

February 28, 2003

Trish Jerman, SUI Program Manager  
c/o Room 702G, Byrnes Building  
University of South Carolina  
Columbia, SC 28208

Dear Trish,

Final report for “Decision making for complex systems under uncertainty: Application to service sector sustainability issues”.

Attached is a set of slides which record the sessions we had with staff of the Clemson Experimental Forest. The individuals were

Roy L. Hedden, Forest Resources  
Thomas J. Straka, Forest Resources  
Silas Knight Cox, Research Specialist  
Stephen E. Perry, Forest Operations Manager

The consensus of the group was that our decision methodology can make a contribution to the long term decision problems faced by the Clemson Experimental Forest.

Respectfully,

James A. Reneke  
Margaret M. Wiecek  
Imtiaz Haque

# Performance-based multicriteria decision making for service sector systems

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March 8, 2002

## Abstract

A decision-maker driven modeling and bottom-up decision making methodology is presented in the context of a service sector system performing under uncertainty. The methodology makes use of stochastic analysis and multicriteria decision making. Complete computations are included.

## 1 Introduction

A service sector system is a man-made system dependent upon other man-made systems as well as natural systems. The former includes political systems, economic systems, social and cultural systems while the latter is related to environmental or other physical conditions. Service sector systems are typically large-scale volatile systems susceptible to market shocks and discontinuities. Due to market dynamics, analysis of service systems through case studies or experiments is not useful and difficult. Service systems are frequently characterized by one-time events so that modeling based on historical data is not applicable. In general, the systems are not easily quantifiable or measurable since data is either not available or subjective or rapidly changing. Decision making in this type of system is a difficult task not only because conditions are variable and subject to change without notice, but also because decisions affect and are affected by a large number of factors, which interact with each other in complex ways. In such situations, the 'optimal' decision may be a surprising and non-intuitive solution to the problem. All unknown, unpredictable, and variable features of the system and its setting are usually reduced to the common denominator of randomness.

In the literature, randomness of the system caused by stochastic variability resulting from inherent fluctuations that the system experiences with respect to time, space, or its individual characteristics, is quantified as risk [1, 12, 13, 22]. On the other hand, randomness due to incomplete knowledge arising when a description of the system of interest cannot be presented with complete confidence because of a lack of understanding or limitation of knowledge, cannot be quantified and is referred to as uncertainty

[1, 10, 14, 22]. The main sources of uncertainty due to lack of knowledge are model, parameter, and decision uncertainty. Model uncertainty reflects, for example, oversimplification of the system model or a failure to capture its important characteristics. Parameter uncertainty is found in the process of developing a specific value for the quantity of concern (e.g., random error in direct measurements). Decision uncertainty arises when there is controversy or conflict concerning how to compare and weigh various criteria. Overall, uncertainty is defined as the inability to determine the true state of affairs of a system.

The multi-faceted complexity of service sector systems calls for the development of a comprehensive decision making methodology attractive to decision makers and resolving issues of risk and uncertainty. In the literature, efforts in this direction have already been undertaken. Some authors focus on the quantification of some properties of service systems [3, 11, 7] while others study certain types of service systems such as financial systems [6], retail systems [2], utility systems [9], school systems [18], marketing systems [8]. Service systems are also analyzed from the point of view of consumer's satisfaction [4]. An integrative risk modeling framework for complex public sector systems is proposed in [1].

We propose a modeling and decision methodology applicable to service sector systems encountered in many areas of human activity. The service system is modeled within a *performance-based* framework with multiple levels of decision making [16]. At every level the system is viewed as a network of mutually interacting tasks (components) that are expected to be performed by means of available methods. The system operates within a range of environments given by exogenous variables representing uncertainty and so the best set of methods might not be optimal for any particular environment. Understanding the tradeoffs leads to better decisions. Because of the interaction of tasks, the focus for the decision maker must be on overall enterprise performance at the top level. Some methods selected for certain tasks may have little impact on overall performance while some other methods chosen for some other tasks could have a large impact.

The paper is structured as follows. In Section 2 we give an overview of the proposed methodology. Section 3 presents a study resulting from the application of the methodology to a generic model of the service sector system. Conclusions are presented in Section 4.

## 2 Overview

The proposed methodology consists of three phases: a decision-maker driven modeling phase, a bottom-up decision phase, and an iterative risk management phase. The modeling phase is based on decision makers' knowledge, experience, and intuition. During this phase the service system is decomposed into multiple levels, each having its own decision makers and consisting of networks describing the interactions of the tasks (components) at that level [1, 19]. The relationships between system tasks are developed from the top level down. Each component at a given level is decomposed into subtasks, and the relationships between tasks are modeled as a network. At every level, the system performs in a random environment and decision makers recognize their lack of knowledge and ability to quantify the randomness. The decomposition

process stops at the lowest level at which a decision maker is willing and able to quantify the randomness of task (component) performance by choosing computational models of methods performing the tasks. Computational models are based on a theory of stochastic linearization of random surfaces recently developed by one of the authors [15].

