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Asset Management Decision Support Tools: Computational Complexity, Transparency, and Realism †

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Abstract: Asset management decision support tools determine which action (maintenance, rehabilitation, or reconstruction) is applied to each facility in a transportation network and when. Sophisticated tools recognize uncertainties and consider emerging priorities. However, these tools are often computationally complex and lack transparency, the models are difficult to evaluate, and the outputs challenging to validate. This paper explores computational complexity, transparency, and realism in transportation asset management decision support tools to better understand how to select the right tools for a particular context. The results provide direction for agencies when selecting decision support tools, and for researchers and tool developers working towards developing the right tool for an application.

Keywords: asset management; decision support; computational complexity; transparency; validation

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1. Introduction

Asset management decision support tools are used by transportation agencies to determine which action (maintenance, rehabilitation, or reconstruction) is applied to each facility in a transportation network and when. These decisions are made considering existing and predicted condition and performance, asset life cycle costs, and user costs. Sophisticated tools recognize uncertainties and consider emerging priorities, such as resilience and sustainability. However, these tools are often computationally complex and lack transparency, the models are difficult to evaluate, and the outputs challenging to validate. This paper explores computational complexity, transparency, and realism in transportation asset management decision support tools to better understand how to select or develop the right tools for a particular context.

The paper reviews different types of decision support tools (ranking, prioritization, thresholds, and optimization) and the goals of state agencies in making decisions. Using a multi-asset roadway improvement scheduling tool [1] as a case study, the analysis compares the computational burdens, the parameters involved, and the range of outcomes for different scenarios.

The results demonstrate four issues in the selection of decision support tools in the context of state agencies in the United States. The first issue is the computational burden; running the decision support tool for a simple network requires several hours. The second issue is the sensitivity of the results to the input parameters. The results show the relative importance of different parameters. The third issue is the differences between simple and complex decision support tools and generalizing the circumstances in which to use one versus another. Some simple heuristics for selecting tools are identified. The fourth issue is the validation of the results. Strategies for qualitative validation are explored.

2. Background

Asset management processes have been adopted by state departments of transportation in the United States in response to aging infrastructure, traffic growth, unanticipated damage to infrastructure assets due to natural hazards, higher performance expectations of users, declining funding bases, and legislative requirements. Decision support tools are a key element of asset management.

The simplest tools rank and prioritize activities [2]. The more sophisticated and complex asset management tools use optimization to make decisions that select and prioritize activities. Formulations, which define the decision variables, objective function, and constraints, are classified as project or network level, single objective or multi-objective, and deterministic, heuristic, or other [3]. Another classification also considers whether the decision variables are discrete or continuous and whether uncertainty is considered or not. Optimization problems can also be classed as activity selection, scheduling, or both selection and scheduling. Invariably, optimization problems focus on a discrete set of locations and activities, a finite period (planning horizon), the condition of the asset, and the costs including agency and user costs. To simplify the solution process or reduce the size of the solution space, assumptions are usually made.

There is a large body of literature on decision support tools for asset management. Building from work in pavement management, the seminal work of Golabi, Kulkarni, and Way [4] is a foundation for advanced and more sophisticated optimization of maintenance and resurfacing decisions for pavements that recognized deterioration and uncertainty and then extended the work to bridges. Reviews of the state of the art provide context. Chen and Bai [3] review over 300 papers on optimization in asset management. Chen et al. [5] provide a review of optimization in transportation asset management for roads and bridges. Chen et al. [6] focus on multi-objective optimization for maintenance decisions. Other papers address the changing needs for asset management tools that embrace resilience, sustainability, and uncertainty [7–9]. Together, these papers provide a clear picture of the variety of approaches to the problem formulation and solution methods, both of which are tailored to a particular application. In this paper, we focus on understanding issues related to the computational complexity, transparency, and realism of tools.

3. Approach

The paper reviews the goals of state agencies in making decisions. The review is based on the Transportation Asset Management Plans submitted by each state department of transportation in 2019 to the Federal Highway Administration as required in the Moving Ahead for Progress in the 21st Century Act (MAP-21) [10].

