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Composite goal methods for transportation network optimization

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A B S T R A C T

Lately the topic of multi-objective transportation network optimization has received increased attention in the research literature. The use of multi-objective transportation network optimization has led to a more accurate and realistic solution in comparison to scenarios where only a single objective is considered. The aim of this work is to identify the most promising multi-objective optimization technique for use in solving real-world transportation network optimization problems. We start by reviewing the state of the art in multi-objective optimization and identify four generic strategies, which are referred to as *goal synthesis, superposition, incremental solving* and *exploration*. We then implement and test seven instances of these four strategies. From the literature, the preferred approach lies in the combination of goals into a single optimization model (a.k.a. goal synthesis). Despite its popularity as a multi-objective optimization method and in the context of our problem domain, the experimental results achieved by this method resulted in poor quality solutions when compared to the other strategies. This was particularly noticeable in the case of the superposition method which significantly outperformed goal synthesis.

1. Introduction

When optimizing transportation networks, several criteria can be used as the optimization goal, criteria such as the shortest distance traveled minimum inventory, minimum transportation cost and highest network resilience. In the case of industry based applications, it is often advantageous to simultaneously consider several of these goals with a view to developing a model that more accurately represents the operation of the actual business. Defining a mathematical model that incorporates the perspective of more than one criterion in itself is not a simple task and often involves the definition of complex non-linear models. Moreover, the goals of such criteria may well be mutually exclusive and result in the definition of a multi-goal model that is not or not always achievable in practice.

A simple way to handle the multi-objective optimization problem is to construct a composite objective function that is the weighted sum of the conflicting objectives (Aslam & Ng, 2010). In the literature this technique is also referred to as the *preference-based strategy* and is the approach most often adopted by academic studies. The preference-based strategy is a trade-off that reduces a multi-goal approach to a single-goal optimization problem. However, in reality as a solution this trade-off has proved to be very sensitive to the relative preferences assigned to the goals (Aslam & Ng, 2010) and in practice it is difficult for practitioners, even those familiar with the problem domain to precisely and accurately select such weightings (Konak, Coit, & Smith, 2006).

As part of this work, we identify the principal alternative methods for use in multi-objective optimization when applied to the solution of real-world transportation network optimization problems. The work reported here is an extension to previously work Veluscek et al. (2014). The problem models and the data sets have been defined in collaboration with a world leading manufacturer of construction and mining equipment and represent a snapshot of the day-to-day complexities and operational challenges faced by our industrial partners business. The aim of this work is to identify and test those multi-objective optimization techniques that better address the complexities of such operating environments.

In the following sections, we identify four generic strategies used to optimize multi-goal problem scenarios and formally present seven implementations of these strategies. The methods have been designed and implemented with a view to solving the transportation network optimization problem reported in Veluscek et al. (2014).

In Sections 2 and 3 we present the background to this work and introduce previously work on multi-goal optimization. In Section 4 we formally describe the methods used to combine single-goal

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optimization problems. In Section 5 we present the outcome of the numerical experiments undertaken to verify and test the effectiveness of the proposed methods.

2. Context and motivations

A robust solution to the multi-goal optimization problem is of particular interest to real-world applications where several optimization objectives are commonly involved. Multi-goal problems usually do not have a single 'best' solution, but are characterized by a set of solutions that are superior to others when considering all objectives (Alaya, Solnon, & Ghedira, 2007). This set is referred to as the Pareto set or as the non-dominated solution (Alaya et al., 2007). This multiplicity of solutions can be explained by the fact that individual objectives are often in conflict (Alaya et al., 2007). For example, Altiparmak, Gen, Lin, and Paksoy (2006) defined three objectives for the transportation network optimization problem: the total cost, the total satisfied customer demand and the equity of the capacity utilization ratio for each production source. The authors then implement a genetic algorithm to find the set of Pareto-optimal solutions. A similar example is presented in Yagmahan and Yenisey (2008) for the flow shop scheduling problem. The multi-objective function in this instance consists of minimizing the distance between the values of all the single-objective functions.

In our experience, most of the solutions proposed for multi-objective optimization problems are either specific to the kind of problem or to the kind of technique used to determine the optimal solution. We have identified four generic solution strategies that in general are used to solve multi-objective optimization problems.

The first strategy is called **Goal Synthesis** and requires the definition of a mathematical model which includes all the single-goal problems. This category is also referred to as the *preference-based strategy* (Aslam & Ng, 2010). The model defines one search space which is a sub-space of the intersection of the single-goal problem search spaces. The best composite solution is then sought on this space along one path. The solution found is feasible for each single-goal problem separately, but it is not necessarily the optimal one. Applying this strategy is no different from solving any other optimization problem: firstly a mathematical model is defined and then an optimal solution is sought using an appropriate optimization algorithm. However, there is no guarantee that the intersection of the single-goal problems exists or that the definition of such a multi-goal model is even possible.

