Integrating Scenario Planning and Goal Programming

Ian Durbach and Theodor J. Stewart
Department of Statistical Sciences, University of Cape Town

keywords: goal programming, scenario planning, uncertainty

Abstract

This paper concerns the integration of goal programming and scenario planning as an aid to decision making under uncertainty. Goal programming as a methodology emphasises the resolution of conflict among criteria; scenario planning focuses on the treatment of uncertainty relating to future states of the world. Integrating the two methodologies is based on the simple formulation of a super-goal program consisting of one scenario-specific goal program in each scenario. Issues relating to the structuring of the super-problem, aggregation both within and over scenarios, and the incorporation of probabilistic information are discussed.

1 Introduction

Many decision problems in the real-world are characterised by two overarching concerns: to consider conflict between the objectives of the problem, and to take into account the uncertainty inherent in making a decision that is dependent on the outcome of unknown future events. For example, in comparing two holidays, it might be necessary to consider the (possibly competing) objectives of minimising cost and maximising the number of sunny days experienced. Both of these criteria may be subject to some degree of physical randomness which should be taken into account in order to ensure a decision which adequately represents the preferences of the decision maker.

Decision making from a goal programming perspective

The first of these concerns, considering conflicting objectives, is the traditional do-main of multicriteria decision analysis (MCDA) techniques, which provide a set of analytical frameworks through which a decision maker can articulate and learn about both the tradeoffs available in the context of the problem and his or her underlying preferences. The systematic exploration of these aspects could lead to the selection of a preferred alternative from a prespecified set of alternatives, the development of a new and superior alternative, or at least a heightened awareness of the problem and corresponding choices at hand. Goal programming (GP) is one of the oldest and most well-established MCDA techniques, dating back to work done in the 1950's (Charnes and Cooper, 1955). At its heart is a simple operationalisation of Simon's concept of 'satisficing' (Simon, 1976), which supposes that a decision maker will search for an alternative offering satisfactory performance on all criteria without necessarily attempting to maximise this performance. The underlying cognitive model is that the decision maker sets goals or aspiration levels for the objectives under consideration, and then evaluates prospective alternatives via a dynamic and iterative comparison with the aspiration levels.

Decision making from a scenario planning perspective

Scenario planning, in contrast, has been applied predominantly in longer-term strategic planning, and was developed primarily through pioneering work done at Royal Dutch/Shell in response to failures of probability-based forecasting techniques (Wack, 1985a), (Wack, 1985b). Internally consistent scenarios are constructed in an approach that focuses on the underlying forces causing uncertainty in order to identify and differentiate predetermined and uncertain elements of the future via cause-and-effect relationships. The approach aims at identifying an alternative that is robust to the range of scenarios that will bound the uncertain future, but it is the focus on these cause-and-effect relationships which gives attention to the sources of uncertainty without necessarily assigning probabilities to them. The scenarios are developed prior to (or at least independently of) the construction of alternatives, so that the process emphasises the articulation of uncertainties rather than charting the possible courses of alternatives. It is in the process of constructing these scenarios that the decision maker may be confronted with new or surprising aspects of the problem that allow for opportunities to learn about and prepare for the future. Scenario planning is therefore first and foremost a methodology concerning physical uncertainty or randomness.

A Motivation for Integration

The approaches of scenario planning and goal programming are at this time both well-established and popular in practice as methodologies aiding decision making. The first question that arises is then why we should consider at all the integration of two independently well-established and successful methodologies. The simplistic answer is that goal programming aims to resolve the conflict between objectives, without necessarily giving full consideration to uncertainty in the outcomes, whereas scenario planning provides a model of uncertainty but uses comparatively unsophisticated evaluation techniques to assess the relative performance of alternatives. Wright and Goodwin (1999) discuss the 'lack of formal procedures in decision analysis for eliciting possible outcomes' in more detail. Essentially, the incorporation of uncertainty into MCDA techniques is in general predicated on alternative-focused thinking (Keeney, 1992) in which the alternatives are considered first, constraining the consideration of future outcomes by what might occur *if each alternative is chosen.* There is therefore nothing inherent in the MCDA makeup to challenge the decision maker to confront unexpected views of the future. In contrast, confronting unexpected aspects of the value system of the decision maker lies at the heart of current MCDA thinking. The situation within the field of goal programming is made somewhat worse by the absence of recognised methods incorporating uncertain outcomes. Only the technique of chance-constrained goal programming (Keown and Taylor, 1980), (De et al., 1982) can claim to have a foothold in this area.

The evaluation of alternatives in a scenario planning environment can take numerous forms depending on the focus of the intervention. The level of quantitative sophistication in the technique, though, is in general low, ranging from flexible qualitative descriptions or 'intuitive logics' (Bunn and Salo, 1993) to suggestions of net present value or more comprehensive sets of performance indicators (Van der Heijden, 1996). Saaty and Kearns (1985) considered the use of AHP as a method for the evaluation of alternatives in the context of scenario planning. Although there are dangers inherent in bringing quantitative techniques to a 'soft' methodology such as scenario planning, there are also substantial benefits in terms of the structure, comprehensiveness and common language provided by such a framework. The evaluation of alternatives in a complex environment is a difficult task that, if not decomposed and explored in a structured, systematic way, might be left to inadequate and simplistic heuristics. In contrast to goal programming, there is nothing inherent in the scenario planning armoury to encourage the exploration and identification of undiscovered values.

