Volume 40(2), pp. 109–133
http://orion.journals.ac.za

ORiON
ISSN 0259–191X (print)
ISSN 2224–0004 (online)

An application of portfolio decision heuristics to support the selection of research grant proposals

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Received: 21 June 2024; Accepted: 14 October 2024

Abstract

Portfolio decisions involve selecting a subset of alternatives that together maximize some measure of value, subject to resource constraints. Exact methods are available to solve portfolio decision problems, but these require time, expertise and effort that may not always be available. In response, recent research has proposed a number of computationally simple, psychologically plausible rule-based heuristics for portfolio decision making. Simulation studies have shown that these portfolio heuristics perform well relative to exact approaches, but portfolio selection heuristics have yet to be applied in a real-world setting. Our study addresses this gap by using portfolio heuristics to support the selection of research grant proposals at a research institute in South Africa. We compare results obtained with portfolio heuristics to those obtained using two more traditional forms of decision support, the standard linear-additive portfolio model, and robust portfolio modelling. We found that portfolios constructed using portfolio heuristics yielded over 90% of the value of optimal portfolios, selected slightly different portfolios potentially useful in a sensitivity analysis role, and were experienced as providing transparent and easy to understand decision support. Heuristic portfolios were slightly but consistently outperformed by portfolios generated with robust portfolio modelling. Collectively, our study contributes to the growing body of evidence supporting the use of psychological heuristics in the realm of portfolio decision-making.

Key words: Multiple criteria decision analysis, Portfolio optimisation, Decision support systems.

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http://dx.doi.org/10.5784/40-2-778

1 Introduction

Psychological heuristics are rule-based models for making decisions that are computationally simple, make partial or incremental use of available information, and have some psychological or cognitive plausibility as models of human decision making (Keller and Katsikopoulos, 2016). The use of psychological heuristics in decision making is often motivated by appeals to bounded or ecological rationality (Simon, 1955, 1956; Gigerenzer et al., 1999), meaning that although these heuristics may not always or even often lead to an optimal solution, they lead very often to a good (or "good enough") solution, and perhaps even to one that is optimal once one factors in the kinds of constraints on time, cognitive resources, and motivation that are nearly always present in real-world decisions.

Psychological heuristics have been widely studied for traditional choice problems, in which the goal is to select one alternative from a set of n candidates. These studies have shown that heuristics can offer surprisingly good performance relative to optimal solutions, as well as the environmental conditions that affect heuristic performance. Decision makers have also been shown to use heuristics, particularly if time or other resources are constrained. However very little equivalent work exists for portfolio problems in which the goal is to select the best *subset* of alternatives from the set of candidates (subject to some constraints that mean one cannot select them all). Portfolio selection problems are especially challenging when benefits and costs are non-additive because some alternatives may interact positively or negatively with one another, for example because they share resources or combine favourably together.

Keisler (1996, 2004, 2008) and more recently Durbach et al. (2020) developed a number of portfolio selection heuristics by extending traditional choice heuristics into the domain of portfolio decisions. Durbach et al. (2020) further showed that portfolio heuristics (a) can be competitive with theoretically optimal models, provided that interactions between alternatives are accounted for in some way; (b) use far less information than approaches needed to find the optimal solution information, i.e. are "frugal" in their use of information; (c) offer a plausible explanation of the choices made by some participants in a behavioural laboratory experiment involving hypothetical portfolio selection.

These findings provide circumstantial evidence that portfolio heuristics may be used to support real-world decision making, especially when time and other resources are limited and so more comprehensive approaches (e.g. multi-objective optimisation, multi-attribute value theory) cannot be carried out. However, to date there have been no application of portfolio selection heuristics in a real-world setting. This paper addresses this gap by using portfolio heuristics to support the selection of research grant proposals at a research institute in Africa, and comparing the results to those obtained using two more traditional forms of decision support – the standard linear-additive portfolio model (Stummer and Heidenberger, 2003) that can be structured and solved to optimality using integer programming; and robust portfolio modelling (Liesiö et al., 2008), which provides upper and lower bounds on the performance of alternatives.

Project selection provides a useful application area for evaluating heuristic-based decision support because multi-criteria methods have been widely used in this setting (see de Souza et al. (2021); Turkmen and Topcu (2021); Mohagheghi et al. (2019) for a review). For example, projects can be R&D projects (Hassanzadeh et al., 2012), transportation projects (Ghaeli et al., 2003), manufacturing companies (Hu et al., 2008), investment projects (Khalili-Damghani and Tavana, 2014), IT demands and strategic planning and customers' contracts (Martins et al., 2017), and oil and gas projects (Tang et al., 2017). Methods used to select projects with deterministic evaluations include, for example, data envelopment analysis (Cook and Green, 2000), equity models (Bana e Costa, 2001; Bana e Costa and Lawrence, 2007; Keeney, 1992), the analytic hierarchical process (Saaty, 2004; Subramanian and Ramanathan, 2012; Yang and Tzeng, 2011), the linear-additive portfolio value model (Pisinger, 1995; Martello et al., 2000; Stummer and Heidenberger, 2003), PROMETHEE V (de Almeida et al., 2014; de Almeida and Vetschera, 2012), ELECTRE-TRI (Mousseau et al., 2002, 2011), and reference point methods (Stewart, 2016; Liesiö, 2014). Where project evaluations are uncertain, selections have been made with robust portfolio modeling (Liesiö et al., 2008; Mild et al., 2015; Lindstedt et al., 2008), data envelopment analysis and the balanced scorecard model (Eilat et al., 2008; Greenberg and Hegerich, 1970; Martello et al., 2000), multi-attribute utility theory (Taylor et al., 1982; Liberatore, 1986), TOPSIS (Collan et al., 2015; Liang et al., 2018), and scenario-based methods (Liesiö and Salo, 2012; Rockafellar and Uryasev, 2000; Dentcheva and Ruszczynski, 2006). These studies have shown that decision makers have been able to integrate both the risk and the value of projects in multicriteria methods for portfolio selection (Ghaeli et al., 2003); to consider both current and future competence requirements (Stummer et al., 2009); to find the best portfolio of sustainable projects (Mohagheghi et al., 2022; Khalili-Damghani and Tavana, 2014); to quantify the degree of certainty with which each project is selected or not in the final portfolio (Mavrotas and Pechak, 2013) and to consider multiple constraints and inter-projects relationships to achieve the compromise between risk and return (Tang et al., 2017).