The second strategy is called **Superposition** and in contrast to the previous method does not require the definition of a multi-objective problem model. Firstly, a solution is computed for each of the single-goal problems and then a combination of them are taken as the multi-goal solution. The applicability of this strategy relies on the definition of a combination operator. Again it is possible that the combination of the single-goal solutions is empty and a feasible solution does not exist. Das and Dennis (1998) designed a method based on this strategy to solve generic non-linear multi-objective optimization problems.

The third strategy is called **Incremental Solving**. Here each single-goal problem is solved sequentially in accordance with a predefined order, and the starting exploration point of the ith problem is the solution or stopping point of the $(i-1)$th problem. The solution for the multi-goal problem depends on the order used to solve the single-goal problems. Boudahri, Sari, Maliki, and Bennekrouf (2011) adopted this strategy to optimize an agricultural products supply chain.

The final strategy is called **Exploration** and is based on a 'brute force' approach. Firstly, a large number of feasible solutions are generated for each single-goal problem and then the multi-goal solution is taken as the solution that represents the 'best' compromise for the set of single-goal problems. Applying this strategy should always lead to a solution, provided a feasible solution exists for at least one of the single-goal problems. In common with many brute force approaches the cost of producing a quality solution is computational expensive. Bevilacqua et al. (2012) adopted this strategy to solve a generic distribution network and employed a genetic algorithm to improve the generation of solutions.

Aslam and Ng (2010) and Ogunbanwo et al. (2014) provide extensive reviews of the work undertaken for the problem of transportation network optimization. We have analyzed the works presented in such reviews and have categorized the reported methods with respect to those developed to solve multi-objective optimization problems. Table 1 and Fig. 1 show the results of that analysis. We can clearly see that in recent years the Goal Synthesis strategy is the dominant method used. Nevertheless, despite its popularity we will show that it may not necessarily be the best choice when solving real-world transportation network optimization problems.

As will be discussed in the following sections, the method used in this work to solve our specific real-world optimization problem is the Ant Colony System algorithm (Dorigo & Gambardella, 1997). García-Martínez, Cordón, and Herrera (2007) analyzed several ant colony optimization variants for multi-goal optimization and presented a taxonomy for them. The authors also performed an empirical analysis for the travel salesman problem and compared their results with two other well-known multi-objective genetic algorithms. It is worth noting that a prerequisite of such analysis is to define a multi-goal model to generate the Pareto optimal frontier. Once again, the authors proposed a model that simultaneously considers all optimization goals (i.e. goal synthesis). This indicates a preference for the goal synthesis strategy over the use of alternatives.

3. Transportation network optimization

A transportation network optimization problem may be express in terms of a minimization objective function, a set of variables and a set of constraints over these variables, regardless of the goal type (functions having to be maximized may be multiplied by -1). Given a vector of variables $x \in \mathbb{R}^n$ and a vector of cost coefficients $c \in \mathbb{R}^n$, a transportation network optimization problem may be defined as:

$$v = \min \left\{ c^T x | Ax = b \wedge \ x \geqslant o \right\} \tag{1}$$

where $A \in \mathbb{R}^{m \times x}$ is a matrix of coefficients, $b \in \mathbb{R}^m$ is a vector of coefficients and $v \in \mathbb{R}^n$ is a vector of assignments for the variables x such that the value of the objective function $c^T x$ is minimum. The matrix A and the vector b define the constraints over the decision variables x and define the problem search space. Therefore, a transportation network optimization problem is defined by the tuple $lp := (x, c, A, b, v)$. A multi-goal optimization problem is a set of tuples representing single-goal optimization problems:

$$LP(x, A, b) = \left\{ (x, c, A, b, v) | \exists c \in \mathbb{R}^{|x|} \wedge \exists v \in \mathbb{R}^{|x|} \right\}, \tag{2}$$

where the vector of variables $x \in \mathbb{R}^n$ and the set of coefficients A and b are the same for all the single-goal problems.

In a transportation network optimization problem, the variables x define the number of products to send on a given network route. The coefficients c usually depend on the goal and are typically information associated with a given route on the network (e.g. having to optimize for minimum transportation cost, $c_i \in c$ is the cost to send products via route i). Typically the constraints defined by A and b are the constraints placed on production capacity and customer demand. The solution v is a distribution plan for the network.