

A Genetic Algorithm for a Green Vehicle Routing Problem

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Abstract

We propose a Genetic Algorithm (GA) to address a Green Vehicle Routing Problem (G-VRP). Unlike classic formulations of the VRP, this study aims to minimise the CO₂ emissions per route. The G-VRP is of interest to policy makers who wish to reduce greenhouse gas emissions. The GA is tested on a suite of benchmark, and real-world instances which include road speed and gradient data. Our solution approach incorporates elements of local and population search heuristics. Solutions are compared with routes currently used by drivers in a courier company. Reductions in emissions are achieved without incurring additional operational costs.

Keywords: Green Vehicle Routing Problem, Genetic Algorithm.

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1 Introduction

The EU directive on decreasing greenhouse gas emissions and the dependency on fossil fuels motivates focus on G-VRP problems. Specific targets have been set for the transport sector. Most VRP software produces schedules for vehicles that minimise economic costs for the logistics service provider. Typically, the numbers of vehicles and drivers and the financial cost of the distance travelled are minimised. However, environmental concerns are beginning to play a role in corporate social responsibility policies [11] and there is a competitive advantage for companies with provably green credentials.

This study was conducted in conjunction with *Xpreso*, a start-up company operating in the IT and logistics sector. *Xpreso*'s business objective is to provide a software communication platform for parcel delivery couriers that provides drivers' route optimisation, real time tracking, time window notification to customers, real time routes adjustments, data gathering and analytics.

We focus on a route optimisation GA that incorporates elements of local and population search to minimise CO₂ emissions. We describe emission models based on 1) EU regulations, 2) vehicle speed, and 3) load weight and road slope. The GA was tested on benchmark, and real world data for deliveries by m homogenous light duty diesel vehicles in the Bristol area of the UK.

2 The Green Vehicle Routing Problem

The Capacitated Vehicle Routing Problem (CVRP) is defined on an undirected graph $G = (V, E)$ with vertices $V = \{1, \dots, n\}$ where node 1 is the depot and the vertices $V = \{2, \dots, n\}$ are customers. Each edge $(ij) \in E$ has an associated cost c_{ij} proportional to distance or travel time. Demand and possibly a service time of each customer are given. The number of homogeneous vehicles m of fixed capacity is either known in advance or expressed as a decision variable of the problem. The goal of the CVRP is to minimise the sum of the costs of routes for the m vehicles beginning and ending at the depot, visiting all customers in the network once to satisfy demand. See for example [1].

The VRP generalises the TSP and is an NP -hard problem. Exact approaches are given in [8, 12]. Approximate algorithms are described in [9] while an evolutionary algorithm is used in [13]. The greedy approach in the Clark and Wright Algorithm, [5] is a construction heuristic. Initial routes are generated and merged if savings can be achieved by merging routes subject to capacity constraints. The local search heuristic in [10] for the TSP can be

adapted for the CVRP. Tour construction approaches can be used to initialise a (set of) tour(s), otherwise the Lin Kernighan heuristic (LKH) proposes random starting solutions. A λ -swap of a tour removes λ arcs and replaces them with λ new arcs in such a way as to generate a new tour. In the LKH λ -opt algorithm, all λ -swaps are tested until no feasible exchange can be found to improve the solution. The LKH implementation in [6] notes that 2- and 3-opt exchanges are most frequently implemented. They give the intuition that for high values of λ , a λ -opt tour is likely to be optimal.

Environmental effects are generally not considered in the classical VRP. G-VRPs are concerned with reducing energy consumption [14]. Routes are designed to optimise both environmental and financial objectives. Changes in distance travelled may provide environmental benefits when fuel consumption (and consequently pollutants) are reduced. The amount of CO₂ emitted by a vehicle is proportional to fuel consumption. Fuel consumption is influenced by several factors such as distance travelled, average driving speed and acceleration, load, engine type and size, road gradient and weather effects such as temperature. Fuel consumption can be estimated using real time on-board measurements. An alternative approach is to use an *analytical emission model* (EM). The EMs in this study are based on the work in [7]. They propose a class of EMs for CO₂ emission for light duty diesel vehicles, based on driving velocity and distance travelled. The goal of the G-VRP in this study is to minimise the CO₂ emissions of the VRP routes of a set of light duty diesel delivery vehicles.

3 Methodology

We consider three EMs for CO₂ emissions over distance d . In the following EF is an emissions factor, g is the road gradient and v is vehicle speed.

