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# A decision support system for project portfolio selection

Pin-Yu Veronica Chu [a,*], Yeh-Liang Hsu [b], Michael Fehling [c]

[a] Institute of Public Affairs Management, National Sun Yat-Sen University, 70 Len-Ha Road, Kaoshiung, Taiwan 80424, ROC
[b] Department of Mechanical Engineering, Yuan-Ze Institute of Technology, 135 Yuan-Tung Road, Taoyuan, Taiwan 320, ROC
[c] Department of Engineering-Economic Systems, Stanford University, Stanford, CA, USA

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**Abstract**

A decision support system (DSS) is developed to help managers select the most appropriate sequences of plans for product research and development (R&D) projects that have strict constraints on budget, time, and resources. The primary objective of the DSS is to provide an optimal combination of R&D projects. The DSS consists of several subsystems, each of which has a specific function. At the core of the DSS are a cost model, which covers time-cost tradeoff analysis, and a strategic selection algorithm, which, based on dynamic programming, provides an optimal development plan for managing R&D projects. A working board supports an interactive environment between managers and the DSS. A data checking system eliminates inconsistent data and plans in advance. This paper identifies key issues in the arrangement of R&D projects and describes various systems that have been interlinked to make the DSS a success. It also reveals that the DSS can be expanded to a decision support system shell to support similar types of problems.

*Keywords:* Decision support system; Research and development; Portfolio selection

## 1. Introduction

A large corporation often faces a decision on the scope of product research and development (R&D) projects. The main criterion for evaluating such projects is that under the budget and timing constraints, the product demonstrates at least an average overall competitive performance. Typically, carrying out an R&D project entails pursuing several subsidiary projects, and the technology associated with each project has a high degree of uncertainty [1]. Therefore, the selection of a balanced R&D portfolio, combining corporation goals, resources, and constraints, is an important but venturesome task [2].

This paper presents a decision support system (DSS) to aid managers in selecting the most appropriate R&D portfolio. We consider a decision-theoretic model in which R&D projects can be chosen and performed sequentially. Major concerns in the DSS are determining the optimal combination of the R&D projects and the best allocation of the corporation's resources to selected projects. Specifically, the DSS incorporates the following features:

1. An environment for comparing intuitive managerial decisions and decisions supported by the DSS, and a mechanism for explaining important aspects of the decision-theoretic model embedded in the DSS.
2. A scientific and systematic product development process to help managers choose the "right"

* Corresponding author.


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project. This choice requires an understanding of which R&D projects have the greatest potential to create value for the corporation and the difficulty of achieving them [3]. A "right" project is a project with a relatively high chance of success and low development cost, including both the monetary cost and time cost.

3. A resource allocation plan to help managers perform the development process "right". Such a plan requires managers to organize tasks and resources (e.g., personnel, material, and equipment) to work on the most valuable project attributes and surmount technical hurdles in the most timely and cost-effective way.

In what follows, we first review pertinent literature on R&D project management, and define the scope of our research. Second, we describe the architecture and functions of the DSS. Next, we illustrate the basic assumptions and the analytical model of the DSS, and then we demonstrate the use of the system via an example. The last section contains the summary and suggestions for further research.

## 2. Related literature

The management of a balanced development portfolio is a typical resource allocation problem in an R&D environment where a company can pursue a limited number of research projects, and the chance of success of some of the projects is highly uncertain. An abundant amount of literature exists on R&D project evaluation and selection, and it refers to hundreds of models using a wide range of mathematically based approaches [4–8]. Various researchers have provided a good review of these approaches to R&D project management. In particular, Oral et al. [9] classify these proposed methods into two categories:

1. Compensatory Models. These models, such as cost/benefit analysis, multi-attribute utility theory [10], and analytical hierarchy process [11], require an unambiguous value (or utility) function to aggregate and evaluate the tradeoff among multiple project criteria. The resulting evaluation not only provides a complete ordering but also a measure of "difference" among the R&D projects. Such models can be used by a single decision maker (DM) or by a group of the stakeholders with a common preference structure that may result from spontaneous choice or from negotiation.
2. Noncompensatory Models. These models include (i) multiple-criteria decision methods (MCDM) such as ELECTRE [12] and PROMETHEE [13]; and (ii) ordinal ranking methods. The first type of models requires a value consensus on weight assigned to attributes and on cut-off parameters. Inspired by social choice theory, ordinal ranking methods, on the other hand, recognize that evaluations by different stakeholders may be heterogeneous, and the ranking is based on "subjective" judgments from experts [14–17].

