Optimisation technologies and environmental applications

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Abstract

In this work, we focus on the interaction between optimisation technologies and the management of natural resources. In recent years, the environmental impact of planning decisions has received increasing attention, as negative effects on the ecosystem may affect production and consumption. Hence, there is a need to assess and quantify environmental services as well as environmental impacts, so that these can be included in the decision-making process. At the same time, recent trends in optimisation software and Internet technology have spawned a new research area in the field of distributed optimisation applications for several domains, including environmental management. We make use of the platform developed within the OSP CRAFT project, and implement an Internet-based Decision Support System (DSS), which embodies a land management stochastic programming model. The platform takes advantage of an Application Service Provision (ASP) architecture, whereby decision-makers are able to access the optimisation model and analyse its solutions on a subscription basis. In this framework, the remote DSS is easily interfaced with existing local repository of environment data, such as pollution measurements, soil and water resources information, as well as global GIS datasets.

Keywords*: Environmental Planning, Dynamic Programming, Stochastic Programming, Application Service Provision.*

1 Introduction

Our work embraces two main objectives:

1. We aim to stress the importance of optimisation technologies in the environmental context through a general overview of possible applications of operations research models to environmental planning problems, such as land and natural resources allocation, waste management and pollution control.
2. We illustrate how advances in Internet technology can be applied to create model-based decision support systems which assist the decision makers in the planning process. In particular, we discuss an original case study concerned with development options of a semi-degraded natural area in the northern part of Italy.

The integration of linear, dynamic and stochastic optimisation models with Internet based decision support system has been carried out in the context of the Optimisation Services Provision (OSP) project (see www.osp-craft.com). OSP is funded by the European Commission under the CRAFT scheme (IST-1999-56410) and involves several partners across Europe, with the common aim of developing an optimisation environment that can be offered as an Application Service Provider (ASP) solution. The project includes research applications for a number of industry sectors, namely finance, supply chain planning, energy distribution and environmental planning.

Most of the environmental problems are characterised by two main features. On one side, environmental processes and resources are often characterised by irreversibility, i.e. their consumption, conversion, exploitation and degradation can be a one-way decision, and therefore appropriate modelling is required. On the other side, the uncertainty deriving from incomplete knowledge concerning natural processes and the effects of our actions on those processes, call for a particular attention in choosing the modelling techniques to be deployed. The theoretical framework for decision making in environmental applications in the presence of uncertainty is the quasi-option value approach, first discussed by Arrow and Fisher [1] and Henry [15] and subsequently investigated, in its different features, in papers by Conrad [6], Hanemann [13] and Coggins and

Ramezani [5], among others. In the same dynamic decision framework, Pindyck, in Pindyck [21], has discussed the problem of global environmental damage mitigation. However, it is for the first time in a work by Clarke and Reed [4] that greater emphasis is given to problems of gradual conversion optimal strategies rather than optimal timing of "jump" decisions, involving a stochastic dynamic programming approach. Finally, other operational research approaches have been largely applied to forestry management, see for example Gassmann [12], and other environmental planning problems.

Decision making in environmental applications can be profitably enhanced by the use of quantitative models, capable of capturing the inherent uncertainty and accounting for both economic and social/environmental aspects of the problems. However, the quantification of some of the parameters and variables at stake can be non trivial. This is particularly true when dealing with public goods (e.g., water, air, landscapes, etc.) that are not exchanged in the market because their value may be only partially or not at all reflected in a price.

In this paper, we are also concerned with the practical implementation and deployment of these models. Several software tools (algebraic modelling languages and solvers amongst others) are available to modelling experts for the development and testing of optimisation models. The maintenance of local installations of these tools can often be time consuming, mainly because the software components required in the modelling and solution process are provided and supported by several different companies. In order to be deployed for decision-making, optimisation models need to be "wrapped" by easy-to-use interfaces. Having taken this into account, we have identified the Application Service Provision (ASP) architecture as a viable approach to:

1. Provide modellers with remote integrated modelling and solution systems for the development and testing of optimisation models
2. Enable decision-makers to remotely access customisable decision support systems based on optimisation models.

In general, Application Service Providers deliver and manage applications and computer services from remote servers to multiple users via the Internet or a private network. Although ASP is a relatively new concept, there are already several companies which provide such services (see McKie [20]). The Application Service

Provider usually offers an integrated package which, besides the use of the software application, also includes upgrades and maintenance, user support, and possibly access to advanced computing resources (Fourer and Goux [11]). This *outsourcing* of software applications often implies reduced costs for the end users. This is particularly true in the case of optimisation software that requires specialised expertise and computing resources.

The rest of the paper is organised as follows: in section 2 we briefly provide a theoretical background on dynamic and stochastic modelling for environmental planning problems, in particular for gradual conversion problems. Section 3 illustrates the Application Service Provision paradigm, while in section 4 we introduce a real case study, which we use to illustrate how the interaction between the modelling techniques here presented and the ASP architecture can prove a viable platform for optimum decision making in the context of environmental planning.

