Using Graphical Information Systems to improve vehicle routing problem instances.

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ABSTRACT

This paper makes the assertion that vehicle routing rearch has produced increasingly more powerful problem solvers, but has not increased the realism or compexity of typical problem instances. This paper argues that the time has come of use realistic street network data to increase the relevence and challenge of our work. A particular benefit of real world street data is the ability to support vehicle emissions modeling. Thus allowing emissions to be used as an optimisation criterion. Two on-line demonstrations are presented which demonstrate the use of GIS data obtained from Open Street Map and Google Maps. The demonstrations prove the concept that Evolutionary Algorithms may be used to solve problem instances that are based upon GIS derrived data.

Categories and Subject Descriptors

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

General Terms

Algorithms

Keywords

Optimisation, Vehicle Routing, Low CO_2 Routing, Real-World Problems

1. INTRODUCTION AND MOTIVATION

Vehicle routing problems have traditionally been presented as problems that require routing within a simplistic 2D space. The range of such problems includes the simplistic Travelling Salesman Problem [3, 9] through to multi-objective logistics based problems such as the Vehicle Routing Problem with Time Windows (VRPTW) [20, 20]. Despite the development of complex single and multi-objective optimisation techniques, it may be argued that the problem instances themselves have not developed at a similar pace. Vehicle routing in the real world requires navigation of a complex road network, with multiple routes between most points, delays due to traffic and environmental conditions and factors such as gradients which can affect the speed of differing vehicles. There also exists a need to consider environmental objectives when optimising routing problems, such objectives may include fuel consumption or emissions.

This paper presents a case for creating more realistic problem instances based upon readily available geographical data provided through Graphical Information Systems (GIS).

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2. PREVIOUS WORK

2.1 Vehicle Routing Problems

The solving and optimisation of problems associated with Vehicle Routing and Planning has a long history within ECO research. Within the area of Vehicle Routing, a number of related problem types exist. The simplest problem is the Travelling Salesman Problem [4, 6, 5, 17] (TSP) which seeks the shortest tour through a number of points. The Vehicle Routing Problem (VRP) [7, 23, 27] requires the construction of a set of tours all commencing from the same point (often referred to as the *depot*). A number of variants of the VRP exist, an overview of which can be found in [28]. For example, the Capacitated Vehicle Routing Problem(CVRP) accounts for limited carrying capacity, whereas the need to deliver within in a particular time-window is addressed in the VRPTW, e.g. [26]. Many VRP variants assume a homogeneous fleet of vehicles, but more recent research accounts for heterogeneous fleets, e.g the Fleet Size and Mix Vehicle Routing Problem [19, 24].

Research to date has mostly concentrated on the use of instances, such as those described in [26] that are based upon a set of points in 2D space (to represent customers, cities, depots etc) with distances taken as being the Euclidean distance between two points.

Environmental issues within organisations and legislative changes are forcing companies to consider the *environmental* impact of their activities. Typically, both academic studies and commercial software vendors focus on minimising economic costs (in terms of distance travelled and vehicles utilised), although this has an implicit environmental benefit in reducing total fuel consumption and thereby emissions. The Time-Dependent Vehicle Routing problem (TDVR) such as proposed by [18] and later used in [14] also implicitly leads to reductions in emissions by preferring solutions which direct vehicles away from congested areas in order to reduce the time taken for a journey. Although this may lead to increased journey distances, for examples by directing traffic from congested urban areas to less congested motorways, the overall effect is to minimise fuel consumption as a result of decreased journey times.

3. VEHICLE EMISSIONS MODELS

Within the context of vehicle routing and planning, it is becomming desireable to be able predict the likely enviromental impact of the solution being proposed. Not only does this inform the organisation of the environmental cost of the propsed solution, but it should facilitate the use of environmental impact as an optimisation criterion.

In order to estimate emissions meaningfully it is necessary to understand the detail of the journey being undertaken. Within traditional vehicle routing problem instances where Euclidean distances are utilised only the distance between points is known, time may be estimated by multiplying the distance by a factor. In order estimate emissions meaningfuly it is necessary to know more about each journey. Typical information required could include dividing the journey into separate sections (e.g. individual roads/streets) and being aware of the individual lengths and average speeds associated with each section. One often overlooked aspect is that of gradient, as the rulling gradient of a road will influence the emissions.

A simplistic approach to modelling CO_2 emissions converts distance travelled to tonnes of CO_2 using a multiplier which assumes a fixed average value of litres of fuel consumed per km and fuel conversion factor appropriate to the vehicle in use, as shown below:

$$totalCO_2 = disttravelled * fuelused * fuelconversionfactor$$

This makes it straightforward to convert distance travelled into emissions for use within an optimisation problem. For example, Harris [13] utilise the above objective measure as one of the objectives in a facility-location problem, where the goal is to minimise the cost of operating a distribution network.