The decision phase starts at the lowest level with the selection of the methods performing the tasks of this level. Selected methods are passed to the higher level, where they are combined to form alternative methods for performing that level's tasks. These, in turn, are passed up to the next higher level. At the top (enterprise) level, a decision maker chooses a most desirable method from among alternatives passed up. At each level, multicriteria optimization is used to resolve decision makers' uncertainty (unquantified randomness) and identify methods that are near optimal over the range of operating conditions.

The modeling and decision phase are complementary in the sense that the process constructs conceptual models working from the top level to the bottom level and evaluates the impact of proposed methods using computational models from the bottom level to the top level. Both phases however aim at reducing the risk of system performance subject to budget constraints. Methods with higher performance risk are likely to be less costly and be selected at particular levels.

In the risk management phase, methods are evaluated in terms of their performance in noisy environments and the contribution of task risk to enterprise risk.

The methodology was originally proposed in [16] in the context of upgrades of complex systems and later applied to a specific decision making problem [17]. The goal of this paper is the application of the methodology to service sector systems viewed as complex systems that lend themselves to the multilevel performance-based approach in which modeling is done by decision maker and for decision making.

## 3 Application to a Service Sector System

We present a model of a service sector decision problem in the context of the proposed methodology. The model closely examines the decision process conducted by a company when choosing an appropriate method for providing customer service in an overseas market (compare with [8]).

### 3.1 Conceptual modeling

When choosing a method for providing customer service the performance of the method must be evaluated for a variety of environments. For simplicity, we consider only two environmental variables, the size of the potential market  $u$  and company's market share  $v$ , i.e., share of total sales. The individual choosing the method has no control over the environmental variables. Hence a choice of method must be related to a performance function depending on  $u$  and  $v$ . Clearly, every choice of method will not perform equally well for all  $u$  and  $v$ . One might expect that some methods are best for certain ranges of values for  $u$  and  $v$  while being far from best for other values. Values for the variables  $u$  and  $v$  vary within ranges and model uncertainty for the decision process. In this example we choose  $1 \leq u \leq 10$  and  $0 \leq v \leq 1$ .

We emphasize that one could develop, at least in theory, a class of detailed models on which the decision process would be based. The models might attempt to capture the local business climate, customer attitudes, financial risk, etc.. Instead we propose to capture the decision maker's experience and intuition of system inputs in a class of input functions and then develop system models as linear transformations of these inputs.

The service delivery decision can be viewed as a series of subdecisions made at two levels. The top level is referred to as the master level. All of the decisions in this example would be made by a single individual or small group at a high executive level. However, the master level decision is different from that of a lower level and therefore we will speak of the master level decision maker and lower level decision makers to allow for other contexts.

The master level decision maker first chooses the environmental variables ( $u$  and  $v$ ), models the input and output functions for the decision, and establishes the overall decision goal.

The input/output functions are defined over a range of environmental variables. We choose an input function  $f = f(u, v)$  to measure customer demand generated outside the system. Customer demand is a function of the size of the potential market and the company's market share. The output for the system resulting from method choices is a measure of customer dissatisfaction  $h = h(u, v)$ . In this example  $f(u, v) = uv$ .

The overall decision goal is to choose a method of providing customer service minimizing customer dissatisfaction within constraints of cost and profitability over the entire range of environmental variables  $u$  and  $v$ .

Planning for a range of environments creates conflicting goals, i.e., a method which does well over the prospective range of potential market size might not do so well over the anticipated range of market share. Resolving these conflicts is best left until the end when the tradeoffs can be identified.

At this point the master level decision maker decomposes the decision into interacting subdecisions. Figure 1 illustrates one possible decomposition. The network is composed of subtasks for providing customer service with appropriate inputs and outputs as follows: "help me" service (HS) with customer demand as input and unmet customer expectations as output, service management (SM) with unmet customer expectations as input and customer dissatisfaction as output, "fix it" service (FX) with customer dissatisfaction as input and increase in customer demand as output, and value added (VA) with customer dissatisfaction as input and increase in customer demand as output.

While the master level represents the entire decision process, the subtasks could be viewed individually and independently at the lower level, see again Figure 1. Possibilities for decomposing the subtasks with additional environmental variables in parenthesis are as follows: "Help me" service (company's profitability) can be modeled as a network of three subtasks: sales and marketing, R&D for special needs/applications, and consulting support. "Fix it" service (customer tolerance for down time) can be decomposed into repair response teams/parts, training for customer maintenance workers, and support for customer maintenance including repair manuals, diagnostic tools, etc.. Value added (company overhead) can be modeled as a network of performance evaluation of existing installations, add-ons or modifications of existing applications, and design services for new installations or upgrades. Finally, service management

(size of customer base) can be decomposed into responding to customer inputs, service quality measurement and management, and the subtask of customer data collection, management, and mining.

In this paper we will not model the decomposition of the subtasks and assume that level one is the lowest level of the model. However, we can use the subsubtasks to guide our choices for computational models of the subtasks.

