Framework for Multiobjective Optimization of Physical Highway Assets Investments

Zheng Wu¹; Gerardo Flintsch, M.ASCE²; Adelino Ferreira³; and Luís de Picado-Santos⁴

Abstract: Optimization-based tools have been included in many engineering management systems for individual infrastructure asset classes such as pavement management systems (PMS) and bridge management systems (BMS). These tools typically include single-objective optimization analyses. However, real-world decisions concerning asset preservation and renewal often involve more than one objective reflecting the various goals of the agency and need to evaluate possible alternatives according to multiple criteria. Traditional single-objective optimization approaches for handling such situations optimize a selected most important objective while either neglecting the less important competing objectives or imposing them as known constraints in the optimization formulation. This approach often does not provide truly optimal solutions. Multiobjective optimization formulations have clear theoretical advantages but increase the complexity of the mathematical formulation. This paper presents a review of the application of multiobjective optimization techniques in various working levels of highway asset management. Some promising techniques for the different infrastructure management functions are identified, and relevant characteristics are summarized and compared. Based on the applications reviewed, it can be concluded that multiobjective optimization could be effective for supporting many infrastructure management business processes. The review also suggests that a synergistic integration of complementary techniques may help develop practical and efficient decision-supporting tools that take advantage of the benefits and avoid potential drawbacks of the individual techniques. DOI: 10.1061/(ASCE)TE.1943-5436.0000458. © 2012 American Society of Civil Engineers.

CE Database subject headings: Optimization; Assets; Resource management; Investments; Highways and roads.

Author keywords: Multiobjective; Optimization; Asset management; Resource allocation.

Introduction

The use of optimization approaches for managing highway assets has received increasing attention in the last few decades because of more stringent budgets, increasing demands, and stricter accountability in transportation investments and policy-setting decisions. Optimization-based tools have been included in many engineering management systems for individual infrastructure asset classes such as pavement management systems (PMS) and bridge management systems (BMS). Without exception, the basic framework of these optimization approaches is the utilization of some type of mathematical programming techniques, such as linear and nonlinear programming. Furthermore, these tools typically include single-objective optimization analyses. However, in general, real-world decisions concerning asset preservation and renewal often involve more than one objective reflecting the various goals of the agency and need to evaluate possible alternatives according to multiple criteria. The traditional approach for handling such situations has been through single-objective optimization analyses. Agencies have often chosen to optimize the most important objective while either neglecting the less important competing objectives or imposing them as known constraints in the optimization formulation. This approach exhibits at least one of the following limitations: (1) how to justify the selected objective as the one that deserves the most attention and does not adversely impair others among the competing objectives; and (2) how to determine the proper range values for those objectives that are not included in the objective function, but instead set as constraints. Such limitations often do not lead to truly optimal solutions compared to those derived directly from multiobjective considerations (Fwa et al. 2000). Multiobjective formulations have clear theoretical advantages but increase the complexity of the mathematical formulation.

Objective

The objective of this paper is to review applications of multiobjective optimization techniques at various working levels [i.e., strategic (cross-asset) level, network level, and project level] of highway asset management and to highlight the advantages of multiobjective optimization techniques over traditional approaches. The paper describes and organizes the multiobjective optimization techniques that hold the most promise for the different highway asset management functions and provides recommendations on how to integrate those as part of the asset management process.

Highway Asset Management

The highway network in the United States forms the backbone of economic development and represents a huge investment in...
monetary value. Since the 1960s, highway agencies in the U.S. have gradually moved from a focus on expansion to one on preservation. State transportation officials at all management levels (state, district, and region) face the challenge of managing a wide range of assets to meet public, agency, and legislative expectations with limited funding. Similar challenges have been reported in other parts of the world (Gilchrist et al. 2008). This significant shift in the transportation field has been fueled by increasingly tighter budgets, an emphasis on preservation, changes in government role/function, and demands for increased accountability. The shift in focus has brought attention to systematic methodologies for effective management of transportation assets.