2 Model Formulation of Basic Decision Problems in Environmental Planning

For the purpose of this work, we classify environmental planning into three main categories. The first category concerns multicriteria optimisation methods (see [3] and [9]): these take into account various environmental goods and are used to determine the basis for sustained land use and to examine the efficiency of economic instruments for the maintenance biodiversity. Multicriteria optimisation methods are typically applied to public management problems that are concerned both with economic efficiency and some environmental impact targets, an example being the development of integrated systems for waste management. Such decision support systems enable the decision maker to evaluate integrated policies in all their aspects (e.g., waste collection, treatment and disposal), both from an economic and an environmental perspective. On one side, alternative policies are analysed in a cost/benefit framework. On the other side, an environmental index is calculated to synthesize impacts associated to each policy, in order to account for environmental externalities which cannot be captured in the economic analysis. Each policy is the result of an optimisation process aiming to minimize financial costs and environmental impact (both aspects can be weighted according to the decision maker attitude). Policies that have shown to be efficient under both criteria are the output of the decision support tool. Although much of the input data can be highly case dependent, a decision support framework may have a general structure that can be personalized by each user through a set of questions and requirements input.

The second category is represented by complete conversion problems modelled as optimal stopping problems. The investment in pollution control or the transformation of an island in a Club Med style tourist village could be examples of environmental problems where the control variable can only take the value 0 and 1. Dynamic programming models, originally developed in order to time and evaluate financial and real projects investments in the presence of market uncertainty, can be fruitfully applied to decisions and investments concerning environmental resources.

Stochastic Programming (SP) is the third approach considered. SP can be applied to model those problems where the main objective is to find the evolution of a portfolio of mixed allocation of environmental resources over time. We refer to these problems as gradual conversion problems, where the control variables can take continuous values.

The following subsections contain more detailed descriptions of the last two categories. The reader can refer to the biography introduced in section 1 for an in-depth treatment of multicriteria optimisation methods.

2.1 The Complete Conversion Problem

The process of designing environmental policies is similar to that of irreversible investments decision-making. Indeed, they both imply giving up the possibility of waiting for new information that might affect the profitability or timing of the expenditure, information that might concern the environmental evolution of the ecosystem as well as the economic value deriving from natural goods and services. Therefore, the goal of an efficient decision process is to include the opportunity cost of such option value in the calculation. In order to do so it is appropriate to use a dynamic approach that takes into consideration the possibility of postponing irreversible decisions, thus providing the decision maker with information including the optimal stopping time (where stopping means, in this case, converting or extracting a natural resource). In complete conversion problems the control variable, u_t, is a binary variable, the decision is a "once and for all" decision that might be delayed but cannot be undertaken gradually. This is often the case when the project or investment at stake is sizeable and not scalable.

The solution of the dynamic programming problem is given by the Bellman equation (see Pindyck [22]) that in its general form can be written as:

$$F_t(x_t, u_t) = \max_{u_t}\left\{\Omega(x_t), \pi(x_t) + \frac{1}{1+\rho} E\left[F(x_{t+\Delta t}) \mid x_t\right]\right\} \tag{1}$$

Where $u_t \in \{0,1\}$ is the control variable; $x_t \in X_t$ is the state variable; $F(x_t, u_t)$ is the function defining the total value of the project or investment at time t that is given by the maximum between $\Omega(x_t)$, that is the termination payoff (the value one would obtain undertaking immediately the decision) and $\pi(x_t)$, that is the flow of benefits accruing while waiting (it could be zero or even negative), plus the factor:

$$\frac{1}{1+\rho} E\left[F(x_{t+\Delta t}) \mid x_t\right] \tag{2}$$

which represents the discounted expected value of the option to undertake the decision in a future period $t+\Delta t$, ρ being the discount rate. While market uncertainty can be captured in the model, this is not the case for environmental (project specific) uncertainty. If the risk of a project is diversifiable, it is possible to compute the value of the project applying "risk-neutral" probability distribution and discounting with the risk-free interest rate. However, environmental uncertainty is domain specific and not diversifiable, thus cannot be hedged by tradable securities. In order to include environmental uncertainty in the model, a common approach is the capital-asset-pricing model that produces a risk-adjusted discount factor, according to the risk category of the project. This may not the best procedure when the level of risk of a project is not comparable with that of other known projects and when dealing with long time horizon projects. An alternative approach to deal with project specific uncertainty has been developed by Smith and Nau [23] and applied to evaluate investments in the field of oil and gas management in McCardle [19]. The procedure involves the use of subjective prior probabilities, regarding possible future states, which are combined with the decision maker inter-temporal consumption preferences.

As an output, this dynamic approach provides the decision maker with a trigger value dividing the region of possible initial value accruing from the decision, thus allowing her or him to choose whether to postpone, reject or undertake such decision. Moreover, it provides indications regarding how long it might be useful to wait if the project has to be postponed.

