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Optimisation and the selection of conservation contracts*

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This paper explores alternative techniques for the selection of conservation contracts under competitive tendering programs. Under these programs, purchasing decisions are often based on the benefits score and cost for proposed projects. The optimisation problem is to maximise the aggregate benefits without exceeding the budget. Because the budget rarely permits all projects to be funded, there is a binary choice problem, known in the operations research published work as a knapsack problem. The decision-maker must choose which projects are funded and which are not. Under some circumstances, the knapsack problem can be unsolvable because computational complexity increases exponentially with the number of projects. This paper explores the use of several decision rules for solving the optimisation problem including the use of advanced meta-heuristics. It is shown that commonly applied techniques for project selection may not be providing the optimal solution. Improved algorithms can increase the environmental programs benefits and staying within budget. The comparison of algorithms is based on real data from the Western Australian Conservation Auction.

Key words: market based instruments, environmental services auction, environment benefits index, conservation planning

1. Introduction

Competitive tendering for conservation contracts is an increasingly popular policy instrument for efficient purchasing of environmental projects. Some major programs based on this approach include the US Conservation Reserve Program (CRP), the Victorian BushTender Program, the NSW Environmental Services Scheme, the European Financial Instrument for the Environment (LIFE program), the Australian Envirofund Program, and the

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Western Australian Conservation Auction. These programs base their purchasing decisions on what can be termed a cost–utility analysis (CUA) framework (Stephens and Lawless 1998; Cullen *et al.* 2001). Under CUA, project costs are measured in dollars via standard means, but the benefits are measured with a non-monetary metric usually comprised of multiple attributes. This paper explores the algorithms used in conjunction with CUA to make purchasing decisions, that is, which projects are funded and which are not.

In most programs, a budget constraint prevents all projects being funded. Often the acceptance rate is quite low. For example, in 2002, the European LIFE Environment Program funded only 23 per cent of proposed projects (EC 2002) and in the 2003 fiscal year the US Environmental Quality Incentives Program funded around 17 per cent (USDA 2003a). In allocating budgets, program managers are confronted with a difficult discrete choice problem. The decision objective is to maximise the aggregate utility from selected projects without exceeding the budget.

In the decision-maker's optimisation problem, the total number of combinations possible is equal to 2^n , where n represents the number of projects. When n is large or several decision rules govern project selection or complex bid interdependencies exist (i.e., the benefits score for one project influences the benefits score for another), then there are too many combinations to generate an optimal solution within a reasonable time frame. Therefore, a heuristic is required. Heuristics are algorithms that search for a near-optimal solution when the true optimum cannot be guaranteed due to excessive computational requirements.

This paper contributes to the extensive literature on conservation planning and reserve selection algorithms (Faith *et al.* 1996; Pressey *et al.* 1996; Arthur *et al.* 1997; Pressey *et al.* 1997; Ando *et al.* 1998; Snyder *et al.* 1999; Polasky *et al.* 2001; Faith *et al.* 2003; Costello and Polasky 2004; Meir *et al.* 2004; Moilanen 2005; Pierce *et al.* 2005). These studies are concerned with issues such as species representativeness, conservation area network design, habitat connectivity, and the sequencing of conservation actions through time.

Our work focuses on the selection of natural resource management projects when there are n projects each with a cost and benefit metric, and an overall budget constraint b . Alternative heuristics are compared by analysing real 'bids' in the Western Australian Conservation Auction, referred to as the 'Auction for Landscape Recovery'. Heuristics, from simple rules to advanced meta-heuristics, are tested for their closeness to an optimal solution. Some simple purchasing rules are found to differ significantly from an optimal solution, whereas others come very close.

2. The knapsack problem

In operations research terminology, the environmental contract purchasing problem can be formulated as a 0–1 binary knapsack problem (Martello *et al.* 2000; Caccetta and Kulanoort 2001). In a knapsack problem (KP), n

items are available for packing into a knapsack. Each item has a cost (in terms of space taken within the knapsack) α_i and a price p_i when sold at the market. The knapsack has a capacity b . The decision-maker must choose which of the n items are packed into the knapsack, with the aim of maximising benefit (Z), that is, total revenue in this case, without exceeding the knapsack's capacity. With a binary decision variable x_i , where item i is selected if $x_i = 1$ and not selected if $x_i = 0$, this can be expressed as an integer linear programming problem (Martello *et al.* 2000):

$$Z = \sum_{i=1}^n p_i x_i \quad (1)$$

Maximise
subject to:

$$\sum_{i=1}^n \alpha_i x_i \leq b \quad x_i \in \{0, 1\} \quad i \in \{1, \dots, n\} \quad (2)$$

Because of the simplicity of the KP formulation, many practical problems can be analysed based on its principles. Examples are: (i) selecting among a set of projects to produce the highest returns given a total budget constraint; (ii) selection of skills to maximise output given total salary budget; and (iii) loading cargo onto a ship with a fixed capacity. The KP is sometimes solved as a subproblem of larger combinatorial optimisation problems, as in the case of the set partitioning problem (Syslo *et al.* 1983). Many extensions of the general KP have also been addressed in the literature, for example, the multi-dimensional KP (Hanafi and Freville 1998), and the multiple KP (Martello and Toth 1980).

3. Purchasing strategies in environmental programs

Although it may appear an abstract concept, the knapsack problem provides satisfactory representation of real-world project funding decisions in many environmental programs. In an environmental program, items are replaced with projects, where the cost of projects is equivalent to the space taken, and the capacity (volume) of the knapsack is represented by the program budget. The decision-maker attempts to maximise the aggregate environmental benefits score subject to the budget constraint. In this section, the manner by which project purchasing decisions are made under several real-world environmental programs is explored.