As for computer-aided systems, there are two streams of information systems for supporting R&D project management. One stream are the so-called decision support systems which apply various analytical methods and models mentioned in this section and provide friendly user environments. The other stream are expert systems which apply heuristic rules to model the process of innovation through project management, and help managers access to analytical tools. In this paper, we take a DSS approach to support R&D project management. In particular, the DSS is based on a cost/benefit model.

## 3. The decision support system

Little [18] first discussed DSS, a philosophy seeking a complementary between technological computer tools and human judgment and discretion. Since then, many researchers [19–21] have presented different definitions of DSS. For instance, Turban [22] describes a DSS as "an *interactive*, *flexible*, and *adaptable* computer-based information system that utilizes *decision rules*, *models* coupled with a comprehensive *database* and the *decision maker's own insights*, leading to specific, implementable decisions in solving problems that would not be amenable to management science optimization".

Various research results [7,23] address the gap between operation researchers and managers in providing an easy-to-use model for R&D project management. In order to provide managers with easy-to-use tools and help them manage R&D projects systematically and scientifically, we have developed an R&D DSS based on Turban's key concepts of DSS. Section 3.1 and Section 3.2 describe the architecture and functions of the DSS.

### 3.1. The architecture of the DSS

The architecture of the DSS developed for R&D project management appears in Fig. 1. We will discuss the development cost ($C$), development time ($T$), and the probability of success ($P$) for each project or task in the figure in more detail in the next section.

This DSS contains four subsystems:

1. The working board is the highest level of the DSS. Through the working board, managers can declare their development projects and tasks, $C$, $P$, $T$, and resource requirements of each task, and request help and explanations of analytical results from the DSS.
2. The data checking system is a gatekeeper for filtering inconsistent input of any estimated parameters for the strategic selection system. It calculates cost, time, and the probability of success for each project and performs consistency checks. It also includes an explanation module that helps managers understand where and why the inconsistent data occur.
3. The strategic selection system is the primary vehicle for finding the optimal development sequence and for performing sensitivity analyses. A dynamic programming algorithm and a graphic tool are implemented in this system.
4. The resource database, which contains the information of the unit cost and the required and available amount of manpower, material, and equipment resources. The information can be provided either directly by the managers or by the accounting database of the corporation.

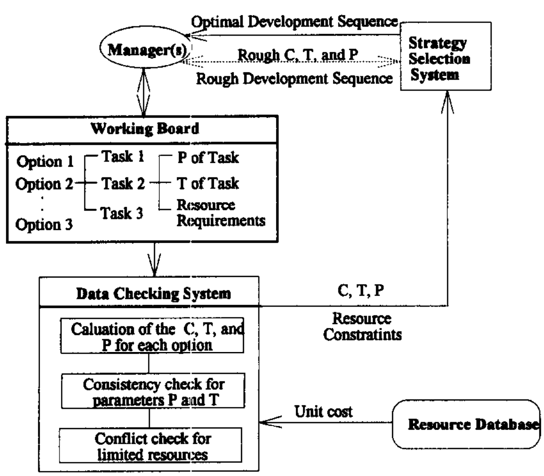


Fig. 1. The architecture of the DSS.

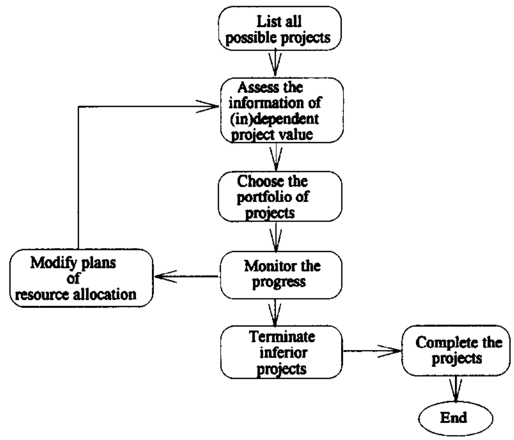


Fig. 2. The process of the DSS.

