ESTIMATING THE OPTIMAL NUMBER OF ALTERNATIVES TO BE EXPLORED IN LARGE DESIGN SPACES: A STEP TOWARDS INCORPORATING DECISION MAKING COST IN DESIGN DECISION MODELS

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ABSTRACT

Exploration of design spaces is an important step in decision-based design. In consumer product development, precise design specifications are not known at the beginning of the design process. It is usually design team's responsibility to find out the specifications as a part of the design process. This results in large design spaces in consumer product development. Furthermore, market window is usually limited. Thus, it is impractical to examine all possible design alternatives. As part of the design process, design teams need to determine how many alternatives to examine and how much evaluation time should be devoted to examining each alternative. This paper presents a model for estimating the optimal number of alternatives to be explored and the optimal evaluation time for each alternative by incorporating cost of decision-making in the overall design decision model. We also describe a design case study and investigate how characteristics of design task parameters influence the optimal number of alternatives and the optimal evaluation time. Our results indicate that it is difficult to intuitively identify the optimal values of the number of alternatives and the evaluation time for even very simple design tasks. We describe the practical issues that need to be addressed to make these decisions and discuss how the model proposed in this paper can be extended to handle more general cases of design tasks.

1 INTRODUCTION

Development of consumer products is an activity through which a product development organization attempts to design and manufacture products to realize profit. This activity usually consists of identifying customer needs and preferences, defining product functionality, identifying design alternatives, identifying alternative ways of manufacturing/procuring components, and selecting a design alternative. Usually the goal of most consumer product development organizations is to maximize profit or a closely related financial metric such as net present value or return on investment.

Product development for consumer products typically has the following characteristics:

- *Design spaces are quite large*. At the beginning of consumer product development, engineering specifications are not available explicitly. They need to be determined as a part of the design process. Let us consider the following scenario to understand this characteristic. Let us assume that a company is interested in developing a frying pan to be used in kitchen. The company can design a utensil with a very long service life that uses very durable but expensive coating. Alternatively, they can design a pan with a short service life and therefore use less durable and less expensive coating. Market exists for both of these types of pans. Which alternative should be selected by the company ultimately depends on which alternative is likely to result in more profit for the company. Unfortunately profits cannot be estimated without some idea about the cost incurred in manufacturing the product and the manufacturing cost cannot be estimated without knowing at least some design details. Therefore, product specifications need to be selected as a part of the design process. Quite often companies need to consider alternatives not only at the design concept level but also at the specification level. This makes design spaces very large in consumer product development.
- *Market window is usually small*. Demand for a particular type of product exists only for a short period of time. Due to changes in customer tastes, economic climate, and advent of new technologies, a particular product usually has a small market window. As an example, consider the following case. Cassette players significantly reduced

demand for record players. CD players significantly reduced demand for cassette players. MP3 players might reduce demand for CD players. Therefore a product needs to be conceived, designed, and marketed quickly for it to have demand and result in profit.

- *Evaluating an alternative from design space takes significant amount of time*. Evaluating a design alternative is not an instantaneous process. Experienced designer might give a design alternative a rough and quick evaluation based on his experience of similar design. But getting more confidence in evaluation, quite often involves simulation and physical prototyping. So evaluating a design alternative is a time consuming process.
- *Uncertainty in evaluation reduces if more time is spent on evaluation*. For example, a coarsely meshed elastic FEA evaluation may take only hours to carry out. On the other hand, a very finely meshed FEA that includes non-linear effects may take days to complete. Testing of a physical prototype may take weeks to complete. Inaccuracies in the evaluation and hence the uncertainty reduces as we go from the first type of evaluation to the third type of evaluation.
- *Evaluating more alternatives improves the possibility of identifying design with superior performance characteristics*. Usually this characteristic is associated with diminishing returns as shown in Figure 1. Initially, the performance improves significantly as more alternatives are evaluated. However, the improvement in performance is not linearly proportional to the number of alternatives being evaluated. The extent of the diminishing returns varies from one design task to another. We use the term "degree of diminishing return on performance with respect to the number of alternatives" to quantitatively characterize this extent.