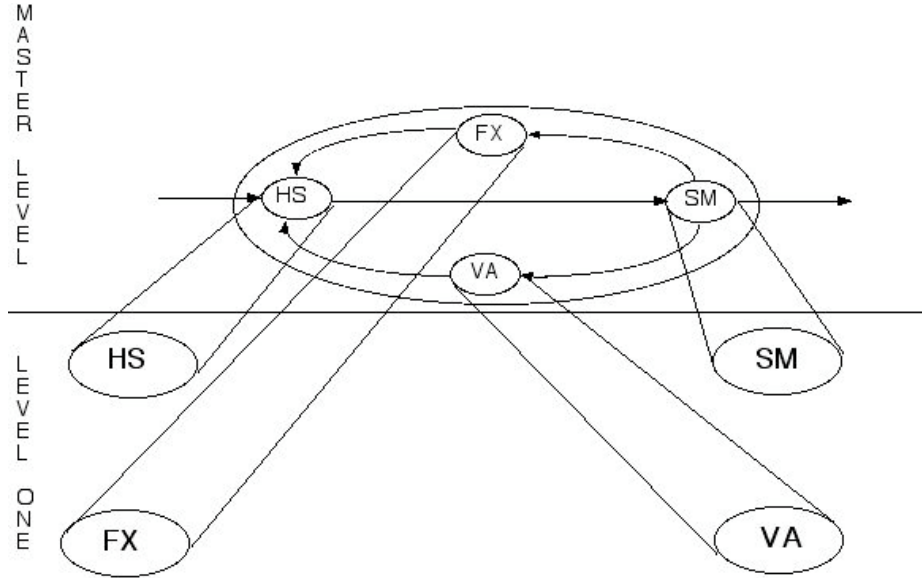


Figure 1: Two level decision process.

### 3.2 Computational models

For each subtask of the master level task the decision maker has the following alternative submethods: (i) use independent agents to provide the services, (ii) use in house service providers at a company service center, (iii) use a combination of in house service providers and outside sourcing managed by a company service center.

Computational models for the submethods allow to combine their effects on the overall task of providing customer support. In general, a network of independent agents is the low cost feasible solution which wins under some conditions of potential market and market share. Everything in house at a company service center is the high cost feasible solution which wins under other conditions of potential market and market share. Modeling attempts to illuminate the tradeoffs in the intermediate area.

The computational models are based on the theory of stochastic linearization [15], a recent development of representations of random surfaces in terms of factorizations of surface covariances. To the authors' knowledge, it is a novel approach to the representation of random surfaces. It offers computational simplicity and enables one to 'shape' the covariance of a random surface. In spite of the abstract mathematical basis of the theory of stochastic linearization, there is a simple algorithm for producing computational models of random surfaces.

The authors bring this new insight into the area of decision making under uncertainty for service sector systems. In the proposed methodology, submethods are

represented as linear operators on functions of environmental variables. The decision maker is expected to choose the computational models for the lowest level components (sub methods) which captures the decision maker's knowledge of the simplest components of the entire system. These models are then combined algebraically to obtain the upper level computational models. In essence, the algorithm requires the decision maker to place confidence bounds on a lowest level methods' performances. This simple act quantifies the randomness of a method's performance (defines the risk in employing the method) and leads to a linear operator representation of the method.

The reciprocal relationship of risk and performance, high risk/low performance, suggests an immediate iterative algorithm for lowering risk or improving performance which constitutes the risk analysis phase of the methodology. We stimulate the enterprise with a Wiener field (the input) and observe the response. (This is done computationally and only involves matrix multiplies.) If the response has too much variation (risk) then we identify the submethod which contributes the most to the variation and eliminate it as an alternative choice. After optimizing using the reduced set of alternatives, we repeat the process. High risk methods are associated with low cost (as well as low performance). Hence the iteration may stop because of budgetary constraints before we reach a lowest risk solution.

The risk analysis phase has not been performed for the service system model presented in this paper. In [16], the risk analysis phase has been completed and helped identify the cheaper and more risky components (methods) with the least effect on risk of the overall system.

### 3.3 Decision making

The decision making process involves the task of finding a preferred method for providing customer service in an overseas market. The preferred method performance is expected to be at its best over the entire domain of environmental variables of interest.

In order to accomplish this task, efficient submethods are generated at the lower level and passed to the higher (master) level. Once a set of efficient methods is produced at the master level, this level's decision maker chooses a preferred method from among the efficient methods which becomes the optimal method for the problem and concludes the decision making process. Efficiency of a method depends on its quality gauged by the method performance that is not available in a closed form but rather in the form a response surface determined by the values achieved at some preselected grid points in the domain of environmental variables. Typically, there is no single response surface representing the best method performance but rather a set of response surfaces competing with each other over that domain.

A surface  $S_i$  associated with a method  $m_i$  is said to dominate a surface  $S_k$  associated with a method  $m_k$  if at each grid point the value of  $S_i$  is not bigger than that of  $S_k$  and the value of  $S_i$  is smaller than that of  $S_k$  at at least one grid point. Thus, nondominated surfaces are those for which every other surface associated with a feasible method yields an inferior value at one or more grid points. The methods associated with each nondominated surface are called efficient.

