Lecture Notes in Management Science (2014) Vol. **6**: 141–149
6th International Conference on Applied Operational Research, Proceedings

ISSN 2008-0050 (Print), ISSN 1927-0097 (Online)

Solving the green capacitated vehicle routing problem using a tabu search algorithm

Sergio Úbeda [1], Javier Faulin [1], Adrián Serrano [1] and Francisco J Arcelus [2]

[1] Department of Statistics and Operations Research. Public University of Navarre, Pamplona, Spain
{sergio.ubeda, javier.faulin}@unavarra.es

[2] Department of Business Administration. University of New Brunswick, Fredericton, Canada
arcelus@unb.ca

Abstract. This paper analyses how the tabu search can be successfully applied to solve the Green Capacitated Vehicle Routing Problems- GCVRP. This kind of problems has been described as the classical Capacitated VRP with a criterion of environmental emissions minimisation. This criterion is based on the calculation of carbon dioxide emissions from mobile sources, which is highly dependent on several factors such as speed, weather conditions, load and distance. A case study is given to show how green routes can be obtained and to analyze whether those routes also meet the efficiency objectives or not. The results show that a tabu search approach adapts the environmental criterion better than other procedures and also produces routes which are distance effective and environmental-friendly.

Keywords: environmental studies; CO2 emissions; distribution; vehicle routing; tabu search

Introduction

This paper discuses a variant of the standard version of the capacitated vehicle routing problem (CVRP) (Toth and Vigo, 2002), but with consideration of environmental issues, which is called the Green Capacitated Vehicle Routing Problem-GCVRP. Then, the estimations of fuel consumption and CO_2 emissions for mobile sources are needed, but these tasks usually require complex calculations. Thus, the only way to calculate emissions from VRP is by applying an average emission value per kilometre, but this procedure has been shown to be inaccurate (Van Woensel *et al.*, 2001) because it will lead to an important underestimation of the effective emissions. The problem studied in the present contribution is distinguished from the standard version of the CVRP by the following feature: the objective is to design routes that generate the lower levels of CO_2 emissions to the atmosphere. Nevertheless, this estimation can only represent an approximation, because of the difficulty of quantifying variables such as driving style, weather conditions, congestion, among others (Palmer, 2007). Thus, in our approach we initially solve the GCVRP with some classical heuristics (Poot *et al*. 2002), but the results were not very close to the optimal ones (Ubeda *et al*., 2011). That is the main reason we implemented a tabu search approach.

In this way, our paper links with those that combine traditional logistics and green issues. But is is not new. Thus, different authors have suggested a set of environmental practices that focuses specifically on logistics such as Bowen *et al* (2001); Carter and Dresner (2001); Sbihi and Eglese (2007); or Zhu and Sarkis (2004). There are authors that focus their research on evaluating the external effects of transport to internalize them through taxation Bickel *et al* (2006) or McKinnon (2006), and we have used some of their contributions to state the theoretical background of our methodology.

The green distance capacitated vehicle routing

The green vehicle routing problem-GVRP has recently shown a great popularity among the routing research community (Demir *et al*., 2014; Lin *et al*., 2014) with important reviews considering its analysis in many real situations. These studies have been performed analyzing different types of pollution costs and environmental impacts (Huang *et al*., 2012; Kopfer *et al*., 2014; Küçükoğlu *et al*., 2013). Therefore, we want to make here our contribution in relation to the practical solving of this problem in the particular case of the Green Distance Capacitated Vehicle Routing Problem-GDCVRP (Toth and Vigo, 2002) applied to a specific distribution company.

CVRP is computationally a NP-hard problem (Lenstra JK and Rinnooy Kan, 1981), and therefore, exact optimization is only possible in small-scale problems. The case study we are going to solve in the Computational Results section is small in size and we could provide an exact solution for it, but we have preferred to use a generic procedure for other practical cases with greater size but related to the case study here presented.

When problems are large, exact algorithms become inapplicable and the use of relatively simple optimization methods such as heuristics and metaheuristics is needed. These methods may not guarantee optimal solutions but produce high-quality ones in relatively short computing times. We propose a Tabu Seach-TS algorithm based on Gendreau *et al*.'s (1994) approach to solve the green distance CVRP. We use the initial TS version due to Gendreau *et al* (1994) in the sake of simplicity: most of the real problems we are going to solve show small size. There is no need to perform more complex approaches.