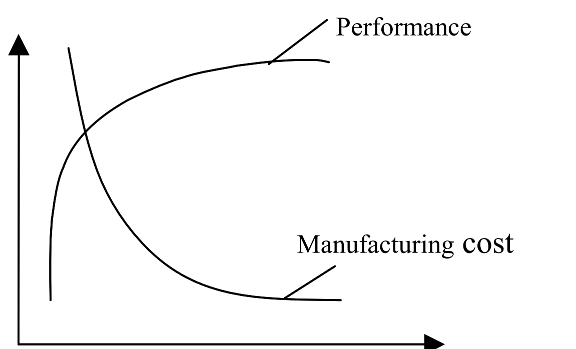


Figure 1: Phenomena of Diminishing Return

Consideration of the above characteristics of product development presents the following dilemma for the product development teams. Market window is finite and design space is very large (possibly infinite). So designers cannot explore all alternatives. Furthermore, a rigorous evaluation reduces uncertainty associated with an alternative. However it takes more time and therefore reduces their ability to consider more alternatives. So a key decision that needs to be taken in this situation is to decide how many alternatives to explore and how much evaluation time to spend on each alternative so that product development team's utility function can be maximized. Determining these two variables also determines how much total time should be spent on product development.

In practice, product managers determine the product development time based on their intuition and prior experience. If more time is needed, due to delay in product development, it is increased based on product manager's discretion. Given a product development time, designers pursue exploration of design space based on their own experiences, intuition, and working styles. Some designers might be linear thinkers and they are likely to examine fewer alternatives. However, they are likely to perform more rigorous evaluation. Some other designers might be lateral thinkers and they may explore more alternatives. However, they will do a less thorough examination of alternatives. In some cases, historical data can be used to construct models of (1) how uncertainty in evaluation changes as a function of evaluation time, and (2) how performance changes as a function of number of alternatives considered. However, explicit models are not constructed in practice. Usually, such information is utilized through designers' experience and plays a valuable role in decision-making. Current situation presents the following challenges. Ability to select the right number of alternatives to explore and the right amount of evaluation time comes from considerable experience. In absence of explicit formal models, it is very difficult to teach these skills to new designers in a short amount of time. Furthermore, as experienced designers leave the company, this information disappears with them.

Decision-based design research is attempting to build formal models of decision-making in engineering design [Haze96, Haze98, Mars98]. However, to the best of our knowledge, the effect of decision-making time and the number of alternatives being considered has not been incorporated into decision models in previous work. Therefore, most models would recommend that all possible alternatives should be examined to the maximal possible extent. This paper shows that once the effect of decision-making cost and time is included into the decision model, there exist an optimal number of alternatives and optimal amount of evaluation time for each alternative to maximize a profit-based utility. We have constructed a model for a simple design task and have shown that the optimal values of number of alternatives to be explored and evaluation time are sensitive to the details of the design task.

Our computational results provide a starting point for constructing models for more complex design tasks. This paper also discusses practical issues that need to be considered in constructing such model. This paper is organized as follows. Section 2 gives an overview of related work in the area of deign space generation and exploration. Section 3 describes our design decision model for a simple design space. Section 4 describes the experiments conducted to test the hypotheses, results of experiments, and their discussions. Section 5 presents the concluding remarks.

2 REVIEW OF RELATED WORK

2.1 Product Positioning

According to Baier and Gaul [Baie99], product positioning and product design are viewed as closely related important problems in marketing research that deal with the generation of promising alternatives for a firm that plan to extend or modify its existing product lines. Recently researchers have also begun to understand and realize the importance of integrating market research and design steps [Urba93, Tric99, Li00, Gupt01]. In the integrated framework, the main role of the design team is to identify various design alternatives. The marketing team conducts customer surveys to identify customer preferences and develops demand estimation algorithms for the design alternatives identified by the design team. Manufacturing team generates plans for physically realizing the design alternatives and develops cost estimation functions for evaluating these alternatives. Finally, an integrated decision-making approach is used to concurrently select engineering specifications, product specifications, and manufacturing/procurement plans.

Most of the research in the product positioning area [Kohl90, and Dobs93] describes conceptual framework for the generation of promising product specifications for a firm that plans to extend or modify its existing product lines. Dobson and Kalish [Dobs93] proposed a quantitative method for assisting managers in designing and pricing a product line. They formalize the problem as a mathematical program where the objective of the firm is either profit or total welfare. Kohli and Sukumar [Kohl90] proposed methods for product line selection using conjoint analysis. Kaul and Rao [Kaul95] extended it by proposing a framework that integrates product positioning and design task into a single decision. They also reviewed the models used in product positioning and product design tasks. They suggested that a firm should optimize its goals with respect to product attributes and then translate these attributes into product characteristics and levels of marketing mix variables. Product characteristics are the different physical features that define the product (e.g. length, weight).