### 3.2. The process of the DSS

Fig. 2 gives a flow chart of the decision-making process supported by the DSS. For the evaluation and selection of the R&D projects, a decision maker (DM) first identifies all possible projects that he or she is currently considering. Second, the DM (or related database) assesses the relevant information in each project, including resource constraints, uncertainty estimation, and decision criteria (i.e., cost and time). Based on the information and calculated data, the DSS provides the DM with an R&D portfolio of projects. A monitoring process follows. Monitoring the progress provides a basis for the comparison of *estimated* cost, time, and the probability of success with the *actual* cost, time, and the probability of success of the various projects. Consequently, the DM can determine whether or not he or she should modify the allocation of development efforts or even terminate some projects. This integrated DSS system provides decision support whenever reallocation of resources or adjustments to the data are required.

The DSS first has been developed on a DEC 5000/2000 workstation using Common Lisp. Currently we are implementing it on Windows and linking it to database systems, e.g., ForPro.

## 4. The cost model and the strategic selection algorithm

### 4.1. Basic concepts of the cost model

For competitive reasons, corporations desire prototype projects with lower development cost $C$, shorter lead time $T$, and higher probability of success $P$. The choice of developing only one prototype at a time may be risky because of the time constraints and the chance of failure. The choice of developing several different prototypes in parallel may be unrealistic because of the budget and resource constraints. Thus, we have developed a cost model and a strategic selection algorithm to filter conflict resources, to evaluate and balance the tradeoff among $C$, $T$, and $P$, and then to choose the optimum combinations of projects.

The criterion for selecting the optimum sequence of R&D project development is to choose the sequence with the lowest total expected development cost among all possible development combinations. The total expected development cost $J$ is defined as a weighted sum of the expected total tangible monetary cost and the expected total intangible time cost, as shown in Eq. (1):

$$J = \lambda_1 \cdot (\text{expected total prototype development tangible monetary cost}) + \lambda_2 \cdot (\text{expected total prototype development intangible time cost}); \quad \lambda_1, \lambda_2 > 0, \tag{1}$$

where $\lambda_1$ and $\lambda_2$ are weights of the development cost and time. They represent the tradeoffs between $C$ and $T$, and the DM decides their values according to his or her various concerns and preferences. The "expected" costs are calculated from the actual costs and $P$. The following section describes these parameters $C$, $T$, and $P$ in more detail.

Note that two assumptions govern the cost model. First, we have assumed that each feasible R&D project provides similar market compatibility. Second, the time required for the development of a product is so short that the interest rate does not play a significant role. Thus, we choose the cost analysis and do not take into account the estimation of the net present value of each project.

In the model, the DM can assess the rough values of these parameters $C$, $T$, and $P$ (as the dash line in Fig. 1 shows). In particular, we have employed a task-driven concept in the data management, which breaks down each product development project into a few sequential subtasks. The purpose of this approach is twofold. First, in order to produce a reliable development plan, the cost model requires more precise data on $C$, $T$, and $P$ for each prototype project. The task-driven approach can motivate the DM to deeply examine each project. Second, there are often similar tasks among different projects, therefore, there exists a mutually dependent and learning relationship. The task-driven approach can also capture the learning effect and take it into account while searching for the optimal project portfolio.

### 4.2. C, T, and P

In this section we derive the mathematical equations to represent three major components in the cost model: (1) the expected tangible monetary cost, (2) the expected intangible time cost, and (3) the probability of success of $n$ R&D projects developed in parallel or in sequence.

#### 4.2.1. Expected tangible monetary cost

The total expected tangible monetary cost of a combination containing $n$ projects ($C_t(n)$) is the sum of the fixed cost ($C_f(n)$) and the expected variable cost ($C_v(n)$):

$$C_t(n) = C_f(n) + C_v(n). \tag{2}$$

In the cost model, the fixed cost includes material and equipment cost and does not vary over time. The variable cost, which covers manpower cost, is proportional to the development time. Two types of combination of $n$ projects are possible:

(1) $N$ projects developed in parallel:

We assume that the company invests in material and equipment at the very beginning. $C_f(n)$ can be expressed as:

$$C_f(n) = \sum_{i=1}^{n} C_f^i, \tag{3}$$

where $C_f^i$ is the fixed cost for project $i$.