The estimation of fuel consumption and CO_2 emission for mobile sources requires complex calculations, which can only represent an approximation, because of the difficulty of quantifying some critical variables as road slopes, driving style, weather conditions, accidents, and the like (Van Woensel *et al*., 2001; Palmer, 2007). Current research calls for either a fuel-based or distance-based methodology to calculate CO_2 emissions (Palmer, 2007; Sheu *et al*., 2005). Table 1, based on The Greenhouse Gas Protocol Initiative

(2005) approach, lists some criteria for determining the feasibility for each approach. On the one hand, in the fuel-based approach, fuel consumption is multiplied by the CO_2 emission factor for each fuel type. On the other hand, in the distance-based method, emissions can be calculated by using distance-based emission factors. A fuel-based emission factor is developed based on the fuel heat content, the fraction of carbon in the fuel that is oxidized, and the carbon content coefficient. The distance-based approach can be used when vehicle activity data is in form of distance travelled, but fuel economy factors are not available. The decision on which approach to take depends mainly on data availability.

Table 1. Fuel-based vs. distance-based methods

	Fuel-based method	*Distance-based method*
Advantages	More reliable	Easy to obtain data
Drawbacks	Not easy to calculate if only data on fuel consumption are available	High levels of uncertainty
Data by vehicle type	- Distance travelled. - Fuel consumption factor - Heating values	- Distance travelled. - Fuel consumption.
Data collection sources	- Fuel receipts. - Fuel expenditure records. - Direct measurement records, including official logs of vehicle fuel gauges or storage tanks.	- Odometer logs. - Company fleet records showing data on fuel economy by vehicle type. - Vehicle manufacturer documentation showing fuel economy by vehicle type.
Calculating emissions	- Collect data on distance travelled by vehicle type and fuel type. - Convert distance travelled data into fuel use values based on fuel economy factors. - Convert fuel estimate to CO_2 emissions by multiplying fuel use values by fuel-specific factors.	- Collect data on distance travelled by vehicle type and fuel type. - Convert distance estimate to CO_2 emissions by multiplying distance travelled by distance-based emission factor.

Obviously, it is easier to apply a distance-based method for calculating CO_2 emissions, which is based on distance travelled and distance-based emission factors, when we want to have a theoretical formulation of this problem. This requires two main steps: a) collection of the data on distance travelled by vehicle type and fuel type (e.g. kilometre or ton-kilometre); and b) conversion of the distance estimates to CO_2 emissions by multiplying the results obtained from (a) by distance-based emission factors.

Furthermore, calculations of CO_2 emissions are based on the assumption that all carbon burned as fuel is mostly emitted as carbon dioxide (CO_2). Then, we assume that this calculation is primarily dependent only on two factors: the type of vehicle and the type and quantity of fuel consumed. As well, this means that emissions are a function of two factors, namely type of transportation (i.e. the vehicle and its load) and the distance travelled (Ferreti *et al*., 2007). Thus, CO_2 emissions estimations vary according to the mass of the vehicle and therefore the load carried is an important parameter (McKinnon, 2007).

The estimation of emission factor is carried out following two main steps as illustrated in Table 2. The first one consists on estimate the fuel conversion factor using the fuel combustion chemical reaction $C_{13}H_{28} + 20\ O_2 \rightarrow 13\ CO_2 + 14\ H_2O$ (Lichty, 1967). Knowing that diesel ($C_{13}H_{28}$) molecular mass is 184 and CO_2 molecular mass is 44, and noticing that for each diesel molecule there are 13 molecules of CO_2, it is easy to calculate that there are $13\times44/184 = 3.11$ CO_2 kilograms for each diesel kilogram. Then, knowing that diesel density is 0.84kg/litre, it is estimated that there are $3.11\times0.84 = 2.61$ kilogram of CO_2 for each litre of diesel consumed. Observe that this theoretical diesel conversion factor estimated is very similar to the 2.63 obtained empirically by DEFRA (2005), which provides greenhouse gas- GHG conversion factors to help businesses to make use of existing data sources and convert them into CO_2 equivalent data. Then, given the fuel conversion factor (2.61 Kg. CO_2 / litre of diesel), the second step to estimate the emission factor (ε) consists on defining a function taking into account data related to the average fuel consumption, which depends on load factor. Table 2 shows the estimation of this factor for several capacity scenarios for a truck with 10 tonne capacity. We use in this approximation the information related to CO_2 emissions instead the CO_2e emissions to follow the methodology traditionally used in Eroski from which we have taken the real case.

