Development of a Natural Resource Management Investment Decision Support System

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EXTENDED ABSTRACT

This article describes the embedded methods of a recently developed multi-criteria analysis (MCA) software containing both multi-criteria analysis functionality and solution methods. It is primarily developed to help natural resources management decision makers to choose a subset of available decision options which return a maximum benefit score whilst adhering to constraints such as budget. The benefit scores are computed with the well known compromise programming technique. To optimise the selection of options subject to the constraints, two meta-heuristics, Local Search and Tabu Search were coded and applied. The MCA and the meta-heuristics are both integrated in the multi criteria analysis tool (MCAT) which is primarily developed to optimise water management decision making in Australia however MCAT is ready to be applied in other fields of natural resources management as well.

Here, we illustrate the use of MCAT through a hypothetical case study where nature conservation sites across the state of Queensland were appraised and selected according to a budget constraint. Since many environmental programs have multiple policy objectives and face budget constraints we believe that MCAT has potential for widespread application.

1. INTRODUCTION

Many environmental programs are established to fund a variety of natural resource management activities (which we refer here to as projects). Usually the total cost of all project proposals exceeds the available program budget thus forcing a selection of submitted project proposals. This selection process is a typical binary combinatorial problem which is comparable to a backpack which has to be filled such that all items being packed in it represent an optimum portfolio where the volume of the backpack is the constraint. In operations research this combinatorial problem is commonly known as the knapsack problem (KP). There are a wide range of applications for the knapsack formulation, including a) selecting a set of projects to produce the highest profitability given a total budget constraint b) selection of skills to maximise output given total salary budget or c) loading cargo onto a ship with a fixed capacity. Though the mathematical formulation of the KP is considered to be simple, such combinatorial problems are computationally intensive if the number of decision options is high. A faster solution to the KP is the use of algorithms based on meta- heuristics. Heuristic methods usually converge to first local optimal solution. This makes them convenient to use for large combinatorial problems. In this paper we will demonstrate the use of the local search and the Tabu Search (Glover, 1989) meta-heuristics.

While meta-heuristic algorithms help solve the combinatorial problem with a given (cost) constraint they need to be combined with other algorithms which compute the benefits associated with each option. The integration of benefit cost analysis (BCA) has not been considered since BCA requires the assignment of monetary values to every issue involved in the analysis which is difficult if social, ecological or historical issues are involved (Acreman, 2001). We therefore decided to integrate a wider decision making approach in terms of multi-criteria analysis. Out of the great variety of available MCA methods we chose compromise programming (CP), which was introduced by Zeleny (1973). CP is mathematically simple and it has proven its efficiency in a variety of applications (e.g. Shiau and Wu 2006, Abrishamchi et al. 2005, Duckstein and Opricovic 1980).

2. COMPROMISE PROGRAMMING

Compromise programming (Zeleny, 1973) uses ideal values, both positive and negative, as reference points. It is assumed that the choice of a decision option depends on its distance to the ideal hence the closer a decision option is to the ideal the higher its utility.

In conventional compromise programming we define u_j^- as the dis-utility of option j, which is calculated as:

$$u_j^- = \left[\sum_{i=1}^{m} w_i \left(\frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-} \right)^c \right]^{1/c} \qquad (1)$$

where:
f_i^+ = the best score (or ideal/target score) for criteria i and f_i^- = the worst (or least ideal value) for criteria i. c is a parameter that reflects the importance of maximal deviation from the ideal solution. w_i is the weight for criterion i, m is the number of criteria.

Where possible f_i^+ and f_i^- can be set to ideal and anti-ideal values, and may be threshold values given in legal guidelines. Where no such ideal or anti-ideal exists, they may be drawn from within the evaluation matrix in terms of the minimum and maximum values across the options. Compromise programming was selected as a suitable approach since it effectively creates scores of criteria within suitable (or expert defined) upper and lower bounds. Compared to the common weighted summation approach, it overcomes the problem of extremely high values of f_{ij} for some criteria, which can create unrealistic biases in the utility score for some options.