2.2 Methodologies for Selecting the Most Preferred Design Alternatives

Li and Azarm [Li00] developed a methodology that accounts for designer's preferences, customer's preferences, and market competition. The model also considers uncertainties in the product design life, market size and its yearly change, cost and its yearly change, price, and discount rate, among others. An iterative two-stage approach consisting of design alternative generation and design alternative evaluation was developed. In design alternative generation stage, for alternatives that are handled in the performance model, multi-objective optimization is performed to generate a set of Pareto design solution. For generating Pareto optimal solutions, multi-objective genetic algorithms are used [Nara99]. For attributes that are not handled by multiobjective optimization a permutation of their levels over all Pareto solutions is performed to generate design alternatives. The design alternative evaluation model evaluated design alternatives based on business goals such as net present value of profit and market share. Customer preferences, competitor products, cost, and the generated design alternative were used as an input to the design evaluation model. Uncertainty was accounted for various factors using Monte Carlo simulation. This approach has limited ability to handle problems where a diverse set of design concepts will need to be used because a common set of design variables cannot be always identified when considering diverse design concepts. It is assumed that cost estimation function is defined in terms of design attributes. In many cases, estimating cost based on assemblies or components cost can provide more accurate cost estimates than the ones based on design attributes.

Zufryden [Zufr77] suggested adapting conjoint analysis methods to product design optimization using integer-programming model. The model assumed that the consumer compares the utility of the test product with that of one's current brand favorite and chooses the one with the higher utility. Mcbride and Zufryden proposed an integer programming formulation to solve the optimal product line selection problem [Mcbr88]. The formulation seeks to find an optimal subset of products that is drawn from a proposed set of product alternatives with specified product characteristics based on individual consumer measurements from conjoint analysis. Dobson and Kalish [Dobs93] proposed heuristics for pricing and positioning a product line using conjoint analysis and cost data. A mathematical programming problem was formulated with objective being to maximize profit.

Trichur and Ball [Tric99] suggested multi-objective integer programming models for product design. They suggested representing the design alternatives available at product design stage as an AND/OR tree using functional decomposition. Integer programming model was applied to find the optimal product design represented using AND/OR tree. The multiple objectives of the product design for example can be to minimize cost and to maximize manufacturing yield.

2.3 Computation Methods to Explore Large Design Space

Josephson et al [Jose98] have developed an architecture and a filtering technique based on a dominance criterion to select a relatively small number of promising candidates from millions of design alternatives for further analysis. Their architecture presents a way to explore large number of design alternatives. However, even with this technique, the exploration workload is still huge. The computational load has to be distributed among a large number of workstations. In some cases, simple evaluation can't be used to determine the non-dominated alternatives from the others. Furthermore, in presence of evaluation uncertainties, it is difficult to identify a small number of non-dominated solutions.

3 DECISION MODEL FOR A SINGLE PARAMETER DESIGN TASK

3.1 Definitions

Performance Attributes: Product attributes that affect a potential customer's decision to buy a given product configuration are called performance attributes. For example, service life is a performance attribute for a kitchen utensil.

Design Parameters: Product attributes that are directly specified by the designers are called design parameters. In general, performance attributes are functions of design parameters. For example, the chemical composition of a coating used in a kitchen utensil is a design parameter. Service life (e.g., a performance attribute) depends on the coating. Sometime simple mapping between design parameters and performance attributes are available. Sometime mappings need to be derived via simulation and testing.

Demand: Demand refers to the number of units that customers are willing to buy for a given product configuration at a given price.

Profit: Profit for a given product (specified by design parameters) at a given price is given by demand times the difference of price and cost i.e., $P = D(R-C)$. Where, P is the profit; D is the demand; R is the price for which the product will be sold and C is the cost.

3.2 Design Task Statement

Consider the task of designing a frying pan for regular kitchen use. The main design task is to select the constituent of the coating. The goal of the company is to make a frying pan that maximizes their utility. We assume that the following data has been gathered based on the market research:

Estimated market window: 3 years

Market Size: 100,000 people in three years period with demand equally distributed over this period

Price ranges from $10 to $100

Performance attribute: service life ranges from 6 months to 120 months

Manufacturing cost ranges from $5 to $100

Coating evaluation time ranges from 1 day to 10 days

Maximum number of coating alternatives are 50

Cost of decision making is $1000 / day

Evaluating all alternatives with the most rigorous possible evaluation will take 500 days and therefore consume a very large portion of the market window. Therefore, the first decision that needs to be made by the design team is:

Identify the number of alternatives to be examined: N.