The United States Conservation Reserve Program (CRP) commenced in 1985 and pioneered much of the contemporary work on design of environmental auction systems worldwide. Since inception, it has been the subject of numerous academic studies exploring methodological issues of auction

design and implementation (Reichelderfer and Boggess 1988; Ribaudó *et al.* 2001). Through the CRP, farmers receive annual rental payments to retire cropland from production and place it under conservation use. The payments system is based on competitive tendering from farmers for 10–15 years conservation contracts. Contract benefits are assessed using a multi-attributed environmental benefits index (EBI). One of the factors comprising the EBI is project cost, which allows bidders to increase their EBI score by lowering their bid. The program's administrators make contract purchasing decisions based on the EBI. All eligible offers are ranked in order of their EBI scores. Funds are then allocated in that order until a cut-off point is reached (USDA 2003b). It can be presumed that the EBI cut-off point is at least partially based on a budget ceiling. This means that project selection occurs in descending order of project benefit scores until a budget constraint binds.

The Victorian BushTender program was run as a pilot auction for biodiversity contracts during 2001–2003 (Stoneham *et al.* 2003). Landholders placed a once-off sealed bid (b) for the provision of biodiversity services. The Victorian Government calculated the benefits of each bid using a habitat services score (HSS) and a biodiversity services score (BSS) (see Parkes *et al.* 2003). Purchasing decisions were made on the basis of a biodiversity benefits index (BBI):

$$BBI_i = \frac{BSS_i \cdot HSS_i}{b_i} \quad (3)$$

Projects were funded in descending order of BBI until a budget constraint applied. All the bids were treated as independent of one another. This meant that the BSS and HSS scores did not change when any one of the projects was selected.

The New South Wales Environmental Services Scheme was also run as a pilot auction for environmental contracts (Grieve and Uebel 2003). Landholder bids were evaluated using a multi-attributed EBI covering factors such as carbon sequestration, biodiversity, salinity, soil health, and water quality. Purchasing decisions were based on three criteria: (i) the EBI; (ii) the project's cost effectiveness determined by the EBI to cost ratio; and (iii) the demonstration value of the project as scored by experts. The demonstration value measured the knowledge gained for other land managers arising from the project. Each of the three criteria was given equal weight and then combined to create an overall benefits score. Funds were allocated to projects in order of benefits until a \$A2 million budget constraint was reached. Some modifications were made to the final selection to ensure both a satisfactory geographical spread of offers and the representation of a sufficient range of farming enterprises.

The European Commission's Financial Instrument for the Environment (LIFE program) involves competitive tendering for environmental projects but covers a much larger range of services than those described above. Under LIFE, citizens of member States submit project proposals to Brussels. A

team of experts scores the performance of the projects against several criteria and an overall performance score is calculated. Projects are ranked according to their overall performance and funds are distributed until a budget threshold is reached. This process is similar to that used in Australia's Envirofund program, which is part of the Natural Heritage Trust. Again, projects are scored by experts against multiple criteria. Some type of aggregate performance function is applied that produces a unified index of performance. Funds are distributed in order of performance until a budget constraint binds.

Table 1 summarises the purchasing strategies used by the programs described above. In each case, the project funding decision fits the 'knapsack' format because:

1. There is a binary decision on each project, it can be either funded or not funded. Substantial re-negotiation of project activities and budget is rarely undertaken due to high transaction costs.
2. The projects all have a cost and benefit, where the benefit is based on a non-monetary multi-attributed metric.
3. The projects are treated as independent. This means that a decision to fund any one project does not explicitly influence the benefits score of another.
4. There is generally a budget constraint for the program. Ultimately, all programs must have some budget constraint, but there are differences in how rigidly a predefined budget is applied.
5. It can be assumed that the objective of funding agencies is typically to maximise the level of benefit and staying within budget. This means selecting the optimum project portfolio.

From these observations, it can be seen that the knapsack formulation of the optimisation problem represents the real decision relatively well. The major way in which the integer program formulation of the knapsack problem fails, or needs more complex definition, is if there exists strong interdependencies between the environmental projects being funded. Bid interdependencies mean that the decision to fund any one project changes the benefits score for other projects. For example, when the goal is regional biodiversity conservation, the biodiversity contribution of a project reflects only those components of biodiversity not yet captured by other funded projects (the principle of 'complementarity'). We return to this issue in the discussion. However, in the majority of other practical environmental and agricultural program applications, an assumption of independence represents the decision problem with sufficient accuracy.

4. Alternative solution methods

There is an extensive published work of techniques applied to find optimal and heuristic solutions to the KP problem. Methods to find an optimal solution include branch and bound and dynamic programming (Horowicz

Table 1 Purchasing strategies used in agricultural land management and environmental programs