The process of finding efficient methods (or nondominated surfaces) can be viewed as a process of generating efficient (nondominated) solutions of a multiple criteria optimization problem in which the grid points become the criteria with respect to

which the method performance is optimized. The decision maker is to choose a method that would be as good as possible across all the criteria. As the criteria are multiple and conflicting, there is no single method optimizing all the criteria simultaneously but a set of efficient methods. Once the efficient solutions are found at the master level, a decision has to be made by the master decision maker on the choice of a preferred solution.

In this context, the service sector problem follows upon two stages of multiple criteria decision making (MCDM): the optimization stage during which efficient solutions are found, and the decision stage during which a preferred efficient solution is selected. However, the service sector problem does not result in a typical MCDM problem in which efficient solutions are found with respect to several (typically less than 10) criterion functions. The service sector problem has a large number of grid points so that the resulting problem has a large number of criteria.

**Generating candidate methods.** According to the model, we allow all three methods to be feasible submethods for every subtask. Additionally we assume that the three submethods are also efficient for every subtask, which would produce a large number of feasible methods (81) for the master level task. However, for this particular application we deal with the following feasibility constraint at the master level: a method is feasible at the master level if it is composed of the same efficient submethod for every subtask at the lower level. The constraint results from the fact that it would not be of interest to the company to perform the subtasks by means of different submethods. Only the same submethod applied to every subtask can be considered. Consequently, there are three feasible methods for the master level task: independent agents, service center, and the combination, and each of the methods is composed of the same submethod for every subtask. The system responses are then generated for the three feasible methods at the master level. All these three methods remain efficient at the master level and become candidate methods from which a preferred method will be selected, which will conclude the decision making phase. Figure 2 depicts their nondominated response surfaces. Note in this figure the surfaces are computed at grid points given by the size of the potential market and company's market share.

**Choosing a preferred method.** The process of choosing a preferred method can be performed in many different ways due to incomplete preference information provided by the optimization problem at the master level and the resulting need to introduce additional information to resolve the selection process. In this study we present three approaches: graphical analysis, ranking, and ranking versus cost.

**Graphical analysis.** The decision maker may choose a preferred efficient method comparing the performance of the nondominated surfaces and checking on the regions of the exogenous environment within which each method works best. Figure 3 shows that while a service center minimizes customer dissatisfaction in a majority of the operating environment, the combination method and the method of independent agents yield the best system performance for small and middle sizes of the potential market, respectively. The decision maker might choose to run a service center as the preferred method for the company.

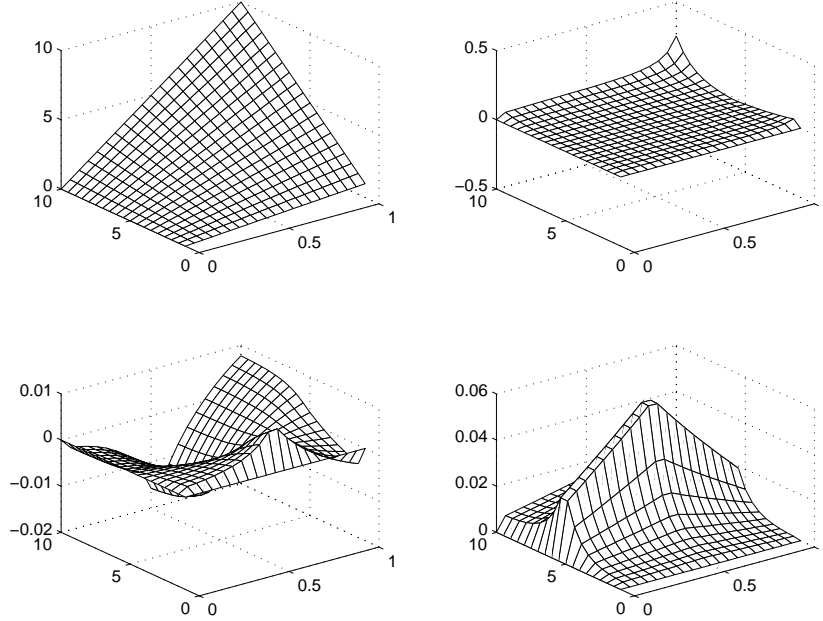


Figure 2: Input and outputs for the three efficient methods. In the first row, we have the input function and the system response to the independent agents method. In the second row, we have the system response to the service center method and the system response to the combination method.

**Ranking nondominated surfaces.** If the target is to minimize customer dissatisfaction, then we can construct the reference surface as follows: At every grid point we find an optimal surface that yields the best system performance, i.e., the smallest customer dissatisfaction. We form a collection of these optimal surfaces and then define a utopia surface as the lower envelope of all the surfaces in the collection (which is made of the portions of the nondominated surfaces visible from 'below'). The utopia surface might not be a response surface but represents ideal system performance over the entire domain of exogenous variables.

We now choose a preferred nondominated surface as the one that is the closest to the reference surface where a norm of choice measures the distance between the surfaces in the multidimensional space of grid points.