$C_v(n)$ is the expected value of the product of $T$ and the manpower unit time cost ($C_m$). Let $T^i$ be the development time of project $i$, and the projects be sorted so that $T^i < T^{i-1}$. For the case of $n$ projects, $C_v$ is

$$C_v(n) = \sum_{l=1}^{n} C_m^l \cdot \sum_{i=l}^{n} \left( T^i \cdot \prod_{j=i+1}^{n} (1 - P^j) \right) \cdot \bar{P}^i, \tag{4}$$

where $\bar{P}^i = 1$ for $i = l$; $\bar{P}^i = P^l$ for $i \neq l$; $C_m^l$ is the manpower unit cost of project $i$; and $P^i$ is the probability that project $i$ will success based on the experience with prior projects.

(2) $N$ projects developed in sequence:

$C_f(n)$ and $C_v(n)$ are expressed as

$$C_f(n) = C_f^1 + (1 - P^1)C_f^2 + (1 - P^1)(1 - P^2)C_f^3 + \ldots = C_f^1 + \sum_{i=2}^{n} \prod_{j=1}^{i-1} (1 - P^j)C_f^i, \tag{5}$$

$$C_v(n) = C_m^1 T^1 + (1 - P^1)C_m^1 T^2 + (1 - P^1)(1 - P^2)C_m^1 T^3 + \ldots = C_m^1 T^1 + \sum_{i=2}^{n} \prod_{j=1}^{i-1} (1 - P^j) C_m^i T^i. \tag{6}$$

#### 4.2.2. Expected intangible time cost

The expected intangible time cost is proportional to the expected total lead time ($T_t$), which is the expected sum of the lead time $T$ of each project. Similarly, there are two types of combination of $n$ projects:

(1) $N$ projects developed in parallel:

For the case of $n$ projects, $T_t(n)$ can be generalized as the following recursive equation:

$$T_t(n) = P^n \cdot T^n + (1 - P^n) \cdot T_t(n-1). \tag{7}$$

(2) $N$ projects developed in sequence:

Similar to Eq. (6), $T_t(n)$ can be derived as

$$T_t(n) = T^1 + \sum_{i=2}^{n} \prod_{j=1}^{i-1} (1 - P^j) T^i. \tag{8}$$

#### 4.2.3. Evaluation of probability of success

The DSS uses the (in)dependent probabilities among tasks to capture the learning effects among different projects. Instead of a rough $P$ for each project, the DSS requests managers to provide $P$ for each task of all projects. We have considered two kinds of learning effects:

(1) Within each project:

Let project $i$ have $n$ tasks $S_l^i$, $l = 1, \ldots, n$, the probability of success of project $i$ ($P^i$) is then

$$P^i = P(S_l^i) \cdot P(S_2^i / S_1^i) \cdot P(S_3^i / S_1^i, S_2^i) \ldots = \prod_{k=1}^{n} P(S_k^i / S_l^i), \quad \text{for } l = 1, \ldots, k-1. \tag{9}$$

When there is no learning effect gained in the tasks, we can define $P(S_k^i / S_l^i)$ as $P(S_k^i)$, for $l = 1, \ldots, k-1$.

(2) Among projects:

For simplicity, we first consider a case that there are two projects $i$ and $j$, and that each project only has two tasks. Given the experience of project $j$, the probability of success of project $i$ is the product of the maximum values of dependent probabilities of tasks $S_1^i$ and $S_2^i$:

$$P(i/j) = \prod_{k=1}^{2} \mathrm{Max}\left(P(S_k^i), P(S_k^i / S_l^j)\right), \quad \text{for } l = 1,2. \tag{10}$$

For the case when project $i$ has $n$ tasks, and project $j$ has $m$ tasks, Eq. (10) can be generalized as

$$P(i/j) = \prod_{k=1}^{n} \mathrm{Max}\left(P(S_k^i), P(S_k^i / S_l^j)\right), \quad \text{for } l = 1, \ldots, m. \tag{11}$$

Therefore, the probability of success of a development combination containing $n$ projects developed in sequence $P(n)$ is

$$P(n) = 1 - \prod_{i=1}^{n} (1 - P(i/D)), \tag{12}$$

where $D$ is the set of projects developed before $i$. Furthermore, for the case of $n$ projects developed in parallel, $P(i/D) = P^i$.