Environmental program	Description	Basis of purchasing decisions
US Conservation Reserve Program	Competitive landholder bidding for the retirement of cropland for conservation purposes. Benefits measured with a multi-attributed environmental benefits index.	Benefit score
Victorian BushTender Trial (Stoneham <i>et al.</i> 2003)	Competitive landholder bidding for the provision of biodiversity and habitat management services. Benefits are measured with a biodiversity services score (BSS) and a habitat services score (HSS). The bids are treated as independent.	Ratio of benefits to costs
NSW Environmental Services Scheme (Grieve and Uebel 2003)	Competitive tendering from landholders to supply environmental services. Benefits are measured with a multi-attribute EBI.	Benefit ranking
Natural Heritage Trust Envirofund	Competitive tendering for a wide range of environmental projects across Australia. Projects are scored by experts against several criteria.	Benefit score
European Commission's LIFE program	Competitive tendering from within Europe for a wide range of environmental projects. Projects are scored by experts against several criteria.	Benefit score
Western Australian Conservation Auction	Competitive tendering by landholders to supply environmental services. Benefits are measured within a systematic conservation planning framework, based on regional biodiversity targets, and supplementary multi-attribute EBI.	Maximising improvement in representation, subject to regional targets and budget

Note: EBI, environmental benefits index.

and Sahni 1974), linear programming relaxation (Ram and Sarin 1988), and more recently branch and bound combined with surrogate relaxation to derive lower bounds (Pisinger 1999). The latter method solved large instances of up to $n = 100\,000$ within a few seconds of CPU time. Although an optimal solution can be found for large instances of a standard KP, the difficulty arises within the methods when additional constraints are added. Such constraints include mutual exclusiveness across sets of projects and profit, p_i , being dependent upon projects selected within the knapsack.

Heuristic methods can be more robust for applications where additional constraints are added. Heuristics for the KP problem can be grouped into three main types: (i) heuristic rules; (ii) greedy/interchange heuristics; and (iii) meta-heuristics. Heuristic rules are the simplest of the three types and are easily incorporated within a spreadsheet. Based on the environmental programs reviewed above, project funding decisions are typically made using the following heuristic rules: (i) fund in descending order of the environmental benefits score until a budgetary threshold is reached; and (ii) fund in ascending order of a cost to utility (e.g., \$/EBI) ratio until a budgetary threshold is reached.

Although simple project selections are used extensively in practice (Table 1), they can produce solutions that are substantially inferior to the optimal. Greedy and interchange heuristics are fast methods for finding a local optimal solution. A common greedy search heuristic starts with an initial solution, say using method (ii) above. It then swaps selected projects with unselected projects, iterating through every available pair in the set. The combination with the highest benefit score (Z) is the solution. The main disadvantage of the greedy search heuristic is that it converges to the first local optimal solution, which may still be a long way from the global optimum.

Meta-heuristics overcome the problem of being stuck in local optimal solutions, and there are a large range of meta-heuristics available. Methods based on local search that have been applied to the KP include simulated annealing (Drexler 1988) and tabu search (Hanafi and Freville 1998). Higgins (2003) applied simulated annealing and tabu search, along with evolutionary methods such as genetic algorithms (Reeves 1996) and ant systems (Bonabeau *et al.* 2000). Higgins (2003) performed an extensive comparison between these meta-heuristics for problems up to $n = 500\,000$. The paper showed the tabu search and ant system meta-heuristics produced the best solutions, although it did depend on the values set for parameters p_i and a_i . For a detailed description of the application of each meta-heuristic to the KP, the reader is referred to Hanafi and Freville (1998) and Higgins (2003).

5. The Auction for Landscape Recovery (Western Australia)

The Auction for Landscape Recovery (ALR) is a voluntary land and nature conservation program for landholders in the wheatbelt agricultural region of the Avon River basin (Gole *et al.* 2005). The auction is one of a series of market-based instrument pilots being conducted around Australia (Australian Government 2002). Rather than prescribe behaviour or technology use, market-based instruments use price signals to change behaviour to benefit the environment. They offer the potential to achieve environmental goals at lower cost to the community and with less disruption to resource users. For example, Stoneham *et al.* (2003) report that a traditional fixed-price scheme would require a budget seven times greater to achieve the same level of benefit delivered from the Victorian BushTender conservation auction.

In the Avon wheatbelt region, there is anecdotal evidence that requirements for landholders to match grant funds were limiting participation in devolved-grant and other cost-sharing environmental programs (Clayton 2004). An auction design, with no restrictions placed upon size of tender and the possibility of full-opportunity cost recovery (including an element of normal profit), was considered worth testing to encourage landholder participation and innovation in environmental management.

The ALR was conducted as a simple sealed bid, price discriminating auction, similar to Victoria's BushTender program (Stoneham *et al.* 2003). Landholders were encouraged to submit a tender describing their proposed management activities, anticipated environmental outcomes, and the remuneration they required to undertake and complete the works (Burton *et al.* 2004). The tender process was communicated simply as rewarding those who would deliver the greatest environmental benefit per dollar funded.

Within the ALR, sufficient data was collected to allow the tenders to be evaluated in two ways (Huggett *et al.* 2004a,b; Gole *et al.* 2005). Tender decisions were based on a consideration of biodiversity complementarity (Faith 1995) within a 'systematic conservation planning (SCP) framework' (Margules and Pressey 2000). This approach selected tenders on the basis of their contribution to achieving target levels of protection for ecosystem types. Essentially, the outcomes from this were the solution to a knapsack problem, with potential complementarity in benefits between tenders.

For the purposes of this paper, with its focus on optimisation rules, the EBI has been used as the basis for assessing the benefits from each tender (and not the SCP). As a result of this, and due to some tenders being screened out by an expert panel (see below), the results generated will not correspond to the actual selections made in the ALR.