2 Data and methods

2.1 Background to the problem

We developed decision support for a South African research institute to assist with the selection of research proposals submitted by researchers in response to periodical funding calls made by the research institution. The setting is typical of competitive academic grant funding schemes, whereby successful applicants receive funding that covers both their salary and research running costs for the duration of the proposed project. Available funding is limited to a fixed amount, and the proportion of submitted applications that can be funded is low. Currently, selections are made by different approaches, depending on the grant, but typically involve two to three referees scoring each proposal against a set of criteria on a 1-5 or 1-10 scale, following which a selection panel makes its final decisions based partly on these quantitative assessments and partly on qualitative discussion among the panel. Depending on the funding call, proposals can be at doctoral or postdoctoral level and thus applicants vary from postgraduate students to established researchers.

In the context of this application, we engaged with both a project manager and a research data analyst, hereafter referred to as the decision maker. They both participated in numerous decision panels and due to their roles, they were well positioned to assess the feasibility and usefulness of the various results from our decision support system. Although we initially planned to present our decision support system to the broader research management team, both staff members left their positions during the course of our application, making it no longer possible to do so. Our approach was thus ultimately not implemented to facilitate future grant selections, but we believe still represents a useful case study in the potential usefulness of heuristic-based decision support for project selection.

The goal of the decision process was to select the subset of proposals that are, in some sense, "best", where this is determined by a number of factors: candidate track record, excellence in the vision and implementation of the proposed research project, and alignment of the proposal with strategic areas defined by the research department. There are also interaction effects between proposals, in that some combinations of proposals would be preferred to others based on how well they, as a group, meet the goals set by the research institution. For example, diversity is valued both in the fields of study that are funded, and in the candidates themselves. The decision maker's highest-level goal is to select the best combination of proposals, i.e. the subset of proposals that would yield the highest value to the institute. A scientifically sound decision support system would streamline the selection process and make it more transparent and effective. Potential areas for improvement in the decision process include a standardised, complete set of assessment criteria, the inclusion of project interactions, and using decision support tools to facilitate the selection process. Our specific interest is in the use of heuristic approaches for decision support.

2.2 Problem structuring

The first step in solving a portfolio decision problem is to define the decision context, i.e. the set of preferences, constraints and policies that have an effect on the decision makers and stakeholders. When conducting multiple criteria decision analysis in a decision context, it is required to first lay a foundation by structuring the problem, then identifying alternatives and interactions between them and finally, building a model. To do this, we had a series of online meetings, one face-to-face meeting and email exchanges with the decision maker to guide the decision process, details of which are shown in Table 1. Face-to-face contact was limited due to the COVID-19 pandemic.

Session	Medium	Subject	Duration
1	Online meeting	Goals and objectives of research institution	80 min
2	Online meeting	Criteria for selection of proposals	90 min
3	Face-to-face	Elicitation of value tree, weights and interactions	150 min
4	Email	Elicitation of value tree, weights and interactions	
5	Email	Introduction of the web-based application	
6	Email	Feedback about the web-based application	
7	Email	New version of the web-based application	
8	Email	Feedback about the web-based application	
9	Email	Discussion of the results	
10	Online meeting	Further discussion of the results	120 min
11	Email	Further discussion of the results	
12	Email	Feedback	

Table 1: Details of meetings and discussions held during the application.

2.2.1 Value tree

A key step in solving a portfolio decision problem is to define the structure of the decision problem. In order to do this, stakeholders and decision makers need to articulate their fundamental objectives and goals. These are also referred to as criteria and are the basis for evaluating alternatives. We conducted a series of interviews with the decision maker to establish a set of criteria, organised into a value tree, i.e. an hierarchy of objectives. We then defined measurable attributes for each criterion using either quantitative or qualitative measurement scales. Previously-used criteria and criteria used in the literature for research proposal selection (e.g. Joshi, 2014) were used to facilitate discussion. We also used the discussions to verify that the decision maker could express preferences for proposals based on each criterion independently of other criteria (preferentially independent criteria), and that the criteria in this study were unambiguous and the decision maker could also specify a scale for each one of them, thus making them measurable and operational. The decision maker was satisfied that the criteria capture all important aspects of the decision problem (Belton and Stewart, 2002).

2.2.2 Construction of partial value functions

Partial value functions convert attribute measurement scores to an underlying value scale (Belton and Stewart, 2002). This serves two main purposes. The first is to ensure that within any criteria two equal-size differences in value (comparing, say 0-10 and 10-20) are equally preferred by the decision maker, since this cannot be assumed to hold at the scale of the attributes themselves (0-10 vs 10-20 previous publications, for example). The second is to place all criteria onto the same measurement scale, facilitating further aggregation.