Table 2. Estimation of emission factors for a 10 tonne capacity truck

State of the vehicle	*Weight laden (%)*	*Consumption (litre/100km)*	*Fuel conversion factor (kg CO_2/litre)*	*Emission factor (kg CO_2/km)*
Empty	0	29.6		0.773
Low loaded	25	32.0		0.831
Half loaded	50	34.4	× 2.61	0.900
High loaded	75	36.7		0.958
Full load	100	39.0		1.018

Green Distance CVRP mathematical model and tabu search application

In this section, we present a mathematical model based on Fisher and Jaikumar (1981) in which our goal will be to build several routes, one for each active (non-idle) vehicle, minimising the sum of the total CO_2 emissions. We imposed the following assumptions: known fleet size, homogeneous fleet, single depot, deterministic demand, oriented network, symmetric distances and driving times. The model represents a green distance capacitated vehicle routing problem- GDCVRP (Toth and Vigo, 2002) and can be described as follows.

Being $V = \{1, 2 \ldots n\}$ a set of n nodes, that are the destination points. Node 1 is the depot. The vehicles are denoted by $Z = \{1, 2 \ldots m\}$. Further, we adopt the following notation:

q_i = Demand of node i.
Q_k = Capacity of vehicle k.
d_{ij} = Distance between i and j.
e_{ij} = CO_2 emitted between i and j.
t_{ij} = Driving time between i and j.
T_k = Maximum allowable driving time for vehicle k.

We define also binary decision variables x_{ijk}, equal to 1 if and only if, in the optimal solution, vehicle k visits customer j immediately after customer i; and y_{ik}, equal to 1 if and only if vertex i is served by vehicle k.

Objective function:

$$Min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} e_{ij} x_{ijk} \quad (i \neq j)$$

Constraints:
All the vehicles begin and end at the depot

$$\sum_{k=1}^{m} y_{1k} = m$$

Each node, except the depot, is visited by a single vehicle

$$\sum_{k=1}^{m} y_{ik} = 1 \qquad (i = 2, \ldots, n)$$

Each node, except the depot, is linked only with a pair of nodes, one preceding it and the other following it.

$$\sum_{i=1}^{n} x_{ijk} = y_{jk} \qquad (j = 1, \ldots, n; i \neq j; k = 1, \ldots, m)$$

$$\sum_{j=1}^{n} x_{ijk} = y_{ik} \qquad (i = 1, \ldots, n; i \neq j; k = 1, \ldots, m)$$

Vehicles cannot be overloaded

$$\sum_{i=1}^{n} q_i y_{ik} \leq Q_k \qquad (k = 1, \ldots, m)$$

Limited time driving

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \left(x_{ijk} + x_{jik} \right) t_{ij} y_{ik} \leq T_k \qquad (i \neq j; k = 1, \ldots, m)$$

Subtours are not allowed

$$\sum_{i \in S} \sum_{j \in S} x_{ijk} \leq |S| - 1 \qquad (S \subset V; |S| \geq 2; k = 1, \ldots, m; i \neq j)$$

The total CO_2 emissions are said to be the environmental matrix (e), calculated taking into account the distance matrix between each pair of nodes and the emission factor (ε) between them.

$$e_{ij} = d_{ij} \times \varepsilon(q_j) \qquad \forall \; i, j \in [1, \ldots t]$$

The direct use of that environmental matrix does not provide the optimal solution of the considered problem, but, we propose it as a way of calculating an initial feasible solution that will be the starting point of the search. Within the TS, we will take advantage of the initial solution to feedback the environmental matrix. So, once an initial solution would be found, we improve it using a TS implementation based on the algorithm proposed by Gendreau *et al* (1994). At each iteration, the cost of performing each feasible move defined by the neighbourhood is calculated. The search perform the best of the examined moves, but moves taken into account must not lead to solutions declared tabu unless it improves the current best solution. After each iteration, when a move is selected, the features of the solution are coded and inserted in the tabu list where they remain for a number of iteration. The process is finished after the execution of a maximum number of not improving iterations or when a maximum number of iterations during the process has been reached. Then, TS returns the best solution ever encountered during the process.

It is also important to highlight that our procedure is based on the hypothesis that the shortest paths between two nodes does not change when time is passing by, because our case study taken from Eroski has very stable delivery routes, and that assumption is plausible. Otherwise we should consider models which use fuel-based approaches (Oberscheider *et al*., 2013; Piecyk, 2012) which is more accurate in many situations.

Computational results: a case study

In order to estimate the emission factor of each vehicle we need a realistic vehicle capacity because it is not appropriate to test the green distance CVRP using the available instances in the literature for the VRP. Therefore, we generated 7 instances based on real date provided by Eroski (http://www.eroski.es), a leading name in the food distribution sector in Spain. The distribution network of Eroski consists of 27 delivery points served directly from only one depot using between 6 and 27 vehicles. Normally, demand follows a regular trend, so we have studied a delivery process taking data from any week (i.e. 7th-13th May 2012).