The EBI comprised a 'biodiversity benefits index' (BBI), which assessed native biodiversity values, and an 'other environmental benefits index' (OEBI), which assessed salt and water management, soil management, and other land management activities (e.g., livestock, fire, and pest plants and animals). These conformed to target environmental goals, outcomes, and measures defined for the project and consistent with regional goals (Avon Catchment Council 2004). The attribute categories and data types for the BBI were largely adapted from site-assessment frameworks used in the Victorian BushTender trial (Parkes *et al.* 2003) and a prototype toolkit for scoring biodiversity benefits in NSW (Oliver and Parkes 2003). The OEBI was largely derived from the NSW Liverpool Plains auction trial (DLWC 2002). Minor adjustments were needed to adapt scores and indices to the condition and range of vegetation types found within the Avon Catchment, to ensure consistency with regional goals, and to account for the capacity of field officers undertaking site assessments (Huggett and Williams 2004). Data to drive the EBI came from on-site assessments and spatial mapping of landholder proposals by the field officers, desk-top spatial analysis of biodiversity and

Table 2 Summary of attributes and scores used in the environmental benefits index for the Auction for Landscape Recovery project (Western Australia)

Index	Attribute type	Number of attributes	Maximum score
BBI	Vegetation or habitat condition	5	32
	Vegetation or habitat complexity	9	48
	Landscape context	8	61
	Conservation significance	4	34
	Area in hectares of land use change	1	n/a
OEBI	Salt, water, and soil management benefits	6	35
	Other environmental benefits (grazing, fire, weeds, and feral animals)	7	44

Note: BBI, biodiversity benefits index; OEBI, other environmental benefits index.

land inventory data, and landholder statements of management objectives and activities submitted with each tender.

The overall design of the EBI used in the ALR program is presented in Table 2. The BBI utilises four surrogate measures of biodiversity: (i) vegetation or habitat condition; (ii) vegetation or habitat complexity; (iii) landscape context; and (iv) conservation significance. A formula adapted from Oliver and Parkes (2003) calculates a biodiversity significance score and a land use change impact score and combines these into an overall BBI. The biodiversity significance score combines and weights conservation significance and landscape context, and the land use change impact score combines and weights conservation significance and vegetation or habitat condition and complexity. The resulting BBI is a multiplicative combination of the biodiversity significance score, the land use change impact score, and a logarithm to base-10 transformation of area in hectares (representing the extent of land use change resulting from successful implementation of on-ground works contained in a tender). The extent of land use change factor effectively weights the BBI. The OEBI attributes were grouped into two categories – salt, water and soil management benefits, and other environmental benefits (grazing, fire, weeds, and feral animals). These were added and a weight of 0.5 applied to the resulting index. The final EBI was calculated as the sum of the two indices. A comprehensive description of the attributes, scores, and weights associated with the calculation of the EBI is given in Gole *et al.* (2005).

The auction was conducted over two rounds. The first round closed at the end of April 2004. Fifty-six bids were received from 38 landholders (some landholders having bid separately on each of their sites), totalling over \$A1.5 million for a \$A100 000 budget. The auction guidelines encouraged flexibility in the way landholders designed their bids – incorporating options for single, multiple, and joint bids (Burton *et al.* 2004). If a landholder submitted multiple tenders, each corresponding to a different site or different project activity on the same site, it is possible that more than one could be selected.

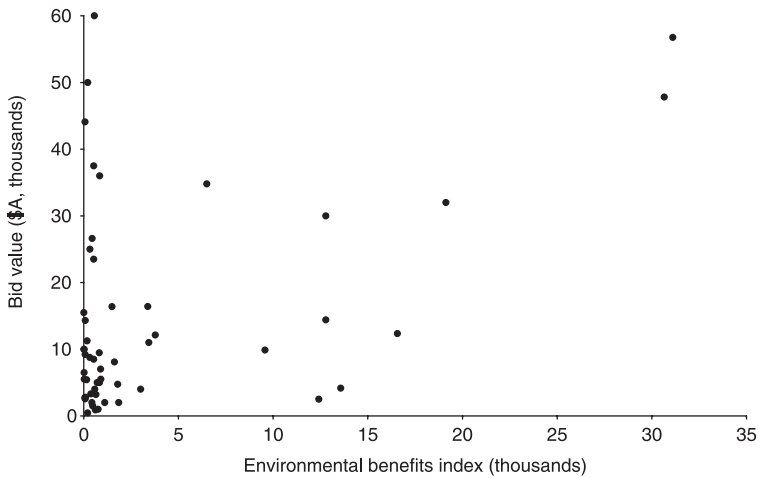


Figure 1 Environmental benefits index scores by bid value in Australian dollars for 54 round 1 tenders in the Auction for Landscape Recovery (Western Australia).

It was also possible for a landholder to develop alternative projects involving the same area of land, or identifying higher levels of management requiring a higher level of payment. In this case, only one of the mutually exclusive tender options would be selected. In recognition that landscape features could extend beyond individual farm boundaries, joint submissions from groups of landholders were also encouraged. For example, if connected areas of remnant vegetation overlapped different farms, then each landholder could submit a single tender and identify its association with a joint tender submitted by a group coordinator. An option existed for landholders involved in joint bids to also have their farm-tender considered as a single bid. In this case, the single bid was a subset of the joint bid and would only be considered if the joint bid was not selected.

Of the 56 Round 1 tenders, only 54 were included in our evaluation. Two tenders did not have accompanying EBI scores and these were not included in the analysis. An additional 'dummy tender' was created as a replicate of an existing tender, but with the tender cost replaced by an estimate of the full cost of material and labour, resulting in 55 tenders being analysed. The 'dummy tender' was selected as providing the most 'generic' environmental outcomes possible, and hence should be replicable across the area. This tender was used to test whether any of the real bids were being overpriced.