Each proposal is scored on every attribute by multiple referees. We denote the rating of proposal $j = 1, \ldots, n$ on criterion $i = 1, \ldots, m$ by referee $r = 1, \ldots, o$ by x_{ijr}. For confidentiality and data privacy reasons, the institution did not want to use the data from an actual application round, and so we generated a second set of scores with $n = 24$, $m = 11$, and $o = 3$ and similar properties to the original data, showed these to the decision maker, and led them through the process described here. We assessed partial value functions using the direct-rating method (Eisenfuhr et al., 2010). The best and worst values on each criterion were specified, and then all alternatives were ranked from best to worst based on the decision maker's preference regarding their performance. We used a local measurement scale, so that the best-performing alternative received a score of 100 and the worst-performing alternative a score of 0. The decision maker then assigned a score between 0 and 100 to each remaining alternative based on a subjective comparison with the best and worst alternatives. Mean value scores across referees are shown in Table 9.

2.3 Criterion weights

Weights of criteria in MCDA are a scaling constant reflecting both the scale of the criterion and its importance, and are necessary because the same size difference in value (say, 10 value units) cannot be assumed to be equally valued by the decision maker (whereas equal-sized *weighted* value differences are). We used the swing method to assess weights, a widely used and accepted approach for weight assessment (Belton and Stewart, 2002). The decision maker first ranked criteria from most to least important based on the value assigned to the improvement (or "swing") from the worst to the best level of achievement on that criterion. The swing deemed most important or valuable was assigned a weight of 100, following which the relative value of swings on other criteria were established by comparison against that largest swing. We assessed weights within families of criteria (higher-level objectives), followed by a comparison of the most highly weighted criterion in each family, and using worst-to-best swings as a basis for that comparison. Criterion weights were standardised to sum to one.

2.4 Interactions between projects

Based on initial discussion with the decision maker, we modelled interactions between projects by defining a multiplicative interaction factor $\gamma_{i\eta}$ that increases the value of any portfolio with η proposals that have an excellent score on criterion i, with the cutoff for "excellent" performance on each criterion assessed by the decision maker. This is similar to the way Liesiö (2014) builds multiattribute value functions for portfolio decision analysis, with the interaction benefit increasing with the number of good alternatives $\gamma_{i\eta} \geq \gamma_{i(\eta-1)}$. Following Stummer and Heidenberger (2003), we define A_k, $k = 1, \ldots, K$ to be interaction subsets, with each interaction subset containing a set of projects that possess an interaction.

2.5 Assessment of portfolio value

Ignoring for now the presence of multiple referees, so that we can write attribute scores as x_{ij} rather than x_{ijr}, the standard linear-additive portfolio model (Stummer and Heidenberger, 2003; Jaszkiewicz, 2002; Martello et al., 2000) specifies the overall value of a portfolio of projects P as:

$$\max V(P) = V(z_1, \ldots, z_n) = \sum_{j=1}^{n} x_j z_j + \sum_{k=1}^{k} B_k g_k \tag{1}$$

where $x_j = \sum_{i=1}^{m} \omega_i x_{ij}$ the weighted additive value of projects j across all criteria, B_k is the incremental change in value if all of the projects in interaction subset A_k are chosen, z_j, $j = 1, \ldots, n$ are binary variables indicating whether project j is included ($z_j = 1$) in the portfolio or not ($z_j = 0$), and g_k, $k = 1, \ldots, K$ are binary variables indicating whether all the projects in interaction subset A_k are included ($g_k = 1$) in the portfolio or not ($g_k = 0$). Thus x_j and B_k are benefits potentially accruing to portfolio P, and z_j and g_k are binary decision variables indicating whether or not these benefits are included or not. For our application we define incremental values $B_k = \gamma_{i\eta}(\sum_{j\in A} x_j)$, where A is the union of interaction subsets A_k and $\gamma_{i\eta}$ is the multiplier associated with interaction subset A_k. The sum of these is then $\sum_{k=1}^{K} B_k g_k = (\sum_{j\in A} x_j) \sum_{k=1}^{K} \gamma_{i\eta} g_k$.

As an illustrative example, suppose a decision maker selects a portfolio made up of projects $\{3, 17, 19, 23\}$ whose x_{ij} values are shown in Table 2. The individual aggregated scores x_j of each of these projects is 63.6, 71.6, 76.8, and 70.6 respectively. The total contribution of individual projects to overall portfolio value is thus 282.7. If there are no interactions then no further calculations are needed and this is the final overall portfolio value. However suppose that an excellence threshold of 90 is used on all criteria. Then projects 17 and 19 are both excellent on criterion C_1, and projects 17, 19, and 23 are excellent on criterion C_3 (Table 2, bold). Each of these defines an interaction subset, i.e., $A_1 = \{17, 19\}$ and $A_2 = \{17, 19, 23\}$, with the union $A = \{17, 19, 23\}$. Suppose further that the interaction multiplier associated with these interactions are $\gamma_{12} = 0.07$ and $\gamma_{33} = 0.05$. The incremental benefit accruing from A_1 is $\gamma_{12}(x_{17} + x_{19} + x_{23}) = 0.07(71.6 + 76.9 + 70.6) = 15.3$, while that accruing from A_2 is $\gamma_{33}(x_{17} + x_{19} + x_{23}) = 0.05(71.6 + 76.9 + 70.6) = 11.0$. Overall portfolio value is thus 282.7+15.3+11=309.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	x_j
P3	70	60	70	70	75	80	70	70	50	45	0	63.6
P17	**90**	70	**90**	80	80	**90**	80	60	40	50	0	71.6
P19	**90**	70	**90**	70	80	80	70	70	70	50	**100**	76.8
P23	80	67	**90**	70	80	70	80	75	70	50	0	70.6
ω_i	0.13	0.11	0.11	0.10	0.10	0.09	0.09	0.08	0.08	0.07	0.05	

Table 2: Inputs to an illustrative example of a calculating overall portfolio with interaction multipliers. The weighted additive value of project j across all criteria is given by x_j. Values in bold are deemed excellent (≥ 90), generating the interaction subsets $A_1 = \{17, 19\}$ and $A_2 = \{17, 19, 23\}$, which are assumed to have corresponding multipliers $\gamma_{12} = 0.07$ and $\gamma_{33} = 0.05$ respectively (see Table 4). Overall portfolio value is $(63.6+71.6+76.9+70.6)+0.07(71.6+76.9+70.6)+0.05(71.6+76.9+70.6) = 309$.