We felt there were some necessary changes in adapting the compromise programming method. Firstly, we wanted a utility score where the larger the value, the better. We therefore redefine

$$g_{ij} = \frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-} \qquad (2)$$

where g_{ij} is a value between 0 and 1 with 0 being best and 1 being worst. Eq. 1 can then be rewritten as

$$u_j^- = \left[\sum_{i=1}^{m} w_i * g_{ij}^{\,c} \right]^{1/c} \qquad (3)$$

By substituting g_{ij} with (1- g_{ij}) a value of 1 would be best and 0 be worst. Therefore, we define the utility function, u_j where the larger value of u_j the better, as

$$u_j = \left[\sum_{i=1}^{m} w_i * (1 - g_{ij})^c \right]^{1/c} \qquad (4)$$

We also needed the ability to use non-linear transformations of the raw scores. For a variety of criteria (e.g. biodiversity measures, water quality) the true benefit of an option j against criteria i cannot be reasonably described with a linear function of the raw f_{ij} within the upper and lower limits f_i^+, f_i^- Moreover criteria are likely to be in different units and different orders of magnitude. Transformation is therefore necessary to bring criteria to a common scale. Besides the linear transform, non-linear transforms that show a sigmoidal, convex or concave shape are integrated in MCAT as well.

3. THE KNAPSACK PROBLEM (KP)

The Knapsack problem is well known in operations research and refers to the situation where a backpack has to be filled with items where each item has a specific volume and value. The items must be packed such that it is best taken advantage of the total volume of the backpack whereby the total value of the packed items must be maximised at the same time. This is a decision constellation which is faced by a lot of decision makers who have to identify an optimum portfolio of decision options (projects) while keeping a budget constraint. The general mathematical formulation of the KP is as follows:

$$\text{Maximise} \quad \sum_{j=1}^{n} f_j x_j \qquad (5)$$

$$\text{subject to} \quad \sum_{j=1}^{n} a_j x_j \le b$$

where:
- x_j is the decision variable (i.e. x_j =1 if item i is included in the knapsack (= project selected), = 0 otherwise)
- f_j is the utility of including item j in the knapsack
- a_j is the cost of item j
- b is the capacity of the knapsack (or the budget)

Though the mathematical formulation of the KP is simple it is known to be NP-Hard (Garey and Johnson, 1979) which means the computational complexity to guarantee an optimal solution increases exponentially with the number of decision variables. An extension of the KP that is used is the Multi-Criteria KP, which requires the following modification to equation (5):

Maximise $\sum_{i=1}^{m} w_i \sum_{j=1}^{n} f_{ij} x_j$ (6)

where

f_{ij} is the score of item (or option) j against criterion i, as defined in Eq. 1.

Multi-criteria KP are not new to the literature and methods are available to find solutions along the Pareto front of the criteria (Gomes da Silva et al, 2006, Captivo et al, 2003, Erlebach et al 2002). In the case of two objectives, multi-objective programming is a suitable method since it produces a range of trade-off solutions along a Pareto front. Many MCA problems in practice, including the case study of this paper have several criteria (or objectives), which make multi-objective programming more difficult to adopt by real world decision makers. In MCAT, we used an alternative approach, compromise programming, which is not only an innovative approach to the multi-criteria KP, but overcomes many of the practical shortcomings of multi-objective programming and weighted summation.

4. SOLUTION METHODOLOGIES

4.1. The Comparison Process

There is an extensive literature of techniques applied to find optimal and near optimal solutions to the KP problem. An overview of exact solution methods can be found in Martello et al (2000). A range of meta-heuristics have also been applied such as Simulated Annealing (Drexl, 1988), Ant Colony Optimisation (Higgins, 2003) and Tabu Search (Hanafi and Freville, 1998). Whilst meta heuristics do not guarantee an optimal solution, they can approach an optimum fairly quickly even for hard KP problems with very large *n,* and Higgins et al, (2007) has shown such methods to find the optimal solution to real world case studies on all occasions. We decided to apply heuristics (instead of exact solution methods) to solve the KP problem for two main reasons:

- we intend to expand the capability of MCAT to handle complementarities and interdependencies between options, which heuristics would be more flexible to accommodate (Higgins et al, 2007);
- we plan to use MCAT for problems of a spatial nature where some problems may require to access GIS data on a raster cell basis. If each raster cell is considered a decision option, the number of decision options can easily reach several millions.

Two meta-heuristics are implemented in MCAT, a common local search “hill climbing” heuristic and the Tabu Search (Glover, 1989). While the local search method terminates when a local optimal solution is found the Tabu Search has features to escape from local optimal solutions and search for better local optimal solutions. The next two subsections describe the applications of these methods in further detail.