2.2 The Gradual Conversion Problem: A Stochastic Programming Approach

Complete conversion decisions are optimal when the relative unit values of wild and developed land/resource are independent of their quantities. However, this is often an implausible assumption. Gradual conversion problems typically occur when the decision maker's objective is to choose among an enormous number of possible configurations (resources allocations, pollution mitigation action, etc.). Rather than an optimal stopping problem (immediate and complete development), the analysis focuses therefore on the sequential decision problem of finding an optimal land/resources portfolio composition through time, i.e. the control variable, u_t, is now a continuous variable rather than a binary one. Indeed, it is often more realistic to assume that an optimal land management program will involve a gradual sequence of conversion decisions through time, evolving as each land allocation/resource value becomes known with more accuracy. As before, the decision problem is commonly a stochastic problem because it deals with future uncertainty. The gradual conversion problem can be modelled as a stochastic optimal control problem as well as a stochastic programming problem. As noted in Wets [24], the first approach stresses the importance of finding a general optimal rule, while the stochastic programming approach puts particular emphasis in finding an optimal first stage decision, and a set of second stage corrective actions. Both approaches can be of fundamental importance in environmental management analysis. The former typically addresses decentralized and local gradual conversion problems, where most of the relevant parameters are generally unchanged each period.

The optimal rule is given to the local manager of the resource by means of some cut off value. Then, each year, he/she will be able to choose the optimal policy just comparing some indicator with the cut off value. Stochastic programming approaches are suited to analyse problems characterized by parameters that change dramatically each period. Therefore, re-optimisation in each period is more indicated than an optimal decision rule. To conform to the case study we present in later sections, we will mainly consider the stochastic programming approach.

In the general formulation of a stochastic problem the main emphasis is on the set of first stage decisions (represented by the vector *x*) that have to be taken without full information about some random events. Subsequently, when full information on the realization of a random vector, ξ on some canonical space *(Ω,F,P),* becomes available, second stage or corrective decisions *y*, are taken. Supposing a decision maker has to choose the least cost mix of pollution mitigation technologies given partial information on each technology performance and on the pollutants effects, it is possible to define a general two-stage stochastic program with recourse as:

$$\begin{aligned} &\min c^T x + E_\xi Q(x,\xi) \\ &s.t. \\ &Ax = b, \\ &x \geq 0 \end{aligned} \tag{3}$$

where: *c* is the cost vector, *A* represents the technology matrix, *b* is the set of abatement targets the policy should meet, and

$$Q(x,\xi) = \min\{q^T y \mid Wy = h - Tx, y \geq 0\}, \quad \xi = (q^T, h^T, T). \tag{4}$$

E_ξ is the mathematical expectation with respect to ξ. This approach allows the decision maker to have an insight of what first stage decisions should be, in the light of later corrective decisions.

3 Internet-based Optimisation

Optimisation techniques are rapidly evolving thanks to the developments in modelling software tools and in solution algorithms. Only recently, however, the availability of powerful desktop computing platforms has been instrumental in the acceptance of optimisation-based Decision Support Systems. This is partially explained by the recent development of optimisation methodologies which exploit problem structures and can be therefore applied to large-scale problems.

As we have discussed in section 2, environmental problems such as land and natural resources allocation, waste management and pollution control can all be investigated by means of optimisation models. In our framework, these models are deployed and used as inference engines for decision-making (Koutsoukis [16]).

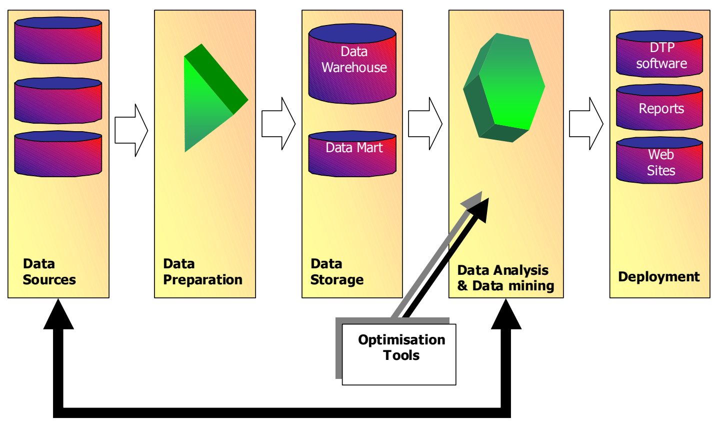


Figure 1: Optimisation as inference engine.

In an environmental problem study, the *information chain* depicted in Figure 1 may for instance involve the collection of soil or water pollution data from one of the several sources of Geographic Information Systems (GIS) data sets available on the Internet. The data is then analysed and fed to an optimisation model for pollution control, which in turn produces the optimum decisions. These can finally be presented and analysed using appropriate tools.

In the past, the steps involved in this process used to be performed "locally" by dedicated computational resources and software tools. However, the modern setting of Digital Economy is creating abundant opportunities for Operational Research (OR) applications through the integration of Mathematical Programming (MP) with Decision Theory and Information Technology. Several research institutes and some commercial companies are now exploiting the distributed nature of the Internet in order to provide their optimisation tools as remote services. These services rely on specialised servers, which can be accessed either via ftp or email, or more recently through web forms or applets. In their exhaustive work, Fourer and Goux [10] identify two categories of optimisation servers, namely solver servers and modelling servers. Amongst these, the most advanced and comprehensive is probably the *NEOS Server for Optimisation* (see Czyzyk [7]). The server enables modellers and practitioners to submit their problems using web forms, e-mail or a TCP/IP based client submission tool, and to choose between a large number of solvers which are accessible by the NEOS server. The general architecture of the NEOS server is shown in Figure 2.

