The Netherlands
Research School for
Transport, Infrastructure
and Logistics

TRAIL

11th TRAIL Congress
November 2010

OPTIMIZATION OF EXTERNALITIES USING DTM MEASURES

A Pareto optimal multi objective optimization using the evolutionary algorithm SPEA2+

Ir. Luc Wismans[1,3]*, Prof. dr. ir. Eric van Berkum[1], Dr. Michiel Bliemer[2,3]
[1]Faculty of Engineering Technology, Centre for Transport Studies, University of Twente, the Netherlands
[2]Faculty of Civil Engineering and Geosciences, Department of Transport and Planning, Delft University of Technology, the Netherlands
[3] Department Tim, Goudappel Coffeng BV, the Netherlands

ABSTRACT

Multi objective optimization of externalities of traffic is performed solving a network design problem in which Dynamic Traffic Management measures are used. The resulting Pareto optimal set is determined by employing the SPEA2+ evolutionary algorithm.

KEYWORDS

Network design, externalities, dynamic traffic management, pareto optimal set, SPEA2+

INTRODUCTION

Optimization of a road transport system is often viewed as a problem to find the best way to expand or improve an existing network. This type of problem is generally referred to as the Network Design Problem (NDP). One specific example of this is to optimize a network through the implementation of dynamic traffic management (DTM) measures which can influence the supply of infrastructure dynamically (e.g. traffic signals and rush hour lanes). Traditionally, this type of optimization is focused on improving accessibility. However, due to the increasing attention for externalities, it may no longer suffice to view a transport system as feasible when accessibility is improved. Therefore, in this paper we focus not only on congestion, but also air quality, climate, noise, and traffic safety.

The NDP is usually formulated as a bi-level problem in which the lower level describes the behavior of road users that optimize their own objectives (travel time and travel costs). The upper level consists of the above mentioned objectives optimized by solving the NDP.

Because of the non convexity of the problem (e.g. [1]), several global solution approaches are used, including genetic algorithms and simulated annealing. There are several studies that formulated multi-objective (MO) NDP in which for example the budget constraint is formulated as a second minimization problem and optimization studies in which externalities, mainly air quality, are used as objective (e.g. [2] and [3]). In the bi-level optimization studies the solution approach using genetic algorithms has been proven successful. These studies, however, have been limited to considering only a few externalities and often focused on local optimization. Further, in the lower level mainly a static user equilibrium was used. Although this choice is understandable, because of the many function evaluations needed, Dynamic Traffic Assignment (DTA) models are more suitable to assess the effects of DTM measures. Different researches have shown that there is a proven relation between the traffic dynamics and external effects like emissions of pollutants and traffic safety. High speeds and speed variation (accelerating, braking) have for example a negative effect on traffic safety and emissions of pollutants [4].

MODEL FRAMEWORK AND METHODOLOGY

The multi objective network design problem (P_i) is formulated as:

$$P_i : \min_S z_i(S) = f_i\big(q(S), v(S), k(S)\big), \quad i = 1, \ldots, I, \quad \text{with } \big(q(S), v(S), k(S)\big) \in \overset{DTA}{\Gamma}\big(G(N, A, S), D\big)$$

In our optimization problem we focus on strategic DTM measures optimizing the objectives in the upper level on the long term. The settings of the available DTM measures like traffic signals and variable message signs are defined in S and is called a solution. Time and settings of the DTM measures are discretized, so the upper level then becomes a discrete optimization problem where for each time period a certain DTM measure with a certain setting is implemented. Each possible solution S leads to certain dynamic traffic conditions which is the result of the optimization of road users in the lower level of their own objective (travel time). This is operationalized by solving the Dynamic User Equilibrium problem $\overset{DTA}{\Gamma}$ using the Streamline traffic model, which is a fast multi user class DTA model with dynamic queueing and spillback [5] and easy to connect to Matlab® which is used to program the SPEA2+ algorithm. Input for this assignment is the supply of infrastructure, a network G with nodes N, links A and the DTM measures defined in S, and the demand for infrastructure defined by D. Output of this model are dynamic speeds v flows q, and densities k for all modes on all links of the network. From this, the level of service of all network elements can be determined as a function of time.

Because objectives can be conflicting, this multi objective optimization in the upper level resorts to a number of trade-off optimal solutions, known as Pareto optimal set of solutions. This Pareto optimal set consists of all solutions for which the corresponding objectives cannot be improved for any objective without degradation of another. Based on an extensive literature review [6] for each objective an objective function f_i is defined, where the input stems from a DTA model. Accessibility is defined as the total travel time in the network, which is a direct result of the DTA. Air quality is defined as the total weighted emission of PM_{10} (or NO_x). The weights are related to the level of urbanization. Climate is defined as the total emission of CO_2. The emissions are determined based on the ARTEMIS traffic situation based emission model [7] which means depend on the level of service of the traffic flows. Traffic safety is defined as the total number of injuries and is determined based on a accident risk based model. Finally noise is defined as the average weighted sound power level is calculated, in which the weights of emissions as for air quality depend on the level of urbanization, and emissions are based on a load and speed dependent emission function [8].

