Decision Sciences

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Abstract
This entry provides a description of the vast area of decision sciences from an operations research/management science (OR/MS) perspective. This means that the focus is on how quantitative models can be used for improving the quality of decisions. After describing and explaining a general conceptual approach to quantitative decision modeling, some important, commonly used decision models and methods are considered in more detail. The list includes both deterministic models such as linear programming (LP), integer programming (IP), and economic lot sizing, as well as stochastic models for safety stock decisions in inventory management. Various generalizations are also discussed together with brief comments and references to other important decision modeling approaches such as game theory, multiple criteria decision making (MCDM), queuing, and simulation.

INTRODUCTION
“Decision sciences” represents a broad area of research with a common focus on advancing the understanding of decision-making processes and improving the quality of decisions, organizational as well as individual. Essentially all types of decisions fall within the realms of the field, but an emphasis is placed on various types of business-related decisions or decisions with an economic dimension. From a methodological perspective, the field contains both behavioral and quantitative modeling research. The former is often closely related to organization theory and psychology, while the latter to a large extent is synonymous with operations research/management sciences (OR/MS), and closely relates to economics, applied mathematics, and statistics. In this entry we restrict our attention to the quantitative modeling (OR/MS) area of decision sciences. The motivation is twofold: first of all, it is arguably the largest area; second, this is where our own backgrounds lie as authors.

Decision sciences research from an OR/MS perspective is usually concerned with improving the quality of decisions. This is done by describing the decision problem in a quantitative model of the real system, then use this model to generate decision alternatives and choose the best among these candidate solutions. The challenges are to model the dynamics and constraints of the underlying system with an appropriate level of detail, and to determine what criteria should be used in assessing what is the best decision. After some reflection most people find this structure intuitively appealing because it fits well with how they make their own decisions (if they are forced to dissect the situation). A set of constraints limits the choices you have and defines the possible alternatives. You then choose between these feasible alternatives according to some objective function that reflects what your goal is with the decision. In the section on “Examples of Common Decision Models and Applications,” we will look at several classical models and methods that illustrate variations of this basic model structure. For the remainder of this section, we will take a closer look at the general approach for quantitative decision modeling sketched above. We will then reflect on the past development, and the future opportunities and challenges of the field.

The general approach when using quantitative models is illustrated in Fig. 1. The goal is to find good decisions for some real system. This is very difficult in many situations. Therefore we can choose to replace the real system by a quantitative model. The model seldom provides a complete description of reality; instead it serves as an approximate, simplified version of the real system. However, an advantage is that the quantitative model quite often can be optimized, that is, we can find the best decisions for the simplified version of the real system. In some cases we cannot find the optimal decisions but still some good ones, for example, by using simulation to evaluate some reasonable alternatives. Because the quantitative model does not take all aspects of the real system into account, decisions that are optimal for the model may not be optimal for the real system. However, presuming the model is a valid description of reality, it should capture the essence of the real system at an appropriate level of detail. Decisions obtained from a validated model can be expected to work well also for the real system. Thus if the model is valid, the model decisions can be implemented in the
real system with good results. It is often quite difficult to design the quantitative model at the right level of detail. If the model is too simple, it may provide a poor approximation of the real system (i.e., the model has poor validity), and it may be dangerous to use the model as a basis for generating decisions to be implemented in the real system. On the other hand, if the quantitative model is too complex it may be too difficult to analyze. Thus, it becomes quite useless as a tool for helping the decision maker to make better decisions.

The approach to use quantitative models to analyze and describe reality is a cornerstone in modern science and dates back to the dawn of our civilization. However, the birth of the OR/MS field, with its focus on modeling complex decisions, is often attributed to military activities during World War II. The war effort induced an urgent need to make vital decisions about allocation of scarce resources at a scale never seen before. The United States and British military services turned to a large number of mathematicians and other scientists to do research on these decision problems, and to develop scientific methods to help solve them. After the war, the success of these efforts spurred an interest to apply the same approaches to decisions in industry and business. The dissemination was fueled by the fast industrial development following the war, and the fact that many consultants and industry people had come in contact with OR/MS methods during their military service. The fast growth of the OR/MS research field after World War II can also be attributed to the groundbreaking research achievements in OR/MS techniques that attracted talented people into the new field. A stellar example is the Simplex method for solving LP problems, originating with George B. Dantzig in 1947, see Dantzig.[1] Other important areas where much progress was done early on were dynamic programming, queuing theory, and inventory theory.