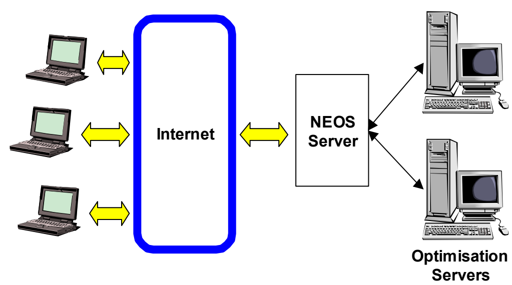


Figure 2: NEOS server architecture.

The NEOS paradigm enables the *outsourcing* of the (expensive) optimisation tasks, allowing the decision makers to focus on the study and analysis of the solutions. The information chain of Figure 1 can be therefore "split" and distributed across the Internet, as both environment data (see for instance the United Nations Environment Programme website at www.unep.net) and the optimisation tools can be accessed remotely. However, existing optimisation severs such as NEOS are currently in a prototype stage, and may therefore lack of the robustness which usually characterise industrial strength applications. One way forward in the provision of commercial optimisation tools through the Internet is represented by the Application Service Provision model, which is embraced by the OSP project.

3.1 The ASP model

The terms ASP and *Application Service Provider* are used to refer to companies providing services via the

Internet. The ASP Industry Consortium defines an ASP as an organization that "manages and delivers application capabilities to multiple entities from a data centre across a wide area network (WAN)." This means a company can rent access to software over the Internet or a WAN for a monthly or pay-as-you-go fee: in essence, software delivered as a service. An ASP employs the personnel needed to install and maintain the application and the servers. Subsequently, ASPs make the application available to customers anywhere in the world via the Internet, either in a browser or through thin client technology. The idea behind ASP is therefore that of *outsourcing*. In the next section we describe the general architecture adopted within OSP for the support of the ASP model.

3.2 Optimisation and ASP: the OSP architecture

As we mentioned earlier in this paper, OSP is an acronym for Optimisation Service Provision, and also the name of the EU sponsored project that involves seven partners across Europe. The main objective of the project is to combine optimisation and the ASP model in order to provide end users with remote decision support services on a subscription basis (Koutsoukis [17]). Besides these "vertical applications", OSP enables practitioners to rent the use of the following set of optimisation tools:

- *Modelling Systems.* Modelling systems enable modellers to declare mathematical programming models using declarative modelling languages. The main purpose of a modelling system within a decision support application is the instantiation of the algebraic model using the model's data. The instance is created in a low level format, which in turn can be processed by a solver.
- *Optimisers (or Solvers).* These are programs consisting of algorithms that are able to process the model and yield a solution based on the current model instance.
- *Database Tools.* Database tools are the repositories of information for the instantiation of optimisation models. Database tools are typically Spreadsheets, Database Management Systems (DBMS), and Middleware components such as Open Database Connectivity (ODBC) tools.

The architecture of the OSP platform is shown in Figure 3.

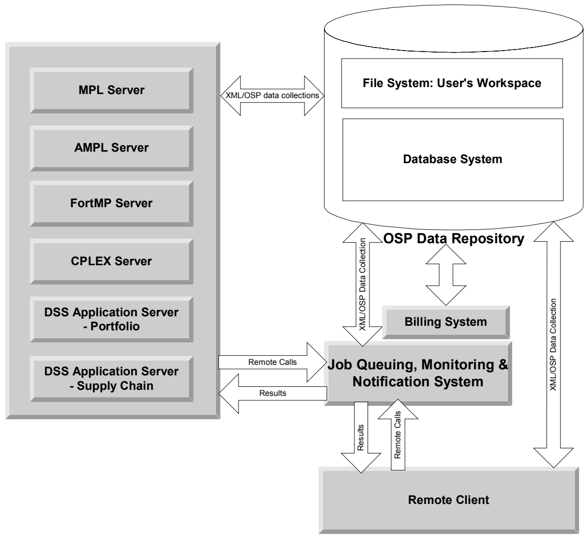


Figure 3: OSP architecture.

The architecture is based on a queuing system built around a database which holds the job requests (the *job queuing, monitoring and notification system*). The web interfaces (clients) send xml records to the database with specific job instructions. The server applications (in our case the MPL and AMPL modelling systems and the FortMP and CPLEX solvers, as well as the various DSS applications) are notified of new requests, and produce results in the user's workspace. The web pages are then updated to display the results to the users. This architecture, which is almost entirely based on xml/soap communications, enables the system to be exploited as a web service. Besides this functionality, the OSP platform provides an information infrastructure which is designed to maximise the effectiveness of its use:

- *Support Services.* Due to the complexity and sophistication of optimisation applications and the resulting DSS, it is common for a user to require the help of an expert in order to understand, use, or customise an optimisation-based DSS to his requirement. Support services may be available in the form of on-line help, on-line tutorials, or physical interaction (discussion) with an expert.
- *Technical Support.* Issues strictly relating to the system's functions, rather than the use of the DSS, are resolved through a technical support help-desk.