In addition to variations in the probability of encountering certain operating conditions, the decision maker may make judgments regarding the importance of achieving optimal performance under such conditions. For example, there may be a rare combination of operating conditions under which optimal system performance is critical. These judgments can be captured by eliciting from the decision maker weights associated with the grid points (or with regions, as above). Larger weights penalize poor performance at those points. Note that the definition of the norm can be extended to treat over-performance and under-performance asymmetrically if appropriate.

In the example, we consider the surface passing through performance level 0 at each grid point to be the reference surface. We choose a preferred nondominated surface as the one that is the closest to this reference surface, where the Tchebycheff norm is the norm of choice [20, 21].

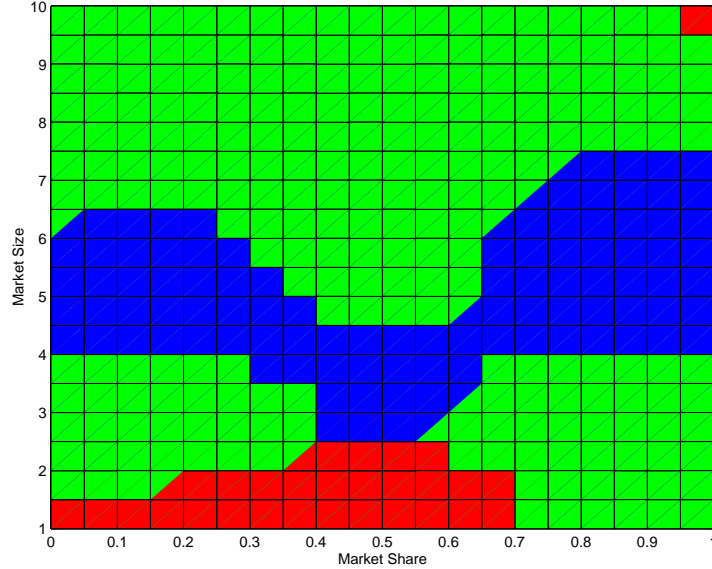


Figure 3: Regions in the space of environmental variables where each of the three efficient methods works best. The black, light gray, and gray areas represent the regions where the independent agents method, the service center method, and the combination method works best respectively.

Table 1 lists the distance of each nondominated surface to the reference surface in column two. It can be seen that the surface with the most desirable distance is the one when the company runs a service center and the decision maker might choose this method as the preferred method for performing the master level task.

**Ranking versus cost.** An alternative approach is to compute for every non-dominated surface its distance from the reference surface and the cost of the efficient method producing this surface. The distance and cost can be treated as two criteria in a bicriteria optimization problem, where nondominated surfaces (based on grid points) are to be compared based on value and implementation cost. The solutions to this higher-order decision problem are nondominated in the sense that any decrease in distance from the reference surface comes at the expense of an increase in cost and any decrease in cost is accompanied by an increase in distance. Identifying such solutions can be accomplished using weighted Tchebycheff norms or other techniques for bicriteria optimization. Table 1 lists the costs for every nondominated surface in column three.

Method	Distance	Cost
Independent Agents	0.2489	1
Service Center	0.0204	1.25
Combination	0.0670	1.11

Table 1: Distance to reference surface and cost for nondominated surfaces.

When the distance and cost are treated as two criteria to be minimized simultane-

ously, all three nondominated surfaces at the master level again remain nondominated with respect to these two criteria. Running a company service center offers the best system performance but turns out to be the most expensive, in fact 25% more expensive than the method of independent agents being the least expensive and having the weakest performance. The decision maker might choose the combination method that offers significant savings and performance close to that of the service center.

## 4 Conclusions

Service sector decision makers currently rely on their knowledge, experience, and intuition to produce 'gut' decisions. There is a clear preference for this *modus operandi* to decisions based on 'detailed' models using estimates and guesses of obscure or even unknowable physical quantities. Detailed predictive models of the type used, for example, in engineering design, when applied in service sector decisions would require many variables to model significant influences on performance and, consequently, would require lots of data. In the service sector, characterized by a requirement for prompt decisions and one of a kind situations, the construction of detailed models would be too slow and too expensive. Finally, fast paced service sector dynamics usually preclude the use of detailed models.

In our decision methodology the conceptual model at each level is based on the lower level decision makers' knowledge, experience, and intuition. The previous level decision maker's uncertainty is modeled by the environmental variables appropriate to that level and decision maker's knowledge is modeled by the input function that is passed down.

At the lowest level computational models are constructed by quantifying the randomness of method performance. In this act, the decision maker is placing limits on what is knowable of method performance and defining the risk associated with that particular method. Our approach simplifies the quantification process by limiting the decision maker to a choice of a computational model (a pair of increasing functions by shape and a pair of positive constants). Efficient choices are passed up and plugged into the conceptual model at the next higher level to produce a computational model at that level. The computational models are decision models, i.e., models which incorporate both the decision maker's knowledge and lack of knowledge.

