2 emission when an HDV truck is fully loaded and is empty equal to 1.096 kg/km and 0.772 kg/km, respectively (Olivera and Viera, 2007), and C is the vehicle capacity. This model is inspired by the works of (Ayadi et al., 2014) and (Elbouzekri et al., 2013), where they did not consider the effect of e_{ij} and t_{ij}.

In addition, given the complexity of the problem to estimate the optimal/near-optimal solution, the ant colony optimization (ACO) algorithm is adopted to solve the optimization problem. Following the optimization process by ACO algorithm is described in detail:

Ant: A vehicle that starts at point *a*, and after visiting all clients and returns to point *a*.

Pheromone trail: The history of all the paths made by vehicle k $(k = 1, \dots, m)$ and change/update the intensity of the routes with each new iteration.

Selection of paths: The random variable r is generated form Uniform distribution $[0,1]$ and if $r \geq r0$ the node j is chosen based on:

$$j = argmax\left(\tau_{ij}^{\alpha}\eta_{ij}^{\beta}\right) \qquad \text{if } (i,j) \notin \mathbf{T} \tag{2}$$

where η is the attractiveness of the move and is the inverse of the Equation (1), τ represents the level of pheromone of the move which indicates how good the move was in the past, and $\mathbf{T}$ is a list of forbidden moves (clients that have already been visited by ant k or clients that ant k does not have the capacity to visit them), and α, β are parameters that are used to establish the relative influence of η against τ.

Pheromone update:

Local update: for a given path (i,j) the pheromone trail updates as follow:

$$\tau'_{ij} = (1-\rho)\tau_{ij} + \rho\tau_0 \tag{3}$$

where ρ represents the evaporation rate of the pheromone trail and, τ_0 is a constant value.

Global update: for a given path (i,j) when an iteration has ended for all ants, and the best route achieved, the pheromone trail updates as follow:

$$\tau'_{ij} = \begin{cases} (1-\rho)\tau_{ij} + \rho\left(\dfrac{1}{\text{best solution}}\right) & \text{if } (i,j) \in \text{best solution} \\ (1-\rho)\tau_{ij} & \text{if } (i,j) \notin \text{best solution} \end{cases} \tag{4}$$

Algorithm: for a given number of ants, iterations, and parameters $(\alpha, \beta, \eta, \tau_0, C, f_1, f_2, t_{ij}, e_{ij}, d_{ij})$, first initialize the τ_{ij}, then for each iteration and each ant, randomly choice and unused truck, build the route for this truck using Equation (2), then locally update the τ_{ij} using Equation (3) until the chosen ant complete its solution. Finally, update τ_{ij} using Equation (4).

III. Analysis

For evaluating the proposed model, a real dataset consists of 38 instances of HDVs, including the information of latitude, longitude, and demand of each client of a company in Mexico is used for further investigation. The summary of the data of clients, the vehicles, and the average demand (in unit box) is presented in Table 1.

For running the ACO algorithm, the unit box is considered to 1 kg, such that the capacity of trucks can satisfy the demand of each store in each day without visiting a client more than one time. Therefore, the maximum capacity of trucks should be at least equal to the maximum demand of clients. Consider this fact, the maximum capacity of the trucks is set to 1.7 tons.

The parameter settings of the ACO algorithm is selected based on (Bouyahyiouy and Bellabdaoui, 2017) and are presented in Table 2.

Table 1. Summary of dataset

# of client to visit	5	6	7	8	9	10	11	15	16	17	18	19	20	21	42
# of vehicle	*32*	*5*	*6*	*8*	*4*	*2*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
Average demand	*2929.33*	*3303.5*	*2414.6*	*3008.17*	*4259.75*	*3602.5*	*3711.5*	*3110*	*4256*	*3583*	*8063*	*5184*	*4502*	*8374*	*9058*

Table 2. Parameter setting of ACO algorithm

Parameter	α	β	ρ	τ_1	r_0	τ_0	# of iterations
Value	*1*	*2.3*	*0.1*	$\frac{1}{d_{ij}} \forall i,j, i \neq j$	*0.9*	*average of* τ_1	*500*

IV. Results and discussions

For validating the performance of the proposed ACO algorithm, it is compared with the Capacitated VRP (CVRP) with the Miller-Tucker-Zemlin (MTZ) subtour elimination constraint (Desrochers, and Laporte, 1991) where for simplicity, the objective function is set to minimize distance instead of CO_2 emission reduction. The problem is solved with a time limit of 20,000 seconds and 200,000 seconds for the simple and complex objective functions, respectively. ACO algorithm is coded in Python 3.6 and tested on a PC with Intel(R) Core (TM) i5 2.40 GHz, 16 GB of RAM Memory, and Windows 10 OS. The GAMS software version 22.6 is used for running the optimization algorithm. In addition, the Python PyMathProg (Pyomo) package is utilized for solving linear mathematical problems. The main hypothesis was to test that shorter distance does not necessarily mean fewer emissions produced by the vehicles, and travel time and elevation can lead to different decision making for better solutions.