Since the early days in the 1940s, the progress of the OR/MS field of decision sciences has been closely connected to the development of the computer and information technology. The revolution in computational power due to the emergence of the digital computer, and later on the emergence of the personal computer, has made it possible to model and solve increasingly complex decision problems. Another important enabler for the development of the field is the tremendous advances in information technology, not least in the present years. Access to an almost infinite amount of information at the press of a button, propels the opportunities for quantitative models to help decision makers evaluate information and decision alternatives. Hence, the need for quantitative decision models, embedded in user-friendly decision support systems, continues to increase as the tideway of information keeps overwhelming the decision makers. From a research perspective, easy access to new and more detailed information in combination with increased computational power creates new interesting challenges and promises an interesting future for the OR/MS area of decision sciences.

Important professional associations, which among other things host some of the most influential conferences and journals in the field, include INFORMS (http://www.informs.org), Decision Sciences Institute (http://www.decisionsciences.org), and EURO (http://www.euro-online.org).

EXAMPLES OF COMMON DECISION MODELS AND APPLICATIONS

In this section we will look closer at some commonly used quantitative decision models. The ambition is to illustrate how the general model building approach discussed above can be applied in different contexts. The models chosen are classical examples but represent a small sample of the entire field, and should not be construed as an exhaustive representation. For specific examples of OR/MS decision models applied in the library and information sciences area we refer to Kraft and Boyce.\[2\]

Deterministic Models

A deterministic model is characterized by the absence of randomness, meaning that all input values are known with certainty (i.e., correspond to a single outcome with probability 1). A model that incorporates randomness belongs to the class of stochastic models (see the section on “Stochastic Models”). To exemplify, consider a decision where the customer demand during next week is an important input parameter. If the demand is known to be 50 units, it is deterministic. If there is a probability of 0.5 that the demand will be 25 and a probability of 0.5 that it will be 75, the demand is stochastic (or random) with a mean of 50. The advantage of deterministic models over stochastic ones is that they are generally easier to solve, thus, larger problems may be dealt with. Clearly, in most real systems there is some uncertainty present. However, in many situations this uncertainty may be low enough for a deterministic model to be an appropriate approximation. In other situations, the
inherent uncertainty may be critical for the decision and must be incorporated into the model; the choice should then fall on a stochastic model.

In this section we will consider three types of deterministic models: LP models, integer programming (IP) models, and the economic lot sizing model. Examples of stochastic models are found in the “Stochastic Models” section.

**LP models**

Linear programming is perhaps the most well known and most widely used decision sciences method to date. It was originally developed by George Dantzig in late 1940s, who proposed the so-called Simplex method for solving large-scale general linear programs. As the name suggests, an LP model is restricted to linear relationships between the decision variables. Programming is, in this case, synonymous with planning, thus LP can be thought of as linear planning.

Generally speaking, an LP model consists of a linear objective function to be maximized or minimized, and a set of linear constraints that limit the decision alternatives. The objective function is a linear equation of the involved decision variables and should reflect how the decision variables impact the overall decision objective. The constraints are also linear equations of the decision variables, describing logical relationships between these variables and how they consume various types of limited resources. Because of its flexibility, the LP approach has been applied to almost any decision situation conceivable, including production planning, scheduling of personnel, investment planning, marketing, logistics, supply chain management, military strategy and tactics, agricultural planning, etc. The most common type of LP application concerns decision problems of allocating limited resources to a number of competing activities in the best possible way (as defined by the objective function). To make the discussion more concrete consider the following example of a classic product mix decision problem.

A production manager who wants to maximize profits is faced with the decision problem of how much to produce of two products A and B during the upcoming planning period. The production process involves three different machines (resources). The times (resource units) to produce a batch of product A and B, respectively, in each of the machines are specified in Table 1. One can also find the available capacity for each of the machines there, and the profit associated with each batch of product A and B sold. Demand is high so we can assume that everything that is produced can also be sold. A restriction is that previous order commitments require that at least 20 batches of product B are produced.