A simple road distance EF model is given in Eq. 1.

$$Emissions = EF * d \tag{1}$$

Limits for light duty vehicles in the EU2020 targets are 147 *grams/Km* giving a simple upperbound on EF , in that case Eq. 1 becomes: $Emissions = 147*d$.

The road distance EF model can be improved by considering the nonlinear relationship between emissions and speed: $EF' = (429.51 - 7.8227 * v + 0.0617 * v^2)$. Eq. 2 is based on the *MEET* report, [7] and yields a speed model.

$$Emissions = EF' * d \tag{2}$$

The road gradient and vehicle load can also affect emissions, Eq. 3 is a gradient-weight model which includes an adjustment based on empirical analysis of sample diesel vehicles in [7]. $k = 1.27$ is a constant to account for load weight; $l = 0.0614$; $q = -0.0011$; $r = -0.00235$; $u = -1.33$ are coefficients.

$$Emissions = \left(k + l * g + q * g^2 + r * v + \frac{u}{v} \right) * EF' * d \quad (3)$$

Figure 1 allows us compare the speed model Eq. 2 on the left and the gradient-weight model Eq. 3 on the right, where emissions are calculated for speeds from 0 to 120 Km/h for a 10 km distance.

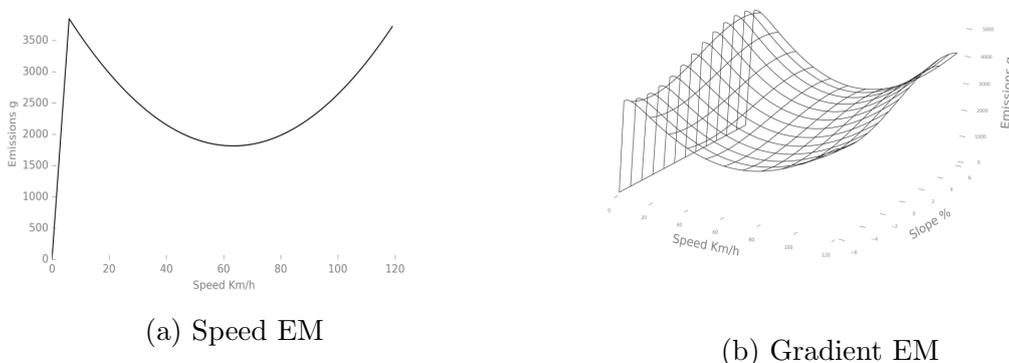


Fig. 1. Comparison of speed and gradient emission models

3.1 Real world test instances

Real world instances were developed from data for parcel deliveries in the Bristol area (UK). The Bristol area is relatively flat, extends to 110 Km^2 within a radius of 6 Km from the city centre. Most deliveries are destined for the city centre which is 12.8 Km from the depot. A homogeneous fleet of light duty diesel vehicles with a net weight $\leq 3.5 tons$ and max operating weight $\leq 7.5 tons$ is used. A sample of the *ex-post* data consolidated by *Xpreso* is shown in Table 1. Latitude and longitude give the position of a customer. Parcels generally have weights $\leq 2000 g$. Delivery time is the clock time of the delivery. The driver code identifies the driver.

Latitude	Longitude	Parcel Weight (g)	Delivery Time	Driver Code
51.503	-2.685	1000	9.345	Driver_1

Table 1
Ex-post data (provided by *Xpreso*)

We used the *Google Maps* commercial API to estimate driving distance and travel time for node pairs in the Bristol delivery area. Queries were launched on weekdays at 10 a.m. to account for traffic congestion and hence allow us estimate driving speed for use in the EMs. The average speed v per node pair is estimated as $\frac{Distance[Km]}{Time[hours]}$. Similarly, the average road gradient is estimated based on the elevation at the origin and destination: Gradient $g(\%) = \frac{Rise}{Run} * 100$, where *Rise* is the difference in elevation and *Run* is the distance between the nodes. This data allows us test the use of the emission models as fitness functions in the GAs.

3.2 The Genetic Algorithms (GAs)

Current business practice is for *Xpreso* to solve m TSPs (as the m drivers are pre-assigned to regions) using third party routing software. In effect m TSPs are solved rather than a single VRP. In this section we describe a set of GAs to solve both the m TSPs and the G-VRP. TSP solutions are converted to VRP solutions using the *split* procedure described in [13]. The procedure can be used to create $\leq m$ routes. Load capacity is not a critical constraint for *Xpreso*'s parcel deliver service due to the vehicle size, but driver time is limited to a maximum number of shift hours D . The emission models are used as alternative fitness functions to traditional distance metrics on the Bristol real world instances as road speed and gradients are available.