Identify the evaluation time to be spent on each alternative: T_e.

We assume that the evaluation time for each alternative is the same.

3.3 Decision Model Construction

We follow a top-down method to construct the design decision model. First, we establish a model mapping NPV of profit to utility, and then we construct the model to compute NPV and develop other models used in the main model.

3.3.1 Modeling Design Team's Risk Preferences

Due to uncertainties in costs and the product demand, there is an uncertainty associated with the change in the financial metric (i.e., NPV change). For example, Figure 2 shows the set of possible outcomes as potential NPV changes for three different design alternatives. If the design team tries to maximize the expected value of NPV, then they will select the first option. However, there is a large standard deviation associated with this option. Therefore this is also the most risky option. The third option has the lowest expected value of NPV, but it is also the least risky. Therefore, some design teams may prefer the third option. This example illustrates that in the presence of uncertainties, risk preferences for the decision maker should be modeled.

Utility theory is being used to account for uncertainties and risks in design decision-making. Uncertainties associated with cost estimates and demand estimates can be converted into uncertainty in NPV. Therefore, Von Neumann and Morgenstern's utility theory [Haze96, Luce57, Neum47] presents an attractive basis for expressing design team's risk preferences in this case. One way to model risk preferences is to use a single number called degree of risk averseness (denoted by m). We model design team's risk preferences using degree of risk averseness in the following manner:

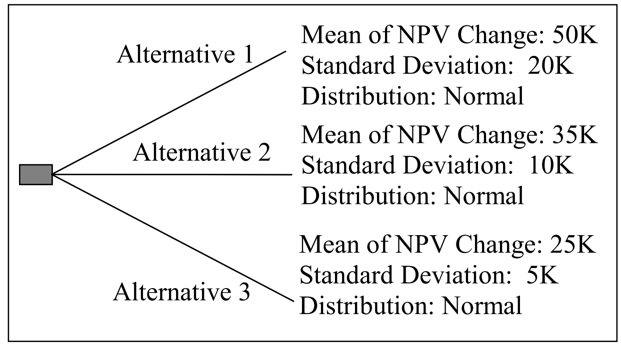


Figure 2: Evaluation of Three Different Alternatives

$$U = k_1 \times V^{1/m}$$

Where U denotes utility, V denotes NPV of profit and k_1 is a scaling constant.

Figure 3 shows relationship between U and V for different values of m.

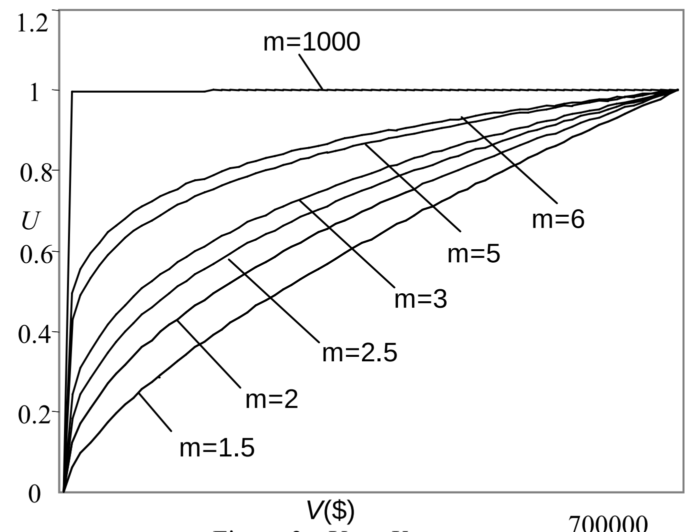


Figure 3: U vs. V

Every potential NPV change will be mapped to a utility value between 0 and 1. The first step in defining a utility function will be to estimate the lower and upper bounds on NPV change by examining various uncertainties in cost and demand estimates. The utility value of 1 will correspond to the maximum possible increase N_{max} in the NPV. The utility value of 0 will correspond to the minimum possible increase N_{min} in the NPV. For every intermediate value of NPV change V, the design team can identify a utility value by using the method described in [Haze96] by expressing their preference for financial risk. Once every possible value of NPV in between the two extreme values have been mapped to a utility value, then we can fit an appropriate function U to map an NPV change to a utility value. This function will characterize the design team's preference for financial risks. As per the expected utility theorem, using the *expected utility* as an objective function will be completely consistent with the design team's preference for financial risk [Haze98].