To formulate this decision problem as an LP, the first step is to define the decision variables, which in this case are the amounts of products A and B to be produced.

\[
\begin{align*}
X_A &= \text{number of batches to produce product A} \\
X_B &= \text{number of batches to produce product B}
\end{align*}
\]

Given these decision variables, the goal to maximize total profits (\(Z\)) translates into the objective function:

\[
\text{Max } Z = 1500X_A + 2000X_B.
\]

Turning to the constraints that limit the amount of product A and B that can be produced, the capacity constraints for resource 1, 2, and 3 can be expressed mathematically as:

1. \(3X_A \leq 150\) (limited capacity in resource 1)
2. \(X_A + 2X_B \leq 140\) (limited capacity in resource 2)
3. \(2X_A + 2X_B \leq 160\) (limited capacity in resource 3)

Similarly, the constraint that at least 20 batches of product B must be produced can be expressed as:

4. \(X_B \geq 20\) (produce at least 20 batches of product B)

Adding the non-negativity constraints, \(X_A \geq 0\) and \(X_B \geq 0\) (assuring that the model solution does not suggest negative production) renders the complete LP model of the product mix problem

\[
\text{Max } Z = 1500X_A + 2000X_B \text{ (maximize total profits)}
\]

Subject to

\[
\begin{align*}
(1) & \quad 3X_A \leq 150 \quad (\text{limited capacity in resource 1}) \\
(2) & \quad X_A + 2X_B \leq 140 \quad (\text{limited capacity in resource 2}) \\
(3) & \quad 2X_A + 2X_B \leq 160 \quad (\text{limited capacity in resource 3}) \\
(4) & \quad X_B \geq 20 \quad (\text{produce at least 20 batches of product B}) \\
(5) & \quad X_A, X_B \geq 0 \quad (\text{non – negativity constraint})
\end{align*}
\]

Note that due to constraint (\(4)\)), the constraint \(X_B \geq 0\) is redundant in this formulation and it is included solely for reasons of completeness.

**Table 1**  Input data for the product mix example

<table>
<thead>
<tr>
<th>Resource</th>
<th>Product A</th>
<th>Product B</th>
<th>Available capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3 hr</td>
<td>-</td>
<td>150 hr</td>
</tr>
<tr>
<td>2</td>
<td>1 hr</td>
<td>2 hr</td>
<td>140 hr</td>
</tr>
<tr>
<td>3</td>
<td>2 hr</td>
<td>2 hr</td>
<td>160 hr</td>
</tr>
</tbody>
</table>

Profit per batch

\[
\begin{align*}
\text{Resource} & \quad \text{Product A} & \quad \text{Product B} & \quad \text{Available capacity} \\
1 & \quad \$1500 & \quad - & \quad 150 \text{ hr} \\
2 & \quad - & \quad 2000 & \quad 140 \text{ hr} \\
3 & \quad - & \quad - & \quad 160 \text{ hr}
\end{align*}
\]
After formulating the decision model, the challenge is to solve it and determine the optimal decisions. For the present example with only two decision variables the problem can be solved graphically as illustrated in Fig. 2.

Scrutinizing the graphical representation in Fig. 2, the bold lines labeled (1)–(4) correspond to constraints (1)–(4) above when satisfied to equality. The gray shaded area corresponds to the feasible region, where all the constraints are satisfied (including the nonnegativity constraint $X_A \geq 0$). The optimal decision must satisfy all the constraints, hence the feasible region defines all decision alternatives of interest. The optimal solution is the feasible solution that maximizes the objective function. The dashed line in Fig. 2 represents the slope (or level) of the objective function, $Z = 1500X_A + 2000X_B$. To maximize $Z$, we increase $X_A$ and $X_B$, which corresponds to parallel-shifting the dashed line in the directions of the arrows depicted in Fig. 2 (mathematically the arrows represent the gradient to the objective function). The optimal solution is the last point on the dashed line which belongs to the feasible region. From Fig. 2 we can see that this corresponds to the corner point of the feasible region where constraint (2) and (3) intersect. Solving the linear equation system defined by constraints (2) and (3) (or by inspecting the graph), the optimal solution $X_A^* = 20$, $X_B^* = 60$ is found. The corresponding objective function value is $Z^* = 150,000$.

Hence, the optimal decision obtained from the LP model is to produce 20 batches of product A and 60 batches of product B, which renders a total profit of $150,000.