It might be true that goal programming (and MCDA in general) has more to gain from scenario planning than vice versa. Nevertheless there are aspects of both methodologies that suggest that the benefit derived from an integrated approach might be greater than the sum of its parts. Stewart (1997) has discussed in an exploratory capacity adapting scenario planning to general MCDA. The following section furthers that discussion by proposing a model integrating scenario planning and goal programming. Goal programming is particularly well suited to integration with scenario planning for two reasons. Firstly, the notion of robustness advocated in scenario planning requires a prospective alternative to perform well under any of the scenarios. Such an idea is closely allied to concepts of satisficing and bounded rationality, and is easily operationalised within the goal programming framework. Secondly, the idea of setting goals specifying levels of desired performance is popular and well-established in the strategic planning areas in which scenario planning is predominantly practised.

2 A scenario-based goal programming methodology

In integrating MCDA with scenario planning it is first necessary to provide a precise mathematical interpretation of a state scenario, which can then be used to express the dependence of the attribute evaluations on future states of the world. Since the attribute evaluations may be considered to be random variables, there is in principal a single multivariate probability distribution governing the joint realisation of all the evaluations. Each realisation of this multidimensional random variable corresponds to a potential future state of the world, so that the underlying form of the distribution is likely to be extremely complex and unattainable from a practical perspective. We therefore make no attempt to specify the full multivariate probability distribution, but rather seek only to *characterise* it using a small number of potential realisations or states, which we term the scenarios. The term 'scenario' is thus used consistently with the scenario planning literature (for example, Van der Heijden, 1996) to refer to an internally consistent future state of the world, although we extend this definition to include a precise probabilistic interpretation. Although we do not make an explicit assumption about the characteristics of these scenarios, they will in general be constructed either as (incomplete) 'snap-shots' of a future state, or a plausible evolution from the present state into the future. We refer to the set of scenarios using the index k, $k \in \{1, \ldots, p\}$.

Problem Structuring

The aim of problem structuring is to identify the material aspects of the decision problem at hand, to demarcate the boundaries of the problem and arrive at a common understanding of the problem that can be taken forward into the analysis stage. Typical outputs may include key objectives, goals, constraints, stakeholders, dependencies, alternatives and uncertainties. The successful structuring of a problem is important in many more areas than just MCDA, and there is a large body of literature on the subject which is more or less relevant to specific applications of MCDA. For this reason, many theoretical developments in preference modelling adopt the position of 'given the problem'; they ignore the structuring of the problem, moving instead directly to the evaluation of potential solutions. Nevertheless, the structuring of an MCDA problem has acquired a certain flavour of its own though the borrowing and gradual adaptation of some problem structuring tools (Belton and Stewart, 2002), (Belton, 1999). The integration of scenario planning and goal programming will take place mostly in these phases of problem structuring. Scenario planning is itself in part a problem structuring technique, with particular attention paid to uncertainty modelling. The use of scenario planning therefore augments the 'traditional' MCDA problem structuring methodology, and would consequently greatly increase the amount of time and effort required by the problem structuring phases. We present the following discussion in terms of the evaluation of discrete alternatives, although much of the formulation carries over into continuous goal programming problems. In a final section, we present some differences that arise in the continuous case, and adapt the SBGP accordingly.

The basic idea behind the scenario-based goal programming (SBGP) model is to formulate a scenario-specific goal program for each scenario, followed (possibly) by an aggregation over all p scenarios. A natural order of problem structuring would therefore see the construction of p scenarios using the scenario planning methodology, followed by the structuring of a goal programming problem within each scenario using 'traditional' MCDA problem structuring techniques. Of course much of the problem structure would carry over from scenario to scenario, so that it would not be necessary or even desirable to start the structuring of the goal program afresh in each scenario. However, it *is* possible that some aspects of the problem structure might change between scenarios. For example, some stakeholders or even certain criteria may become irrelevant under certain scenarios. Although the latter case would be contrary to existing MCDA practice, it might easily be handled in the SBGP framework by assigning zero importance weights in those scenarios in which certain criteria are irrelevant. The fleshing out of the qualitative circumstances of each scenario leads to a heightened understanding of the aspects of uncertainty that may not be gained using conventional MCDA techniques. Some practical applications or even behavioural studies would be instructive in this regard.

The main objective of the scenario-based model is evaluating the performance of each alternative under each scenario. The output of a scenario-based approach must include separate evaluations for performances under each scenario if it is to contribute to the conclusions of robustness that are so fundamental to the philosophy of scenario planning. This motivates the treatment of scenarios as part of the objectives hierarchy i.e. the value tree, which naturally brings about questions of where in the hierarchy to place them. Consideration of the objectives hierarchy as a framework reducing composite objectives into lower-level objectives i.e. decomposing the global value function into marginal value functions, clarifies the issue to some extent. The demand that aggregation across scenarios be delayed until the end if it is to be carried out at all means that it is natural to include the scenarios as the second level of the hierarchy. This has the effect of creating a 'super-GP' problem consisting of p generally closely related problems. Including the scenarios at lower-levels will necessarily require aggregation across scenarios in order to progress to further evaluations, which has already been dismissed as undesirable. Figure 1 shows the second-tier positioning of the scenarios for a hypothetical decision process.