We assume a symmetric cost matrix which holds for the distance and speed models on an undirected graph. Further work on asymmetric matrices to cater for the gradient method is not described in this paper. Time window constraints are not included as the *Xpreso* customer interface sends parcel recipients the estimated time of arrival before the driver workday begins and allows them to accept or reject a delivery. Our GA implementation is similar to [13] with the novel addition of 3-Opt moves as a mutation operator. The GA design decisions are:

- (i) Chromosomes - a sequence of n nodes;
- (ii) Population - small populations P of size N / no clones allowed / high elitism;
- (iii) Fitness $F(P_i)$ - the tour cost of the i^{th} member of population P ;
- (iv) Initialisation - include good heuristics solutions in the initial population;
- (v) Mutation - λ -opt local search with probability p_m of 2-Opt and p_{3opt} of 3-Opt;
- (vi) Population management - an offspring can substitute for a chromosome of worse fitness.
- (vii) Exploration phase, followed by R restarts.

Nearest Neighbour, the Clark Wright and Random Insertion construction heuristics are used to initialise three members of the population. The remaining members are initialised randomly. We store the fitness and tour sequence of each chromosome. Chromosomes are sorted in increasing order of fitness $F(P_i)$. We keep the populations in our GAs small and do not allow individuals with the same fitness level (even though they might not be clones). Nor do we allow clones, which are detected using a bisection search.

Parents are selected by a binary tournament. A new child only enters the population if it has a better fitness value than the current chromosome to be replaced (very high elitism). We use the ordered crossover approach (OX) for TSP-like problems to produce two valid children from two parents. A summary of the GA is shown in Algorithm 1.

Algorithm 1 *Genetic Algorithm*

initialise population and parameters

while *Number of restarts* < R **do**

while $\alpha < \alpha_{max}$ and $\beta < \beta_{max}$ **do**

Select two parents P_i and P_j by binary tournament

Apply OX to generate C_1 and C_2

Select one child C randomly

Select $rand \in [0, 1]$

if $rand < mutationprobability$ **then**

Call local search mutation on C

Select $k = random.integer(\lfloor n/2 \rfloor, n)$

if *VRP* **then**

 | *Call Split procedure on C*

end

if $F(C)$ *not in the population and* $F(C) < F(P_k)$ **then**

 | $P_k = C$

end

$\alpha = \alpha + 1$

end

Sort the population

if P_1 *has not changed* **then**

 | $\beta = \beta + 1$

end

end

end

Mutation is performed as a local search operator. Instead of simple moves of swapping nodes, we use 2- and 3-Opt moves combined with other node swap strategies [10, 13]. This provides a faster convergence of the GA, while

taking advantage of the diversification of the GA. A child is mutated with probability p_m by performing a 2-Opt local search. A 3-Opt operation may then be applied with probability p_{3opt} . Generally 3-Opt exchanges produce better solutions, but it is much slower; $O(n^3)$ compared to the $O(n^2)$ 2-opt algorithm.

The GA stops when it reaches a maximum number of successful offsprings, α_{max} , or when it reaches a maximum number of unsuccessful offsprings, β_{max} , without improving the best solution. The population is re-sorted (so the best solution to date is P_1), and restarted R times using a partial replacement procedure.

4 Results and Analysis

All algorithms were implemented in Python on an i7 core laptop with 8 GB RAM running Windows 7. The GAs were tested on benchmark CVRP instances such as [2, 3] along with the real world instances from Bristol.

Two GA variants were selected. GA-VRP1 has a population of size $N = 30$, $p_m = 0.1$, $\alpha_{max} = 300$, $\beta_{max} = 3000$. GA-VRP2 has $N = 50$, $p_m = 0.05$, $\alpha_{max} = 300$, $\beta_{max} = 1500$. GA-VRP1 produces better solutions with a higher running time. GA-VRP2 produces tours with a high gap but in shorter run times. $p_{3opt} = 0$ for VRP instances and $p_{3opt} = 0.5$ for TSP instances.

Sample results for benchmark VRP instances minimising road distances, (i.e., the fitness function is Eq. 1 with $EF = 1$), are shown in Table 2. Run times (RT) are in seconds. GA-VRP1 was used on problem set E in [3]. GA-VRP2 was used on problem set M in [4]. For our purpose of solving real world VRP instances with emissions objectives, the average gap for GA-VRP1 is reasonable when the number of nodes is ≤ 100 . Otherwise GA-VRP2 is applied.