The EBI scores by bid cost for 54 tenders are presented in Figure 1. One tender is not shown because it is an outlier with a very high bid value (> \$A500 000). This did not prevent it being included in the analysis set. Most of the tenders were single, independent bids. Two sets of multiple tenders – three in one group and two in another, were mutually exclusive. Two sets of tenders were flagged as being linked to joint bids, with the option

Table 3 Total environmental benefits index of projects selected using each of the methods†

Solution method	$n = 32$ instance	$n = 55$ instance	$n = 55$ instance with mutual exclusiveness between projects
i	72 619.0 (96.5)	79 225.0 (77.6)	87 531.1 (92.9)
ii	75 030.8 (99.7)	101 805.9 (99.7)	90 798.8 (96.4)
iii	75 222.7 (100)	102 010.1 (99.9)	90 798.8 (96.4)
iv	75 222.7 (100)	102 153.6 (100)	94 170.4 (100)
v	75 222.7 (100)	102 153.6 (100)	94 170.4 (100)

Note: †The percentage of maximum achievable benefits reported in parentheses.

of being included as single bids. These single and joint bids were mutually exclusive. Other multiple tenders were independent (i.e., different sites and/or different activities on sites) and were treated as single tenders.

Before evaluation, the tenders were assessed for feasibility by an independent reference group comprising scientists, land managers, and landholders. The management actions proposed by some landholders were not considered feasible or were deficient in explanation and therefore would not satisfy the requirements of a management contract if selected. The review process reduced the set of tenders for evaluation to 32. For benchmarking purposes, the full set of 55 tenders were evaluated and compared with the results from the feasible set of 32 tenders.

6. Performance of purchasing strategies

In the present study, we re-examined the data for the $n = 32$ and $n = 55$ instances of the Western Australian Auction for Landscape Recovery case study. Solutions were found using the following methods: (i) fund in descending order of the environmental benefits score until a budgetary threshold is reached; (ii) fund in ascending order of a cost to utility (\$/EBI) ratio until a budgetary threshold is reached; (iii) greedy search algorithm; (iv) tabu search meta-heuristic; and (v) optimal using a commercial software package GAMS OSL 3 (Brooke *et al.* 1988), based on linear relaxation.

For both instances of the case study, a budget ceiling of \$A100 000 was used. Table 3 contains the total EBI under each method (and the percentage of the maximum EBI achieved by each method) and Table 4 shows the unallocated funds. The last column is in the case where there was mutual exclusiveness between some sets of projects. Mutual exclusiveness between projects is represented by the following additional constraints:

$$\sum_{i \in E_j} x_i = 1 \quad \forall j \quad (4)$$

where E_j is the j th set of mutually exclusive projects.

Table 4. Unallocated funds (A\$)†

Solution method	$n = 32$	$n = 55$	$n = 55$
	instances	instances	instances with mutual exclusiveness between projects
i	178	598	875
ii	2095	1005	8325
iii	295	555	8325
iv	295	5	75
v	295	5	75

Note: †Total budget was \$A100 000. We note that, for these data, when the optimal solution was found, there was minimal budget remaining. However, this is not a general property of optimal solutions.

The most noticeable effect in Table 3 was the gain in EBI when using methods recognised for combinatorial optimisation (iii, iv, and v) versus simple heuristic rules commonly used in practice (i and ii). The method based on descending order of environmental benefits, method (i), performed the worst and for $n = 55$, produced a total EBI slightly more than 75 per cent of the optimal EBI. The method based on ascending order of cost utility, method (ii), produced a solution with up to about 5 per cent less total EBI compared with the optimal. For the two small instances in Table 3, the tabu search was able to find the optimal solution. When the optimal solution was found, there was minimal budget remaining (Table 4), compared with the methods that produced solutions far from optimal. Given that the optimal solution was found (using GAMS) within 1 second of CPU time, the application of a meta-heuristic may be considered unnecessary for the Western Australia case study. However, meta-heuristics will handle more readily additional complexities than optimal solution methods in large instances, such as the EBI of projects being co-dependent.

When mutual exclusiveness was incorporated into the $n = 55$ instance, method (ii) was further away from the optimal than without mutual exclusiveness (third column of Table 3). Furthermore, the relatively simple greedy search heuristic (iii) was unable to improve upon the benefit-to-cost ratio ranking (ii) with the decision rules. This highlights the value of improved solution methods for combinatorial optimisation (methods iv and v) when further complexities are added to the model formulation.

7. Discussion

The results presented above show that considerable efficiency gains were possible by applying improved optimisation algorithms. By progressing upwards through methods (i) to (v), the environmental benefit was significantly increased without crossing the budget threshold. The six environmental programs reviewed in this study, in practice, have employed method (i), and in fewer cases (ii), although the ALR, in its on-ground implementation, used

a form of (iii), with benefits not defined by an EBI. If the decision-maker's objective is to maximise benefits and staying within budget these are not the best approaches.

Although GAMS determined the true optimal solution using method (v), this may not always be possible. If the number of projects is large, or there are additional rules (e.g., mutual exclusiveness rules) or several bid interdependencies, then standard computers may not produce a result within a reasonable time frame. This means a true optimal solution may be unavailable and a heuristic will be required (iii or iv). In the Western Australian case, the meta-heuristic produced the same result as the GAMS optimal solution, adding to the confidence in its application where problem complexity prevents true optimisation.