### 4.3. The strategic selection algorithm

This section demonstrates how the strategic selection algorithm provides a systematic method for evaluating projects and generates an optimum development sequence.

Let $U$ be the set of all development projects. First, select a subset $u_1 \subset U$ for parallel development. If at the end of the development, we discover that one or more of the projects are successful, we terminate further exploration of prototypes; if none of them is successful, we select a subset $u_2 \subset U \setminus u_1$ and continue the analysis, and so on.

The optimal value in the $k$th stage of $J$ ($J^*$) (see Eq. (1)) can be expressed as the following dynamic programming equation:

$$J^*\left(U \setminus \overline{U}, \overline{U}_k\right) = \underset{\overline{U}k \subset U \setminus \overline{U}_k}{\text{Min}} \left\{\left[\lambda_1 C_t\left(\overline{U}_k(n)\right) + \lambda_2 T_t\left(\overline{U}_k(n)\right)\right] + J^*\left[\left(U \setminus \overline{U}, \overline{U}_k\right), \overline{U}_{k+1}\right]\left[1 - P\left(\overline{U}_k / \overline{U}\right)\right]\right\}, \tag{13}$$

where $J^*(U \setminus \overline{U}, \overline{U}_k)$ is minimum remaining cost for projects in $U \setminus \overline{U}$, given that $U$ has been tried and failed; $P(\overline{U}_k / \overline{U})$ is the probability that projects in $\overline{U}_k$ will succeed, based on the prior experience with projects in $\overline{U}$; $C_t(\overline{U}_k(n))$ is the expected tangible monetary cost for $\overline{U}_k$ with $n$ projects in $k$ stages (see Eq. (2)); and $T_t(\overline{U}_k(N))$ is the expected intangible time cost for $\overline{U}_k$ with $n$ projects in $k$ stages (see Eq. (8)).

We can determine the optimal R&D project development combination by solving Eq. (13) with the following processes:

1. $J^*(u | U \setminus u) = \lambda_1 C_t(u) + \lambda_2 T_t(u)$, $\forall u \in U$,
2. $l = 2$ and $u^l$ is an $l$-tuple in $U$. Solve $J^*(u^l \mid U \setminus u^l)$ for using $P(i/D) = P^i$ for all $u^l$ in $U$.
3. Let $l = l + 1$ and repeat through (2) until $J^*(U)$ is calculated via Eq. (13),
4. The optimal set of R&D project prototypes $\overline{U}_k^l$ to be carried out in parallel is

$$\underset{\text{Arg}\,\overline{U}_k \subset U}{\text{Min}} \left\{\left[\lambda_1 C_t\left(\overline{U}_k(n)\right) + \lambda_2 T_t\left(\overline{U}_k(n)\right)\right] + J^*\left[\left(U \setminus \overline{U}_k\right)\right]\left[1 - P\left(\overline{U}_k\right)\right]\right\}.$$

## 5. An example

In this section we use a simple example to demonstrate the capabilities of the DSS and to show how a fairly sophisticated analysis can be performed by the DSS.

First, a DM declares possible R&D projects, tasks of each project, and overall resource constraints. In this example, there are six possible projects $O_i$, $i = 1, \ldots, 6$ under consideration, each project has two tasks, and the constraint of the total lead time is 20 *units*. Second, the DM specifies $C$, $T$, $P$, and resource requirements for each project and task. Table 1 summarizes this part of information. For example, project 1 ($O_1$), with two tasks $S_1^1$, and $S_2^1$, roughly requires 68 *units* of monetary cost. Moreover, task $S_1^1$, with a probability of success 0.5, needs 5 *units* of development time to complete its work. Similarly, task $S_2^1$, with a probability of success 0.6, needs 7 *units* of development time to complete its work.