According to [29], emissions are dependent not only on distance but on a number of factors, which can be categorised into four classes:

- travel related (e.g. speed, acceleration, vehicle loading)
- driver behaviour
- physical road characteristics (e.g. class of road)
- vehicle characteristics

Of these factors, they note that speed plays a major role in influencing emissions, and therefore that simply minimising distance is not equivalent to minimising emissions. A number of models exist that relate speed to total emissions, generally falling into two broad categories: those which assume an average speed over each link of a journey (e.g. [2, 1]) and those which apply a driving cycle to each link in order to estimate emissions on a second by second basis [8]. The latter category (known as instantaneous models) provide a precise description of emissions behaviour but tend to be complex and require precise measurements of vehicle operation and location in order to be accurate, information which is expensive to collect and tends to restrict their use to an academic modelling community [8].

The ability to specify a vehicle type is advantageous, especially if the problem being examined has a heterogeneous fleet, the ability to specify the journey as a series of stages, each with a differing average speed, potentially allows for greater accuracy and takes advantages of GIS systems than can supply specific driving details. To be used effectively models such as COPERT [10] require journey and vehicle data, it also may have to be used iteratively throughout a journey potentially increasing CPU time in applications such as an EA fitness function that require many executions of the model.

Category	Speed (kph)
default	30
secondary	30
residential	30
primary	32
tertiary	32
trunk	32
motorway-link	72.4
motorway	72.4

Table 1: Average speeds allocated to OSM link classes. For any link class not in the list, the default value (30kph) is used. Values are obtained from Scottish Government figures

In the case of the problem instances discussed, the authors utilise the National Atmospheric Emissions Inventory(NAEI) [12] to calculate emissions as follows:

$$\begin{aligned} EF(gCO2/km) = (&a + bv + cv^2 + dv^e + f.ln(v) \\ &+ gv^3 + h/v + i/v^2 + j/v^3).x \end{aligned}$$

In this case v is the average speed for a given link parameters and a to x are coefficients that relate to a specific type of vehicle. NAEI supplies parameters for a to x for 58 different vehicle classes. A vehicle class is a combination of type (Car, Truck, Bus , Motorbike etc), fuel type, engine type and size. NAEI supply their model as a spreadsheet, in this case the model was implemented in Java. Models contained within the NAEI registry are used extensively within the UK to support carbon footprint calculators. The simplicity of the NAEI model should increase its suitability in situations where frequent calculations are required.

4. CREATING MORE REALISTIC PROBLEM INSTANCES

4.1 Graphical Information Systems

Recent years has seen the increasing availability of on line Graphical Information Systems. The three most commonly used being Google Maps, Microsoft Bing Maps and the Open Streetmap Project [22]. All of these systems allow the user access to street network data. With access to the street network data, additional information about journeys may be obtained, such as individual roads traversed and average speeds and distance for each journey segment. Typical road classes and speeds may be seen in table 1. A realistic time may also be supplied by the GIS for a journey.

An important property of real-world street networks is the availability of many multiple routes between points. Routing algorithms such as A* or Highway Hierarchies may be used to find the optimal route between points, and each journey may have criterion such as time, distance and predicted emissions. When multiple routes exist some routes may have differing criterion. For example there may be two routes between points A and B, the first route taking less time, but incurring higher emissions, the other taking longer but having lower predicted emissions. Depending on the problem objectives differing routes between the same points may be used. Real-world road networks are also affected by traffic conjestion, which may result in increased time and emissions associated with certain routes at specific times.

4.2 Incorporating Real World GIS data within an EA

Acces to GIS data may be via a web service (e.g.Google Maps API or Bing API) or in some cases the data may be downloaded and stored in a dedicated local store (Open Steet Map). The amount of data required to represent a real-word road network as a graph is considerable. In the case of the City of Edinburgh, UK 80,000 nodes are required to represent the street network as a graph. In such cases the computational resource required to find routes between points on the graph is non-trivial. If the GIS is a web service there is the communications overhead and processing time on the server to consider, if the data is held locally there is still processing and database access times to consider.

The addition of the Distance Matrix service to the Google Maps API (Version 3) allows the calculation of many routes using only one API call. This considerably speeds up the creation of an origin destination matrix between locations being used within a problem compared to having to make a separate request for each individual distance.

As well as online GIS, Open Street Map (OSM [22]) supports the downloading of road network data as XML files. This data may then be stored localy in a database. A number of API tools are available that allow the user to construct routes using such local data stores. Because OSM is open source, there's no restriction on the caching of routes constructed, whereas online commercial GIS systems often specifcly prohibit the caching of results or data locally.