3.3.2 Modeling NPV

The cover all NPV is computed by subtracting the decision-making cost from the profit earned during the market window. To compute the NPV of decision making cost, money spent during the design phase is summed up and converted to present value by considering the discount rate. The profit is computed by multiplying the estimated average daily demand and unit profit. It is converted to the present value. These relationships can be expressed using the following formula:

$$V = -\sum_{i=1}^{t_d} \frac{C_d}{(1+r)^i} + \sum_{j=t_d+1}^{t_m} D \frac{(P-C)}{(1+r)^j}$$

Where V denotes NPV of total profit, D is the demand, P is the price, C is the manufacturing cost, C_d is unit decision-making cost, t_d is total decision-making time (i.e. the time of exploring the design space), t_m is the market window time, r is the discount rate, i and j are variables denoting time intervals.

3.3.3 Modeling Influence of Number of Alternatives Explored on Product Performance

Exploring more alternatives result in improvement in product performance. As explained earlier such improvement usually has diminishing returns. We model the relationship between number of alternatives explored and the mean value of performance in the following manner:

$\mu_L = k_2 \times N^{1/l} + a_2$

Where μ_L is the mean value of performance, N is the number of alternatives explored, l is the degree of diminishing return of mean performance value with respect to number of alternatives explored, k_2 and a_2 are design environment dependent constants. Figure 4 shows relationship between μ_L and N for different values of l.

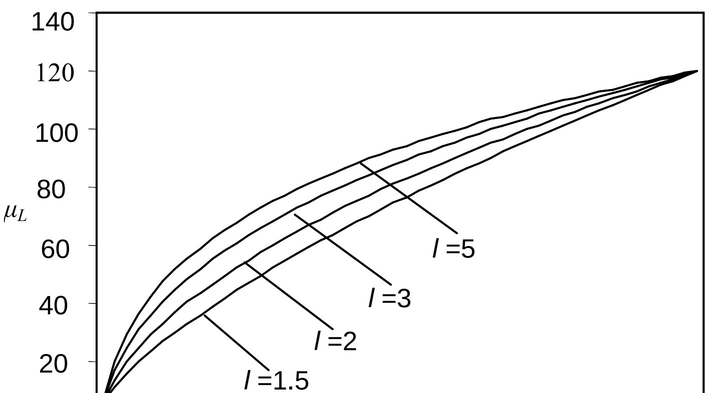


Figure 4: μ_L vs. N

3.3.4 Modeling Demand

Demand model is used to capture the relationship between product's demand and its performance and price. Demand is one of the key variables that determine the profitability of a proposed product design. We assume that for the design task described in Section 3.2, the model has the following boundary points (L_S, P, D): (120,10,93), (120,100,10), (6,10,40), (6,100,0). We use the following model to estimate demand for the design task described in Section 3.2:

$D = 168.86 \times (L_S^{0.244}) / (P^{0.724}) - 9.30$

Where D is the demand, P is the price, L_S is the life of the product. Figure 5 shows relationship between D, L_S and P.

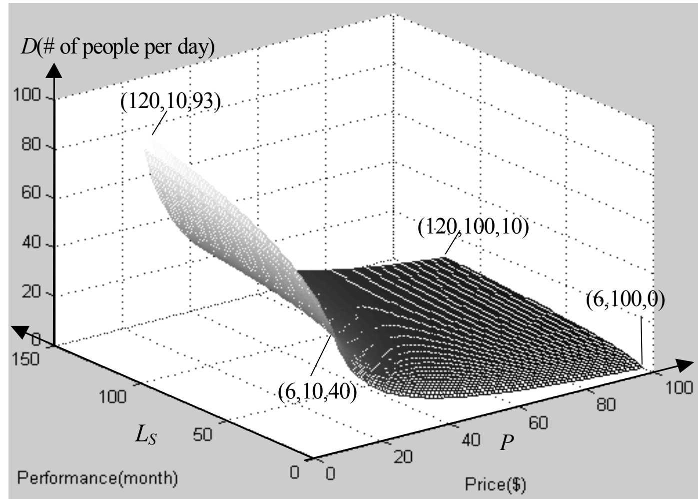


Figure 5: D vs. L_S and P

Although simplified, this model preserves the basic relationships of estimated demand with respect to performance and cost. That is, demand decreases with increasing price and increase with increasing product performance. Analytical demand models can be constructed by fitting a surface to demand points produced by conjoint analysis [Gree81, Gree90, Hair95].