2.6 Portfolio selection

Portfolios were selected using three different methods: an integer programming solution of the linear-additive portfolio value model with average (over referees) project scores, robust portfolio modeling, and portfolio heuristics, with the decision maker shown the results from all three methods. In addition, we asked the decision maker to select portfolios without facilitation, i.e. without looking at the portfolios suggested by the above methods, but by only considering the average profile of the projects, the weights attached to the criteria and specified interaction values. Portfolios were selected in the four-, five-, and six-proposal settings i.e., a maximum of four, five and six projects, respectively, could be selected at once in each round.

2.6.1 Solution by integer programming

Formulation of the linear-additive portfolio value model as an integer programming model is standard (Stummer and Heidenberger, 2003), maximizing (1) subject to constraints on resources. We solved the problem assuming that either four, five, or six projects could be selected. We used the mean of the ratings across referees to represent the score associated with each project on each criterion, i.e., $x_{ij} = \sum_{r=1}^{3} x_{ijr}/3$, when three referees are involved.

2.6.2 Robust portfolio modelling

The robust portfolio model (RPM) extends the standard portfolio optimisation model above to cases where weights or scores are uncertain. Here, we assume uncertainty arises due to the use of multiple referees that may not provide the same rating.

The RPM model presented by Liesiö et al. (2008) models portfolio selection in the presence of incomplete performance score and weight information. The set of feasible scores is given as $S_x = \left\{ X \in \Re^{m \times n} \mid \underline{X} \leq X \leq \overline{X} \right\}$ where $\underline{X}$ and $\overline{X}$ are the lower and upper bounds of the score interval, respectively. Here, lower and upper scores correspond to the worst and best assessment given by a referee. Weights can be treated similarly, but are assumed known with certainty here. RPM identifies the set of non-dominated portfolios consistent with scores in S_x, where portfolio P dominates portfolio P' if and only if the value of portfolio P for the lowest performance scores $\underline{X}$ is higher than the value of portfolio P' for the highest performance scores $\overline{X}$. Liesiö et al. (2008) presents an algorithm in which pairwise comparisons are conducted to construct the set of the non-dominated portfolios. A partial enumeration of portfolios is made possible by the elimination of portfolios that cannot become non-dominated. In this application, we were able to enumerate all portfolios because of the reasonable size of the portfolio selection problem. We identified portfolios that were non-dominated – these are the RPM portfolios.

In order to assess the quality of portfolios, RPM defines a project's core index CI_j as the proportion of non-dominated portfolios that include that project. Based on this index, projects can be classified as core (they are part of every non-dominated portfolio, $CI_j = 1$), borderline (they belong to some non-dominated portfolios but not to all, $0 < CI_j < 1$) and exterior (they belong to none of the non-dominated portfolios, $CI = 0$). A portfolio made up of core alternatives is thought to be more robust than other portfolios.

2.6.3 Heuristics

We selected portfolios using two heuristics identified as promising in Durbach et al. (2020): unit value with synergy and added value. These are both extensions of the unit value heuristic, which adds projects in descending order of their value-to-cost ratios until the resource constraint is reached, with values based on individual project values only. We assume equal costs for all projects, so that projects are effectively ranked by their values only.

The *Unit Value with Synergy* heuristic adds projects according to the unit value heuristic, but restricts the pool of available projects to those involved in at least one positive interaction, i.e. projects are sorted by their marginal value-to-cost ratios and added in this order. Projects are added until the set is exhausted. Then, if any space in the portfolio remains, it adds alternatives from outside the set, again using the unit value heuristic to do so.

The *Added Value* heuristic adds the project whose inclusion would lead to the largest increase in overall portfolio value per unit cost. Gains include both marginal values of the project and interaction values resulting from a combination of projects being simultaneously part of the portfolio. The added value heuristic searches across projects not added yet to see whether their inclusion would complete any interaction subset.

2.6.4 Comparison of selection approaches

We assessed the quality of portfolios produced by heuristic methods and RPM against optimal portfolios by calculation the proportion of the optimal portfolio value achieved using these two approaches, and by calculating the proportion of projects in the optimal portfolio that were selected by heuristic methods or RPM.

2.7 Decision support system

We developed a web-based application implemented in R Shiny to provide support to the decision maker in choosing the best set of projects. The application consisted of seven tabs that provide the user with instructions, data input and manipulation capability, and implementation of the approaches above, and displaying of results.

Three tabs provide instructions and basic functionality to the user. An initial landing page gives a general description of the application and the remaining tabs, lists the portfolio selection methods used by the application, briefly describes the results provided, and finally includes instructions for users. An upload tab allows the user to upload input files in Excel format, containing the scores of projects, interaction values and labels. This requires a fixed format input that is described on the instructions tab. It also allows the user to view and adjust weight values, that are displayed as input sliders. A display tab provides the user with a visual summary of the input data, prior to optimisation. Slider bars provide the user with control over (a) which criterion is shown and (b) which projects are shown. Weights, scores, and interaction values are all shown via charts or tables.

Another four tabs are the core of the application and provide portfolio selections. Three tabs provide the user with the portfolios selected by heuristics, RPM, and the linear-additive portfolio value model respectively. These methods are only run once the user clicks a Run button. The sheets show the projects selected, and information about each of the projects and the overall portfolio value. A fourth tab allows the user to construct their own portfolios through the use of checkboxes, again displaying the projects selected, and information about each of the projects and the overall portfolio value. This allows the user to experiment with any selected portfolios and conduct sensitivity analysis. In all four of these tabs the user can change the number of projects allowed in the portfolio.