The losses, in percentage terms, from using a suboptimal solution will depend on the size of individual tenders relative to the overall budget. The maximum possible increase in total EBI that could be achieved under the more complex algorithms is given by the ratio of the residual budget generated by method (ii) to the cost-to-utility ratio of the marginal tender under method (ii). Thus, the existence of a number of 'small' tenders in the ranked list around the budget constraint will mean there is a relatively small residual budget, and hence, a small potential gain. Conversely, the identification of the true optimal set of tenders using the proposed advanced algorithms will be particularly important in cases where the selected set will comprise a small number of expensive projects.

In practice, decision-makers are likely to have additional objectives that introduce further constraints and interdependencies. For example, the New South Wales Environmental Services Scheme required selection of projects that were representative of multiple agricultural industries and all regions. In other words, an even or equitable spread of funding was required. The introduction of these requirements need not necessarily lead to the abandonment of improved optimisation algorithms. They can be handled by introducing constraints, for example, select n projects from region Y and m projects from region X .

It is possible that improved optimisation algorithms are not used in practice due to their complexity. Although it is relatively easy to justify project selection on the basis of methods (i) or (ii), it will be much more difficult to explain methods (iii), (iv), and (v) to stakeholders. For example, a project proponent will find it difficult to understand why their project was not funded if it obtained a higher benefit score than a funded project. Therefore, the use of suboptimal project selection procedures might be justified based on perceptions that these provide better reflections of transparency, accountability, and auditability.

Perhaps another reason why algorithms are not used is the failure of program designers to frame the purchasing strategy as an optimisation problem. With some exceptions, environmental programs are often not explicit about the program's aim to maximise the benefits score subject to a budget constraint. Sometimes program managers have flexibility over the budget, and are able to allocate more funds if a particularly beneficial set of projects is proposed.

Nonetheless, at some point a budgetary allocation is fixed and funds limit project selection. Therefore, it will be appropriate to structure the problem as an optimisation KP problem. However, as the projects' benefits scores become more sophisticated, and interdependency between bids occurs, then the KP problem also becomes more complex.

Optimisation decisions are made more difficult when interdependencies are present. For example, Barton *et al.* (2003) describe a regional trade-offs framework for targeting payments to private landholders for biodiversity conservation in Costa Rica. They used a heuristic selection algorithm to incorporate complementarity values and highlighted gains in efficiency relative to conventional scoring approaches.

The discussion about the relative merits of optimal versus heuristic methods parallels the general debate about methods for reserve selection. These methods often consider biodiversity complementarity, and involve some consideration of 'costs'. Faith (1995) describes general approaches linked to multicriteria analyses, whereas Church *et al.* (1996) identify the 'maximal covering location problem', which tries to maximise the conservation benefit of a reserve system given some maximum number of sites.

The issue of optimality and heuristics was raised early in systematic conservation planning (e.g., Underhill 1994; Pressey *et al.* 1996). Recently, Moore *et al.* (2003) argued that, for their reserve selection case study, there was no time penalty in using optimal methods. But time considerations have been critical in many other studies. For example, Church *et al.* (1996), who interpreted the selection of a set of conservation management areas as a multi-dimensional knapsack problem, observed that even moderately sized problems required 'an inordinate amount of computer time' to solve optimally. Consequently, they focused on the design of robust heuristics. Similarly, Sarkar *et al.* (2004) found little reason to prefer optimal to heuristic area-selection algorithms for their probabilistic data sets. For their large data sets, the optimal algorithms often required long computation times and produced no better results than the heuristic ones.

Pressey *et al.* (1996), in response to Underhill (1994), argued that 'suboptimality is not necessarily a disadvantage for many real-world applications' and that the criteria for judging utility of methods must be broader than simple mathematical optimality. One related issue in the present context is the degree of doubt about values of EBI (see Huggett *et al.* 2004a,b). The large confidence intervals for EBI scores may mean that little is gained by small increments in apparent optimality (see Table 3). Given such doubts about the data and indices, some workers (Cowling *et al.* 2003) have suggested that expert opinion may match the quantification of algorithms.

Another consideration in addressing uncertainties is that, in practice, the selected set of places may never be implemented as a whole. Thus, selecting the optimal set may be less important than flexibility, and finding ways to schedule selections in response to changing constraints (e.g., see the dynamic selection work of Drechsler 2005). Faith *et al.* (2003, p. 13) argued:

In spite of a decade or more of work on reserve selection methods, no complete set of areas produced by such computer algorithms, to our knowledge, has been implemented anywhere in real-world regional biodiversity planning. Yet much effort now is going into computational algorithms (e.g. Rodrigues and Gaston 2002) to incorporate additional constraints and to better estimate sets of areas corresponding to a “global optimum”. . . . Alternative directions for research and applications may link complementarity values to economic instruments, through (1) scenarios analyses that focus more on the fate of individual areas than whole-sets, or (2) what we will call “policy-based” algorithms, that do address strategies for selecting whole-sets of areas, but over the life of a government conservation policy.

The consideration of biodiversity complementarity (where the value of a place depends on what else is selected) suggests that this will remain a challenging area for future research.

8. Conclusion

It can be concluded that many large environmental programs could deliver improved outcomes while meeting budget constraints merely by using improved optimisation algorithms in project selection. The reasons for the use of suboptimal project selection procedures might include the difficulty of explaining advanced algorithms to project proponents and a failure to frame the purchasing strategy as an optimisation problem. The consequences are lower levels of environmental services than could otherwise be attained. This suggests that future research is needed to develop means by which complex optimisation algorithms can be more easily accessed and understood by decision-makers and stakeholders.