Using a multi-asset roadway improvement scheduling tool [1] as a case study, the analysis compares the computational burdens, the parameters involved, and the range of outcomes for different scenarios. The tool is a bilevel program that prioritizes and schedules roadway improvement activities recognizing users' costs and disruption. The upper level involves a Markov decision process (MDP) to identify and prioritize potential roadway improvement actions. The lower level seeks to determine traffic flows based on a network user equilibrium solution across paths that is affected by capacities determined through actions determined at the upper level. The problem is solved using a reinforcement learning method.

4. Results

4.1. State Perspectives

A review of select state DOTs' Transportation Asset Management Plans revealed that most states aim to optimize their investments but do not optimize in the mathematical sense of the word [11]. At best, the states optimize investment in their bridge program or pavement program. Most conduct scenario analysis and explore alternative strategies. However, the TAMPs do recognize the value of optimization, the potential gains, and the importance of good models and reliable data.

Overall, the states are aiming to develop optimal plans that deliver the best serviceability given the budget constraints. Invariably, the implementations focus on independently reached optimization decisions for pavements and bridges based on a predefined set of scenarios. Essentially, the objective function is computed for each scenario that meets the constraints and the "optimal" solution chosen. Given the fact that there are many tradeoffs in terms of actions, timing, and location, it is possible for an optimal solution to be overlooked. However, given that scenarios are developed based on experience and data, the optimal solution selected is likely to be very desirable, and for the given problem and objective, either optimal or near optimal.

Thresholds for determining when to undertake a maintenance or improvement activity, decision trees, simulation, and scenario analysis are widely used in practice. While the strategies have proven to be effective for pavements and bridges independently, the need to consider cross-asset tradeoff and integrate more complex objectives, such as users' costs, disruption, and sustainability, adds to the complexity. On the other hand, the "black box syndrome" means that agencies are skeptical of the outputs from elaborate mathematical models. Wang and Pyle [12] recommend engaging the users, verification of results, and continued validation.

Another important gap in developing and implementing optimal decisions is the difficulty in assembling the required data. This is important because data collection is costly, and resources for maintaining and improving roads are scarce. Taking advantage of innovative data collection methods, more accurate and more timely data, and making better use of resources is important. Although agencies may not implement an "optimal" solution, exploring alternative solution methods provides insight into the factors that influence these decisions and will ultimately help agencies to deliver better transportation services.

4.2. Case Study

Using a simple network consisting of 10 nodes and 11 links with some redundancy, the case is used to demonstrate the computational complexity of the problem, sensitivity to input parameters, comparison of the solution using simple thresholding, and a brief discussion of the challenges involved in validating the results.

A single run of the simple case study on a Windows computer (16 GB RAM CPU with Intel Core i5 processor of 2.20 GHz speed) takes 3 h. Given this computational burden due to complex interactions among traffic, and activities, these types of problems do not encourage the exploration of alternatives or changes in the parameters. However, to explore the sensitivity of the solutions to changes in the parameters, we solved the problem for 1024 different scenarios using a designed experiment capturing changes in the deterioration rate, user cost, maintenance costs, discount factor, traffic factor, and observation accuracy for pavements and bridges. Using a Sobol global sensitivity analysis, we found that the solution was only sensitive to one parameter, the discount factor, suggesting that the time value of money is the most important parameter, but reasonable values for the other parameters should be selected.

A comparison of the results with optimal thresholds indicated that while the results are more efficient using the optimization methods, the differences are modest [11], suggesting that complex tools are not needed for uncongested networks or a network with a high degree of redundancy. Validation is also challenging. The results are optimal given the inputs. However, other parameters or omitted variables may influence the solution. The most common assessment is based on logic; outputs reflect the appropriate order of magnitude, and changes in outputs reflect changes in inputs in the right direction.

In summary, the results demonstrate four issues in the selection of decision support tools in the context of state agencies in the United States. The first issue is the computational burden; running the decision support tool for a simple network requires several hours. The second issue is the sensitivity of the results to the input parameters. The results show the relative importance of different parameters. The third issue is the differences between simple and complex decision support tools and generalizing the circumstances in which to use one versus another. Some simple heuristics for selecting tools are identified. The fourth issue is the validation of the results. Strategies for qualitative validation are explored.

5. Conclusions

Based on the case study results, the analysis suggests that the Sobol sensitivity analysis provides direction for agencies when selecting parameters for models, and that complex decision support tools are not always warranted. The results also serve as a reminder to researchers and tool developers of issues that must be considered in developing the right tool for an application. Further research can provide a more specific direction.

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