Incorporating Emissions Models within a Multi-Objective Vehicle Routing Problem

Neil Urquhart
Centre for Emergent Computing
Edinburgh Napier University
10 Colinton Road,
Edinburgh, UK
n.urquhart@napier.ac.uk

Catherine Scott
Centre for Emergent Computing
Edinburgh Napier University
10 Colinton Road,
Edinburgh, UK
c.scott@napier.ac.uk

Emma Hart
Centre for Emergent Computing
Edinburgh Napier University
10 Colinton Road,
Edinburgh, UK
e.hart@napier.ac.uk

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ABSTRACT

The vehicle routing problem with time windows (VRPTW) has previously been investigated as a multi-objective problem. In this paper estimated carbon emissions is added as an objective alongside the number of vehicles required and distance travelled. We term this new problem formulation (E)VRPTW. In order to estimate emissions we require detailed information regarding the nature of the route to be taken. As previous benchmark VRPTW problem instances do not supply such information we generate new problem instances based upon street network data from Open Street Map. Results suggest that by adding emissions as the third objective, in many cases the search may be directed to areas that allow improvement in the distance and vehicles objectives. As emissions and distance are inherently related, we do not search for pareto fronts. Rather we attempt to find solutions that either minimise distance or minimise vehicles used. Adding the third emissions objective is shown to enable a multi-objective EA to find improved solutions in terms of minimal vehicles or minimal distance when compared to the same multi-objective EA using only two objectives.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic methods, Scheduling*

General Terms

Algorithms

Keywords

Multi-Objective Optimisation, Vehicle Routing, Low CO_2 Routing

1. INTRODUCTION AND MOTIVATION

The optimisation of problems associated with Vehicle Routing has a long history both in OR and ECO research. The objective of this paper is to present a multi-objective formulation of the VRP problem in which a multi-objective evolutionary algorithm (MOEA) are used with three objectives measures; vehicles, distance and CO_2 emissions. We investigate the extent to which incorporation of the explicit emissions objective influences the solutions found in terms of the more traditional objectives of number vehicles required and distance travelled. Previous VRPTW research [4, 5] found that it was not possible to generate meaningful Pareto fronts. This is due to the nature of the objectives, the number of vehicles being determined by the decoding of a grand tour.

Our interest is not in the absolute values of CO_2, but in its impact on the other two objectives (distance and vehicles). Within the EAs investigated, absolute values are not required it is only necessary to be able to rank solutions so that they may be evaluated. In this work we use the COPERT [1] emissions model to model and predict vehicle emissions.

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2. PROBLEM INSTANCES AND DEFINITION

We define our variant of the VRPTW, as the Emissions Vehicle Routing Problem with Time Windows (E)VRPTW. The principle addition to the classical VRPTW definition is the addition of emissions as a third constraint.

The third objective (minimise emissions) may be expressed as:

$$f_3 = \sum_{i=1}^{i=V} e_{V_i} \quad (1)$$

where e_{V_i} represents the total emissions for each vehicle, calculated according to the COPERT emissions model.

Problems instances are generated, containing 50, 100, 150 and 200 customer nodes respectively (placed at randomly selected locations on a map of the city of Edinburgh) and with time windows of length 5,10,30,60,120 and 720 minutes, giving a total of 24 problem instances. Time windows are allocated within a total time span of 12 hours, the median of each window is selected randomly within 12 hours. Time windows do not start earlier than 30 minutes into the problem time span.

3. THE ALGORITHM

The 24 problem instances were solved using an implementation of the NSGA-II algorithm[3, 2]. This uses the representation and operators developed for the VRPTW problem by Ombuki et. al. [4]. The representation is that of a grand-tour (all customers held in one permutation). Prior to evaluation, the tour is sub divided into separate tours for each vehicle. A local-search operator is used to customers between tours to improve the solution. Each solution may be evaluated in terms of distance, emissions and no of vehicles required, the NSGA-II algorithm using all three criterion to rank the population and calculating crowding distance.