(((Figure 1 approximately here)))

The goal programming methodology demands that two pieces of preference information are elicited: aspirations indicating desired levels of performance, and importance weights specifying tradeoffs between criteria. Within each scenario k, it is necessary to specify aspirations for each criterion j, giving an aspiration level g_{jk} for the criterion-scenario combination jk. The ability of decision makers to think preferentially about scenarios is an open question, although the elicitation of preferential information might be expected to become a cognitively more difficult task as the scenario becomes more extreme in nature i.e. more divergent from the status quo. Such difficulties are linked to well-known heuristics such as availability and representativeness. In thinking about aspiration levels on a particular scenario, a decision maker might first think about the aspirations for the current status quo, and then adjust those aspirations based on a mental comparison of the two scenarios. Studies in the psychological laboratory in the context of probability judgement indicate that such adjustment is likely to be insufficient. In extreme scenarios, the use of such heuristics might break down due to the disparity to the status quo, or be replaced by other strategies. Such a breakdown might not be without merit; the lack of an easy simplification strategy may force the decision maker into a deeper consideration of the decision problem. However due to the increased cognitive difficulties the setting of aspirations should be integrated with the construction of scenarios in order to make use of the illuminating powers of the scenario planning methodology.

The second piece of preferential information, comprising the importance weights, is considerably more complex. What are desired are swing weights in the usual sense i.e. weights denoting the relative importance of a swing between best and worst performance on each criterion (which we term a 'worst-to-best swing'), within each scenario, where best and worst performance levels can either be derived from the attribute evaluations or externally assessed. The importance weights, however, must also be comparable between different scenarios – we therefore need to consider scenarios as well as criteria in the elicitation of importance weights. It should be emphasised that the importance weights do not capture information about the relative likelihood of each scenario – only the relative importance of tradeoffs between criteria within each scenario. Two lines of questioning can be followed in the elicitation of importance weights: the first attempts to simultaneously capture importance information on both criteria and scenarios i.e. to elicit the joint weights directly, while the second elicits separately the importance information for criteria and scenarios before aggregating them into a joint weighting. In the scenario-based decision problem, the direct joint weighting is a rather straightforward extension of the elicitation of *cumulative* weights (Belton and Stewart, 2002) that considers each criterion-scenario combination as a bottom-level criterion, so that we may ask 'In which criterion-scenario combination is a worst-to-best swing most desirable?'. Although technically this may appear simple, practically it is likely to be far less so. The elicitation procedure demands that DM's weigh up different criteria and different scenarios simultaneously, which might be particularly difficult if the two are not independent i.e. if some criteria become relatively more important under different scenarios. Furthermore the elicitation of all mp criterion-scenario weights is likely to prove tedious for even moderate-sized problems.

In response to these difficulties we may turn to the second elicitation approach, in which information about the relative importance of criteria and scenarios are elicited separately. In this process we initially consider each of the p scenarios separately, eliciting *relative* criterion weights within each scenario using questions such as 'Is the worst-to-best swing for criterion 1 preferable to the worst-to-best swing for criterion 2 under the conditions of scenario 1?'. The proposed line of questioning addresses the relative importance of each criterion, but no scenario information is elicited. The result is a set of p $m \times 1$ vectors of relative criterion weights ψ_{jk}, one vector for each scenario, indicating the weight of criterion j under the conditions of scenario k. In order to arrive at a cumulative weighting it is still necessary to obtain an estimate of the relative importance of each scenario. The elicitation and interpretation of weights for higher-level criteria is not always straightforward. A suggestion here is to obtain the relative scenario weights by extracting one criteria from each scenario and comparing them in the usual swing weighting sense. We would suggest the choice of the same criterion j in each scenario in order to focus the DM's attention on the fact that it is *scenario* weights that are being elicited, although there are no algebraic reasons why different criteria cannot be used. The elicitation process can and should be repeated with other criteria as a consistency check. The choice of the criteria used should ultimately be based on the ease with which the decision maker is able to think about the available trade-offs, and is at the discretion of the analyst. In any case, the result is a set of p relative scenario weights ϕ_k. The joint or cumulative weighting w_{jk} can be found by multiplying the relative scenario weights ϕ_k by the relative criterion weights ψ_{jk}. An important point is that if all that is desired is a rank ordering in each of the p scenarios, we need not even consider the scenario weights.

As a final point on the issue of weight elicitation, we mention the possibility of a second approach for eliciting the relative weights. Instead of first eliciting the importance of criterion j given scenario k, we may invert the process to consider the weight of scenario k given criterion j, using questions of the form 'Is a worst-to-best swing on criterion 1 more preferable under scenario A or B?'. This relative scenario weighting would be followed by the elicitation of relative criterion weights by extracting one scenario from each parent criterion, analogously to the process already outlined. Although either weighting approach is technically valid, we restrict further attention to the latter approach on the basis that it appears more compatible with scenario thinking by obtaining information *within* each scenario.