Clearly, LP problems of practical interest are considerably larger than the small example studied here (often including thousands or even millions of variables and constraints), which prohibits a graphical solution technique. Instead, these large-scale problems can be solved using, for example, an efficient algebraic technique called the Simplex method. This method utilizes the fact that an optimal solution to an LP problem is always found in a corner point to the feasible region (a consequence of the linearity of all equations). In principle, the method searches through the set of feasible corner point solutions in a structured fashion until a set of optimality conditions are fulfilled, and the optimal solution is found. More details about the Simplex method and other aspects of LP, such as duality and sensitivity analysis can be found in basic OR/MS textbooks such as Hillier and Lieberman. For more theoretical treatment of the subject one can turn to books like Dantzig and Vanderbei.

### IP models

One limitation with LP models is that the decision variables must be continuous. Hence, it is just a coincidence that the optimal solution to the product mix example above turned out to be in full batches ($X_A = 20$, $X_B = 60$) rather than fractional. If integer restrictions of the decision variables are added to an LP model, it transforms into an Integer Programming (IP) model. If some variables are allowed to be continuous while others are integer, the model is often referred to as a Mixed Integer Programming (MIP) model.

Solving a problem which contains integer variables is much more difficult than solving a LP model. The reason is that there is no longer a guarantee that an optimal solution is found in a feasible corner point solution. As a result, the number of candidate solutions to investigate increases tremendously. To avoid complete enumeration, which would severely restrict the size of the problems worth considering, much research has gone into finding good solution methods for various kinds of IP problems. One common solution approach is the family of Branch and Bound algorithms. The underlying principle with Branch and Bound is to divide a difficult problem into subproblems that are easier to solve, and then use these subproblems to bind the optimal solution. The subproblems may, for example, be linear programs. For more details about Branch and Bound techniques and other solution approaches for IP models one can turn to, for example, Wolsey. For a more general introduction to IP models, including examples of formulated problems is an excellent starting point.

A special case of integer-valued decision variables are binary variables, which are restricted to be either 0 or 1. The binary variables are important in decision modeling because they can be used to describe Yes/No decisions, either or alternatives, fixed charges and stepwise changes. They can also be used for representing general integer variables.

To exemplify the use of binary variables, we return to the product mix example in the “LP Models” section. After further analysis it turns out that there is a fixed
The versatility of IP models means that they can be used to describe almost any kind of deterministic decision situation with a single objective. Their usefulness in practical applications may however be limited by the computational effort involved in solving large size problems. Still, the situation is continuously improving thanks to increased computer capacity and better solution algorithms. One of the most widely used software packages for solution of large-scale IP (and LP) models is CPLEX, a product sold and developed by the company ILOG.

It may be worth noting that when dealing with reasonably large integer variables it is usually an acceptable approximation to use an LP model and then round the solution to integers (although there is no guarantee that the rounded solution is feasible). However, in case of binary variables, this approach is generally not feasible.

### Economic lot sizing model

Let us now consider a simple nonlinear decision model that has been around for a long time but still is very important in production and inventory management, the so-called classical economic order quantity (EOQ) model.

Consider an inventory location that replenishes its stock of an item from an external supplier. The problem is to determine a suitable batch quantity, that is, to decide on the size of a replenishment order. This decision is mainly affected by two costs. First there is usually a fixed “ordering cost” associated with each replenishment (independent of the batch size). This cost can be due to administrative costs associated with the handling of orders and to costs for transportation and materials handling. The other important cost that needs to be considered is a “holding cost” per unit and time unit. The holding cost includes an opportunity cost for capital tied up in inventory, but may also include other costs that increase with the inventory on hand.

Our simple model assumes that the known demand is constant and continuous. Furthermore, the batch quantity is not changed over time, the whole batch quantity is delivered at the same time, and no shortages are allowed. We shall use the following notation:

- \( h \): holding cost per unit and time unit,
- \( A \): ordering or setup cost,
- \( d \): demand per time unit,
- \( Q \): batch quantity,
- \( C \): costs per time unit.

Clearly, a batch should arrive and be placed in stock just as the previous batch is depleted. The development of the inventory level can therefore be illustrated as in Fig. 3.
We wish to determine the optimal batch quantity \( Q^* \). The relevant costs to consider in the decision model are therefore the costs that vary with the batch quantity \( Q \). We get

\[
C = \frac{Q}{2} h + \frac{d}{Q} A
\]

The first term represents the holding costs, which we obtain as the average stock, \( Q/2 \), multiplied by the holding cost \( h \). The average number of orders per unit of time is \( d/Q \), and multiplying by the ordering cost \( A \), renders the ordering costs per unit time in the second term.