After all the required information is completed by the DM, the DSS performs data consistency and

Table 1
$C$, $T$, $P$, and resource requirements for each project and task

| Projects | Project cost $C$ | Project's tasks | Task lead time $T^S$ | Probability of success $P^S$ |
|---|---|---|---|---|
| Project 1, $O_1$ | 68 | $S_1^1$ | 5 | 0.5 |
| | | $S_2^1$ | 7 | 0.6 |
| Project 2, $O_2$ | 87 | $S_1^2$ | 6 | 0.6 |
| | | $S_2^2$ | 3 | 0.45 |
| Project 3, $O_3$ | 58 | $S_1^3$ | 5 | 0.5 |
| | | $S_2^3$ | 8 | 0.3 |
| Project 4, $O_4$ | 53 | $S_1^4$ | 2 | 0.6 |
| | | $S_2^4$ | 3 | 0.45 |
| Project 5, $O_5$ | 75 | $S_1^5$ | 5 | 0.5 |
| | | $S_2^5$ | 6 | 0.55 |
| Project 6, $O_6$ | 90 | $S_1^6$ | 15 | 0.3 |
| | | $S_2^6$ | 10 | 0.2 |

resource conflict checks to examine the inconsistency between the rough data provided by the DM and the exact data computed by the DSS. According to the results of the consistency checks, the DM can either modify his or her original data or prune infeasible projects in advance. For instance, project 6 ($O_6$) with a lead time (i.e., 25) longer than the overall time constraint (i.e., 20), is infeasible for the corporation. Therefore, the system prunes out project $O_6$ at the beginning,

In this example, the DM also declares the learning effects in terms of conditional probabilities. The learning effects in this example are $P(S_2^3/S_1^4) = 0.5$, and $P(S_1^5/S_2^5) = 0.7$. $P(S_2^3/S_1^4) = 0.5$ represents that there is an inter-project learning effect between project $O_3$'s task $S_2^3$ and project $O_4$'s task $S_1^4$. With this learning effect task $S_2^3$'s probability of success increases from 0.3 to 0.5. $P(S_1^5/S_2^5) = 0.7$ means that there is an intra-project learning effect between task $S_1^5$ and task $S_2^5$, and that with this learning effect task $S_1^5$'s probability of success increases from 0.5 to 0.7.

Based on various values of $\lambda_1$ and $\lambda_2$ chosen by the DM, the DSS performs the strategic selection analysis. As a result, not only an optimal combination of development projects but also a resource allocation plan can be provided to the DM (see Table 2). In particular, with a $\lambda_1/\lambda_2$ ratio 10, the optimal development sequence ($A$) is $[(O_1,O_5),O_2,O_4,O_3]$, which means that without considering any learning effects, the DM should first develop projects $O_1$ and $O_5$ in parallel, and then projects $O_2$, $O_4$, and $O_3$ in sequence when projects $O_1$ and $O_5$ both fail.

With a high $\lambda_1/\lambda_2$ ratio (e.g., 10), which indicates that the development cost is more critical than the lead time, the optimal development sequence $A$, $[(O_1,O_5),O_2,O_4,O_3]$, is meant to develop projects in sequence in order to save monetary cost. On the contrary, with a low $\lambda_1/\lambda_2$ ratio (e.g., 0.1), which indicates that the lead time is more important than the development cost, the optimal sequence $C$, $[(O_1,O_4,O_5),(O_2,O_3)]$, is meant to develop projects in parallel to save the development time. Thus, project $O_4$ with its shorter lead time is moved in front of project $O_2$ in sequence $C$. Moreover, sequences $D$ and $E$ show that project $O_3$ with a learning effect from project $O_4$ is naturally moved in front of project $O_2$.

Table 2
The optimal combinations of development projects

| $\lambda_1/\lambda_2$ | Optimal development sequence (without learning effects) | |
|---|---|---|
| $10/1 = 10$ | $[(O_1,O_5),O_2,O_4,O_3]$ | (Sequence $A$) |
| $1/1 = 1$ | $[(O_1,O_4),O_5,O_2,O_3]$ | (Sequence $B$) |
| $1/10 = 0.1$ | $[(O_1,O_4,O_5),(O_2,O_3)]$ | (Sequence $C$) |
| $\lambda_1/\lambda_2$ | Optimal development sequence (with learning effects) | |
| $1/1 = 1$ | $[(O_1,O_4),O_5,O_3,O_2]$ | (Sequence $D$) |
| $1/10 = 0.1$ | $[(O_1,O_4,O_5),(O_2,O_3)]$ | (Sequence $E$) |