3.3.5 Modeling Influence of Evaluation Time on Manufacturing Cost

Mean value of manufacturing cost for a design alternative is a function of average evaluation time. This is due to the following reason. We assume that evaluation time is also used to perform manufacturability analysis and apply DFM rules. Therefore spending more time on evaluation helps in reducing manufacturing cost.

We use the following model to model the relationship between evaluation time and mean value of manufacturing cost:

$\mu_C = k_3 \times T_e^{-n} + a_3$

Where μ_C is the mean value of performance, T_e is the evaluation time per alternative, n is the degree of diminishing return of manufacturing cost with respect to T_e, and k_3 and a_3 are design environment dependent constants. Figure 6 shows relationship between μ_C and T_e for different values of n.

3.3.6 Modeling the Uncertainty in Performance As a Function of Evaluation Time

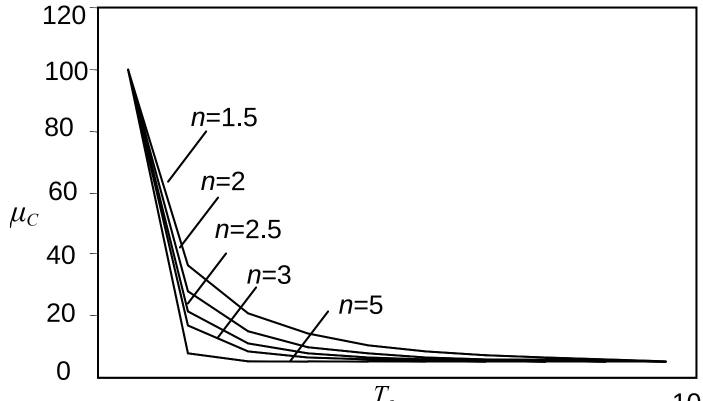


Figure 6: μ_C *vs.* T_e

Evaluation time contributes to reducing the uncertainty in determining the performance of the product since the more details become known with the increase in the evaluation time. We use the following formula to express this relationship:

$\sigma_L = k_4 \times T_e^{-n} + a_4$

Where σ_L is the standard deviation of performance, T_e is the evaluation time per alternative, n is the degree of diminishing return of σ_L with respect to T_e, k_4 and a_4 are design environment dependent constants. We currently use the same value of n as in the model described in Section 3.3.5. Figure 7 shows relationship between σ_L and T_e for different values of n.

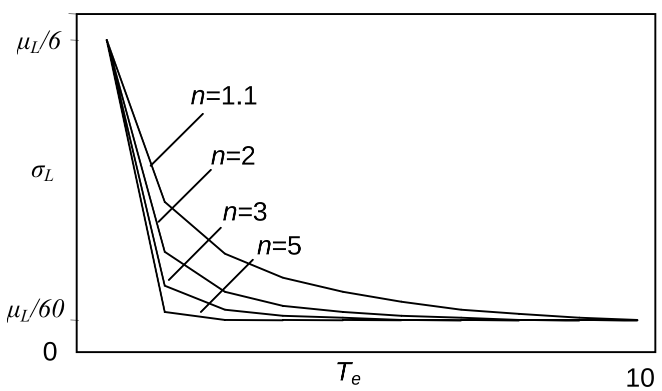


Figure 7: σ_L vs. T_e

3.3.7 Modeling the Deviation of Manufacturing Cost and Evaluation Time

Evaluation time also contributes to reducing the uncertainty in determining the manufacturing cost of the product. We use the following formula to express this relationship:

$\sigma_C = k_5 \times T_e^{-n} + a_5$

Where σ_C is the standard deviation of performance, T_e is the evaluation time per alternative, n is the degree of diminishing return of σ_C with respect to T_e. k_5 and a_5 are design environment dependent constants. We currently use the same value of n as in the model described in Section 3.3.5. Figure 8 shows relationship between σ_C and T_e for different values of n.