4.2. Local Search

The local search heuristics is a much faster approach than Tabu search however this comes with the cost of terminating as soon as the first local optimal solution is found. For small problems with n<60, it has been shown by Hajkowicz et al, (2006) to produce solutions within 2% of the optimal. The quality of the local optimal solution is highly dependent on the initial solution though. MCAT generates the initial solution by sorting the options in descending order of benefit to cost ratio, f_j/a_j first. The selection is performed by stepping through the sorted list of options, starting from the highest f_j/a_j options where all options are selected until the sum of costs of the selected options reaches the budget constraint. This is the initial solution. The local search works by iteratively progressing through the list and swapping between selected and unselected options. If a swap produces a better solution and the budget constraint is satisfied, this new solution is kept, otherwise the old solution remains. The process continues until no more swaps yield a better solution.

With this rather simple approach to solving the KP, instances consisting of a larger number of projects can be solved within fractions of a second. Even though the returned solution may be inferior to the Tabu search, local search heuristics may be first choice when the number of decision options is small or an interactive sensitivity analysis is performed where results must be quickly updated because of user changes in analysis boundary conditions.

4.3. Tabu Search (TS)

Tabu search is a meta-heuristic approach which can be used to solve combinatorial optimization problems and is based on flexible memory structures in conjunction with strategic restrictions (Glover et al. 1995). Unlike local search, TS escapes local optimal solutions by allowing non-improving moves to be performed when no improving moves are available. Tabu search starts with a randomly generated initial solution which satisfies the constraint (e.g. the budget constraint).

Next, a variety of candidate moves which are referred to as the neighbourhood are performed. This basically implies the testing of new combinations (solutions) of options and a subsequent check if the sum of benefits is improved whilst the constraint is satisfied. In MCAT, two neighbourhood searches are integrated: 1) add or remove an item from the knapsack; and 2) exchange an item in the knapsack with one that is not. Note that each combinatorial change leading to an improvement is kept in a list in memory which is the Tabu list (TL). A move is Tabu if it (or the reverse move) is one of the TL most recent moves applied. When the neighbourhood search is done, the best solution found overrides the current solution if it is better and overrides the current solution if it is worse but not in the Tabu list which helps to escape local optimums.

5. THE MULTI CRITERIA ANALYSIS TOOL (MCAT)

Since the 1970s MCA has been increasingly applied in natural resource management (NRM). Before the development of MCAT started a literature review done by CSIRO Sustainable Ecosystems identified 113 water management MCA applications published in academic journals from around the world (Hajkowicz and Collins, 2007). Many more studies exist that cover other fields of NRM such as fisheries, forestry and more. Not included is the number of applications in the ‘grey’ literature such as unpublished government reports. In addition to that the need for tools that are able to solve problems in demand management, supply augmentation, infrastructure selection, siting, policy appraisal taking into account multiple objectives and multiple stakeholders has repeatedly become apparent whilst talking to experts from various policy levels.

Based on these professional experiences and based on the results of the literature review the MCAT development was initiated by the eWater CRC, a **c**ooperative **r**esearch **c**entre focussed on the business needs of the Australian water industry. This CRC develops solutions that integrate environmental aspects in water resources planning and operations, provides education for water managers and delivers a range of software tools that will help facilitate and improve sustainable water management. MCAT was assigned to the water management research program which aims to develop analyses, modelling and optimisation tools for water management decision making. MCAT was developed with .Net and is, despite some complexity in the implemented solution methods, an easy to use decision support tool where the user is guided step by step through the whole optimisation process. Moreover it provides sensitivity functions and a set of useful analysis charts which help the user to optimise funding expenditures. Interested readers are asked to visit eWater CRC’s toolkit website (www.toolkit.net.au/) for the latest beta version of MCAT. The software is still under development and is therefore regularly updated.

6. MCAT TEST APPLICATION

6.1. Queensland NatureAssist program

Whilst developing MCAT, we tested the software along a variety of real world datasets taken from finished natural resource management projects. Here we evaluate a dataset of the Queensland NatureAssist Program (NAP). The NAP is an incentive scheme for landholders and provides financial assistance to protect natural assets on their property. Landholders can bid for financial support through a competitive tender process. In return landholders have to undertake a variety of activities that protect or maintain areas of high conservation value on their properties. Bids will be evaluated regarding their environmental benefit and chosen such that the benefit is greatest with respect to investment. The NAP is coordinated by the Queensland Environmental Protection Agency (QEPA).). As our purpose is to illustrate an application of MCAT we use a hypothetical budget ceiling of A$2 million. To measure the performance of the conservation tenders an environmental benefits index (EBI) was developed (Hajkowicz et al. 2007). This EBI comprises a set of indicators which can be grouped into three main categories: site-suitability, management suitability and contract security. These indicators were then further divided into numerous sub-criteria covering hydrologic aspects as well as biodiversity issues and cultural assets. In the end a set of 25 criteria was established on the lowest hierarchy level. Whilst a variety of criteria values could be retrieved from digitally available data in a GIS, some were assessed by means of field inspections and/or expert judgement. The criteria weighting was performed by a team of experts from the QEPA.

