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Discrete Optimization

The bi-objective Pollution-Routing Problem

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ABSTRACT

The bi-objective Pollution-Routing Problem is an extension of the Pollution-Routing Problem (PRP) which consists of routing a number of vehicles to serve a set of customers, and determining their speed on each route segment. The two objective functions pertaining to minimization of fuel consumption and driving time are conflicting and are thus considered separately. This paper presents an adaptive large neighborhood search algorithm (ALNS), combined with a speed optimization procedure, to solve the bi-objective PRP. Using the ALNS as the search engine, four *a posteriori* methods, namely the weighting method, the weighting method with normalization, the epsilon-constraint method and a new hybrid method (HM), are tested using a scalarization of the two objective functions. The HM combines adaptive weighting with the epsilon-constraint method. To evaluate the effectiveness of the algorithm, new sets of instances based on real geographic data are generated, and a library of bi-criteria PRP instances is compiled. Results of extensive computational experiments with the four methods are presented and compared with one another by means of the hypervolume and epsilon indicators. The results show that HM is highly effective in finding good-quality non-dominated solutions on PRP instances with 100 nodes.

1. Introduction

Freight transportation lies at the forefront of logistics planning. Until now, the planning of freight transportation activities has mainly focused on ways of saving money and increasing profitability by considering internal transportation costs only, e.g., fuel cost, drivers' wages (see, e.g., Crainic, 2000; Forkenbrock, 1999, 2001).

Freight transportation in the United Kingdom (UK) is responsible for 22% of the CO_2 emissions from the transportation sector, amounting to 33.7 million tonnes, or 6% of the CO_2 emissions in the country, of which road transport accounts for a proportion of 92% (McKinnon, 2007). The 2008 Climate Change Act commits the UK to an ambitious and legally binding 80% reduction in greenhouse gases (GHG) emissions by 2050, from a 1990 baseline. The situation in Europe is not much different. According to the TERM 2011 Report published by the European Environment Agency, transport (including international maritime) contributed 24% of the overall GHG emissions in the EU-27 countries in 2009, with road transport accounting for 17% of the total GHG emissions Vicente (2011). The transportation sector therefore has an important role to play, as one of the largest GHG contributor, in achieving reduction targets (Tight, Bristow, Pridmore, & May, 2005).

The carbon dioxide equivalent (CO_2e) measures how much global warming a given type and amount of GHG may cause, using the functionally equivalent amount or concentration of CO_2 as the reference. The selection of GHGs to include in the carbon footprint is an important issue. Wright, Kemp, and Williams (2011) suggest that a significant proportion of emissions can be captured through measurement of the two most prominent anthropogenic GHGs, CO_2 and CH_4. The emissions of CO_2 are directly proportional to the amount of fuel consumed by a vehicle. This amount is dependent on a variety of vehicle, environment and traffic-related parameters, such as vehicle speed, load and acceleration (Demir, Bektaş, & Laporte, 2011). On the other hand, the emissions of CH_4 are a function of many complex aspects of combustion dynamics and of the type of emission control systems used.

Freight companies also generate significant amounts of air pollution besides GHG, including particulate matter (small particles of dust, soot, and organic matter suspended in the atmosphere), carbon monoxide (colorless, odorless, poisonous gas produced when carbon-containing fuel is not burned completely), ozone (formed when emissions of nitrogen oxides (NO_x) and volatile organic compounds (VOCs) chemically react in the presence of sunlight) and hazardous air pollutants, also referred to as air toxics (chemicals

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emitted into the atmosphere that cause or are suspected to cause cancer or other severe health effects) (PSRC, 2010).

Freight transportation planning has many facets, particularly when viewed from the multiple levels of decision making. Arguably the most famous problem at this level is the well-known Vehicle Routing Problem (VRP), which consists of determining routes for a fleet of vehicles to satisfy the demands of a set of customers. The traditional objective in the standard VRP is to minimize a cost function which is traditionally considered to be the total distance traveled by all vehicles. Taking a more explicit look at externalities of freight transportation, and in particular vehicle routing, Bektaş and Laporte (2011) introduced the Pollution-Routing Problem (PRP) which aims at minimizing a total cost function comprising fuel and driving costs in the presence of time windows.

Most real-world problems involve multiple objectives. In the context of the PRP, two important objectives should be taken into account, namely minimization of fuel consumption and the total driving time. Fuel consumption depends on the energy required to move a vehicle from one point to another, and is proportional to the amount of emissions. As discussed in Demir, Bektaş, and Laporte (2012) for each vehicle there exists an optimal speed yielding a minimum fuel consumption. However, this speed is generally lower than the speed preferred by vehicle drivers in practice. Another important issue in road transportation is time management. In freight transport terminology, time is money and it is essential for firms to perform timely deliveries in order to establish and keep a good reputation. In practice, drivers' schedules tend to be flexible, with different numbers of hours worked each day, subject to driving time regulations. If a saving of one hour can be achieved on a given vehicle route, this would imply reducing the corresponding driver's costs by an hour (Fowkes & Whiteing, 2006). Reduction in time spent on a route can be achieved by traveling at higher speed, but this, in turn, increases fuel costs and emissions. Since the two objectives of minimizing fuel and time are conflicting, the problem requires the use of multi-objective optimization to allow an evaluation of the possible trade-offs.