The upper level optimization was solved using the Strength Pareto Evolutionary Algorithm 2+ (SPEA2+) described in [9]. This algorithm contains some interesting features by using neighborhood crossover and an archive mechanism to maintain diversity of the solutions in the objective as well as in the solution space. We used the S-metric, size of the dominated space, and the C-metric, coverage of two sets both described in [10] as convergence criteria and used the HSO algorithm, Hypervolume by Slicing Objectives, described in [11] to calculate the hypervolumes needed in the S-metric. Although determination of the Pareto optimal set in stead of combining the objectives beforehand using certain weighting factors has several advantages (i.e. no introduction of uncertainty in weighting factors and information about the sensitivity of different weighting factors), there is just one solution which can be chosen. The Pareto optimal set of solutions can become large, especially when the objectives are mainly opposed. As a consequence the Pareto optimal set may become difficult to comprehend, so we propose a method to reduce it. This method determines the solutions part of the edges of the convex hull which are the relevant solutions when linear weighting between objectives is used to choose one solution.

APPLICATION AND CONCLUSION

A case study on a small hypothesized road network consisting of one OD pair, three routes and four DTM measures (11 possible settings, 6 time periods) is conducted, to show the feasibility of the solution approach and the results of a Pareto optimal multi objective optimization of externalities. Although the network was small, it did incorporate the major elements like urban and non-urban routes when using DTM measures to optimize the externalities. Moreover, these objectives were modeled in a realistic manner incorporating traffic dynamics.

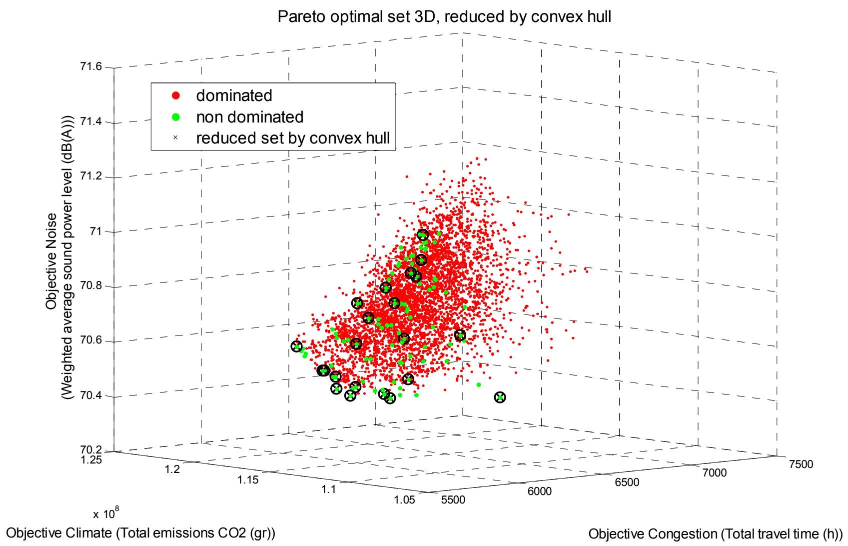

Figure 1: Example of Pareto optimal set reduced by the convex hull method

Figure 1 gives an example of the results of an optimization of noise, climate and congestion and the reduction of the Pareto optimal set by determination of the convex hull. Every point represents a possible solution and their resulting outcome on the objectives. In this case study the objectives concerning climate and congestion are aligned and that these objectives are opposite to noise, air quality and traffic safety. This can be explained, because optimizing congestion aims at avoiding congestion using full capacity of all available routes. Optimizing traffic safety aims at maximizing the use of the relatively safe highway route and avoiding use of the urban route. Optimizing emissions aims at avoiding congestion, but for air quality also searches for the best trade of between minimizing traffic using the urban roads and the level of congestion on the highway. Optimizing noise aims at lowering the driving speeds as much as possible and avoiding traffic using the urban routes. The Pareto optimal sets of solutions of the different combinations of conflicting objectives show a large diversity of settings of DTM measures. This means that a Pareto optimal set can not easily be characterized using simple rules of thumb and proves that a multi objective optimization needs an optimization framework as used in our study. Using the convex hull method when three objectives are simultaneously optimized, reduced the Pareto optimal set on average to less than 25 percent of the original size. To enhance the efficiency of the solution approach our research will continue with investigating several Evolutionary Multi Objective algorithms and possibilities to incorporate local function approximation in order to reduce the number of time consuming function evaluations. Although the convex hull method has proven to be effective it does not guarantee an even spread of solutions in the objective space and assumes linear weighting. Therefore, we are also investigating clustering techniques.

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