Both uncertainty and risk are incorporated in the proposed methodology. While the choice of the computational model on the lowest level is an effort to quantify randomness, the uncertainty is resolved at each level with multicriteria optimization. The global risk information is contained in the response surfaces of the overall system while the partial risk information is available through such surfaces at every level.

The presented model of a service system is preliminary and therefore simplified. The three submethods that are efficient for every subtask at the lower level remain the efficient methods at the master level. The example does not show the details of passing up efficient methods and introducing them into the higher level model. The final iterative phase of risk management is under development and will be included in the future. Furthermore, we plan to investigate more sophisticated approaches to choosing a final preferred method.

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Roy L. Hedden, Forest Resources

Thomas J. Straka, Forest Resources

Silas Knight Cox, Research Specialist

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The consensus of the group was that our decision methodology can make a contribution to the long term decision problems faced by the Clemson Experimental Forest.

# A Marketing Decision Model for the Clemson Forest

January 10, 2003

## Modeling and Decision Making

- Modeling
  - Network of tasks
  - Uncertainties
  - Inputs
  - Methods for every task
- Decision making
  - Choosing a best method for every task

## Major Uncertainties

- Bidder response

Decisions are heavily influenced by bidder considerations, i.e., the decision makers try to make the offerings attractive to bidders by increasing tract size, eliminating isolated parcels, etc.

- Smaller bidders increase decision maker alternatives.
- $0 \leq u \leq 1$ : bidder consolidation

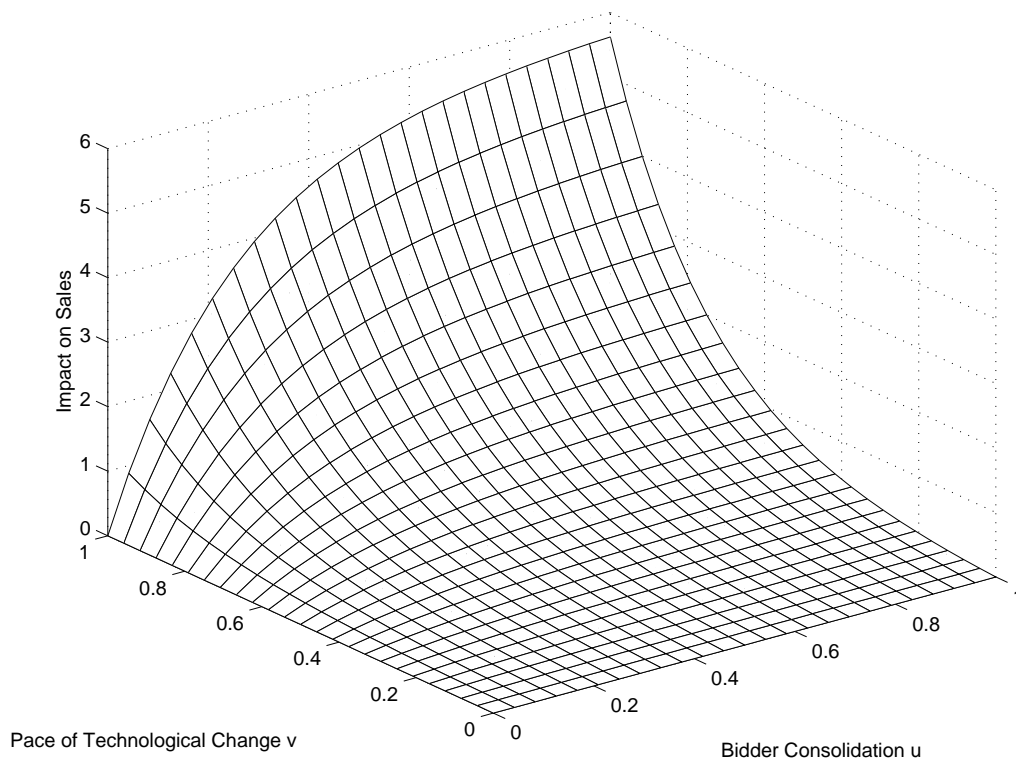
## More on Major Uncertainties

- Emerging technologies
  - Wood/fiber utilization (affects demand)
  - Harvesting technologies (affects tract size, etc.)
  - Proximity of ultimate use (affects competitive position of Clemson Forest)
  - $0 \leq v \leq 1$ : pace of change forced by emerging technologies

## Inputs

- $f_1(u)$ : impact of bark beetle infestations
- $f_2(v)$ : impact of tract size in sales offerings
- $f(u, v) = f_1(u) \cdot f_2(v)$