Transportation engineers have adopted the concept of asset management, which originated from private business practices, to refer to the development, maintenance, operation, improvement, and upgrading of highway assets in a systematic manner. With tangible benefits of optimal benefit-cost maximization and long-term cost reduction and intangible benefits such as safe, convenient, and comfortable highway systems, highway asset management can be used as a tool to communicate between system users, stakeholders, state government officials, and managers (U.S. DOT 1999; Zarghampour 2008). Successful examples can be found not only in the United States, but also in Australia, Canada, England, New Zealand, Germany, Sweden, and Japan, as introduced in an international scanning tour [Federal Highway Administration (FHwA) International Technology Exchange Program 2005] and the work of Technical Committee 4.1.1 of the World Road Association (Gilchrist et al. 2008).

Asset management is essentially a strategic approach that combines engineering principles with business practices and economic theory and is targeted toward the optimal allocation of resources for the management, operation, and preservation of transportation infrastructure [FHwA 1999; Organization of Economic Cooperation and Development (OECD 2001)]. Sound transportation asset management is policy-driven, performance-based, and has a long-term view [Cambridge Systematics, Inc. (CS) 2006; Backer et al. 2008].

Functional Framework for Highway Asset Management

A thorough look at the generic asset management framework (FHwA 1999) reveals that asset management is, at its core, a process of resource (e.g., budget, labor, and facility) allocation and utilization. Moreover, this process occurs at several levels of decision making; namely, across asset class levels (e.g., pavement versus bridge), across categories of works (e.g., preservation versus capacity expansion), and across projects within a given asset class and work category (e.g., geographic region A versus geographic region B and project C versus project D), as shown in Fig. 1.

The foundation of the highway asset management system is a database with asset inventory, condition, usage, and maintenance strategies. Such information is integrated and analyzed through a series of modular applications. Strategic decision-support tools allow analyzing trade-offs among competing infrastructure assets and programs to satisfactorily balance the overall goals of system performance and the agency’s policies. Network- or program-level tools are used to assess and predict asset performance over time, identify appropriate investment strategies for maintenance, rehabilitation, replacement, or expansion of each asset, prioritize/optimze allocation of resources, and generate different kinds of work plans and programs. Decisions made at this level affect the entire network and involve trade-offs between projects and activities. Project-level tools are employed for the trade-off of

![Fig. 1. Framework of resource allocations for highway asset management](image-url)
alternatives for each specific section/project and design of the particular treatment, among other functions. The data-driven infrastructure management cycle continues with feedback loops to maintain its vitality.

For efficient and cost-effective preservation and operation of highway assets (i.e., pavements, bridges, and culverts) both holistically and individually, it is necessary for highway asset management to incorporate relevant analytical tools for rational and integrated decision making. Accordingly, specialized tools for resource allocations at various working levels that characterize different features are required. This paper reviews how multiobjective optimization techniques can be used to develop some of these tools.

**Multiobjective Optimization**

Single-objective optimization identifies the best feasible solution in terms of a single measure of value, leaving decision makers on some occasions the dilemma of either accepting or rejecting this single solution without learning anything about how the solution compares to other feasible solutions. However, according to various human aspirations, it is often not appropriate to select a decision based on one evaluation criterion only. This is especially true in a public decision-making context such as the highway network management, in which there is often more than one objective that needs to be considered. Typically, these multiple, often conflicting, objectives are not only incommensurate, but they might also have significantly different impacts on the resulting solutions. For example, a transportation agency may wish to find suitable maintenance strategies that minimize the agency cost while simultaneously maximizing the network performance, but a strategy that maximizes pavement performance would require that pavements be maintained at a high level of service, which in turn will increase agency cost significantly.

In contrast to the single-objective optimization problem, the multiobjective optimization problem involves finding a vector of decision variables that satisfies constraints and optimizes various objective functions. These constraints and objective functions together form a mathematical description of performance criteria that are usually in conflict with one another. It is generally true for multiobjective optimization problems that are optimal that one of the objectives is usually nonoptimal for the remaining objectives. The concept of Pareto optimality (Pareto 1906) was introduced to define such an optimal solution. A feasible solution to a multiobjective optimization problem is considered Pareto optimal if no other feasible solution exists to yield an improvement in one objective without causing detriment to at least one other objective. In this respect, the term optimizing virtually means finding such a solution that would analyze the trade-offs and give the values of all the objective functions acceptable to the decision maker (Oszczka 1985).