The OSP web site (www.osp-craft.com) currently offers internal access to some prototypes applications. One of such applications is the land management decision support system illustrated in the next section.

4 A Real Case Study: a Land Management problem.

In this section, we present a Decision Support System for land management. The system is based on a multistage stochastic programming optimisation model, and has been implemented within the OSP framework, so that it can be accessed through the use of web browsers on a subscription basis. Decision makers (in this case a local manager) are provided with a set of forms and web pages, which enable the input of the data relating to the specific problem. The DSS provides the decision maker with optimal first stage decisions, and some additional indications concerning the profitability of investing extra money in order to acquire more information before taking any decision. The optimum decision will be recalculated for each decision period without having to bare specific software and specialised human capital costs, but simply periodically renting the optimisation software offered by OSP.

In the next sections, we introduce the stochastic programming model used in the DSS, and discuss the techniques used in the generation of the scenarios for the optimisation. We then give an overview of the OSP interface and analyse the results obtained for a case study concerning a semi-degraded natural area located in northern Italy, Parco di Tradate e Appiano Gentile, with data relative to year 2001.

4.1 Problem Statement

Consider a relatively degraded area that supports a minor recreational activity and that exhibits some environmental degradation as a result of the activity itself (e.g., streets constructions, dump, etc.). We will refer to the land portion left to this initial state, as Status Quo (SQ). The portion of the area where the environmental damage has been remediated and that has been turned to a more natural state offering some recreational services, will be referred to as Natural Park (NP). Finally, the portion of the initial area that has been remediated and committed to an organized and accessorized Natural Park is denoted as Organised

Natural Park (NPO)[1]. The conversion directions (see Figure 4) can be as follows: land can be remediated from the SQ and turned to the NP state; land can be remediated and converted to a highly organised natural park both from SQ and from NP, irreversibly. Indeed, from state NPO it is not possible to go back to the other two states. The construction of infrastructures, created in order to allow visitors to benefit from organised activities will irreversibly change the equilibrium of the ecosystem.

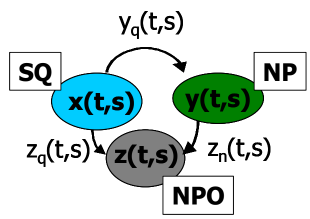


Figure 4: Conversion directions.

Uncertainty in the model affects mainly the value of benefit flows that accrue from each of the three land states. We assume, as in most of stochastic optimisation theory, that the evolution of each of the three values can be approximated through a Geometric Brownian motion. Through data on historical visitation rates we are able to estimate the parameters μ (mean) and σ (standard deviation) of each of the three stochastic processes. We use these values to sample a set of scenarios for the land value in the three states.

It is often plausible to assume that the marginal value of the land decreases with the land size. Thus we use piecewise linear approximations to express the land value as a function of the allocated land size.

4.2 Model Formulation

The stochastic programming model can be formulated as follows:

Indices

$t = 0,..,\|T\|$	T: Set of time periods in the planning horizon;
$s = 1,..,\|S\|$	S: Set of Scenarios
$n= 0,..,\|N\|;$	N: Set of segments in the linear approximations;

Data

[1] Services that could be offered include horse riding, a natural science museum, etc.

The following data are defined for each time period and scenario:

$\pi(t,s)$ value of benefit flows deriving from land in state SQ.
$\nu(t,s)$ initial marginal value of benefit flows deriving from land in state NPO;
$\kappa(t,s)$ initial marginal value of benefit flows deriving from land in state NP;
$\alpha(t,s)$ discounted value of variable costs deriving from converting the area from SQ to NP;
$\beta(t,s)$ discounted value of variable costs deriving from converting the area from NP to NPO;
$\gamma(t,s)$ discounted value of variable costs deriving from converting the area from SQ to NPO
$I\alpha(t,s)$ the initial sunk costs required to start the conversion of the area from SQ to NP;
$I\beta(t,s)$ the initial sunk costs required to start the conversion of the area from NP to NPO;
$I\gamma(t,s)$ the initial sunk costs required to start the conversion of the area from SQ to NPO;

The following data are defined for each scenario:

prob(s) scenario probability

Piecewise Linear Approximation Data

$A(n)$ Points in the linear approximation, where (A(n)=n/N);
$d_K(n)$ Decrement of the marginal value of NP in land size interval [A(n), A(n-1)];
$d_V(n)$ Decrement of the marginal value of NPO in land size interval [A(n), A(n-1)];
$K(n,t,s)$ value of the linearly approx NP value at point A(n);
$V(n,t,s)$ value of the linearly approx NPO value at point A(n);

The values of K(n,t,s) and V(n,t,s) are calculated as follows:

$$\begin{aligned} &K(n,t,s) = 0 && n = 0 \\ &K(n,t,s) = \sum_{n' \le n} \kappa(t,s)(A(n') - A(n'-1))d_K(n') && n > 0 \quad \text{For each } s \in S,\ t \in T \end{aligned} \tag{5}$$

$$\begin{aligned} &V(n,t,s) = 0 && n = 0 \\ &V(n,t,s) = \sum_{n' \le n} \nu(t,s)(A(n') - A(n'-1))d_V(n') && n > 0 \quad \text{For each } s \in S,\ t \in T \end{aligned} \tag{6}$$

An example of piecewise linear function for the value of NP for N=4 (four segments) is shown in Figure 5.