The implication for policy makers who design and implement environmental programs based on competitive tendering for conservation contracts is that the initial proper structuring of the decision problem is essential. By structuring the decision task as an optimisation problem, subject to financial and non-financial constraints, and applying appropriate algorithms it is more likely that a greater return on public environmental investment will occur. This is particularly important in a policy arena where funds can be limiting.

References

- Ando, A., Camm, J., Polasky, S. and Solow, A. (1998). Species distribution, land values, and efficient conservation, *Science* 279, 2126–2128.
- Arthur, J.L., Hachey, M., Sahr, K., Huso, M. and Kiester, A.R. (1997). Finding all optimal solutions to the reserve site selection problem: formulation and computational analysis, *Environmental and Ecological Statistics* 4, 153–165.
- Australian Government (2002). *Investigating New Approaches: A Guide to the National Market-Based Instruments Pilots Program*. Department of Agriculture Fisheries and Forestry Australia (AFFA), Canberra.

- Avon Catchment Council (2004). *The Avon NRM Strategy: The Regional Natural Resource Management Strategy for the Avon River Basin*, Final Draft Version 11–30th July Avon Catchment Council, Perth.
- Barton, D.N., Faith, D.P., Rusch, G., Gjershaug, J., Castro, M., Vega, M. and Vega, E. (2003). *Spatial Prioritisation of Environmental Service Payments for Biodiversity Protection*, Report SNR 4746/2003, Norsk institutt for vannforskning, Oslo, Norway.
- Bonabeau, E., Dorigo, M. and Theraulaz, G. (2000). Inspiration for optimisation from social ants behaviour, *Nature* 406, 39–42.
- Brooke, A., Kendrick, D. and Meeraus, A. (1988). *GAMS: a User's Guide*. Scientific Press, Washington DC.
- Burton, M., Clayton, H. and White, B. (2004). Auction design: supplementary report. In: *Auction for Landscape Recovery (Southwest Australia) Project 21*. Supplementary Report to the First Quarterly Report Commonwealth, 17 Feb 2004 (unpublished), WWF Australia, Perth.
- Caccetta, L. and Kulanoot, A. (2001). Computational aspects of hard knapsack problems, *Nonlinear Analysis* 47, 5547–5558.
- Church, R.L., Stoms, D.M. and Davis, F.W. (1996). Reserve selection as a maximal coverage location problem, *Biological Conservation* 76, 105–112.
- Clayton, H. (2004). Section 3: Background Report: past and existing incentive schemes – an overview of environmental incentive programs in the Avon River Basin, Western Australia, in *Auction for Landscape Recovery (Southwest Australia) Project 21*. Third Quarterly Report to the Commonwealth 14 July 2004 (unpublished), WWF Australia, Perth, pp. 48–60.
- Costello, C. and Polasky, S. (2004). Dynamic reserve site selection, *Resource and Energy Economics* 26, 157–174.
- Cowling, R.M., Pressey, R.L., Sims-Castley, R., le Roux, A., Baard, E., Burgers, C.J. and Palmer, G. (2003). The expert or the algorithm? – Comparison of priority conservation areas in the Cape Floristic region identified by park managers and reserve selection software, *Biological Conservation* 112, 147–167.
- Cullen, R., Fairburn, G.A. and Hughey, K.F.D. (2001). Measuring the productivity of threatened species programs, *Ecological Economics* 39, 53–66.
- Department of Land and Water Conservation (2002). *Liverpool Plains auction trial*. New South Wales State Government, Sydney.
- Drechsler, M. (2005). Probabilistic approaches to scheduling reserve selection. *Biological Conservation* 122, 253–262.
- Drexler, A. (1988). A simulated annealing approach to the multi-constraint 0–1 knapsack problem, *Computing* 40, 1–8.
- European Commission (2002). *LIFE – Environment Projects*. European Commission, Brussels.
- Faith, D.P. (1995). *Regional Sustainability Analysis*. CSIRO, Canberra.
- Faith, D.P., Carter, G., Cassis, G., Ferrier, S. and Wilkie, L. (2003). Complementarity, biodiversity viability analysis, and policy-based algorithms for conservation, *Environmental Science and Policy* 6, 311–328.
- Faith, D.P., Walker, P.A., Ive, J. and Belbin, L. (1996). Integrating conservation and forestry production: exploring trade-offs between biodiversity and production in regional land-use assessment, *Forest Ecology and Management* 85, 251–260.
- Gole, C., Burton, M., Williams, K.J., Clayton, F., Faith, D.P., White, B., Huggett, A. and Margules, C. (2005). *Auction for Landscape Recovery: ID 21 Final report, September 2005*. Commonwealth Market Based Instruments program, WWF Australia. Available from URL: <http://www.npswq.gov.au/mbi/round1/project21.html> [accessed 18 Aug 2006].
- Grieve, A. and Uebel, K. (2003). *The NSW Environmental Services Scheme – Progress Report on Outcomes and Experience Developed during its Implementation*. New South Wales Government, Sydney.
- Hanafi, S. and Freville, A. (1998). An efficient tabu search for the 0–1 multidimensional knapsack problem, *European Journal of Operational Research* 106, 659–675.