As implicit from the concept of Pareto optimality, there is no single global solution for a multiobjective optimization problem. Mathematically, all the Pareto optimal points are equally acceptable solutions of the multiobjective optimization problem. However, it is practically desirable for the decision maker to select a satisfactory solution from a set of Pareto optimal solutions based on his or her own judgment or preferences. Consequently, it is necessary for the user of the multiobjective optimization to articulate preferences in some capacity, which leads to two different categories of methods for modeling the preferences of a decision maker: (1) methods with a priori articulation of preferences (top-down, that is, first specifying preferences in terms of the relative importance of the objectives or in terms of the goals, then running the optimization algorithm); and (2) methods with a posteriori articulation of preferences (bottom-up, that is, first generating the set of Pareto optimal solutions, then choosing which satisfactory/acceptable solution will be selected). Fig. 2 illustrates the general framework for solving multiobjective optimization problems. Some iteration/interactive method techniques [e.g., the Tchebyche method by Steuer (1986)] may lie between these two different categories and require the decision maker to continually provide input during the solution process, which is relatively efficient in terms of computational effort but is impractical in many real cases.

The application of multiobjective optimization to highway asset management is not as prevalent as in operations research and control theory. However, it is believed that multiobjective optimization will be used more often when the concept of optimization permeates into the transportation agency’s decision processes and more supporting information (e.g., performance data and institutional streamlining) becomes available. Some of the intrinsic characteristics of the highway system that make the use of multiobjective optimization techniques particularly attractive for managing highway assets include the following:

- Environmental considerations, in addition to traditional economic considerations, are being increasingly considered in the management of highway assets. Furthermore, sustainable development requires that economic and environmental goals must be met, along with social goals. To achieve this triple bottom line (Richards 1999), management decisions concerning highway assets should be placed in a context of economic development, ecological sustainability, and social desirability. As a result, the relevant decision-supporting analysis is increasingly emphasizing simultaneous consideration, preferably in some way of optimization, of core objectives from these three broad categories.
- A highway system can be envisioned in terms of a three-dimensional matrix of system objectives, highway facilities, and operational functions, all of which interact with one another (Sinha and Fwa 1987). Consequently, the highway management process can be viewed as a multiobjective system that the optimization modules of traditional highway management systems are not designed to handle (McNeil and Herabat 2006). Decisions on how to allocate resources, whether across asset categories, work categories, or projects within a given asset class and work category, often involve some kind of trade-off. Trade-off tools based on single-objective optimization are found to suffer certain technical difficulties that may not lead to truly optimal solutions. Moreover, quantitative trade-off tools that can handle multiple policy objectives and/or multiple managing levels are scarce, as clearly emphasized in the FHWA international scanning tour (FHWA 2005).
- The management of individual highway assets (e.g., roads and bridges) typically computes an (near) optimal solution based on the objective of lowest cost (agency cost, user cost, or both) or highest level of service. Because of increasing public awareness and involvement, highway asset managers are finding that their constituents require asset conditions to be substantially better than the conditions resulting from a least-cost solution while at the same time demand that the cost associated with better conditions remain low. Multiobjective optimization considerations, in this regard, can help make more rational, balanced, and cost-effective decisions.

Because of these reasons, the highway management field is a fertile ground for the application of multiobjective optimization techniques, as demonstrated by some applications reported in the literature and listed in Table 1. Various techniques have been used to formulate and solve multiobjective optimization problems in highway management with various degrees of success. These
include the weighting sum method, goal programming, compromising programming, the \( \varepsilon \)-constraint method, the multiattribute utility theory, the analytic hierarchy process (AHP), and genetic/evolutionary algorithms.

Some of the main characteristics of the various multiobjective optimization techniques reviewed are summarized and compared in Table 1. The review covers a wide variety of tools, including optimization methods used to formulate the problem, techniques used to weigh the various criteria (e.g., AHP), and heuristics to solve the resulting mathematical model (e.g., genetic algorithms). Furthermore, it needs to be emphasized that no single multiobjective optimization technique is superior regarding all key factors such as computational cost, user-friendliness, and availability of required information (e.g., performance data and problem structure).

### Applications in Highway Asset Management

Multiobjective optimization has been utilized to allocate resources at various working levels of highway asset management, as listed in Table 2. Some of the most noteworthy implemented and potential highway asset management applications at the various levels are discussed in the following sections.