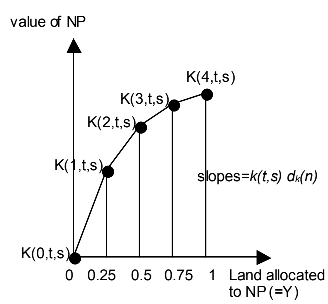


Figure 5. Piecewise linear value of NP.

Decisions

Binary variables

$\lambda_{qn}(t,s)$	it takes value 1 if conversion from SQ into NP starts at time t;
$\lambda_{qd}(t,s)$	it takes value 1 if conversion from SQ into NPO starts at time t;
$\lambda_{nd}(t,s)$	it takes value 1 if conversion from NP into NPO starts at time t.

Continuous variables

$x(t,s)$	defines the SQ area
$y(t,s)$	defines the NP area
$z(t,s)$	defines the NPO area
$z_q(t,s)$	defines the area converted from SQ into NPO;
$z_n(t,s)$	defines the area converted from NP into NPO;
$y_q(t,s)$	defines the area converted from SQ into NP;
$dY(n,t,s)$	Used in the piecewise linear approximation of NP;
$dZ(n,t,s)$	Used in the piecewise linear approximation of NPO;

Objective function

The objective function seeks the optimal land portfolio for the relevant time period. The algebraic representation of the objective function is as follows:

$$Z = \max \quad \sum_{s\in S} p(s) \sum_{t>0} [\pi(t,s)x(t,s)] + \tag{7}$$

$$\sum_{s\in S} p(s) \sum_{t>0} \sum_{n\in N} K(n,t,s) dY(n,t,s) + \tag{8}$$

$$\sum_{s\in S} p(s) \sum_{t>0} \sum_{n\in N} V(n,t,s) dV(n,t,s) + \tag{9}$$

$$\sum_{s\in S} p(s) \sum_{t>0} [\alpha(t) y_q(t,s) + \beta(t) z_n(t,s) + \gamma(t) z_q(t,s)] - \tag{10}$$

$$\sum_{s\in S} p(s) \sum_{t>0} [I_\alpha(t)\lambda_{qn}(t,s) + I_\beta(t)\lambda_{nd}(t,s) + I_\gamma(t)\lambda_{qd}(t,s)] \tag{11}$$

Where (7) indicates the revenues accruing from land in state SQ, (8) is the piecewise linear value for the land in NP state, (9) is the piecewise linear value of the land in NPO state, (10) is the total variable conversion cost and (11) is the total fixed conversion cost.

Relationships

Initial conditions

$$\begin{array}{lll} x(t,s) = 1 & z_q(t,s) = 0 & \\ y(t,s) = 0 & z_n(t,s) = 0 & \text{For each } s\in S, \text{ with } t=0 \\ z(t,s) = 0 & y_q(t,s) = 0 & \end{array} \tag{12}$$

Development conditions

$$\begin{aligned} &x(t,s) = x(t-1,s) - y_q(t,s) - z_q(t,s) \\ &y(t,s) = y(t-1,s) + y_q(t,s) + z_n(t,s) \\ &z(t,s) = z(t-1,s) + z_q(t,s) + z_n(t,s) \\ &z_n(t,s) \le y(t-1,s) \end{aligned}$$ For each $s \in S$, with $t>0$ (13)

Initial Investment conditions

$$z_q(t,s) \le \sum_{t' \le t} \lambda_{qd}(t',s) \qquad \sum_t \lambda_{qd}(t,s) \le 1$$ For each $s \in S$, with $t>0$ (14)

$$z_n(t,s) \le \sum_{t' \le t} \lambda_{nd}(t',s) \qquad \sum_t \lambda_{nd}(t,s) \le 1$$ For each $s \in S$, with $t>0$ (15)

$$y_q(t,s) \le \sum_{t' \le t} \lambda_{qn}(t',s) \qquad \sum_t \lambda_{qn}(t,s) \le 1$$ For each $s \in S$, with $t>0$ (16)

Piece-wise linear value of land constraints

$$y(t,s) = \sum_{n=0}^{N} A(n) dY(n,t,s) \qquad \sum_{n=0}^{N} dY(n,t,s) = 1$$ For each $s \in S$, $t \in T$ (17)

$$z(t,s) = \sum_{n=0}^{N} A(n) dZ(n,t,s) \qquad \sum_{n=0}^{N} dZ(n,t,s) = 1$$ For each $s \in S$, $t \in T$ (18)

Conservation constraint

$$x(t,s) + y(t,s) + z(t,s) = 1$$ For any $s \in S$ and $t \in t$ (19)

Bounds

$0 \le x(t,s) \le 1$, $\quad 0 \le z_q(t,s) \le 1$,
$0 \le y(t,s) \le 1$, $\quad 0 \le z_n(t,s) \le 1$,
$0 \le z(t,s) \le 1$, $\quad 0 \le y_q(t,s) \le 1$. For any $s \in S$ and $t \in t$ (20)

$0 \le dY(n,t,s) \le 1$,
$0 \le dZ(n,t,s) \le 1$. For any $n \in N$, $s \in S$ and $t \in t$ (21)

Non anticipativity

An additional set of constraints, needs to be added to the model in order to account for non-anticipativity, that is each decision taken at a given stage cannot include information that will be revealed at subsequent stages.