Evaluation of Alternatives

Assuming that aspirations can be set for each criterion-scenario combination, the goal programming formulation for scenario k is given by selecting the alternative minimising Δ_{ik}, where

$$\Delta_{ik} = \left[\sum_{j=1}^{m} [w_{jk}\delta_{ijk}]^{\alpha} \right]^{\frac{1}{\alpha}} \tag{1}$$

where w_{jk} is the weight applied to the deviation δ_{ijk} of each evaluation from the goal g_{jk} for each criterion j and scenario k, and α denotes the choice of norm. Deviations may be constrained to be non-negative i.e. in the spirit of satisficing, once the aspiration level has been achieved, no further improvements are sought, or can represent both shortfalls and surpluses i.e. as in the Wierzbicki scalarizing function, depending on the context of the decision problem. The application of (1) in each scenario results in k rank orders, each scenario being represented by a $n \times 1$ vector of deviations from which a rank order can be trivially obtained. The results comprising the k rank orders and deviation vectors contain important information in themselves. In fact strict scenario planning applications do not consider the aggregation of results over the set of scenarios to be appropriate, in contrast to most MCDA methodologies where the progression to a single rank order occurs almost naturally. However, if MCDA is to be meaningfully integrated with scenario planning, it is important to accommodate the philosophical differences that may arise. Thus while the rank ordering produced by an aggregation over scenarios should certainly not be excluded, the information contained in the scenario-wise results should be considered as an important output in its own right. This information should be carefully interpreted and scrutinised before proceeding with any further aggregation.

After considering the scenario-wise results, the deviation vector in each of the scenarios may be grouped together to form a $n \times p$ matrix of deviations i.e. precisely the form of the input for a conventional goal program. In this sense the SBGP appears as a 'super-GP' taking the form of a complete goal programming approach applied on the input table of deviations. Specifically, a metric other than the α used in the p individual problems may be used to aggregate the super-problem. This presents an interesting opportunity to incorporate the different preference philosophies encompassed by the different metrics.

Formally the full SBGP model may be written as

$$\min \Delta_i = \left[\sum_{k=1}^{p} \left[\left[\sum_{j=1}^{m} [w_{jk}\delta_{ijk}]^{\alpha} \right]^{\frac{1}{\alpha}} \right]^{\beta} \right]^{\frac{1}{\beta}} \tag{2}$$

where α and β are appropriate metrics for the individual problems and super-problem respectively. In what follows we limit discussion to the Archimedean norm of 1 and the Tchebycheff norm of ∞. Any comparisons of the Archimedean and Tchebycheff aggregations should be mindful of the fact that the two aggregations model different behavioural aims. The Tchebycheff approach is associated with notions of robustness and strong performance over all scenarios or criteria, while the Archimedean aggregation is more compensatory in that it searches for alternatives that are on average stronger. Which is more appropriate will most often be decided by taking into account the specific problem context and decision maker psychology. However, two comments are possible. Firstly, the aim advocated by the scenario planning philosophy, that is the search for a robust alternative that performs satisfactorily under all scenarios, is best furthered by the Tchebycheff super-aggregation i.e. $\beta = \infty$. Such an aggregation will consider the *worst* relative performance across scenarios i.e. in terms of the deviations, to be the indicator of an alternative's merit, however the performance is measured. There has been some discussion as to the suitability of such an evaluation strategy. Pomerol (2001) has argued to the effect that both MAXIMIN and satisficing strategies are overly pessimistic in their search for a robust solution, while Bunn and Salo (1993) state that 'a decision-making rule of selecting the strategy which has the least maximum misfit across the chosen scenarios is vulnerable to incoherence according to how well the scenarios actually partition the future'. Both of these are valid concerns. However, it does seem important to draw a distinction between the MAXIMIN criterion i.e. selecting from a set of alternatives based on which has the best 'worst-case' level of performance, and the implementation of a satisficing heuristic. In particular, the goal programming interpretation of satisficing, when combined with an interactive element, is highly flexible with regards to the implied level of optimism or pessimism. The dependency of the results on the integrity of the scenarios is farther reaching, but it is difficult to see what, if anything, could be done about this from a modelling perspective. A model is only a constructed representation of a real-world process, and thus is able to incorporate only those aspects of reality that are in fact perceived. This does, however, emphasise the importance of careful scenario construction in the problem structuring phases.

The second issue relates to aspects of the decision maker and decision making that may be described by the four possible combinations of metrics shown in table 1. Case 1 ($\alpha = 1$, $\beta = 1$) is the most accommodating combination in a compensatory sense, and allows poor performance both in a scenario or on a criteria within a single scenario to be compensated for by corresponding good performance. It is most applicable for the decision maker who is wholly unpersuaded by the call for robustness issued by scenario planning experts; a decision maker that might be more comfortable in a value theory framework. Case 4 ($\alpha = \infty$, $\beta = \infty$) is, in direct contrast to case 1, the least compensatory combination, evaluating alternatives based on their maximum weighted deviation over all criterion-scenario combinations. Although it is in line with scenario planning thinking, the possibility that just one poor performance on any criteria in any scenario can lead to the exclusion of an alternative is perhaps too restrictive for many decision makers. This option might be appropriate where the decision maker is sure of his or her aspirations, for example in a repetitive decision making environment; it is for the strictly satisficing decision maker who in a sense wants to 'know what they are getting'.