#### Strategy Level

Highway asset management at the strategic level is aimed to make funding allocation decisions across competing asset groups (e.g., pavement, bridge, and culvert) and programs (e.g., safety, maintenance, and expansion) and to provide executives of the state department of transportation with information based on integrated asset data and analysis across the whole department. In this working level, the main difficulty encountered when optimizing the maintenance strategy selection across various types of assets is “how to measure and compare benefits?” (Gharaibeh et al. 1999) It is generally difficult to quantify the benefits received from maintenance actions across various types of assets in a standardized way, such as in the case of comparing agency savings, cost-effectiveness of bridge improvement, reduction of traffic delays, and sign replacement (McNeil and Herabat 2006). There has been a limited number of efforts addressing this problem, and approaches able to provide a uniform measure of received benefits from maintenance actions would therefore be desirable. Multiobjective optimization techniques are appropriate in this regard because they are capable of formally constructing a preference order from the perspective of the decision maker based on various performance criteria.

To allocate resources across different types of highway infrastructure assets, the analyst should evaluate the benefit generated for each dollar spent and the quality of service of each infrastructure type to the public (Lee and Deighton 1995). Gharaibeh et al. (2006) recommended the use of the efficiency of a particular type of highway infrastructure that reflects user concerns as a comparative performance measure to help measure and compare benefits across competing asset components. The researchers defined the efficiency of linear assets, such as pavements, as “the ratio of vehicle
<table>
<thead>
<tr>
<th>Techniques</th>
<th>Key features</th>
<th>Advantages</th>
<th>Weaknesses</th>
<th>Cited references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighting sum method</td>
<td>Combines various objective functions into a single-objective function by assigning positive weights to each of the objective functions and parametrically varying the weights to generate the Pareto optimal set.</td>
<td>• An easy-to-understand approach sufficient for Pareto optimality and simple to implement.</td>
<td>• A priori selection of weights not necessarily guarantees the final solution will be acceptable; • Different weight sets may generate the same Pareto optimal set; • May not be able to obtain the Pareto optimal set in case of nonconvexity; • Varying the weights consistently and continuously may not necessarily result in an even distribution of the Pareto optimal set;</td>
<td>Zadeh (1963); Das and Dennis (1997); Miettinen (2001); Marler and Arora (2004)</td>
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<tr>
<td>Goal programming</td>
<td>Minimize the weighted sum of deviations of all objective functions from their respective goals; Can be categorized based on the setting of weights into two types: nonpreemptive and preemptive.</td>
<td>• Applicable for decision maker to capture the essential elements of a problem and formulate these into goals and constraints; • Conceptually easy to understand and simple to implement.</td>
<td>• Global optimality convergence is not guaranteed in some cases; • Weighted goal programming and preemptive goal programming can result in non-Pareto optimization solutions;</td>
<td>Charnes et al. (1955); Ignizio (1976); Chames and Cooper (1977); Zeleny (1982); Lee and Olson (1999)</td>
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<tr>
<td>Compromise programming</td>
<td>Identifies solutions that are closest to the ideal solution by some measures of distance, of which the most common is the minimization of the normalized deviation from the ideal solution measured by the family of metrics.</td>
<td>• Results in a reduction of the Pareto optimal set and the procedure is easily understandable; • Does not have to be restricted to continuous settings; it can be adapted to discrete settings as well.</td>
<td>• Two types of parameters are in general involved in compromise programming: the exponent that reflects the importance of the maximal deviation from the ideal value and the weights reflecting the relative importance of each objective. Accordingly, how to properly select the exponential parameter and determine the importance of each objective constitutes the main limitations of this method;</td>
<td>Zeleny (1973); Yu and Leitmann (1976); Zeleny (1982); Goicoechea et al. (1982)</td>
</tr>
<tr>
<td>$\varepsilon$-Constraint method</td>
<td>Optimize one arbitrarily selected objective while converting all the remaining objectives into constraints with specified bounds.</td>
<td>• A properly designed systematic variation of $\varepsilon$ theoretically can yield a set of Pareto optimal solutions; • Conceptually easy to understand and simple to implement.</td>
<td>• Improper selection of $\varepsilon$ (or setting the constraints) can result in a formulation with no feasible solution; • Either different problems (depending on the number of objective functions considered) have to be solved, or a unique solution that is not necessarily easy to verify has to be obtained to ensure Pareto optimality.</td>
<td>Haimes (1971); Goicoechea et al. (1982); Miettinen (1999); Marler and Arora (2004)</td>
</tr>
<tr>
<td>Multiattribute utility theory</td>
<td>An axiomatized mathematical framework for analyzing and quantifying choices involving multiple competing outcomes.</td>
<td>• Capable of quantifying a decision maker’s preferences over the available alternatives to a decision; • Easy to combine with other optimization methods to generate the optimal solution(s).</td>
<td>• Applications generally must be guided by specialists in the field; • The validity of this method is debated based on the reasoning that mathematical operations on utility functions are incorrect.</td>
<td>Keeney and Raiffa (1976); Goicoechea et al. (1982); Patidar et al. (2007)</td>
</tr>
<tr>
<td>Techniques</td>
<td>Key features</td>
<td>Advantages</td>
<td>Weaknesses</td>
<td>Cited references</td>
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<tr>
<td>Analytic hierarchy</td>
<td>Designed for subjective evaluation, providing a vector of weight expressing the relative importance of a set of alternatives based on multiple criteria.</td>
<td>* Allows for the incorporation into the decision-making process of subjective judgments and user intuition by producing a formal and numeric basis for solution selection.</td>
<td>* In situations in which a vast number of alternatives need to be considered, the comparison process can be highly subjective and bias to inaccurate outcomes.</td>
<td>Saaty (1980); Vargas (1989); Holland (1975); Goldberg (1989); Flintsch and Chen (2004); Holland (1975); Goldberg (1989); Flintsch and Chen (2004)</td>
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<tr>
<td>Genetic algorithm</td>
<td>A search technique based on the mechanics of natural selection for solving complex combinatorial optimization problems. The search is run parallel to a population of solutions, each generation of solutions is evaluated and the best solutions are used to create the next generation.</td>
<td>* Requires high computational complexity.</td>
<td>* Uncertainty about the range of judgments used to express preferences is difficult to handle.</td>
<td>Fuzzy-set-based weighting method (Tonon and Bernardini 1999).</td>
</tr>
</tbody>
</table>

