MCDM 2019 XXV

Istanbul
June 16-21

THE 25TH INTERNATIONAL CONFERENCE ON MULTIPLE CRITERIA DECISION MAKING

BEYOND THE INFORMATION AGE

BOOK OF ABSTRACTS

MCDM İTÜ DOĞUŞ UNIVERSITY

outcome values. This Decision Impact Model is automatically transformed into optimization problems, simulation routines or scoring algorithms, without any intervention from the end user. Solutions generated by the software can then be compared using the built-in dashboards making it simple to benchmark business-as-usual or challenger solutions from a simulated decision process against optimized solutions generated by the solver. The optimization problem that is automatically produced by Decision Optimizer is a Generalized Assignment Problem. Each account in the portfolio is assigned a treatment which corresponds to a set of predefined actions. The global constraints of the GAP are used to model resource limits like budget or available offers. A typical instance of this application has 150 treatments, 1M accounts and between 5 to 20 global constraints. The two functionalities we will present during this talk allow the user to explore the objective function value space and discover the relationships between various objectives by solving multiple objective combinatorial optimization problems: • In the first approach, the user specifies what are the objectives or constraints to explore, defines ranges and the exploration step size and lets the optimizer search for optimal solutions in the partitioned feasible space. This approach can be seen as a simplified version of the epsilon constraint method described by Haimes, Ladson and Wismer [1] in which the epsilons are uniformly sampled over a distribution defined by the end user. The optimization problem is solved for every partition and the optimal solutions are displayed on a two-dimensional efficient frontier graph for which the two axes are taken from the set of objectives. We show that this predefined partitioning of the feasible space is a tractable approach for large optimization problems. • With the second method the user can choose to apply a more dynamic approach based on an implicit enumeration of all possible epsilon values as proposed by Kirlik and Sayin [2]. This latter approach ensures that all non-dominated solutions will be found but is computationally more demanding. We will give preliminary results comparing the time and memory requirements of the two approaches.

[1] Haimes, YY, Ladson, LS & Wismer DA, "Bicriterion formulation of problems of integrated system identification and system optimization." IEEE Transactions on Systems Man and Cybernetics, vol. 3, pp. 296, 1971
[2] Kirlik G, Sayin S, "A New Algorithm for Generating All Non-dominated Solutions for Multiobjective Discrete Optimization Problems." European Journal of Operational Research, Vol. 232, pp. 479—488, 2014

3. On Combining Explainable Artificial Intelligence and Interactive Multiobjective Optimization in Data-Driven Decision Support

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Nowadays, many decision making processes are driven by data and, thus, the term data-driven optimization has been widely used. Data can be coming, e.g., from different sensors due to rapid rise of Internet of Things, experimental measurements or social networks. The amount of available data is often huge and it poses challenges for decision making in i) how to find and apply relevant data for the problem at hand and ii) how to use that in supporting decision making. On top of that, the problems often have multiple conflicting criteria that need to be optimized simultaneously, thus, requiring multiple criteria decision making (MCDM) techniques in finding a most preferred solution. Machine learning (ML) tools are often essential in building the optimization problem from the data. In addition, ML can be used to learn decision maker's (DM's) preferences in order to propose promising solution candidates during the solution process. If the DM does not understand why certain solutions are proposed, it may hinder the DM in trusting those recommendations resulting in not considering them at all. Therefore, the ML tools used should also give an explanation why the solutions are proposed to the DM . These methods belong to explainable artificial intelligence which is an emerging research field due to high popularity of applications of artificial intelligence. So far, explainable ML methods have been used to explain performance of ML algorithms but they have not been used much as a decision support for MCDM (i.e. in a prescriptive analytics context). By explaining their reasoning to the DM, the ML-based decision support tools become more easily trusted and accepted by them. This means that when the DMs understand better the reasons behind the decision support, they are equipped to make more transparent and trustworthy decisions. This is especially the case when dealing with multiple conflicting objectives, where understanding the trade-offs between the objectives is crucial. In this paper, we discuss the challenges of combining explainable ML with interactive multiobjective optimization in a data-driven context. By using an example case study, we show how these two distinct approaches can be combined and what kind of issues must be considered in order the combination to be effective. To our knowledge, this has not been done before. Typical to interactive methods is that the human DM actively participates in the solution process and provides preference information when the most preferred solution is searched. The challenges include 1) which way to utilize ML within the optimization process, 2) what kind of explanations to provide for the DM, and 3) how to present the explanations to the DM . The first challenge deals with identifying the role of ML as a part of the whole solution process and what kind of ML tools to use. It is commonly known that there exists a trade-off between the performance and explainability of ML models. For example, deep learning with neural networks has recently become popular ML approach for complex data. While those models have a good performance, their explainability is very low. On the other hand, decision trees have high explainability but may not perform so well with complex data. Secondly, the type of explanations depends on the ML models used as well as the application considered and they can be, e.g., visual or descriptive. Finally, how to communicate the explanations to the DM is also important and requires a graphical user interface (that is also an important element in interactive multiobjective optimization methods) utilizing, e.g., techniques from visual analytics to communicate the message.

4. Multicriteria Project Prioritization in Transportation Asset Management

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Transportation systems all over the world continue to grow rapidly and to become increasingly complex. To better program and respond to the many resulting challenges, Transportation Asset Management (TAM) deals with the planning, building, operating, maintaining, upgrading or expanding of the underlying transportation infrastructure and its physical assets including roads, bridges and any other transportation facilities. Hence, in their most general form, TAM goals are to optimize overall system performance including cost effectiveness and efficiency, resource allocation and utilization as well as the general satisfaction of all users and system stakeholders. It follows that TAM is inherently multi-criterion in nature so that its decisions and any related decision-making procedures should ideally follow best business and engineering practices and be conducted based on quality, relevant and credible information with well-defined objectives for a meaningful tradeoff and decision analysis. Following a general discussion of transportation asset management in practice, this presentation then will focus specifically on one "real-world" situation based on a recent collaboration with a major transportation agency in the United States. In agreement with the mission, vision and general goals of its recent strategic management plan, we will begin to briefly outline the underlying objectives hierarchy which includes system performance and general organizational excellence, safety and health, stewardship and efficiency as well as sustainability, livability and economy. In particular, having been invited to review and further propose associated multi-objective decision analysis (MODA) approaches for its optimal resource allocation and project prioritization, we will highlight a few specific lessons we have learned. First, we will shortly revisit the original suggestion to merely use a standard cumulative benefit for a classical benefit-cost knapsack heuristic and comment on its well-known drawbacks and perceived disadvantages in comparison to some of its other more positive benefits. Second, we will