3 Results

3.1 Problem structuring

3.1.1 Value tree

The assessed value tree (Table 3, first two columns) contained four higher-level criteria (applicant quality, proposal quality, relevance of proposal, and equity). Applicant and proposal quality could be further broken down into four and five attributes, while proposal relevance and equity could each be measured directly with a single attribute. Criteria were defined as follows:

- Recognition of prior work: A grant applicant who has received a number of awards for their research work or for their academic achievements is highly recognised. Achievement on this criterion is measured by the number of awards received by the grant recipient.
- Quality of publications: the quality of the applicant's publications are rated based on the substance of their publications. Achievement on this criterion is measured by the number of letters/communications, articles, supplementary articles, review articles or research notes published by the applicant. Each of the outputs denotes a given degree of contribution to the research field.
- Impact of prior work: the impact of prior research work in terms of the number of publications and the number of citations. A combination of both the number of publications and the number of citations provides a scale to measure achievement on this criterion.
- Mentorship: this criterion assesses whether the applicant has shown the ability to supervise, teach or tutor students. It is measured by the number of students being supervised, taught or tutored.
- Potential impact of proposal: A research proposal can fall within either applied or pure research. If it is applied research, the aim may be to inform policies and seek to find a solution for an immediate problem facing society, or an industrial/business organisation. The impact of the proposal, in this case, is to bring about socio-economical and environmental changes. If it is pure research, the aim is to bring a deeper understanding of the theoretical aspects of a phenomenon and formulate a theory. The impact of the proposal, in this case, is mainly knowledge creation. Achievement on this criterion is measured according to whether the project falls within applied or pure research and whether it has potential to be published.
- Feasibility & risk: The feasibility and risk associated with a proposal is based on the applicant's academic strength and likelihood of completing the project. The selection panel would evaluate the methodology and decide whether the applicant could implement the project within the time frame. Achievement on this criterion is measured by the likelihood for the applicant to complete the project based on previous related work, clarity of definition of the project, etc.
- Scientific merit: A research proposal should represent good science. A good research proposal entails both clear research objectives and questions and pertinent hypotheses. Reputation is key for a science institution. They would not want to be associated

with any project that would damage their brand if the methodology was found to be wrong or end results turned out to be scientifically incorrect. Achievement on this criterion is rated based on problem design, methodology, objectives and potential contribution to knowledge. A project that does well on each of these items is highly scored.

- Novelty: A proposal should generate knowledge and uncover hidden information. This would indicate the likelihood of the final results being published or contribute to solving a pressing problem. Achievement on this criterion is measured by the degree of novelty of a project: whether it is groundbreaking, i.e. it opens up entire new areas of research or whether it repeats existing research or extends it.
- Respond to a challenge in Africa: the degree to which proposal directly addresses a challenge in Africa. The project receives a score based on whether it is purely theoretical or whether it is still theoretical but has a limited applied aspect or whether it is applied research and gives a solution to a practical problem.
- Focus areas: Most funding calls are made with specific aims and objectives in mind, expressed as themes. Proposals should clearly specify how they align with these objectives. Achievement on this criterion is measured by the degree to which the proposal is aligned with the thematic areas outlined in the call for funding proposals: Science, Technology, Engineering and Mathematics.
- Gender: this criterion aims to redress the imbalance between men and women in the research field. Often women are at a distinct disadvantage in the African context, having less opportunities than men and facing more obstacles than men in their pursuit of a career, especially in sciences. The same criterion was used in Belton and Stewart (2010).

3.1.2 Weights

Weights were reasonably equally distributed across criteria, with the most important criterion, impact of prior work, receiving a weight a little under three times as large as the least important criterion, gender ($w = 0.13$ vs $w = 0.05$, as seen in the *Cumulative Weights* column in Table 3). Out of the families of criteria, applicant rating was rated most important, followed by proposal quality, relevance of proposal, and gender equity. All criterion weights are shown in Table 3.

3.1.3 Interaction effects

Elicited values of $\gamma_{i\eta}$ are shown in Table 4. For instance, on the criterion "Impact of prior work", $\gamma_{12} = 0.07$ for 2 projects, $\gamma_{13} = 0.10$ for 3 projects, $\gamma_{14} = 0.12$ for 4 projects, etc. A

Family of Criteria	Criteria	Cumulative Weights	Relative Weights
Applicant quality	Recognition of prior work	0.08	0.19
	Quality of publications	0.11	0.28
	Impact of prior work	0.13	0.31
	Mentorship	0.09	0.22
Proposal quality	Potential impact of proposal	0.09	0.20
	Feasibility and risk	0.11	0.25
	Scientific merit	0.08	0.18
	Novelty	0.07	0.15
	Respond to a challenge in Africa	0.10	0.23
Relevance of proposal	Focus area	0.10	0.10
Equity	Applicant gender	0.05	0.05

Table 3: Criteria swing weights. Cumulative weights are weights standardised across all criteria to sum up to 1, while relative weights are weights standardised within families of criteria.

threshold of 90 was used to identify excellent projects on each criterion. Based on this, the sets of projects with excellent average scores on criteria i and thus for which interaction effects exist are (see Table 9 for scores):

- *Impact of prior work*: $\{15, 17, 19\}$
- *Quality of publications*: $\{6, 20\}$
- *Feasibility and risk*: $\{9, 10, 13, 14, 15, 17, 19, 20, 21, 22, 23, 24\}$
- *Respond to a challenge in Africa*: $\{14, 17, 18, 22\}$

Interaction subsets A_k are formed whenever any two or more of the projects in the four sets above are included in a portfolio. The interaction set A is the union of all interaction subsets A_k and represents all projects involved in interactions.