## Possible Input $f(u, v)$

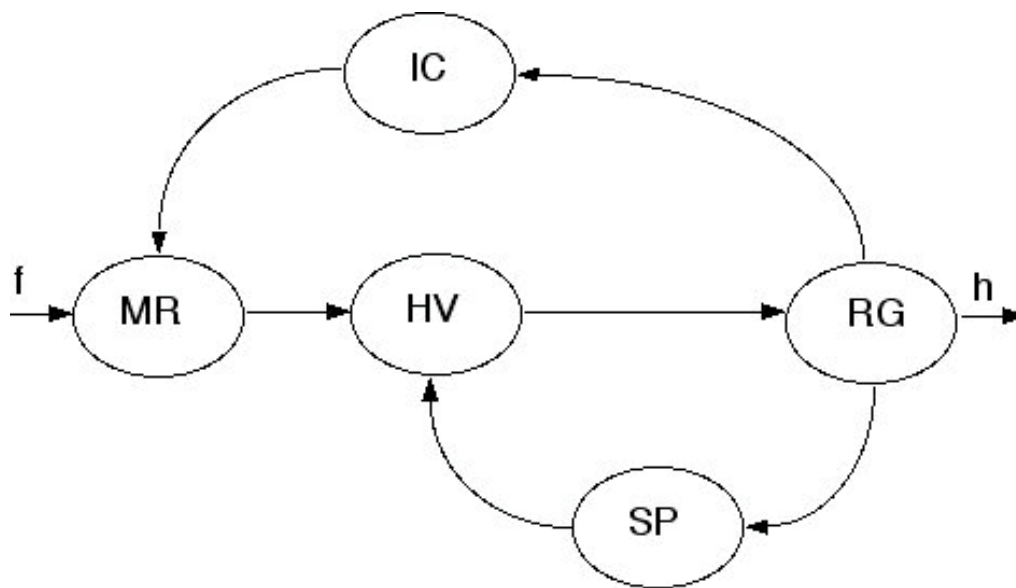


The functions  $f_1(u)$  and  $f_2(v)$  were chosen to illustrate the theory. The function  $f(u, v) = f_1(u) \cdot f_2(v)$  has average value 1.

What are the major tasks?

- Harvesting (HV)
- Regeneration (RG)
- Site preparation (SP)
- Intermediate cuttings (IC)
- Marketing (MR)

## Market Model

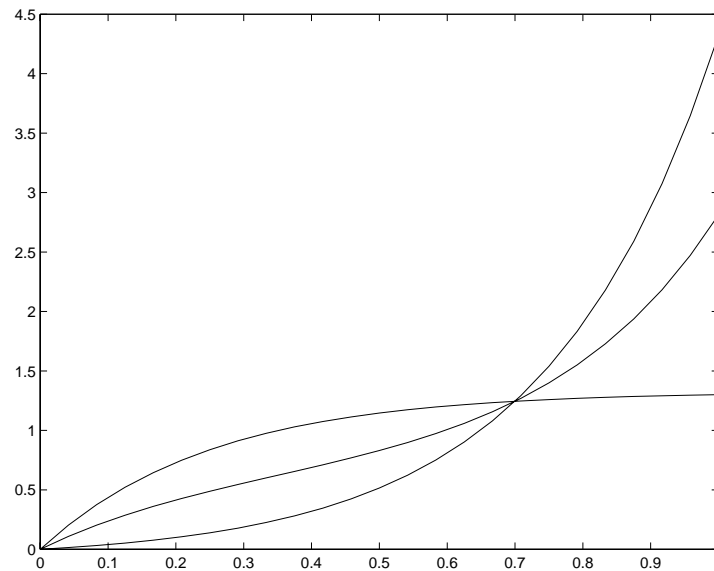


The input function  $f$  represents the negative impact of beetle infestation and large tracts in sales offerings on sales. The output function  $h$  represents the residual impact. The decision goal is the reduction of the residual impact.

## Alternative Methods for Marketing (MR)

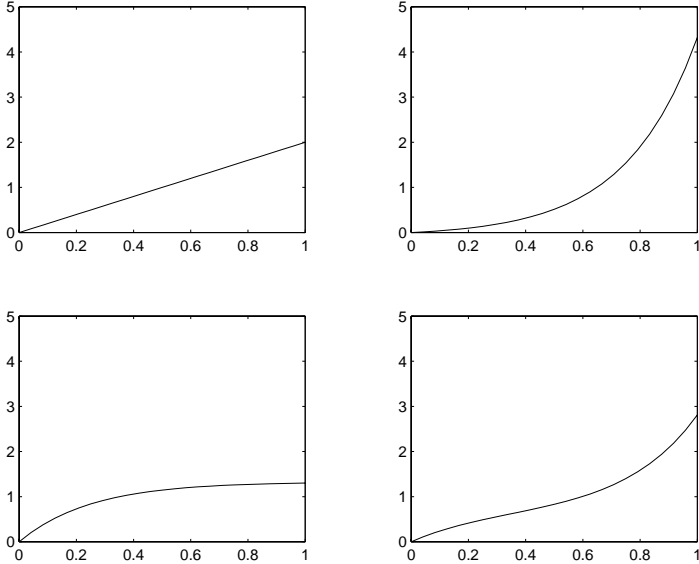
- Historical: Three small offerings (400/400/200)
- Current: One large offering and one small offering (800/200)
- Future: One very large offering (1000)