Among the various applications, the weighting sum method enjoys a wide popularity because of its simplicity in integrating different objective functions (Dissanayake et al. 1999; Pesti et al. 2003; Wang et al. 2003; Xiong and Shi 2004; Gabriel et al. 2006; Wu et al. 2009). An improvement to the weighting sum method that incorporates the decision maker’s imprecise and/or uncertain judgments on each objective function was obtained with the fuzzy-set-based weighting method (Tonon and Bernardini 1999). Enhancements to mitigate the random subjectivity involved in setting weights and to formally capture the decision maker’s
preferences include the application of the multiattribute utility theory (Davis and Campbell 1995; Li and Sinha 2004; Gharaibeh et al. 2006; Patidar et al. 2007).

As nontraditional techniques achieve optimal control of resources for highway facility management, heuristics, such as genetic algorithms, have also received wide attention from researchers because of their capability of providing good solutions regardless of whether it is a simple linear optimization problem or a difficult combinatorial optimization problem (Liu et al. 1997; Miyamoto et al. 2000; Fwa et al. 2000; Chan et al. 2003; Neves et al. 2006). Goal programming is another useful technique for multiobjective optimization because of its flexibility to be integrated with other techniques (Sinha et al. 1981; Ravirala and Grivas 1995; Ravirala et al. 1996; Hsieh and Liu 1997; Wu and Flintsch 2007; Wu et al. 2008). Because of its limitation in setting the constraints, the \( \varepsilon \)-constraint method has not attracted as much attention as other techniques, although some applications have been reported (Lounis and Vanier 1998; Chowdhury et al. 2000; Miyamoto et al. 2000).

The primary differences among the various techniques being applied pertain to the information basis and type and form of the objectives evaluated.

### Project Level

At the project level of highway asset management, decisions are made about specific projects, such as pavement homogenous sections, individual bridges, culverts, and road signs, in a desire that the actual implementation of a scheduled project is carried out in the most cost-effective way so that the allocated funds are used to construct, rehabilitate, or maintain a longer lasting highway infrastructure (Uddin 2006). Accordingly, the perspective of with certain time horizon or further life cycle is highly emphasized in the various steps of the project-level analysis.