It is easy to optimize the cost function. We just set the derivative with respect to \( Q \) equal to zero (as one can show that \( C \) is a convex function).

\[
\frac{dC}{dQ} = \frac{h}{2} - \frac{d}{Q^2} A = 0
\]

Solving for \( Q \) we get the EOQ:

\[
Q^* = \sqrt{\frac{2Ad}{h}}
\]

This result was first derived by Harris in Harris\footnote{Note} There is also a well-known early paper by Wilson, Wilson,\footnote{Note} providing the same result.

As we have discussed in the introduction, it is common to use decision rules that are based on certain simplified assumptions also in settings where these assumptions are not really satisfied. For example, in practice it is common to use the classical lot size formula also in case of stationary stochastic demand. The constant demand \( d \) is then usually replaced by the demand forecast. It can be shown that this approximation, in general, works quite well. The considered simple lot size formula has been implemented in an enormous number of inventory control systems. There are also many related models, see, for example, Axssäter.\footnote{Note}

### Stochastic Models

In many situations, the inherent uncertainty or randomness of decision input information is the main obstacle for making good decisions. Intuitively understanding the consequences of random behavior on the system performance is difficult for most people, including decision makers. This emphasizes the need for quantitative decision models that explicitly incorporate randomness and evaluates its consequences. Describing uncertainty and randomness mathematically involves the use of probability theory and stochastic variables. To make the discussion more concrete and to illustrate the usefulness of stochastic decision models, we will in this section look closer at the classical newsvendor model, which is the foundation on which many stochastic inventory models are built.

Before turning to the newsvendor model, it is worth emphasizing that the complexity associated with stochastic behavior often prohibits the use of detailed analytical models. In these situations computer-based simulation models may be very useful for evaluating different decision alternatives and analyzing the dynamics of complicated stochastic systems. Particularly, modern discrete event simulation software packages with graphical interface represent a flexible and easy to use decision support tool. For further details on simulation modeling and the use of modern discrete event simulation software, one can turn to Law and Kelton\footnote{Note} and Laguna and Marklund.\footnote{Note} The latter also provides an introduction to analytical modeling of simple queuing systems (see also Hillier and Lieberman)\footnote{Note} which represents another important area in stochastic decision modeling.

#### The newsvendor model

In this section we consider the classical newsvendor model. In its original form, the problem deals with a newsvendor who can buy copies of a newspaper in the morning for a certain price, and sell them during the day for a higher price. The stochastic demand during the day is known through its probability distribution. The newsvendor is not paid anything for unsold copies of the newspaper.

We shall deal with a slightly more general formulation of the problem and introduce the following notation:

- \( X \) = stochastic period demand,
- \( f(x) \) = density of the stochastic period demand,
- \( F(x) \) = cumulative distribution function of the stochastic period demand, that is, the probability that the demand \( X \) is less than or equal to \( x \),
- \( S \) = ordered amount,
- \( c_o \) = overage cost, that is, the cost per unit for inventory remaining at the end of the period,
- \( c_u \) = underage cost, that is, the cost per unit for unmet period demand.

Let us for a moment go back to the newsvendor interpretation of the problem. The period length is then one day. Assume that the newsvendor pays 25 cents for a copy of the newspaper and sells them for 75 cents during the day. We then have \( c_o = 25 \), and \( c_u = 75 - 25 = 50 \). Note that \( c_u \) in this case corresponds to the opportunity costs for lost sales.