(((Table 1 approximately here)))

Cases 1 and 4 are both philosophically 'pure' in the sense that they do not mix methods of aggregation. Cases 2 and 3, on the other hand, are conciliatory in that they do mix the two aggregations. Case 2 ($\alpha = \infty$, $\beta = 1$) considers a Tchebycheff satisficing heuristic *within* each scenario, but aggregates *over* scenarios in a more compensatory way by using summation. It is therefore not in line with scenario planning, but might be more applicable than case 4 in circumstances where the decision maker wishes to follow a traditional Tchebycheff goal programming approach, but is prepared to tolerate the risk of poor performance in one or more scenarios in search of an alternative that performs better on average. This may occur wherever the implications of poor performance are not as life-and-death as in strategic planning. Case 3 ($\alpha = 1$, $\beta = \infty$) computes average performance within each scenario, but uses the maximum operator to consider only the scenario in which each alternative performs worst in evaluating the alternatives globally. This maintains a compensatory spirit between criteria while remaining aligned with the scenario planning philosophy. Such an approach might be appropriate where the consequences of poor performance in any scenario are sufficient to warrant the exclusion of that alternative, but where the decision maker desires a more accommodating approach than the one represented by case 4.

Incorporation of Relative Likelihood Information

The presentation thus far has been faithful to the scenario planning philosophy of not assigning any form of probabilistic information to the scenarios. However, if the decision maker feels comfortable in making at least some judgements regarding the relative likelihood of each scenario, there seems no good reason why this information should not be used, bearing in mind that the aggregated rank order is not considered to be the only output of the SBGP. This information is easily incorporated into the following form

$$\min \left[\mathrm{E} \left[\sum_{j=1}^{m} [w_{jk}\delta_{jk}]^{\alpha} \right]^{\frac{1}{\alpha}} \right] \tag{3}$$

The expectation aggregation procedure can be considered a more general form of the Archimedean procedure, and superior based on its ability to incorporate likelihood information where available. The Tchebycheff super-aggregation can be similarly adapted, in which case the relative likelihood of scenario k, $\Pr(k)$, acts as a weight for the performance measure obtained from the within-scenario aggregation. Each of the formulations in table 1 may therefore be adapted to reflect the incorporation of relative likelihood information, resulting in the modified formulations shown in table 2.

(((Table 2 approximately here)))

It is not the intention of this section to say that probabilistic information need be *automatically* included in the SBGP model; merely that such a consideration is not out of the question either. In all cases the inclusion or exclusion of relative likelihoods should be based on (particularly) the aims of the analysis, the preferences of the decision maker and the context of the decision problem. Again, the history of scenario planning is instructive in understanding this. Given that scenarios are constructed to be *plausible* rather than just *possible*, the scale of the long-term strategic planning in large organisations is of such a nature that ruin in any scenario need not incorporate any probabilistic information to be considered further; ruin in any scenario, given that that scenario is plausible, is sufficient warning. However, this may not always or even often be the case. It is evident that the aims of the decision analysis and the problem context to which scenario planning was traditionally applied, rather than any general theoretical concerns, led to the exclusion of probabilistic information in scenario planning.

Extensions to Continuous Goal Programming

In the case of continuous goal programming, where linear programming algorithms generate solutions by optimising over a constrained decision space, there is no reason to treat the p decision spaces separately where a robust decision is desired. The notion of robustness requires a prospective 'optimal' solution to perform well on all objectives under any of the scenarios. In the continuous case, consideration of the problem as being composed of p separate subproblems is likely to return p quite different decision vectors. Each of these vectors may perform best in the relevant scenario, but performance on any other scenario is unknown and may in many circumstances be poor. Some discussion may be possible on the basis of the outcomes of the p scenario-specific goal programs, but the discussion is unlikely to be as rich as for the discrete case, where complete rank orders are obtained in each scenario.

Within the context of the Tchebycheff framework, an extension of the notion of satisficing to choice under uncertainty requires that the decision maker focuses on attaining an acceptable performance level on the most important scenario-objective combination before considering other scenario-objective combinations. If the problems are considered separately, this dynamic movement between scenarios is not possible, and satisficing can only occur in a local sense. The concepts of satisficing and robustness are thus closely related. In contrast to the discrete GP frameworks that generally splits the super-MCDM problem into p separate parts, the continuous GP formulation should consider the super-MCDM problem in itself. As a result, the continuous GP framework is less well suited to the scenario-based approach, although the extent to which this affects its potential usefulness is difficult to estimate without practical experience.

3 An Illustrative Example

To illustrate the ideas of the previous section, let us consider a hypothetical example based on the evaluation of five alternatives $\{\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D}, \mathrm{E}\}$ over a set of five criteria $\{C_1, C_2, C_3, C_4, C_5\}$, all defined in an increasing sense i.e. more is preferred to less. Suppose that several key uncertainties that might have substantial impacts on the outcomes have been discussed and incorporated into three distinct scenarios $\{1, 2, 3\}$. The consequences in terms of each criterion for each alternative are as given in tables 3 to 5.