3.2 Selected portfolios

Left unsupported, the decision maker selected projects by sorting projects by their weighted average value and selecting projects until they reached the desired number of projects, in the four-, five-, and six-proposal settings. This approach is equivalent to the *Unit Value* heuristic. In the current application, *Unit Value* portfolios are the same as those selected using the *Unit Value with Synergy* (see Tables 5 to 7), although this would not be true in general.

η	Imp. of work	Qual. of public.	Feasib & risk	Resp. to chal.	Focus area	Recognit.
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0.07	0.05	0.03	0.02	0.01	0.01
3	0.10	0.07	0.05	0.03	0.02	0.01
4	0.12	0.09	0.06	0.04	0.03	0.02
5	0.13	0.11	0.08	0.06	0.03	0.02
6	0.15	0.13	0.09	0.07	0.04	0.03

Table 4: Interaction between projects generate value benefits, also called interaction benefits. An interaction benefit is a factor of the sum of weighted additive value of projects involved in interactions. The interaction value ($\gamma_{i\eta}$) increases with the number of projects (η) in the portfolio that have an excellent score on a given criterion.

Heuristic solutions achieved over 90% of the value of the optimal portfolio (Table 5 to 7). The *Added Value* heuristic performed better than the *Unit value with Synergy* heuristic, returning 99%, 97%, and 95% of the optimal value for portfolios of four, five, and six projects respectively (the corresponding performance of the *Unit Value with Synergy* heuristic was 93%, 90%, and 95%. This relatively excellent performance was achieved despite selecting quite different projects to the optimal portfolio. The *Added Value* heuristic selected three of four optimal projects (75%) in the four-proposal setting, and three of five and four of six optimal projects (60% and 67%) in the five- and six-proposal settings respectively. The corresponding performance of the *Unit Value with Synergy* heuristic was again lower: 50%, 40%, and 67% of projects in the optimal portfolio were selected in the four-, five-, and six-proposal settings.

On average RPM solutions, also known as non-dominated solutions, performed better than heuristic solutions. The latter scored an average of 95% of the value of the optimal portfolio whereas the former scored an average of 99%. For each problem size, we observed that the optimal portfolio was among RPM portfolios but not among heuristic solutions. RPM solutions also had more projects in common with optimal solutions in terms of portfolio composition than heuristic solutions. RPM solutions had on average 89% of the projects contained in optimal portfolios, while heuristic portfolios contained 60%. For problems involving five projects, we observed that the RPM portfolio was the same as the optimal portfolio.

Core indices are shown in Table 8. Projects $\{15, 17, 19\}$ had a mean score of 1, being part of every RPM portfolio and were therefore strongly recommended by RPM. These projects were also part of every optimal portfolio (Table 5 to 7). Projects that were part of optimal portfolios, i.e., projects $\{6, 15, 17, 19, 20, 22\}$ stood out from the rest. They scored 80 or 90 points on two or three of the most important criteria: recognition of previous work, quality of publications and impact of prior work. When they performed below 80 points on any of

Portfolio	Selected projects	% Opt.	N_{Opt}
Optimal	$\{15, 17, 19, 22\}$	100	4
Unsupported	$\{14, 19, 20, 22\}$	93	2
Added Value	$\{15, 19, 20, 22\}$	99	3
UV w Synergy	$\{15, 19, 20, 22\}$	93	2
RPM1	$\{9, 15, 17, 19\}$	96	3
RPM2	$\{14, 15, 17, 19\}$	99	3
RPM3	$\{15, 17, 19, 20\}$	100	3
RPM4	$\{15, 17, 19, 22\}$	100	4
RPM5	$\{15, 17, 19, 23\}$	98	3
RPM6	$\{15, 17, 19, 24\}$	97	3

Table 5: Four-project portfolios selected using linear-additive portfolio value model (Optimal), robust portfolio modeling (RPM) and portfolio heuristics (*Added Value* and *Unit Value With Synergy*), with the proportional value achieved by each porfolio (% Opt = percentage of the value achieved by the optimal portfolio) and the number of projects in common with the optimal portfolio (N_{Opt}).

Portfolio	Selected projects	% Opt.	N_{Opt}
Optimal	$\{6, 15, 17, 19, 20\}$	100	5
Unsupported	$\{1, 14, 19, 20, 22\}$	90	2
Added Value	$\{14, 15, 19, 20, 22\}$	97	3
UV w Synergy	$\{1, 14, 19, 20, 22\}$	90	2
RPM1	$\{6, 15, 17, 19, 20\}$	100	5

Table 6: Five-project portfolios selected using linear-additive portfolio value model (Optimal), robust portfolio modeling (RPM) and portfolio heuristics (*Added Value* and *Unit Value With Synergy*), with the proportional value achieved by each porfolio (% Opt = percentage of the value achieved by the optimal portfolio) and the number of projects in common with the optimal portfolio (N_{Opt}).

Portfolio	Selected projects	% Opt.	N_{Opt}
Optimal	$\{6, 15, 17, 19, 20, 22\}$	100	6
Unsupported	$\{1, 14, 15, 19, 20, 22\}$	95	4
Added Value	$\{1, 14, 15, 19, 20, 22\}$	95	4
UV w Synergy	$\{1, 14, 15, 19, 20, 22\}$	95	4
RPM1	$\{6, 9, 15, 17, 19, 20\}$	97	5
RPM2	$\{6, 14, 15, 17, 19, 20\}$	99	5
RPM3	$\{6, 15, 17, 19, 20, 22\}$	100	6
RPM4	$\{6, 15, 17, 19, 20, 23\}$	99	5
RPM5	$\{6, 15, 17, 19, 20, 24\}$	98	5

Table 7: Six-project portfolios selected using linear-additive portfolio value model (Optimal), robust portfolio modeling (RPM) and portfolio heuristics (*Added Value* and *Unit Value With Synergy*), with the proportional value achieved by each porfolio (% Opt = percentage of the value achieved by the optimal portfolio) and the number of projects in common with the optimal portfolio (N_{Opt}).

the three criteria, they compensated for this by performing exceptionally well (90 points) on the other two criteria (See Table 9).