In practice, companies would like to minimize their total operating cost, including those related to fuel and time. However, costs of fuel, emissions and time might differ from one organization to another, and in some cases rather significantly. As an example, it is found that driver costs are paid as hourly wages in some countries (e.g., UK and USA) whereas they are a monthly salary in others. Fuel costs also differ between countries. Finally, carbon costs vary significantly (£60–£225 per tonne) as discussed in Bektaş and Laporte (2011). In this paper, we investigate a bi-objective vehicle routing problem in which one of the objectives is related to fuel consumption and the other to driving time. The two objectives are treated in their natural units of measurement in order to eliminate the bias resulting from the cost differences just mentioned. The benefit is that managers or users of the approach described in the paper can attach cost figures relevant to their organization and can produce tailored trade-off curves for their operations.

We propose a solution method based on an enhanced adaptive large neighborhood search (ALNS) and a specialized speed optimization algorithm described in Demir et al. (2012). The scientific contribution of this study is threefold: (i) to introduce of a bi-objective variant of the Pollution-Routing Problem, (ii) to apply and test multi-objective techniques to solve the bi-objective PRP, and (iii) to perform extensive computational experiments using four *a posteriori* methods evaluated by means of two performance indicators. In contrast to existing studies on the "green" VRP (for which a brief review is presented below), this paper breaks away from the literature by considering two objectives, one of them being a comprehensive emissions function incorporating the effect of load and speed. This study also contributes to the multi-objective optimization literature by presenting a comprehensive comparison of four methods on the bi-objective PRP.

The remainder of this paper is organized as follows. In Section 2 we provide a general overview of multi-objective optimization and we summarize the existing literature on multi-objective and "green" VRPs. Section 3 presents the bi-objective PRP along with a mathematical programming pformulation. Section 4 includes a brief description of the heuristic algorithm. Section 5 presents the generation of the instances and the results of extensive computational experiments, together with managerial insights. Conclusions are stated in Section 6.

2. Multi-objective optimization

Multi-objective optimization (MOO), also known as multi-objective programming, multi-criteria or multi-attribute optimization, is the process of simultaneously optimizing two or more conflicting objectives subject to a number of constraints. In this section, we consider a MOO problem of the form

$$\text{(MOO)} \quad \text{minimize} \quad \{f_1(x), f_2(x), \ldots, f_k(x)\} \tag{1}$$

$$\text{subject to} \quad x \in \mathcal{S} \tag{2}$$

where f_k: $\Re^n \rightarrow \Re$ are $k \geqslant 2$ objective functions to be minimized simultaneously. The decision variables $x = (x_1, \ldots, x_n)^T$ belong to a non-empty feasible region (set) $\mathcal{S} \subseteq \mathcal{R}^n$. If there is no conflict between the objective functions, then a solution in which every objective attains its optimum values can be found. In this case, no special methods are needed. To avoid such trivial cases, we assume that no such solution exists. This means that the objective functions are at least partly conflicting. They may also be incommensurable, i.e., measured in different units (Miettinen, 1999), as is the case in this paper.

For non-trivial multi-objective problems, one cannot identify a single solution that simultaneously optimizes every objective. While searching for solutions, one reaches a point such that, when attempting to improve an objective, other objectives suffer as a result. A solution is called non-dominated, Pareto optimal, or Pareto efficient if it cannot be eliminated from consideration by replacing it with another solution which improves upon one of the objectives without worsening another. Finding such non-dominated solutions, and quantifying the trade-offs in satisfying the different objectives, is the goal of setting up and solving a MOO problem. The next section presents formal definitions of Pareto optimality.

2.1. Multi-objective optimization methods

In this section, we review several methods for solving MOO problems and for generating Pareto optimal solutions. General references on this topic can be found in Ehrgott and Gandibleux (2002) and Jozefowiez, Semet, and Talbi (2008a).

Methods for MOO can be classified in various ways. One of them is based on whether many Pareto optimal solutions are generated or not, and on the role of the decision maker in solving the MOO problem (Rangaiah, 2009). One possible classification is where the methods are initially grouped into two: (i) generating methods and (ii) preference-based methods. The former group of methods aims at generating one or more Pareto optimal points without any prior input from a decision maker. In contrast, the latter uses extra information from a decision maker as part of the solution process. Generating methods are further divided into three: (i) no-preference methods, (ii) *a posteriori* methods using a scalarization approach, and (iii) *a posteriori* method using a multi-objective approach.

No-preference methods do not require any prior information and generally yield only one Pareto optimal point. Examples of