Regarding the parameter settings, we have performed an exploratory testing to find good parameters values in terms of the quality of solutions and the computational time. We vary widely the number of iterations and the tabu list in order to find the best initial solution. This best initial solution was provided by comparing 3 classical heuristics: the nearest neighbour insertion algorithm (NNI) (Bodin *et al*, 1983); the savings algorithm (CWS) (Clarke and Wright, 1964); and an extension of savings algorithm (MJ) (Mole RH and Jameson SR, 1976).

The case study results are given in Table 3. Thus, we can say that our green TS algorithm shows interesting reductions in CO_2 emissions in some of the days under scrutiny (12 May 2012) considering the total involved distance, while other days show much more modest reductions. In this analysis, all customers with positive demand are visited each day (although there are customers with zero demand in some specific days). These results help to understand the importance of optimising logistics processes taking into account environmental criteria.

Table 3. Comparison of Green TS results

Instance	*Method*	*Distance (km)*	*Emissions (Kg. CO_2)*	*Distance increase (%)*	*Emissions REDUCTION (%)*	*Number of vehicles involved*
7th May 2012	TS	3,395.9	3,325.9	5.84%	-0.27%	20
	Green TS	3,594.1	3,316.8			
8th May 2012	TS	3,256.4	3,005.1	0.00%	0.00%	19
	Green TS	3,256.4	3,005.1			
9th May 2012	TS	2,600.8	2,498.2	0.00%	0.00%	14
	Green TS	2,600.8	2,498.2			
10th May 2012	TS	2,989.9	2,933.3	0.00%	0.00%	15
	Green TS	2,989.9	2,933.3			
11th May 2012	TS	2,938.3	2,829.5	8.06%	-0.88%	18
	Green TS	3175.0	2,804.5			
12th May 2012	TS	656.9	843.7	13.66%	-21.26%	8
	Green TS	746.6	664.3			
13th May 2012	TS	1,471.2	1,313.3	0.00%	0.00%	11
	Green TS	1,471.2	1,313.3			

Conclusions

The present study shows the potential of the introduction of green approaches in transportation management. We propose a new application of the well-known TS to solve the CVRP, which main objective is to find out the cleanest routes. This approach has been successfully applied on a set of instances obtained from the company Eroski producing the cleanest solutions in all cases.

The application of the green TS to solve the CVRP shows how fleet planning may balance total pollution and total costs in a more effective way. This means that some extra costs related to those changes aimed at cutting their negative environmental effects would appear, but also the environmental care improvement would give some competitive advantages. Nevertheless, this econometric discussion could be studied in depth in further research. Moreover, further work on quantifying some of the exogenous factors, previously mentioned, such as type of road, driving style, weather conditions and so on, lead us to calculate the distances and emissions more accurately, facilitating the search for cleaner routes. The study of these and other issues justifies additional research.

Acknowledgments— The authors appreciate the financial support of the Cooperative Group Eroski in the development of the present research. We would also like to thank their help and advice in the discussion stage of this paper and for supplying a great amount of useful data. This work has been partially supported by the Spanish Ministry of Science and Innovation (TRA2010-21644-C03) and by the Ibero-American Program for Science, Technology and Development (CYTED2010-511RT0419), in the context of the ICSO-HAROSA program (http://dpcs.uoc.edu). Similarly, we appreciate the financial support of the Sustainable TransMET Network funded by the Government of Navarre (Spain) inside the Jerónimo de Ayanz program.

References

Bickel P, Friedrich R, Link H, Stewart L and Nash C (2006). Introducing environmental externalities into transport pricing: Measurement and implications. Transp Rev 26 (4): 389-415.

Bodin L, Golden B, Assad A and Ball M (1983). Routing and scheduling of vehicles and crews. The state of the art. Comp and Oper Res 10: 63-212.

Bowen FE, Cousins PD, Lamming RC and Faruk AC (2001). The role of supply management capabilities in green supply. Prod and Oper Manag 10: 174-189.

Carter C and Dresner M (2001). Purchasing role in environmental management: Cross-functional development of grounded theory. J Supply Chain Manag 37 (3): 12-26.

Clarke G and Wright JV (1964). Scheduling of vehicles from a central depot to a number of delivery points. Oper Res 12: 568–581.

DEFRA (2005). Guidelines for company reporting on greenhouse gas emissions. DEFRA: London.