	Projects									
Size	P6	P9	P14	P15	P17	P19	P20	P22	P23	P24
4	0	0.17	0.17	1	1	1	0.17	0.17	0.17	0.17
5	1	0	0	1	1	1	1	0	0	0
6	1	0.2	0.2	1	1	1	1	0.2	0.2	0.2
Ave.	0.67	0.12	0.12	1.00	1.00	1.00	0.72	0.12	0.12	0.12

Table 8: Core index of projects defined as the relative frequency at which each project appears across RPM portfolios, also known as non-dominated portfolios, for portfolios of different sizes. A score of 1 indicates that the project is found in every non-dominated portfolio and a score of 0 indicates that the project is not found in any of the non-dominated portfolios.

	Imp of work	Qual of publ	Feasib Risk	Resp to Chal	Focus Area	Imp of prop	Mentors	Scient Merit	Recog of work	Novelty	Gender
P1	70	80	80	70	80	70	80	70	60	40	100
P2	80	70	75	60	70	60	70	55	60	60	100
P3	70	60	70	70	75	80	70	70	50	45	0
P4	70	70	70	65	70	80	90	60	55	40	100
P5	70	70	80	60	70	70	90	65	50	70	0
P6	80	90	80	70	70	80	90	60	40	50	0
P7	70	70	65	50	70	70	80	70	53	70	100
P8	80	70	60	70	90	70	80	70	70	60	0
P9	80	60	90	65	70	70	60	70	47	40	0
P10	70	70	90	70	65	65	90	75	60	60	0
P11	70	70	80	55	70	65	80	70	45	60	100
P12	60	60	70	70	62	70	80	75	70	50	0
P13	70	60	90	70	70	57	90	55	20	40	100
P14	80	70	90	70	70	90	80	60	40	50	100
P15	90	70	90	80	80	60	80	70	60	60	0
P16	70	60	70	80	70	75	80	50	65	60	100
P17	90	70	90	80	80	90	80	60	40	50	0
P18	80	80	80	90	57	90	80	53	60	40	0
P19	90	70	90	70	80	80	70	70	70	50	100
P20	80	90	90	70	70	70	70	70	60	60	100
P21	70	50	90	60	90	80	90	60	80	50	0
P22	80	80	90	60	90	90	80	70	50	50	100
P23	80	67	90	70	80	70	80	75	70	50	0
P24	80	80	90	60	70	70	75	60	70	45	0

Table 9: The research institute awards funding to the best portfolio of research projects. We could not show the real scores assigned to projects by independent assessors because of confidentiality issues. We generated scores with similar properties as the real ones. The table shows the average scores generated for the research projects of twenty-four applicants over three referees. Scores are assigned on a scale of 0-100 for each criterion.

3.3 Sensitivity Analysis

Sensitivity analyses were conducted in two ways: first by varying criterion weights and regenerating portfolios, and then by manually removing and adding projects from the selected portfolios. The first of these assessed whether selected portfolios would still be optimal even if the decision maker's preferences were to change. The second was a more open-ended exploration of the set of available portfolios.

The decision maker developed five scenarios translating the weight changes they wished to make. Initial and subsequent weights are shown in Table 10. Initial weights (weight set 1) lead to the following optimal portfolios for sizes four to six, respectively: $\{15, 17, 19, 22\}$, $\{6, 15, 17, 19, 20\}$ and $\{6, 15, 17, 19, 20, 22\}$. We subsequently computed optimal portfolios using the other weights (weight sets 2 to 6) and observed the resulting portfolios as displayed by the application. In each instance (weight sets 2 to 6), the resulting portfolio was the same as the initial one for five and six proposal-solutions. For 4 proposal-solutions, we got a different portfolio in weight set 5: project 22 was dropped and replaced by project 20. We note that project 20 had a higher mean core index than project 22 (Table 8). Based on this, the decision maker was satisfied that portfolio $\{6, 15, 17, 19, 20\}$ and $\{6, 15, 17, 19, 20, 22\}$ (5 and 6 proposal-solutions) were robust choices. Portfolio $\{15, 17, 19, 22\}$ (4 proposal-solution) was almost robust and only ceased to be the optimal solution when the last two sets of weights were applied, these being fairly extreme, e.g. the first criterion gets a weight worth 40% to 50% of total impact of weights. For this reason, we believe that this portfolio should still receive favorable consideration.

Sets	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
1	0.13	0.11	0.11	0.1	0.1	0.09	0.09	0.08	0.07	0.07	0.05
2	0.2	0.11	0.11	0.1	0.1	0.09	0.09	0.05	0.05	0.05	0.05
3	0.2	0.13	0.13	0.12	0.1	0.07	0.07	0.05	0.05	0.05	0.03
4	0.3	0.2	0.1	0.09	0.08	0.07	0.06	0.04	0.03	0.02	0.01
5	0.4	0.3	0.2	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01
6	0.5	0.3	0.07	0.05	0.02	0.01	0.01	0.01	0.01	0.01	0.01

Table 10: Sets of weights used during sensitivity analysis. Initial weights are shown in the first row.