For a certain demand \( X \) the costs are:

\[
C(X) = (S - X)c_o \quad \text{if } X \leq S \\
C(X) = (X - S)c_u \quad \text{if } X > S
\]
Using this we can express the expected costs \( C = E \{ C(X) \} \) as:

\[
C = c_o \int_0^S (S-x)f(x)dx + c_u \int_S^\infty (x-S)f(x)dx
\]

It is relatively easy to show that the expected costs are minimized when \( S \) is chosen so that

\[
F(S) = \frac{c_u}{c_o + c_u}
\]

This means that the optimal \( S \) can be obtained from a very simple decision rule,

\[
S = F^{-1}\left( \frac{c_u}{c_o + c_u} \right)
\]

The newsvendor model has many important applications, especially when considering ordering and capacity decisions regarding products with a short selling season or product life cycle, for example, in the fashion industry. The model is also closely related to many multiperiod inventory models dealing with an infinite horizon. Assume that there are many periods and associated replenishment opportunities. The average cost in a period is then the cost to carry a unit in stock to the next period, that is, a holding cost. Similarly, the underage cost can be interpreted as the cost for letting a customer wait to the next period, that is, a backorder cost. For overviews of different types of stochastic inventory models see, for example, Axsäter\[11\] and Silver et al.\[14\]

### Other Types of Decision Models

So far we have considered two types of decision models, deterministic and stochastic models. For both types of models we have assumed a single decision maker who wants to find the best decision for a considered system as a whole. However, there may also be situations where there are several decision makers interacting (competing or cooperating). If the behavior and responses of these different decision makers are important to understand in order to make good quality decisions, the dynamics need to be incorporated into the quantitative decision model. To analyze game situations where there are several decision makers with different goals, different types of game theoretic models can be used. Such situations are very common in practice.

Let us return to the newsvendor model in “The Newsvendor Model” section. In this model we only studied a single decision maker. However, it is quite natural to extend the model to include two decision makers. We let the newsvendor have the same role as in “The Newsvendor Model” section. But the newsvendor now buys the newspapers from a supplier with a certain production cost per unit. The supplier can choose the price he wants to charge the newsvendor. In this setting both the supplier and the newsvendor want to maximize their individual profits. What decisions should be taken by the two players? Will the resulting solution be optimal for the system as a whole? It turns out that the answer to the latter question is no. However, if we change the considered “wholesale-price contract” to a “buyback contract” where the supplier pays the newsvendor for left over inventory a coordinated solution may be reached. This means that it is possible to instigate a pricing and contract mechanism so that we can let the supplier and the newsvendor optimize their individual profits and still get a solution that is optimal for the system as a whole.

We refer to Cachon\[15\] and Chen\[16\] for overviews of the literature on coordination and contracts in such systems.

An underlying assumption for all the models we have considered in this entry is that there is a single, well-defined objective for each decision maker, for example, maximizing profits, minimizing costs, etc. However, in many situations the decision maker can be faced with several different objectives that may not be aligned, or may even be in direct conflict. For example, the objective to retain the present workforce may not be aligned with maximizing profits, the objective to maximize environmental friendliness may conflict with an objective to minimize costs, etc. Modeling and analysis of decision problems with multiple (conflicting) objectives is the focus of the multiple criteria decision making (MCDM) area. A basic question when approaching these problems is whether there is a clear order of priority between different objectives or not. An associated question is how to translate different objectives into a common scale. Monetary terms may not always be the best choice. For more about MCDM one can turn to, for example, Bouyssou et al.\[17\]

### CONCLUSIONS

In this entry we have provided a description of the broad area of decision sciences from a quantitative modeling (OR/MS) perspective. An overarching objective with most research in this field is to use quantitative models to improve the quality of decisions. This means that the model is viewed as a tool for helping decision makers to generate, evaluate, and choose good decision alternatives. With this as a starting point, we have explained the conceptual approach underlying the use of quantitative decision modeling. We have also illustrated this general approach by considering some commonly used deterministic and stochastic decision
models in more detail. The model types we have discussed include LP, IP, economic lot sizing, and the newsvendor model. We have also briefly commented on extensions and other modeling approaches such as game theory, MCDM, queuing, and simulation.

Looking at the development of the field, one can conclude that it is in many ways linked to the development and wide spread use of information technology and computers. With the increasing access to vast amounts of information, there is a growing potential for making better decisions that capture the value hidden in the information flow. This accentuates the need for quantitative decision models and decision support systems to help the decision makers sort, evaluate, and process input information into concrete decision alternatives. The increasing amounts of information also suggests more complex and large size models to evaluate, which can be done thanks to the fast development in computer technology, and more efficient solution methods. Altogether one can conclude that this paints a bright and interesting future for the field. However, an important challenge, in order for quantitative decision modeling to reach its full potential, is to bridge the gap between the complex quantitative model and the decision maker. The foundations for those bridges are carefully designed software packages, and easy to use decision support tools.

REFERENCES