4.3 Scenario Generation

Data required from the local manager belong mainly to two categories. The first set of data concerns the value of annual benefit flows deriving from each of the three possible allocations. As mentioned data was collected through a contingent valuation study that was conducted from July to October of 2001; from statistical analysis a distribution of willingness to pay per person per day (in Euros) related to each of the land allocations has been inferred (data are summarised in Table 1).

Values	**SQ**	**NP**	**NPO**
Gross Annual Revenues	38067	69590	77616
Costs	**SQ to NP**	**SQ to NPO**	**NP to NPO**
Conversion Costs	1000	3000	5000
Investment Costs	30000	32000	35000

Table 1. Values expressed in €.

Unit conversion costs and initial conversion investment costs are esteems based on similar projects and are approximated values. The second set comprises the historical data concerning annual visits to the parks, required to proceed with scenario generation. We assumed that the net benefit of the three options would be proportional to the number of visitors and used time-series data to estimate the mean drift, μ, and standard deviation, σ, of the visits rate. With estimates of μ and σ for each option, it is possible to generate the scenario tree through random sampling.

Accurate time series data for the Appiano Gentile Park are not available, as, of course, it is not available for the hypothetical allocations NP and NPO. Therefore we have therefore used data concerning similar parks (parks that may be perfect substitutes of the three states considered in the model). Table 2 shows time-series data for Parco delle Groane (the comparable land for Appiano Gentile in the SQ state), for Parco della Maremma (the comparable for Appiano Gentile in the NP state) and Parco Nazionale dello Stelvio (the comparable land for Appiano Gentile in the NPO state).

Year	SQ	NP	NPO
1992	9225	521842	40000
1993	9375	447961	36000
1994	11750	522201	50873
1995	12575	547018	40542
1996	13275	560691	37189
1997	13700	603533	45628
1998	16075	595675	11688
1999	13075	583890	71403
2000	15850	676485	102965
2001	16800	857864	98478

Table 2. Values are expressed in annual number of visitors.

For each option we sought the values μ_i and σ_i which would maximize the log likelihood function:

$$\ln(\mathrm{L}_i) = -(\frac{T_i}{2})\ln(2\pi) - (\frac{T_i}{2})\ln(\sigma_i) - \left[\frac{1}{2\sigma_i^{\ 2}}\sum_{t=0}^{T_i-1}\ln(\frac{X_{i,t+1}}{X_{i,t}}) - (\frac{\mu_i - \sigma_i^{\ 2}}{2})\right]^2 \qquad (22)$$

where T_i is the number of years we have data for, $X_{i,t}$, is the visitation rate to park i in year t and the time step is assumed to be $\Delta t=1$. The estimated parameters are given in Table 3.

Parameter	SQ	NP	NPO
μ	0,07945803	0,06585245	0,03416473
σ	0,16031936	0,14574861	0,1007731

Table 3. The Geometric Brownian motion estimated parameters.

Using these values, we sampled a set of 16 scenarios. The resulting scenario tree is shown in Figure 6.

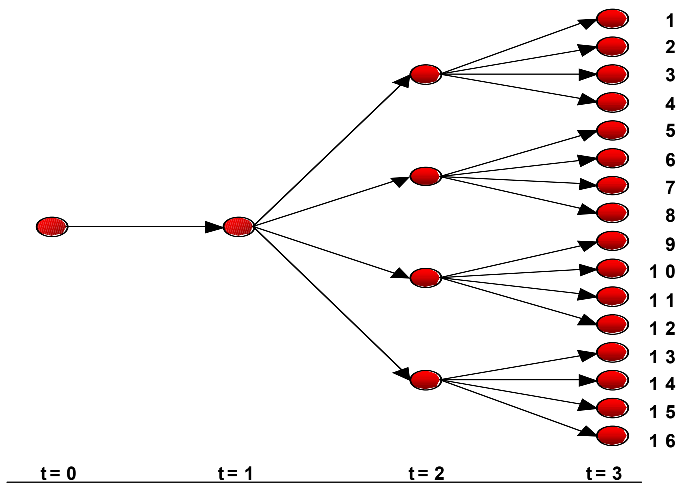


Figure 6: The Scenario Tree for the Appiano Gentile Park

4.4 Problem investigation with the OSP platform

The OSP web site hosts a prototype of a decision support system based on the land allocation model illustrated in this paper. The scenarios data have been stored on a remote database that is accessible by the DSS by means of ODBC connections. Once logged in, the user can access and modify the model's data and solve the model using the *workspace management* area (Figure 7).