4.3 Evolutionary Algorithms

Within a population based approach such as an Evolutionary Algorithm (EA) there many be frequent calls to the GIS from within the evaluation function.

The experience of the authors suggests that using a population based approach within an EA could result in so many calls to the data source that the time and financial penalties incurred may potentially outweigh the benefits of using an evolutionary problem solver. The use of fitness approximation due to a high cost fitness function has been dealt with previously in evolutionary and non-evolutionary optimisation methods notably in [11] and [16]. Three schemes for approximating fitness have been identified [15] which provides an overview of research in this area. Problem approximation attempts to replace the problem being solved with a simpler, yet equivalent problem. The simpler problem is solved and then the solution translated to the original more complex problem. Such an approach requires there to be an equivalent problem with a relationship that allows such a transformation to take place. The second approach identified is that of functional approximation, where an alternative fitness function is constructed that allows a less complex evaluation of the original problem. Thirdly evolutionary approximation may be used within evolutionary algorithms. This is based on the concept of not evaluating the fitness of each child, instead the fitness is estimated by basing it on the fitness of the parents [25]. Within the context of vehicle routing problems there are a number of approaches to dealing with this:

- Make use of an approxamation function (e.g. Euclidean distance) for some of the evalutions.
- Cache the calculated routes within a local data store
- Store the GIS data locally to reduce communications overheads

The first option is explored in section 4.4. The second option is useful, but the caching of data locally may be prohibited by GIS providers. Storing the GIS data locally is practical if using a provider such as OSM, but the amount of infrastructure required to store data for a large geographical area (e.g. North America or mainland Europe) makes this a non-trivial exercise.

	Distance	**Time**	**Emissions**
Urban	87.88%	82.25%	37.23%
Capitals	91.15%	83.85%	44.92%

Table 2: The % of journey pairs that are ranked in the same order as when using Euclidean distance.

4.4 Relating Euclidean distances to actual distances, times and emissions values

It is useful to examine the relationship between Euclidean distances and what we will term "real" distances, travel times and emissions calculated using a GIS.

Whe using Evolutionary Algorithms it may be argued that the relative distance between two journeys, rather than not the actual distance between two but journeys is the main focus for decision making when planning. For instance if the distance from a, b, c is less than a, c, b a different planning decision may be required. It has been argued that Euclidean distances could be used in place of actual distances, on the basis that they would allow journeys to be ranked in the correct distance order, even if the actual distance values were incorrect.

To test the above theory a simple experiment was carried out using Google Maps. Two sets of journeys were created, the journeys being grouped into unique pairs. For each pair of journeys the following values were calculated:

- The Euclidean distance between start and end
- The caluclated journey distance between the start and end using the Google Maps API
- The caluclated journey time between the start and end using the Google Maps API
- The estimated emissions between the start and end using the Google Maps API and the NAEI [12] emissions model

Each journey pair can now be ranked in order to each of the above values, our interest being the number of instances where the Euclidean ranking order matches that of the other criterion. Two sets of journeys were used, the first named Urban consisted of 462 pairs of journeys made within an urban area (the journeys being between 1.3 and 7.5 km in length). The second dataset named Capitals comprised 306 longer journey pairs that were made between cities on the European continent (the journeys being between 399 and 3399.1 km in length).

The results of the experiment are shown in table 2. From the results we can note that in 90% of cases the journey rankings arrived at by Euclidean Distance are the same are those using the actual distance. This drops to 82% when considering time and to less than 50% when considering emissions. This simple experiment suggests that the solutions to a routing problem will change when the fitness criterion is altered from Euclidean distance to actual distance, time or emissions.

In [30] it was proposed to reduce the calls to the real distance function within the GIS, is to commence the evolutionary process using a Euclidean distance based fitness function and to switch to real distances. In [30] a car pooling problem was investigated, this problem required the construction of routes for groups of employees taking part in car sharing. The problem was solved using an evolutionary algorithm, which began by using Euclidean distances and at a given point changed to a fitnes function that calculated the actual routes through the street network and based its distance values on that. As might be expected, the best quality solutions are produced when using a higher number of real distance based evaluations. The findings of [30] suggested that the more use was made of actual distance calculations the more optimal the final result. Using Euclidean estimation has a negative effect on the final result. The results in table 2 suggest that this approach [30] will be ineffective when time and emissions are being taking into account.