The second aspect of the sensitivity analysis was done by the selection and deselection of projects in order to improve the initial portfolio selected by the decision maker without facilitation. The decision maker had the following question in mind: Can I improve on my initial portfolio by adding and dropping projects? The decision maker used the selection/deselection feature found on the web-based application to conduct the sensitivity analysis. At each step, they either added or removed projects. The decision maker explained that they followed a process of trial and error to improve their portfolio, but they were guided by the overall values of portfolios as displayed by the web-based application, which include interaction values. The decision maker was able to generate many portfolios, among which was the optimal portfolio. The decision maker retained the optimal portfolio as their best portfolio because it had the maximum overall value among the generated portfolios.

4 Discussion

In a recent literature review spanning the years 2006 to 2019, Liesiö et al. (2021) found that roughly half of the decision support systems use exact algorithms, leading to (globally) optimal solutions, whereas the other half use approximate algorithms, leading to reasonably good solutions without guarantees of optimality. The vast majority of software deal with MCDA problems involving the selection of a single, best alternative from a larger set of potential options. There are only a handful of software applications that deal with portfolio decision making, some of which involve interactions and sensitivity analysis: HiPriority, PROBE, Expert Choice, DPL 8, etc. Weistroffer and Li (2016). Where interactions are required, optimisation and approximate algorithm need these to be exhaustively assessed, which is a substantial undertaking for a decision maker. On their part, portfolio heuristics have the advantage of adding projects sequentially, and thus of processing information incrementally. This means that not all interaction information is required. Decision support based on portfolio heuristics may thus be reasonable under similar conditions to the use of heuristics in general – when environmental conditions are such that time, cognitive, or motivational resources are limited.

We emphasize that where an approach returning an optimal portfolio of projects can be implemented, e.g. linear-additive portfolio value model, there is little doubt that this should be the preferred course of action. However, that will not always be feasible, and in those cases heuristic decision support may be better than no support at all. In our application, portfolios returned by heuristics were of a high quality, achieving most of the overall value of the optimal portfolio and performing similarly or slightly worse than the robust portfolio model. An interesting result was that heuristics chose a different set of projects to the optimal portfolio, but performed nearly as well as the optimal portfolio. Since they are straightforward to compute, these alternative heuristic portfolios might be generally useful as a basis for discussion or for sensitivity analysis even if the optimal approach can be used.

In our application, the use of heuristic-based decision support was experienced as useful. We observed that for each problem, the decision maker selected the *Unit Value* portfolios instead of optimal portfolios when selecting without facilitation. This suggests that the decision maker was not able to account for interactions in their selections. This highlights the value of the decision support that explicitly include interaction values, even if heuristic-based.

In the feedback, the decision maker reported that the web-based application was intuitive and easy to use. They also found the visualisation of project data and portfolio solutions in both graphical and tabular format useful. In their view, the application made it easy to assess interaction benefits and identify optimal portfolios. They found the ability to select projects at will and determine the size of portfolios to be useful features. They observed that the web-based application reduces processing time for the selection of projects, and removes a lot of manual processes used in the past and speeds up the process of identifying the best projects among the set of available projects. Finally, based on their previous experience in selecting portfolios of projects, they concluded that the web-based application reduces the associated biases in the unfacilitated selection of projects. Developing and maintaining general software for decision support is a substantial undertaking beyond the scope of this paper, but for the purposes of this application the feedback we received suggested that the developed support system was experienced as useful.

One aspect that we have not discussed in detail is the opportunity for the decision maker to learn about their preferences and the decision problem that they face. This is a key goal for decision support (Belton and Stewart, 2002), and optimal or traditional multicriteria approaches offer quite different opportunities for learning than heuristic-based decision support. In traditional multicriteria approaches the decision maker primarily learns through the elicitation process, as they are asked to provide inputs like weights, value functions or other preference information, project interactions, and then through interrogation of results, especially through sensitivity analysis. Heuristics require less input information and thus potentially offer less opportunities for learning, although the reduced information allows for a better understanding of those inputs that are assessed. Incremental assessment of information is also likely beneficial for learning, as the decision maker is exposed to relationship between inputs and outputs (portfolios) earlier in the process than with traditional approaches. As mentioned, the fact that heuristics are so quick to use and heuristic portfolios are easy to generate mean that they may be useful for learning about alternative portfolios in a sensitivity analysis setting, even when an optimal approach is used to select the portfolio. For the same reasons, it may also be advantageous to show portfolios constructed using heuristics to the decision maker.

5 Conclusions

This paper reports the first real-world application using psychological heuristics to support portfolio decision making. Portfolio heuristics are a recent extension of fast-and-frugal or psychological heuristics to the domain of portfolio decisions, where the goal is to select the best subset of alternatives from a larger set of candidates. Portfolio heuristics have been previously shown to perform well in a simulation setting, and to explain some participants' selections in a laboratory setting (Durbach et al., 2020). Here we supported the selection of research grant projects using three methods of differing complexity: a standard approach to portfolio optimisation, i.e. the linear-added portfolio value model (solved as an integer program), robust porfolio modelling, and two portfolio heuristics (*Added Value* and *Unit Value with Synergy*) identified as most promising in Durbach et al. (2020). We found that if no decision support was used, the decision maker tended to select a portfolio of projects by ignoring project interactions and sequentially adding projects in order of their individual values until the resource constraint was reached. Portfolio heuristics returned over 90% of the value of the optimal portfolios, although by selecting somewhat different projects to those found in the optimal portfolio. Heuristic portfolios were slightly but consistently outperformed by portfolios generated with robust portfolio modelling. Feedback on the use of decision support in general, and portfolio decision support in particular, was gathered informally, but was generally positive. Taken together, our application adds to the growing evidence that the utility of psychological heuristics extends into the domain of portfolio decisions.

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