Demir, E., Bektas, T., Laporte, G. (2014). A review of recent research on green road freight transportation. European Journal of Operational Research, 237: 775-793.

Ferreti I, Zanoni S, Zavanella L and Diana A (2007). Greening the aluminium supply chain. Int J Prod Econ 108: 236-245

Fisher M and Jaikumar R (1981). A generalized assignment heuristic for vehicle routing. Networks 11: 109-124.

Gendreau M, Hertz A and Laporte G (1994). A tabu search heuristic for the vehicle routing problem. Manag Sc 40: 1276-1290.

Huang Y, Shi C, Zhao L, Van Woensel T. (2012). A study on carbon reduction in the vehicle routing problem with simultaneous pickups and deliveries. IEEE International Conference on Service Operations and Logistics and Informatics. 8-10 July 2012. Suzhou, China.

Kopfer HW, Schönberger J, Kopfer H (2014). Reducing greenhouse gas emissions of a heterogeneous vehicle fleet. Flexible Services and Manufacturing Journal, Volume 26, Issue 1-2: 221-248.

Küçükoğlu I, Ene S., Aksoy A., Öztürk, N. (2013). A Green Capacitated Vehicle Routing Problem with Fuel Consumption Optimization Model. International Journal of Computational Engineering Research, Vol. 3(7): 16-23.

Lenstra JK and Rinnooy Kan AHG (1981). Complexity of vehicle routing and scheduling problems. Networks 11: 221-227.

Lichty LC (1967). Combustion engine processes. McGraw-Hill Education.

Lin, C., Choy, K.L., Ho, G.T.S., Chung, S.H., Lam, H.Y. (2014). Survey of Green Vehicle Routing Problem: Pasta and Future Trends. Expert Systems with Applications, 41(4, part 1): 1118-1138.

McKinnon A (2006). A review of European truck tolling schemes and assessment of their possible impact on logistics systems. Int J Logist: Res and Appl 9 (3): 191-205.

McKinnon A (2007). CO2 emissions from freight transport: an analysis of UK data. In: Lalwani C, Mangan J, Butcher T and Coronado-Mondragon A (eds). Logist Res Network 2007 Conference Proceedings. University of Hull: Hull, pp 9-14.

Mole RH and Jameson SR (1976). A sequential route-building algorithm employing a generalised savings criterion. Oper Res Q 27: 503-511.

Oberscheider, M., Zazgorkik, J., Henriksen, C.B., Gronalt, M., Hirsch, P. (2013). Minimizing driving times and greenhouse gas emissions in timber transport with a near-exact solution approach. Scandinavian Journal of Forest Research, 28(5): 493-506

Palmer A (2007). An integrated routing model to estimate carbon dioxide emissions from freight vehicles. In: Lalwani C, Mangan J, Butcher T and Coronado-Mondragon A (eds) Logist Res Network 2007 Conference Proceedings. University of Hull: Hull, pp 27-32.

Piecyk, M. (2012). Carbon auditing of companies, supply chains and products. In: McKinnon, A., Browne, M., Whiteing, A. (eds) Green Logistics- Improving the environmental sustainability of logistics. Kogan Page, London-Philadelphia-New Delhi

Poot A, Kant G and Wagelmans APM (2002). A savings based method for real-life vehicle routing problems. J Oper Res Soc 53: 57-68.

Sbihi A and Eglese RW (2007). Combinatorial optimization and green logistics. 4OR: Q J Oper Res 5 (2): 99-116.

Sheu JB, Chou YH and Hu CC (2005). An integrated logistics operational model for green-supply chain management. Transp Res, Part E 41: 287-313.

The Greenhouse Gas Protocol Initiative (2005). Calculating CO2 emissions from mobile sources. Guidance to calculation worksheets. http://www.ghgprotocol.org/standard/mobile.doc. Accessed 1 September 2013.

Toth P and Vigo D (2002). The vehicle routing problem. SIAM Monographs on Discrete Mathematics and Applications: Philadelphia.

Toth, P. and Vigo, D. (2002). The Vehicle Routing Problem, SIAM- Society for Industrial and Applied Mathematics. Philadelphia.

Ubeda S, Arcelus FJ and Faulín J (2011). Green Logistics at Eroski: A case study. International Journal of Production Economics 131 (1), 44-51

Van Woensel TV, Creten R and Vandaele N (2001). Managing the environmental externalities of traffic logistics: the issue of emissions. Prod and Oper Manag 10: 207-223.

Zhu Q and Sarkis J (2004). Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. Journal of Operations Management, 22: 265-289.