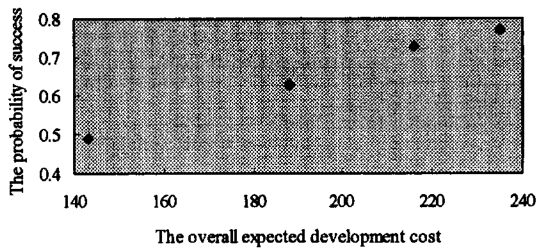


Fig. 3. The overall expected development cost vs. the overall probability of success of sequence $A$.

Fig. 3 reveals a monotonic relation between the overall expected development cost and the overall probability of success of sequence $A$. The monotonic relation indicates that with a higher budget for a project, the DM can pursue more projects with a higher probability of success.

## 6. Conclusions and future research

This paper introduces a DSS, a planning and scheduling tool that helps managers evaluate and analyze schedules and resource requirements for project development. Major concerns are (1) tradeoffs among the development cost, time, and the uncertainty; (2) the overall resource allocation for the best sequence of projects development; and (3) the learning effects among the projects.

Three areas for further research seem promising: First, the DSS can be expanded to such a system that helps a DM, who has limited resources, manage any multiple risky alternatives (projects). Conceptually, the DM can *subjectively* assess the cost, effective time, and probability of success of each alternative.

Based on the criterion of minimizing the expected "total cost" (i.e., a weighed sum of intangible cost and tangible cost), the DSS can guide the DM to manage his or her alternative effectively.

If we strip the current DSS of its specific application, it may become a decision support system shell (DSSS) that can be used to support various kinds of decisions. Analogous to an expert system shell, the DSSS may include the following components:

1. Data acquisition system. The DM can specify each option by its hierarchical attributes (e.g., tasks, subtasks, etc.) and resource requirements;
2. Decision engine. The DSSS may contain a dynamic programming algorithm or other analytical methods that help the DM find his or her optimal portfolio.
3. Data checking subsystem. The DSSS may provide data checking functions that help the DM filter inconsistent and infeasible data beforehand.

Second, as shown in Fig. 3, the relationship between the overall probability of success and the overall expected development cost appears to be discrete. Indeed, the probability of success can be a continuous function of the development cost. Since dynamic programming can handle only discrete stages, implementing a continuous cost-probability function will call for major changes in the strategic selection system.

Third, Taiwanese government and R&D agencies provide a major thrust toward effective management of R&D projects. Unfortunately in many organizations, well planned approaches are absent and an ad hoc R&D infrastructure is often applied. This may lead to directionless R&D resulting in disjointed irrelevant developments which are totally out of phase with the organizations' objectives and poor profitability. Thus, further research ought to aim at helping managers in local industries adopt the DSS methodology to develop proper R&D managerial plans.

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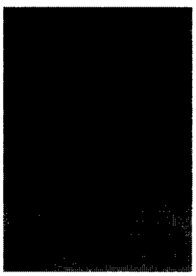

**Pin-Yu Veronica Chu** has been an Associate Professor in the Institute of Public Affairs Management at National Sun Yat-Sen University since 1994. She holds the degree of B.S. in Electronic Physics from National Chiao-Tung University, and an MS and Ph.D. in Engineering-Economic Systems from Stanford University. She has research and teaching interests in decision analysis, decision support systems, and conflict management.

**Yeh-Liang Hsu** has been an Associate Professor in Mechanical Engineering at the Yuan-Ze Institute of Technology since 1992. He holds the degree of B.S. in Mechanical Engineering from National Taiwan University, and an M.S. and Ph.D. in Mechanical Engineering from Stanford University. He has research and teaching interests in mechanical design optimization, geometrical modeling, and finite element analysis.

**Michael Fehling** is an Associate Professor (Research) at Department of Engineering-Economic Systems, Stanford University and the director of the organizational dynamics center. He holds his Ph.D. in Psychology from Stanford University. He has research and teaching interests in exploring, modeling, and developing support technology for resource-constrained rational agents and their organizations.