(((Tables 3 to 5 approximately here)))

For each of the five attributes, we specify a goal and a factor for scaling deviations to comparable magnitudes. Suppose these were chosen according to the values in table 6:

(((Table 6 approximately here)))

Let us assume that after some discussion it has been decided that goals are constant over scenarios, although this need not always be the case. Furthermore no information regarding the relative likelihood of the various scenarios has been included. Also note that once the aspiration level has been reached, further increases in the attribute level do not increase the attractiveness of an alternative – the deviation remains zero for all attribute values above the aspiration level. This is done in this particular example for reasons of simplicity, but can also be a reasonable strategy in practice for well-chosen goals. By treating the decision problem in each scenario as a deterministic goal program, we can aggregate over criteria in the usual way, by employing some metric. Which metric is most appropriate for the criterion-wise aggregation is dependent on the decision maker; but for the purposes of this illustrative example we consider both the Archimedean and Tchebycheff metrics ($\alpha = 1$ and $\alpha = \infty$ respectively). The resulting aggregate deviations in each scenario are presented in table 7 below. The position of each alternative in each scenario's rank order is given in parentheses next to the deviation.

(((Table 7 approximately here)))

We first consider the results of the Archimedean criterion-wise aggregation, and reiterate that the analysis and discussion of results at this stage should focus, in the spirit of scenario planning, on performance in each scenario, without necessarily considering aggregation over scenarios just yet. Alternative D performs best in both scenarios 1 and 3, but only moderately in scenario 2. In contrast alternative B performs best in the second scenario, but offers only average performance in the other two scenarios. Alternative E, although never the best alternative, offers strong performance in all three scenarios. Alternatives A and C appear, on the basis of the Archimedean aggregation at least, not to be attractive options.

Turning now to the Tchebycheff aggregation, we obtain a quite different set of results. Alternative B is again a strong alternative, performing best in scenarios 1 and 2, and second-best in the third scenario. Its only real rival in becoming the preferred alternative is alternative A – which performed consistently poorly according to the Archimedean aggregation, but under the less compensatory Tchebycheff metric performs much better – in fact it performs best in scenarios 1 and 3. In contrast alternatives D and E are penalised by the Tchebycheff metric and offer relatively poorer performance in scenarios 1 and 3 than indicated by the Archimedean aggregation results.

The criterion-wise aggregation results highlight the importance of correctly representing decision maker preferences, not only in terms of the traditional areas – aspiration levels, criterion weights, etc – but also in terms of the type of aggregation metric used. Under the more compensatory Archimedean aggregation the choice of preferred alternative appears to be between alternatives D and E and possibly alternative B, while under the Tchebycheff aggregation the preferred alternative seems to be either alternative B or A. The reasons for the discrepancies can naturally be traced back to the attribute evaluations for further discussion. If we examine the performances under scenario 1, for example, alternative A satisfies the aspirations on only 2 of the 5 criteria, while alternative D satisfies all but one aspiration level. However, for that unsatisfied criterion, the magnitude of the deviation is large and alternative D is consequently heavily penalised under the Tchebycheff aggregation.

Having considered the performances in each scenario and equipped with that information, attention can be turned to the aggregation of results over the set of scenarios. Again we consider only two metrics for scenario-wise aggregation: the compensatory Archimedean metric $\beta = 1$ and the Tchebycheff metric $\beta = \infty$. Each of these scenario-wise aggregations can be applied to each of the two criterion-wise aggregations presented in table 7, which gives four different aggregation combinations. Again, which is most appropriate will depend on the decision maker; for the purposes of illustration we present all four in table 8 below.

(((Table 8 approximately here)))

The results reinforce to a large extent the discussion following the criterion-wise aggregation: restricting our attention for the time being to the first two columns (Archimedean criterion-wise aggregation), the choice of preferred alternative appears to be between alternative D and E, with alternative D performing better in a fully compensatory environment ($\alpha = 1, \beta = 1$), but worse when more robust performance is desired *over scenarios* ($\alpha = 1, \beta = \infty$). The magnitudes of the differences though, are so small that a conclusion of indifference is probably prudent until a full sensitivity analysis can be carried out. The results displayed in the third and fourth columns, indicating Tchebycheff criterion-wise aggregation, show that alternative B is the preferred alternative, being best in the Tchebycheff scenario-wise aggregation and sharing the top position in the Archimedean scenario-wise aggregation. The magnitude of the superiority of alternative B over alternative A is slight, so that again no definitive selection may be justified until some sensitivity analyses have been performed.

An interesting aspect of the results is the consistency between the Archimedean and Tchebycheff scenario-wise aggregation metrics (that is the final results differed only very slightly depending on whether $\beta = 1$ or $\beta = \infty$), a clear indication that in this case it is the nature of the *criterion-wise* aggregation that determines to a large extent the final rank order. Although we have constructed an extremely simple illustratory example, in practical cases there is no reason why the same conditions might not appear, and given the ease with which, once the problem has been properly structured, the different metrics can be employed it is suggested that such checks are used to gauge which aggregations significantly affect the results. In this case, for example, many of the scenario planning arguments for and against robust performance over scenarios can be ignored or at least assume lesser importance – they simply do not impact materially on the results. In contrast, the criterion-wise aggregation has an enormous impact, and detailed attention may be required to faithfully represent the decision maker's preferences. In other cases the opposite may be true, with the scenario-wise aggregation assuming greater importance.