5. DEMONSTRATION APPLICATIONS

Two demonstrations of the Vehicle Routing Problem with Time Windows (VRPTW) with real-world data have been constructed and may be viewed at http://vrptwemissions.appspot.com/ (example 1) and http://www.soc.napier.ac.uk/ cs88/vrptw.html (example 2). Both of these applications solve instances of the VRPW problem based upon the road network of the City of Edinburgh. The problem instances are solved using three criterion, distance, vehicles and emissions using a Multi Objective GA (MOGA) base upon that described in [21].

In example 1, (see figure 1) the underlying underlying GIS data is sourced from Open Street Map [22], and is stored in a MYSQL database. A Java implmentation of The A* algorithm is used to find paths through the data. The application is hosted upon Google App Engine, to speed up runtimes, distances, times and emissions values for journeys are cached, to minimise the number of calls to the database and the A* algorithm. The EA is implemented in Java and runs on Google App Engine, the client calls the EA service, passing problem parameters to it, the EA then runs for a number of generations and returns the solution found. In this problem, the customers to be visited are pre-set, cached values for distances, emissions and times between customers are stored on the server. This approach looses flexibility as customers have be enetered off-line and added to the caches, but has the advantage that relatively large instances (up to 100 customers) can be solved.

Example 2, uses the Google Maps API as its GIS provider, unlike example 1 the customers may be entered at run-time. The Google Maps Distance Matrix API, allows distances times and between multiple points to be obtained using just one API call, this allows the construction of origin-destination matrixes for distances, times and emissions. Having constructed the matrixes the EA is then executed locally (within the client browser). The Java based EA is translated into JavaScript using Google Web Toolkit.

Example 2 has the obvious advantage of allowing the user to enter customer details at runtime, but given restrictions on the frequency of calls to the Distance Matrix API, it is not feasible (at present) to work with problem instances of larger than 25 customers. The approach of cross-compiling the EA to Javascript for client-side execution simplifies the implementation, but does potentially impose limits on the processing power available.

6. CONCLUSIONS

The availability of GIS data both online and downloadable via OSM means that any researcher can now access realistic street network data. The use of such data can add extra challenges to solving the problem, such as the ability to specificy predicted emissions as an optimisation criterion.

The use of such data should also increase the adoption of vehicle routing techniques by industry. Increasing developments in the speed of API response makes their incorporation within EAs (and other nature inspired methods) more realistic. The two on-line demonstrations prove the concept that accessing real-world GIS data from within an EA is feasible and technically simple. Given recent improvements the author would recommend the use of the Google Maps API over Open Streetmap, given the amount that the API will do (e.g. finding routes and allowing the visualisation of results).

Given that individual routes used within a solution may be optimised towards different criterion e.g. minimise distance or minimise CO_2. It may no longer be sufficient for a fitnes function to simply request a route between x and y, but for the fitness function to request a route between x and y using a specific routing criterion. The criterion could either be specified within the representation or else decided on by a heuristic within the evaluation function.

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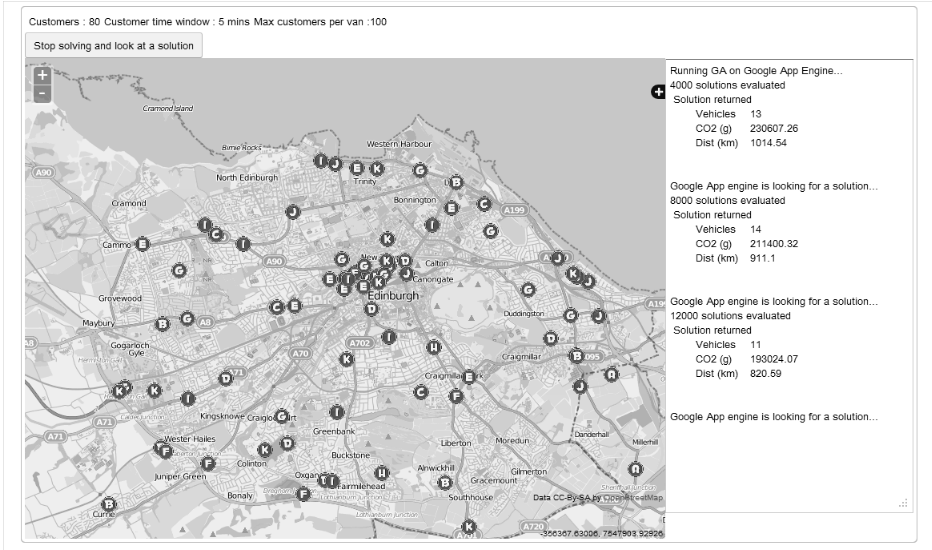

Figure 1: The demonstration application showing a VRPTW problem being solved using a Multi Objective GA (MOGA) as described in the text.

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