	Ranking D , V	
	Lowest Vehicles	Lowest Distance
50-5	462.32 , 6	434.15 , 8
100-5	736.56 , 11	692.15 , 12
150-5	1168.39 , 17	1032.71 , 19
200-5	1049.05 , 17	1045.76 , 18
50-10	436.49 , 7	411.71 , 8
100-10	702.27 , 9	664.36 , 11
150-10	1018.86 , 15	1003.79 , 16
200-10	1203.21 , 17	1058.07 , 19
50-30	408.85 , 6	391.93 , 7
100-30	620.91 , 8	616.36 , 9
150-30	975.01 , 13	924.73 , 15
200-30	979.55 , 13	887.67 , 14
50-60	345.72 , 5	343.44 , 6
100-60	576.28 , 7	575.87 , 8
150-60	823.95 , 10	789.78 , 14
200-60	855.76 , 11	844.39 , 12
50-120	324.84 , 3	306.23 , 3
100-120	524.3 , 5	490.78 , 6
150-120	711.08 , 8	680.06 , 9
200-120	725.85 , 9	686.95 , 10
50-720	200.16 , 1	200.16 , 1
100-720	308.46 , 1	259.29 , 1
150-720	356.79 , 1	312.22 , 1
200-720	343.57 , 1	332.44 , 1
	Ranking D , V , E (Copert)	
	Lowest Vehicles	Lowest Distance
NSGA		
50-5	**448.54 , 5 , 156.2**	**395.2 , 7 , 137.8**
100-5	668.14 , 11 , 233.2	**662.39 , 12 , 231.2**
150-5	1134.29 , 17 , 395.5	1067.46 , 18 , 371.6
200-5	1053.76 , 18 , 366.9	**1040.67 , 19 , 362.7**
50-10	**387.75 , 5 , 134.9**	**372.13 , 6 , 129.4**
100-10	652.35 , 11 , 227.7	**652.35 , 11 , 227.7**
150-10	1040.85 , 16 , 363.6	1005.98 , 17 , 351.9
200-10	1034.02 , 16 , 359.3	**1023.46 , 17 , 355.6**
50-30	**391.68 , 4 , 136.6**	**377.68 , 5 , 131.8**
100-30	599.96 , 8 , 209.5	**598 , 9 , 208.8**
150-30	955.99 , 14 , 333.1	**894.4 , 16 , 311.2**
200-30	925.01 , 13 , 322.6	897.52 , 14 , 313.1
50-60	**496.73 , 3 , 173.5**	**340.36 , 5 , 118.5**
100-60	629.73 , 8 , 220.3	601.38 , 9 , 209.5
150-60	837.51 , 11 , 292.3	818.15 , 12 , 285.4
200-60	878.6 , 12 , 306.6	**858.01 , 12 , 299.3**
50-120	270.66 , 3 , 94.9	**270.66 , 3 , 94.9**
100-120	498.98 , 5 , 174.3	**480.43 , 6 , 168.4**
150-120	761.76 , 9 , 265.4	720.81 , 11 , 251.2
200-120	719.08 , 9 , 249.7	**683.76 , 10 , 237.9**
50-720	216.53 , 1 , 75.4	**162.27 , 1 , 56.7**
100-720	288.83 , 1 , 100.8	267.93 , 1 , 93.8
150-720	323.18 , 1 , 113.3	316.99 , 1 , 110.3
200-720	322.34 , 1 , 112.6	**322.34 , 1 , 112.6**

Table 1: A summary of results obtained. Problem instances are named <customers>-<time window>. Solutions are presented as<distance>, <vehicles>,<emissions>. Items highlighted in bold represent solutions where the addition of the emissions parameter has improved one or more of the objectives.

4. RESULTS AND CONCLUSIONS

The 24 problem instances were solved using the algorithm described in 3. Each algorithm was run 20 times on each problem instance. For each problem instance we record the best results obtained for the vehicles and distance objectives. This is the same methodology used in [5, 4].

The authors set out to examine the effect of adding emissions as an objective within the VRPTW problem. From table 1 those solutions highlighted in bold are those where one or both of the objectives was improved upon when the emissions objective was added. NSGA-II is able to find 37 improved solutions and the Ombuki Ranking EA only finds 22. As might be exected the addition of the third objective is more likely to result in an improvement in distance rather than vehicles. In attempting to reduce the emissions objective areas of the search space are being reached that were not being explored otherwise. If we examine the relationship between the emissions values and the distance values given in table 1 we find a Pearson correlation coefficient of 0.99, suggesting a very strong relation. If we perform the same calculation on emissions and vehicles objectives, we find a coefficient of 0.96 overall. The strong relationship between emissions and distance will account for low emissions solutions being likely to also have low distance values. When the search is expanded to include the emissions objective there is a likelihood that when solutions which exhibit low emissions are found they will have low distance values. The slightly less significant relation between emissions and vehicles may account for the fact that less solutions with fewer vehicles were discovered when the third parameter was added.

5. REFERENCES

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