## Risks for Alternative Methods



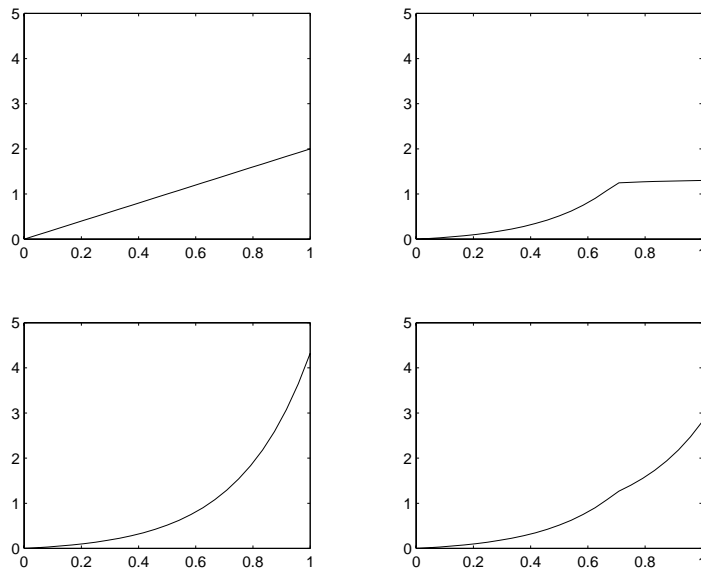
Computational models for methods are constructed from the assumed risks which are functions of either  $u$  or  $v$ .

# Risks for Alternative Methods for MR as functions of bidder consolidation $u$



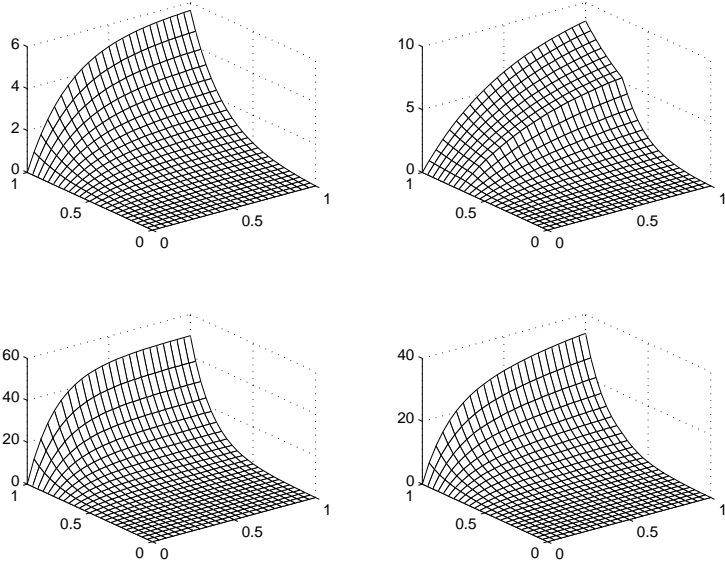
Starting in the upper lefthand corner and proceeding clockwise, the risk for the null case, Historical (low/high), Current (medium/medium), and Future (high/low).

# Risks for Alternative Methods for MR as functions of the pace of technological change $v$



Starting in the upper lefthand corner and proceeding clockwise, the risk for the null case, Historical (low/low), Current (low/medium), and Future (low/high).

# Responses for Alternative Methods for MR



Starting in the upper lefthand corner and proceeding clockwise, the input and the response of each of the three alternative methods for MR.

Alternative Methods for Harvesting (HV) with  
risk a function of  $v$

- Clear cut (low/high)
- All pines/hardwoods (medium/medium)
- Selected trees (high/low)

Alternative Methods for Regeneration (RG)  
with risk a function of  $u$

- Planting (high/low)
- Seed tree (medium/medium)
- Shelter seed tree (high/low)

## Alternative Methods for Site Preparation (SP) with risk a function of $v$

- Minimal (low/high)
- Medium (medium/medium)
- Intensive (high/low)

## Alternative Methods for Intermediate Cuttings (IC) with risk a function of $u$

- Once (low/high)
- Twice (medium/medium)
- Three times (high/low)

## Using response surfaces

- A response surface represents the performance of a method or system.
- Response surfaces offer the possibility of
  - Comparing various combinations of methods in a system.
  - Choosing an “optimal” combination of methods.
  - Analyzing tradeoffs between “good” methods when no optimal method exists.

## Optimal Solution for Historical Marketing Strategy

- Harvesting (*HV*): Selected trees (high/low)
- Regeneration (*RG*): Planting (high/low)
- Site preparation (*SP*): Minimal intensity (low/high)
- Intermediate cutting (*IC*): Twice (medium/medium)

## Comparing Marketing Strategies

- For each marketing strategy an optimal selection of methods for the other tasks was found.
- The response surfaces for the three systems were compared.
- The percentages of scenarios where each selection excelled was computed.
- The results are summarized in the following table.

## Comparison of Marketing Strategies

Strategy	Risk	Percentages
Current	m/m & l/m	(70.08, 0)*
Future	h/l & l/h	(22.08, 0)
Historical	l/h & l/l	(92.16, 92.16)

\* % of scenarios in which the current strategy is better than the future or historical strategies.

- $l$  = low
- $m$  = medium
- $h$  = high