4 Conclusions

The decision aiding methodologies of goal programming and scenario planning complement each other very well. Goal programming is a technique with a highly developed sense of resolving conflict between criteria, but with limited ability to model uncertainty relating to future states of the world. In direct contrast, scenario planning provides a very flexible and mature uncertainty treatment without containing sufficiently powerful evaluation mechanisms for the typical multi-criteria problem. Scenario planning and goal programming are both driven by a search for an alternative that performs satisfactorily in the eyes of the decision maker: scenario planning using notions of robustness over the constructed set of scenarios and goal programming using the concept of satisficing over criteria. We have argued that the Tchebycheff metric provides a bridge between the two philosophies by being accessible to both notions of robustness and satisficing. Finally, the goal programming framework sits comfortably in the goal-driven environment of strategy formulation for which scenario planning is commonly used.

A simple mathematical SBGP model was provided, based on the decomposition of the decision problem into k closely related scenario-specific goal programming problems, one for each scenario. Most of the effort of integrating scenario planning and goal programming therefore manifests itself in the problem structuring phases. This took the form of an initial construction of p scenarios using the tools of scenario planning, followed by the structuring of a goal programming problem within each scenario. In this way it is possible to take into account both the future-focused thinking advocated by Wright and Goodwin (1999) and the value-focused thinking advocated by Keeney (1992) by constructing scenarios first, values second, and alternatives third. It was suggested that the results obtained from the SBGP formulation were initially presented separately for each scenario as a fundamental output of the process, in the spirit of scenario planning. Further aggregation over scenarios is delayed until this information has been considered.

The main modelling issue concerning the implementation of the SBGP relates to the choice of aggregation metrics. The two-stage aggregation, first over criteria within each scenario and then over scenarios, allows four different combinations of the Archimedean and Tchebycheff aggregations to be considered. Each of these combinations represents a different type of decision making strategy. In assessing the type of decision making, two questions are relevant: does the decision maker consider robust (implying Tchebycheff aggregation) or compensatory (implying an Archimedean aggregation) behaviour over criteria more desirable? and does the decision maker consider robust or compensatory behaviour over scenarios more desirable? Probabilistic information about the scenarios, in the form of relative likelihoods, may easily be incorporated into the SBGP model.

As a final point we highlight the need for a real-world application of scenario-based goal programming to investigate some of the more practical issues around the use of the model. Specific questions include: are decision makers able to give preference information incorporating scenarios i.e. importance weights, aspirations? How can the setting of metrics for aggregation be performed in a defensible and transparent manner? Are strategic planners willing to accept a more rigorous mathematical decision making framework than they are used to? Is the construction of the scenario-based goal program prohibitively time- and resource-consuming? Answering these and other practical questions may give the best insight into the potential for widespread application of scenario-based goal programming.

References

Belton V. 1999. Multi-criteria problem structuring and analysis in a value theory framework. In Gal T, Stewart T, and Hanne T (eds). *Multicriteria Decision Making: Advances in MCDM Models, Algorithms, Theory, and Applications*, chapter 12. Kluwer Academic Publishers, Dordrecht.

Belton V, Stewart T. 2002. *Multiple Criteria Decision Analysis: An Integrated Approach*. Kluwer Academic Publishers, Boston.

Bunn D, Salo A. 1993. Forecasting with scenarios. *European Journal of Operational Research*, 68:291–303.

Charnes A, Cooper W. 1955. Optimal estimation of executive compensation by linear programming. *Management Science*, 1:138–151.

De P, Acharya D, Sahu K. 1982. A Chance-Constrained Goal Programming Model for Capital Budgeting. *Journal of the Operational Research Society*, 33:635–638.

Keeney R. 1992. *Value-Focussed Thinking*. Harvard University Press, Cambridge.

Keown A, Taylor B. 1980. A Chance-Constrained Integer Goal Programming Model for Capital Budgeting in the Production Area. *Journal of the Operational Research Society*, 31:579–589.

Pomerol J-C. 2001. Scenario development and practical decision making under uncertainty. *Decision Support Systems*, 31:197–204.

Saaty T, Kearns K. 1985. *Analytical Planning.* Pergamon, Oxford.

Simon H. 1976. *Administrative Behaviour.* The Free Press, New York.

Stewart T. 1997. Scenario analysis and multicriteria decision making. In Climaco J (ed.), *Multicriteria Analysis*, pages 519–528. Springer-Verlag, Berlin.

Van der Heijden K. 1996. *Scenarios: The Art of Strategic Conversation.* John Wiley & Sons, New York.

Wack P. 1985a. Scenarios: shooting the rapids. *Harvard Business Review*, Nov/Dec:139–150.

Wack P. 1985b. Scenarios: uncharted water ahead. *Harvard Business Review*, Sept/Oct:73–89.

Wright G, Goodwin P. 1999. Future-focussed thinking: Combining scenario planning with decision analysis. *Journal of Multicriteria Decision Analysis*, 8:311–321.