Table 3 presents a summary of the results. The number of clients to visit is used to express the complexity of the problem. According to the result, the method that performed the worst is the MTZ algorithm solved with GAMS software, and the ACO algorithm with the objective of minimizing CO_2 is the one which performed best. The ACO algorithm is compared to the MTZ has 0.74 % better performance in terms of emission reduction, however, if the complexity of the problem (clients to visit) to be considered as a weighted average, the ACO algorithm performed 2.62 % better than the MTZ algorithm as shown in Table 3.

Table 3. Summary of the results obtained by each method.

		ACO_CO2		**ACO_distance**		**MTZ (in Pyomo)**		**MTZ (in GAMS)**	
		Result	*Difference to GAMS*	*Result*	*Difference to GAMS*	*Result*	*Difference to GAMS*	*Result*	*Difference to GAMS*
Weighted Average	*CO_2 Emission*	*3091.04*	*-2.62*	*317.13*	*-0.01*	*348.31*	*8.95*	*317.15*	*-*
	Distance	*245.99*	*1.99*	*241.09*	*0.00*	*261.98*	*7.97*	*241.08*	*-*
Average	*CO_2 Emission*	*194.93*	*-0.74*	*199.57*	*1.61*	*202.44*	*3.00*	*196.37*	*-*
	Distance	*163.02*	*2.63*	*160.83*	*1.30*	*162.80*	*2.50*	*158.73*	*-*
	Run time	*34.73*	*-21000*	*28.57*	*-26000*	*17000*	*56.11*	*7400*	*-*
	Trucked used	*2.76*	*-1.9*	*2.79*	*-0.94*	*2.76*	*-1.90*	*2.82*	*-*

Regards the distance performance, the MTZ algorithm performed similarly to other algorithms; however, it runs out of time after 27.7 hours. After that, the ACO algorithm with distance reduction objective has the second-best performance, and the algorithm that performed the worst is the ACO algorithm for the CO_2 reduction objective.

It is worth to point out that, the optimal result for ACO with CO_2 reduction objective is achieved in a fraction of the time (215 times faster on average) and also used the minimum number of trucks unlike the MTZ algorithm solved by GAMS that used one more truck in two instances and the ACO algorithms that minimizes distance that used one more truck in one instance. Overall, the ACO algorithm for minimizing distance performed very good in comparison to the GAMS software and was the fastest amongst all other methods.

The obtained results show that for small and simple instances (less than ten clients to visit), the difference between optimizing the distance and the emissions are almost negligible, however for a more complex system, the deviation is more significant (see Figure 1 and 2). In this situation, a better decision is to control the load of the trucks, the travel time, elevation, and distances between transition points.

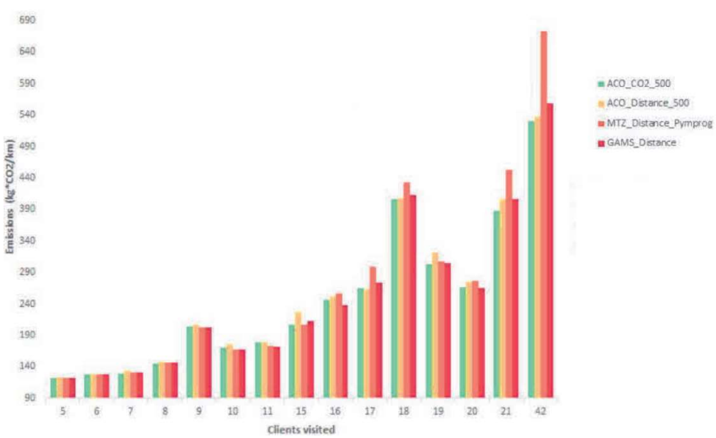

Figure 1. The result of CO_2 emission reduction for each algorithm.

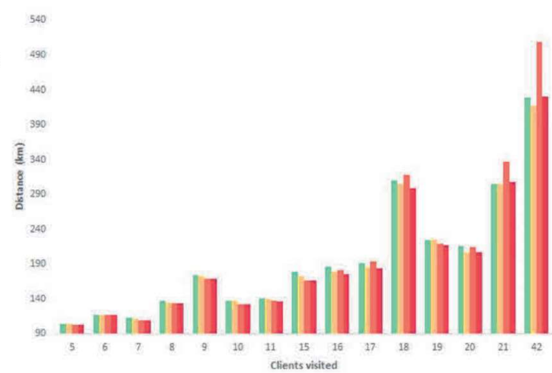

Figure 2. The result of distance reduction for each algorithm.

It is also worth noting that the stopping criteria for ACO algorithms were the number of iterations. We used 500 iterations for the ACO algorithms because we found it to be a good balance between the optimal solution and a decent running time, 100 iterations did not achieve a good result, and 1,000 iterations achieved just a 0.33% improvement by almost doubling the average running time.

V. Conclusions

In this study, an optimization solution to deal with CO_2 emissions produced by heave-duty vehicles (HDVs) considering the travel time and elevation for each path using information from Google Earth are proposed by avoiding or penalizing steep and slow roads. The result is vastly relevant, especially in Latin America where the

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population, the topography of big cities, and the height above the sea level is higher than the average of the world (2,400 meters compared with 2,240). Therefore, the way street routes are made play a huge role in the carbon footprint. For the future research, the problem can consider the same issue for the combination of vehicle routing problem (VRP) and location-inventory problem (Fathi et al., 2015; Mousavi et al., 2019), in a team-oriented supply chain (Hu et al., 2018).

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