- Higgins, A.J. (2003). *A comparison between existing and new heuristics using the knapsack problem*, Queensland, Proceedings of the 5th Australian Society of Operations Research (ASOR_QLD) Conference, pp. 88–100.
- Horowicz, E. and Sahni, S. (1974). Computing partitions with applications to the knapsack problem, *Journal of the ACM* 21, 277–292.
- Huggett, A. and Williams, K. (2004). Site assessment, environmental benefits index and environmental outcomes, in *Auction for Landscape Recovery (Southwest Australia) Project 21*. First Quarterly Report to the Commonwealth 14 January (Unpublished). WWF Australia, Perth.
- Huggett, A., Williams, K. and Faith, D. (2004a). First round tender evaluation process methods for round 1 evaluation of tenders in NEWROC: approaches, issues and resolutions, in *Auction for Landscape Recovery (Southwest Australia) Project 21*. Third Quarterly Report to the Commonwealth 14 July (unpublished). WWF Australia, Perth.
- Huggett, A., Williams, K., Faith, D. and Beecham, B. (2004b). Section 2: methods for tender evaluation in NEWROC, in *Auction for Landscape Recovery (Southwest Australia) Project 21*. Second Quarterly Report to the Commonwealth, Corrected, version 1. July (unpublished). WWF Australia, Perth, pp. 6–93.
- Margules, C.R. and Pressey, R.L. (2000). Systematic conservation planning, *Nature* 405, 243–253.
- Martello, S., Pisinger, D. and Toth, P. (2000). New trends in exact algorithms for the 0–1 knapsack problem, *European Journal of Operational Research* 123, 325–332.
- Martello, S. and Toth, P. (1980). Solution of the 0–1 multiple knapsack problem, *European Journal of Operational Research* 4, 276–283.
- Meir, E., Andelman, S. and Possingham, H.P. (2004). Does conservation planning matter in a dynamic and uncertain world? *Ecology Letters* 7, 615–622.
- Moilanen, A. (2005). Methods for reserve selection: interior point search, *Biological Conservation* 124, 485–492.
- Moore, J.L., Folkmann, M., Balmford, A., Brooks, T., Burgess, N., Rahbek, C., Williams, P.H. and Krarup, J. (2003). Heuristic and optimal solutions for set-covering problems in conservation biology, *Ecography* 26, 595–601.
- Oliver, I. and Parkes, D. (2003). *A Prototype Toolkit for Predicting the Biodiversity Benefits (and Disbenefits) of Land Use Change*, version 4.0, Centre for Natural Resources, New South Wales Department of Land and Water Conservation, Sydney.
- Parkes, D., Newell, G. and Cheal, D. (2003). Assessing the quality of native vegetation: the ‘habitat hectares’ approach, *Ecological Management and Restoration* 4, S29–S38.
- Pierce, S.M., Cowling, R.M., Knight, A.T., Lombard, A.T., Rouget, M. and Wolf, T. (2005). Systematic conservation planning products for land-use planning: interpretation for implementation, *Biological Conservation* 125, 441–458.
- Pisinger, D. (1999). An exact algorithm for large multiple knapsack problems, *European Journal of Operational Research* 114, 528–541.
- Polasky, S., Camm, J. and Garber-Yonts, B. (2001). Selecting biological reserves cost effectively, *Land Economics* 77, 68–78.
- Pressey, R., Possingham, H. and Day, J. (1997). Effectiveness of alternative heuristic algorithms for identifying minimum requirements for conservation reserves, *Biological Conservation* 80, 207–219.
- Pressey, R.L., Possingham, H.P. and Margules, C.R. (1996). Optimality in reserve selection algorithms: when does it matter and how much? *Biological Conservation* 76, 259–267.
- Ram, B. and Sarin, S. (1988). An application for the 0–1 equality knapsack problem, *Journal of the Operational Research Society* 39, 1045–1049.
- Reeves, C. (1996). Hybrid genetic algorithms for bin-packing and related problems, *Annals of Operations Research* 63, 371–396.
- Reichelderfer, K. and Boggess, W.G. (1988). Government decision making and program performance: the case of the Conservation Reserve Program, *American Journal of Agricultural Economics* 70, 1–11.

- Ribaudo, M.O., Hoag, D.L., Smith, M.E. and Heimlich, R. (2001). Environmental indices and the politics of the conservation reserve program, *Ecological Indicators* 1, 11–20.
- Rodrigues, A.S. and Gaston, K.J. (2002). Optimisation in reserve selection procedures – why not? *Biological Conservation* 107, 123–129.
- Sarkar, S., Pappas, C., Garson, J., Aggarwal, A. and Cameron, S. (2004). Place prioritization for biodiversity conservation using probabilistic surrogate distribution data, *Diversity and Distributions* 10, 125–133.
- Snyder, S., Tyrell, L. and Haight, R. (1999). An optimization approach to selecting research natural areas in national forests, *Forest Science* 45, 458–469.
- Stephens, T. and Lawless, P. (1998). *Cost–Utility Evaluation of Natural Heritage Biodiversity Conservation Projects*. Department of Conservation, Wellington.
- Stoneham, G., Chaudhri, V., Ha, A. and Strappazzon, L. (2003). Auctions for contracts: an empirical examination of Victoria’s BushTender trial, *The Australian Journal of Agricultural and Resource Economics* 47, 477–500.
- Sylo, M., Deo, N. and Kowalik, J.S. (1983). *Discrete Optimisation Algorithms with Pascal Programs*. Prentice Hall Inc., Englewood Cliffs, NJ.
- Underhill, L.G. (1994). Optimal and suboptimal reserve selection algorithms, *Biological Conservation* 70, 85–87.
- United States Department of Agriculture (2003a). *Financial Year EQIP Unfunded Application Information*. USDA, Washington DC.
- United States Department of Agriculture (2003b). *Conservation Reserve Program Sign-up 26 Fact Sheet*, May 5–June 13. USDA, Washington DC.