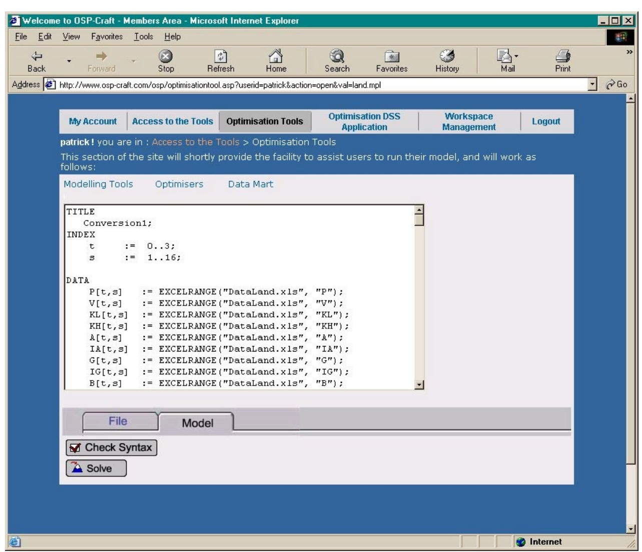
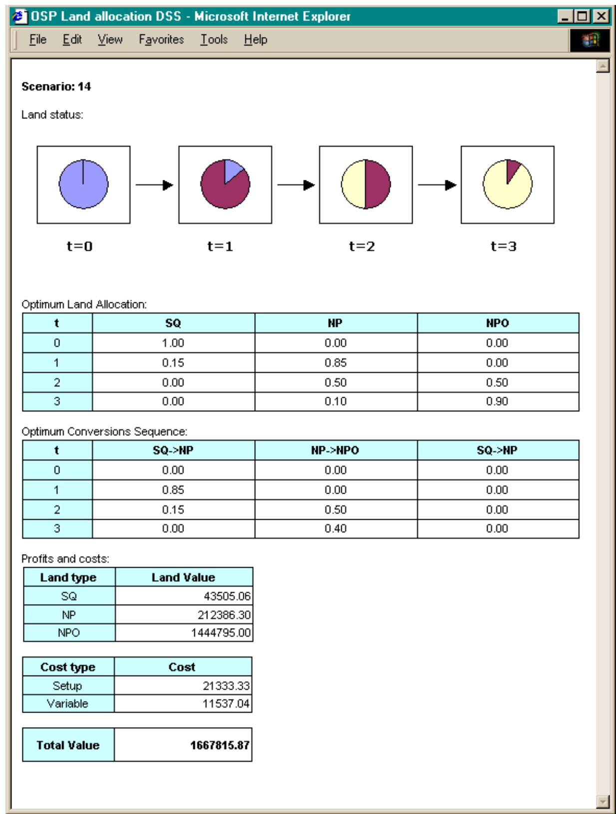


Figure 7: OSP interface prototype.

A new user interface is under currently being developed. This will enable the users to have easier access to the decision support system, without the need to understand the underlying model formulation; scenario generation features will also be accessible via web pages on OSP.



t	SQ	NP	NPO
0	1.00	0.00	0.00
1	0.15	0.85	0.00
2	0.00	0.50	0.50
3	0.00	0.10	0.90

Optimum Conversions Sequence:

t	SQ->NP	NP->NPO	SQ->NP
0	0.00	0.00	0.00
1	0.85	0.00	0.00
2	0.15	0.50	0.00
3	0.00	0.40	0.00

Profits and costs:

Land type	Land Value
SQ	43505.06
NP	212386.30
NPO	1444795.00

Cost type	Cost
Setup	21333.33
Variable	11537.04

Total Value	1667815.87

Figure 8: OSP Solution Report.

The optimum decisions and the optimal objective value to the stochastic programming model are obtained using the FortMP solver system (Ellison [10]). The solution vectors are represented in the form of a decision tree. Using our data instance, we observe that the optimal policy suggested by the model is to transform 85% of the land area into Natural Park at time period t=1. This decision provides the flexibility to convert the land into developed area at later stages, depending on the actual scenario. Figure 8 shows an example of an html solution report for a specific scenario. The decision data (solutions of the model) can also be communicated from the remote OSP decision support system to a local machine, where the decision maker can perform analysis with other specialised software tool that he or she may possess.

5 Conclusions

When dealing with environmental planning problems, one of the main goals is to compare development versus conservation opportunities trying to capture all sources of value from a private as well as a social perspective. Environmental models are often common to several classes of end users, at a national and, sometimes, global level. Pollution levels, constraints on minimum natural area size or on development of natural reserves, are generally imposed at a national level. However, data is frequently extremely case specific and should be collected and managed at a local level. Therefore, the local manager should be able to remotely communicate information concerning data specific to the problem and ask for the most suited model and a rapid and clearly comprehensible summary of the results. Inversely, in some cases, data may be very difficult and costly to be collected, but can then be exported to several domains or applications (as for example data on public good valuation). Taking into account these considerations, it becomes immediately clear that the availability of decision-making tools via an ASP model is a very valuable resource in investigating this kind of problems. In this work, we have introduced the OSP platform and a Decision Support System for a land allocation problems based on a stochastic programming model. The Appiano Gentile Park was chosen as a case study because it is emblematic of a class of problems arising in the European context of environmental management, where wilderness areas are scarce and investments in land remediation are often required. We believe that the outsourcing of such decision tools through ASP is a viable and promising approach, considering the growing acceptance and interest in OR based methods for environmental planning problems.

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