Applications of multiobjective optimization at the project level have focused mainly on maintenance planning (Pilson et al. 1999; Liu and Frangopol 2005; Miyamoto et al. 2000; Neves et al. 2006) and construction (Zheng et al. 2005; El-Rayes and Kandil 2005). Because the combinatorial optimization problem is the main type at this working level, genetic algorithms (GA) are frequently utilized to find a solution (Pilson et al. 1999; Miyamoto et al. 2000; El-Rayes and Kandil 2005; Liu and Frangopol 2005; Zheng et al. 2005; Wang et al. 2007) and are sometimes combined with other techniques (Neves et al. 2006).

For example, Pilson et al. (1999) described the formulation of a typical project-level pavement management problem solved using GAs. In their research, an example of a relatively large project-level problem involving four maintenance actions and a 25-year analysis period was considered. The results showed that while such a problem was not solvable by the authors using the general integer programming formulation on a PC optimization software, it was quite tractable using GAs.

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### Table 2. Summary of Multiobjective Optimization Applications in Highway Asset Management

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Reference</th>
<th>Highway</th>
<th>Bridge</th>
<th>Other assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Priori articulation of preferences</td>
<td>Davis and Campbell (1995)</td>
<td>✓</td>
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<tr>
<td>Weighting sum method</td>
<td>Dissanayake et al. (1999)</td>
<td>✓</td>
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<td></td>
<td>Wang et al. (2003)</td>
<td>✓</td>
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<td></td>
<td>Sadek et al. (2003)</td>
<td>✓</td>
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<tr>
<td></td>
<td>Xiong and Shi (2004)</td>
<td>✓</td>
<td></td>
<td></td>
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<tr>
<td>Goal programming</td>
<td>Sinha et al. (1981)</td>
<td>✓</td>
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<tr>
<td></td>
<td>Ravirala and Grivas (1995)</td>
<td>✓</td>
<td>✓</td>
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<td></td>
<td>Patidar et al. (2007)</td>
<td>✓</td>
<td>✓</td>
<td></td>
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<tr>
<td>Multiattribute utility theory</td>
<td>Pesti et al. (2003)</td>
<td>✓</td>
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<tr>
<td></td>
<td>Li and Sinha (2004)</td>
<td>✓</td>
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<td></td>
<td>Gharaibeh et al. (2006)</td>
<td>✓</td>
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<td></td>
<td>Patidar et al. (2007)</td>
<td>✓</td>
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<td>AHP</td>
<td>Rezzallah et al. (1999)</td>
<td>✓</td>
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<td></td>
<td>Cafiso et al. (2002)</td>
<td>✓</td>
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<tr>
<td></td>
<td>Li and Sinha (2009)</td>
<td>✓</td>
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<tr>
<td>Genetic algorithm</td>
<td>Chan et al. (2003)</td>
<td>✓</td>
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<tr>
<td>Fuzzy logic</td>
<td>Sandra et al. (2007)</td>
<td>✓</td>
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<tr>
<td>Grey relation + Goal programming</td>
<td>Hsieh and Liu (1997)</td>
<td>✓</td>
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<tr>
<td>Fuzzy set + Weighting sum method</td>
<td>Tonon and Bernardini (1999)</td>
<td>✓</td>
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<tr>
<td>Goal Programming + AHP</td>
<td>Wu et al. (2008)</td>
<td>✓</td>
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<tr>
<td>Posterior articulation of preferences</td>
<td>Weighting sum method</td>
<td>Gabriel et al. (2006)</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( \varepsilon )-constraint method</td>
<td>Chowdhury et al. (2000)</td>
<td>✓</td>
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<td></td>
<td>Chowdhury and Tan (2005)</td>
<td>✓</td>
<td></td>
<td></td>
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<tr>
<td>( \varepsilon )-constraint method + Compromise programming</td>
<td>Lounis and Vanier (1998)</td>
<td>✓</td>
<td></td>
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<tr>
<td>Genetic Algorithm</td>
<td>Liu et al. (1997)</td>
<td>✓</td>
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<td></td>
<td>Pilson et al. (1999)</td>
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<td></td>
<td>Zheng et al. (2005)</td>
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<td></td>
<td>El-Rayes and Kandil (2005)</td>
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<td></td>
<td>Liu and Frangopol (2005)</td>
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<td></td>
<td>Neves et al. (2006)</td>
<td>✓</td>
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<td></td>
<td>Wang et al. (2007)</td>
<td>✓</td>
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<td></td>
<td>Morcous (2007)</td>
<td>✓</td>
<td></td>
<td></td>
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<tr>
<td>( \varepsilon )-constraint method + Genetic algorithm</td>
<td>Miyamoto et al. (2000)</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compromise programming + Genetic algorithm</td>
<td>Fwa et al. (2000)</td>
<td>✓</td>
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</table>
Liu and Frangopol (2005) formulated the life cycle maintenance planning of deteriorating bridges as a multiobjective optimization problem that treats the lifetime condition and safety levels and life cycle maintenance cost as separate objective functions. A multiobjective GA is used to automatically locate a large pool of different maintenance scenarios that exhibits an optimized trade-off among conflicting objectives. This trade-off provides improved opportunity for bridge managers to actively select the final maintenance scenario that most desirably balances life cycle maintenance cost, condition, and safety levels of deteriorating bridges.