	$\alpha = 1$	$\alpha = \infty$
$\beta = 1$	$\sum_k \sum_j w_{jk}\delta_{ijk}$	$\sum_k \left[\max_j [w_{jk}\delta_{ijk}]\right]$
$\beta = \infty$	$\max_k \sum_j w_{jk}\delta_{ijk}$	$\max_k \left[\max_j [w_{jk}\delta_{ijk}]\right]$

Table 1: Possible formulations of the SBGP problem

	$\alpha = 1$	$\alpha = \infty$
$\beta = 1$	$\sum_k \Pr(k) \sum_j w_{jk}\delta_{ijk}$	$\sum_k \Pr(k) \big[\max_j [w_{jk}\delta_{ijk}]\big]$
$\beta = \infty$	$\max_k \big[\Pr(k) \sum_j w_{jk}\delta_{ijk}\big]$	$\max_k \big[\Pr(k) \big[\max_j [w_{jk}\delta_{ijk}]\big]\big]$

Table 2: Possible formulations incorporating relative likelihood information

Alternative	C_1	C_2	C_3	C_4	C_5
A	1100	100	100	100	100
B	1000	400	150	50	70
C	300	500	180	80	50
D	800	75	200	150	120
E	200	200	300	175	100

Table 3: Attribute values for scenario 1

Alternative	C_1	C_2	C_3	C_4	C_5
A	1100	100	75	90	80
B	1000	400	125	40	70
C	300	500	130	80	50
D	800	50	100	110	80
E	200	120	180	160	80

Table 4: Attribute values for scenario 2

Alternative	C_1	C_2	C_3	C_4	C_5
A	1050	90	90	80	80
B	800	250	110	30	60
C	200	350	165	65	50
D	600	50	100	100	100
E	150	160	175	150	75

Table 5: Attribute values for scenario 3

Criterion	Goal	Scaling Factor
C_1	600	500
C_2	300	300
C_3	150	90
C_4	150	150
C_5	100	50

Table 6: Goals and scaling factors for the example problem

	$\alpha = 1$				$\alpha = \infty$		
	Scen 1	Scen 2	Scen 3		Scen 1	Scen 2	Scen 3
A	0.31 (4)	0.46 (4=)	0.45 (4)	A	0.67 (1=)	0.83 (3=)	0.70 (1)
B	0.25 (3)	0.32 (1)	0.44 (3)	B	0.67 (1=)	0.73 (1)	0.80 (2)
C	0.41 (5)	0.46 (4=)	0.47 (5)	C	1.00 (5)	1.00 (5)	1.00 (5)
D	0.15 (1)	0.41 (3)	0.34 (1)	D	0.75 (3)	0.83 (3=)	0.83 (3)
E	0.23 (2)	0.36 (2)	0.37 (2)	E	0.80 (4)	0.80 (2)	0.90 (4)

Table 7: Criterion-wise aggregated deviations

	$\alpha = 1$			$\alpha = \infty$	
	$\beta = 1$	$\beta = \infty$		$\beta = 1$	$\beta = \infty$
A	0.41 (4)	0.46 (4)	A	0.73 (1=)	0.83 (2=)
B	0.34 (3)	0.44 (3)	B	0.73 (1=)	0.80 (1)
C	0.45 (5)	0.47 (5)	C	1.00 (5)	1.00 (5)
D	0.30 (1)	0.41 (2)	D	0.81 (3)	0.83 (2=)
E	0.32 (2)	0.37 (1)	E	0.83 (4)	0.90 (4)

Table 8: Scenario-wise aggregated deviations

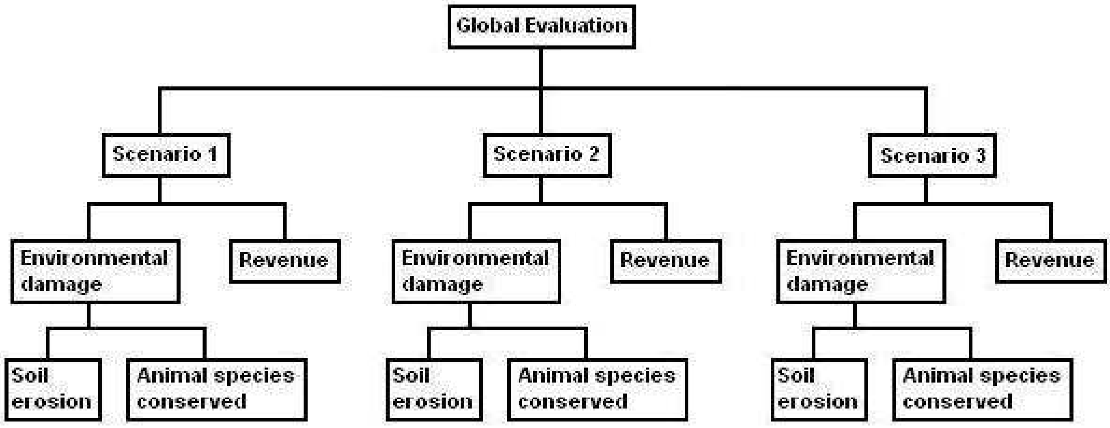

Figure 1: Position of scenarios in the value tree