Having validated the GAs on traditional VRP instances, we then tested the GAs on the *Xpreso* Bristol G-VRP instances, i.e., the recorded m TSP routes with the road network speed and gradient data extracted from the API. We compared solutions from solving m TSPs, one for each driver against VRP solutions created using the *split* procedure. We separately tested the use of the three different emission reduction fitness functions - 1) Eq 1 the Road Distance (RD) with the EU upperbound $EF = 147$; 2) Eq 2 the Average Speed Emissions Model (SP-EM) and 3) Eq 3 the Load and Road Gradient Emissions Model (GD-EM).

Results for a sample 70 node instance, *Bristol70*, are shown in Table 3. The columns show the objective, the tour distance and the emissions for the

Instance	n	Opt	Best	GA	Gap(%)	RT(s)
E-n22-k4	22	375	375	VRP1	0.0	6.39
E-n33-k4	33	835	835	VRP1	0.0	28.6
E-n51-k5	51	521	521	VRP1	0.0	82.78
E-n76-k7	76	682	691	VRP1	1.3	150.24
E-n101-k14	101	1067	1099	VRP1	3.0	200.46
M-n101-k10	101	820	831	VRP2	1.3	96.21
M-n151-k12	151	1015	1086	VRP2	7.0	203.2
M-n200-k16	200	1274	1371	VRP2	7.6	380.98

Table 2
GA Results on benchmark VRP problems using distance metrics

Objective	RD(Km)	EU20-EM(gram)	SP-EM(gram)	GD-EM(gram)
DRIVER	146.73	21,569.31	33,469.67	38,358.61
Eq. 1 RD	131.46	19,324.62	30,329.93	35,108.79
Eq. 2 SP-EM	132.07	19,414.29	30,018.98	34,764.00
Eq. 3 GD-EM	133.59	19,637.73	30,516.56	34,082.58

Table 3
Sample Single Driver *Bristol70* Results

three tests. The first row shows as our base line the recorded route performed by the driver (DRIVER) using symmetric distances for consistency. The recorded route covered 146.73 km with estimated CO₂ emissions of 21.5, 33.5 or 38.4 kg depending on which *EM* is used. The remaining rows show results for each green objective function. Solving the GA with Eq 3 as the objective found a solution 133.59 km in length that would produce 34.1kg (or 19.6 or 30.5 if that route were measured by Eq. 1 or Eq 2). There are similar improvements in emissions when other real instances are solved using the SP-EM and GD-EM models. The more accurate EM models offer better estimates of the emissions produced. The amount of reduced emissions is proportional to increased road distances in some cases. The effects of speed and road gradients play a role in achieving CO₂ reductions.

We also compare the *mTSP* approach currently employed by the business to a G-VRP where the *Split* procedure finds at most m routes. We show results for a sample instance with $m = 3$ and $n = 133$ in Table 4. The

Objective	RD(Km)	EU20-EM(g)	SP-EM(g)	GD-EM(g)	Algorithm
DRIVER	245.52	36,281.07	62,681.54	71,603.09	Recorded
Eq. 1 RD	158.43	23,300.97	38,440.25	43,260.41	3-TSP
Eq. 2 SP-EM	159.09	23,133.39	38,071.61	43,094.19	3-TSP
Eq. 3 GD-EM	159.66	23,246.58	38,368.47	42,885.85	3-TSP
Eq. 1 RD	130.05	19,117.35	32,055.16	36,609.87	G-VRP
Eq. 2 SP-EM	130.75	19,220.24	31,963.99	36,360.07	G-VRP
Eq. 3 GD-EM	130.75	19,220.24	31,963.99	36,360.07	G-VRP

Table 4
3-TSPs versus G-VRP Results

resulting G-VRP solution is compared to the sum of the original m TSPs.

We see the gains in solving a (G-)VRP instead of an m TSP with a reduction -17.91% (158.43 Km vs 130.05 Km) in distance travelled using a distance-based objective function. Emissions are also affected with a reduction of -15.22% (36,360.07 g vs 42,885.85 g) for GD-EM. Furthermore, the VRP solution used just two drivers to visit all stops within a seven hour shift. This has implications for the business practice.

5 Conclusions

This work presents a novel approach to the G-VRP. By focusing on CO₂ reductions, not only are green house gases reduced but resulting routes may be financially more cost effective. Savings arise through reduced fuel consumption and can be measured by the emission models when road speed and gradient data are available. The m TSP provides a useful practical approach to solving small VRPs for three or four drivers but our work shows that further emissions savings can be achieved using G-VRP approaches. Our results proved useful to the business in terms of care of the environment, and also allows the company to gain a valuable competitive advantage by using green credentials.

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