El-Rayes and Kandil (2005) developed a multiobjective optimization model to transform the traditional two-dimensional time-cost trade-off analysis to an advanced three-dimensional time-cost-quality trade-off analysis for highway construction. The model is designed to search for optimal resource utilization plans that minimize construction time and cost while maximizing quality.

### Implementation Issues

Multiobjective optimization has been applied in the fields of engineering and science since the mid-1970s (Stadler 1984). Because of the many potential advantages for using multiobjective optimization techniques to support highway asset management processes, multiobjective optimization is steadily finding its way into mainstream infrastructure management. The process has been slow mainly because of reservations that transportation agencies and practitioners still have about implementing such techniques. These reservations usually result from one or more of the following: resistance to change the current practice, lack of understanding of some complex techniques, difficulty in integrating the principles and techniques with existing practices and legacy systems, lack of quantitative evidence supporting the benefits of using the technologies, and lack of adequate information (data) to develop reliable models.
For example, multiobjective optimization is mathematically suited for the cross-asset resource allocation (e.g., how much money should be allocated to the pavement program versus the bridge program). However, the organizational structure at many agencies is such that different assets are handled in functional silos by separate groups. Practically, the budgets available for program categories such as bridge preservation, pavement preservation, safety improvements, roadside improvements, and expansion are not transferable across one another (Li and Sinha 2004). As a result, the analyses of different assets are largely conducted in isolation (Guerré et al. 2007).

Aside from the aforementioned reservation issues, there may also be some other issues that hamper the implementation of multiobjective decision making. For example, Kaliszewski (2004) and Ogryczak and Vetschera (2004) considered two separate levels in decision making: the methodological level and the technical level. They say that the decision maker is usually interested only in the rules and the methodology defining the choice process, and not in the technical details of underlying mathematical methods. However, while it is acceptable to develop the two levels independently, it is mandatory to establish a common standard of communication between the methodological and technical levels of method implementations to effectively improve the decision making. The review of available techniques presented in this paper can guide agencies interested in implementing multiobjective optimization approaches for resource allocation on the selection of the technique or combination of techniques that best fit their needs and capabilities.

Summary and Conclusions

Real-world decisions concerning asset preservation and renewal often involve more than one objective, reflecting the various goals of the agency, and need to evaluate possible alternatives according to multiple criteria. Multiobjective optimization tools are particularly appropriate for supporting these types of decisions. A general framework for solving multiobjective optimization problems was proposed and relevant characteristics of some promising techniques were summarized and compared.

A review of the application of multiobjective optimization techniques in various working levels of highway asset management allowed drawing the following conclusions:

- Techniques currently used for supporting infrastructure management decisions considering multiple objectives include the weighting sum method, goal programming, compromising programming, the $\varepsilon$-constraint method, the multiattribute utility theory, AHP, and genetic algorithms.
- Multiobjective optimization tools provide appealing alternatives for supporting many infrastructure management business processes. No single multiobjective optimization technique is superior; rather, the extent of applicability will ultimately depend on the particular conditions of the infrastructure management decision being considered, the type of information available, and the user’s preferences and requirements, among other factors.

Furthermore, the review of techniques conducted suggests that a synergistic integration of complementary techniques may help develop practical and efficient decision-supporting tools that take advantage of the benefits and avoid potential drawbacks of the individual techniques. A favorable organizational culture and willingness to adopt best practices in asset management are very important for achieving the full benefits of multiobjective optimization. It is necessary to eliminate, preferably in a practical and effective way, the reservations some transportation practitioners may have about multiobjective optimization techniques for a wide application of these techniques to be implemented in mainstream infrastructure management.

References


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