The total dataset cannot be shown in this paper due to its large size. The dataset used for this case study contained 95 tenders across the whole state of Queensland which is considered small for a KP instance. The total cost of all tenders was around A$3,000,000 which exceeded the available hypothetical budget of A$ 2,000,000. The problem was then to select those tenders whose summed benefit returned the maximum aggregate EBI whilst not exceeding the A$ 2,000,000 budget constraint.

After the environmental benefit score was determined for each tender, it was multiplied with the area of the property for which the tender was submitted which ensured that property sizes were reasonably integrated as well. Then the selection process of projects (= tenders) taking into account each project's benefit and cost as well as the total budget constraint was initiated. Local search returned a selected set of 71 tenders whose summed (dimensionless) EBI was 71132.3 with a total cost of A$ 1,998,637. Tabu search slightly outperformed the local search returning a portfolio of 69 tenders with a slightly higher total EBI of 71134.5 at a total cost of A$ 1,999,865. Since both methods are of a heuristics nature differences in results are not surprising since there is never a guarantee that the true optimum or the same results will be reached. However the selections were identical for 94% of all tenders. The differences in results of local search and Tabu search are very small in this case study. In most real world problems such a difference may not be meaningful since the returned results are - prior to final approval by the decision makers at QEPA - subject to further discussion and changes.

The number of evaluated options in this case study is fairly small and it may be hard to defend the use of Tabu search given the subtle differences in results and the lower computational speed. However, in the medium term we intend to integrate interdependencies between projects where the selection of a project is conditional on the inclusion of another project. By means of real world data and parametric studies it has recently been shown (Higgins et al., 2007) that with increased interdependencies Tabu search was able to find an optimal solution where the local search terminated at the first local optimum.

7. FUTURE ENHANCEMENTS

Though MCAT covers a useful set of functions, we are aware that there is need for further improvements. Medium to long terms enhancements include the implementation of

- project interdependencies,
- group decision making approaches and
- simulation routines based on Monte Carlo simulation.
- optimisation algorithms that return the true optimum (branch and bound).

Especially in a spatial context, project interdependencies play an important role in that the selection of two projects A and B with benefits b_A and b_B may give a total benefit which is greater than ($b_A + b_B$) or the contrary, the selection of two projects may lead to a decrease in the overall benefit with ($b_A + b_B < b_{AB}$). Other important enhancements will include a net based group decision making module which enables the online participation of a variety of stakeholder groups where each stakeholder group can define its own set of preferences. Moreover MCAT will be tackling uncertainty of input values by letting the user specify distribution functions for specific criteria of project options. The range of distributions which can be used will be kept to a minimum and will include simple distribution types that do not require the specification of a variety of parameters. This is because we see MCAT as a tool that will offer a set of useful easy-to-understand functions. We therefore do not intend to overload MCAT with too many functions where a non-expert might have difficulties to follow the procedures. The latter aspect is certainly a dilemma of virtually every decision support tool where developers must find a balance between user comprehension and the integration of more complex but also more sophisticated methods.

8. CONCLUSION

We conclude that the multi-criteria analysis tool (MCAT) well combines aspects of multi-criteria analysis and optimisation techniques. Compromise programming as the implemented multi-criteria analysis technique has the advantage that the user can define ideal and anti-ideal values and is therefore well suited to be applied once legally provided guidelines or expert defined best and worst values have to be taken into account. Some users may prefer applying other approaches to derive benefits or consider other MCA methods more appropriate for a specific decision problem and may be in need to specify a defendable optimum portfolio of options. MCAT therefore offers the possibility to bypass the compromise programming interface by directly importing externally computed benefits and costs of a whole set of projects and directly accessing the optimisation routines. We believe that MCAT offers a fairly intuitive user interface and is – despite some complexity in the applied meta-heuristics – an easy to use tool. It offers a portfolio of functions which will make it attractive for a lot of decision problems not only in water management but in natural resources management as such.

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