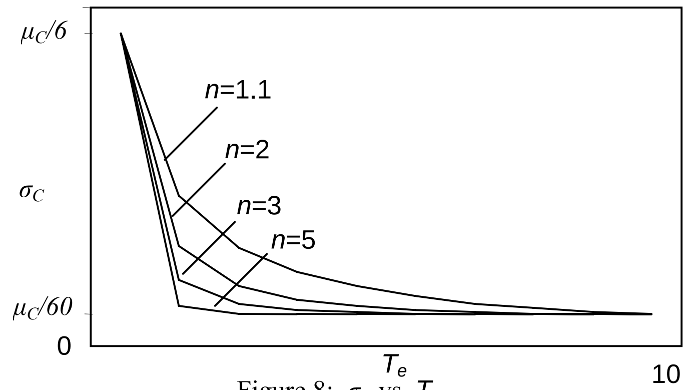


Figure 8: σ_C vs. T_e

4 COMPUTATIONAL EXPERIMENTS

4.1 Goals

We plan to explore the following hypotheses:

Hypothesis 1: The optimal values of number of alternatives to be explored and evaluation time are sensitive to the characteristics of the design task. Therefore, these cannot be guessed intuitively.

To investigate this hypothesis, we conducted an experiment (called *Experiment 1*) in the following manner. We create several combinations of variables m, n, l (main variable that characterize the design task) by assigning them certain values. For each such combination, we enumerated different values of number of alternatives, and evaluation time and computed the NPV and its utility. Therefore for each combination of m, n and l, we determined the number of alternatives and evaluation time that leads to highest value of utility. Based on this experiment, we study whether or not m, n and l influence N and T_e.

Hypothesis 2: Optimal value of the number of alternatives decreases as l is increased. Furthermore, l does not have any effect on the optimal value of the evaluation time.

To investigate this hypothesis, we conduct an experiment (called *Experiment 2*) in the following ways. We fix the values of variables m and n, while varying the value of l. we enumerate different values of number of alternatives, and evaluation time and compute the NPV and its utility. Therefore for each combination of m, n and l, we determine the number of alternatives and evaluation time that leads to highest value of utility. Then we observe how N and T_e change with the change in l.

Hypothesis 3: Optimal value of the evaluation time decreases, as n is increased.

To investigate this hypothesis, we conduct an experiment (called *Experiment 3*) in the following ways. We fix the values of variables m and l, while varying the value of n. we enumerate different values of number of alternatives, and evaluation time and compute the NPV and its utility. Therefore for each combination of m, n and l, we determine the number of alternatives and evaluation time that leads to highest value of utility. Then we observe how N and T_e change with the change in n.

4.2 Computational Procedure for Conducting Experiment

4.2.1 Monte Carlo Simulation

In order to consider the uncertainties in performance and manufacturing cost, Monte Carlo simulation is conducted to compute the expected utility. The key is to generate randomly distributed values of two intermediate variables: performance and manufacturing cost. In this experiment, triangular distribution is used to describe the randomness of performance and manufacturing cost. This distribution [Haze96]:

- enables us to grab the essence of most of the physical systems;
- has an analytical mathematical form to be used conveniently.

The steps to generate random values are:

Generate uniformly distributed random numbers using Lewis algorithm [Haze96]. It passes both the histogram test and the correlation test.

Map the uniformly distributed random numbers to the desired distribution.

The advantage of triangular distribution enables us to compute the random numbers analytically, saving the trouble of approximating the CDF. In fact, the triangular distributed variables can be derived by:

$$Z = \begin{cases} L + \sqrt{R(M-L)(U-L)} & for\, 0 \le R \le \dfrac{M-L}{U-L} \\ U - \sqrt{(1-R)(U-M)(U-L)} & for\, \dfrac{M-L}{U-L} \le R \le 1 \end{cases}$$

Where,

R: the uniformly distributed random number

L: the lower bound of the variable Z

U: the upper bound of the variable Z

M: the mean of the variable Z

The upper and lower bounds of random variable in this model are derived by:

$U = M + 3\sigma$

$L = M - 3\sigma$

Where σ is the standard deviation of variable Z.

4.2.2 Experimental Procedure

We ran the program on a PC with the following configuration:

CPU: Intel Pentium II 400MHz

Memory: 128MB

Since the computation goes through a loop at times of permutation of three parameters (N, T_e and P), and for each loop we conduct a Monte Carlo simulation, it requires substantial computing time. In our experiment, we developed C++ programs to reduce the running time and divided the experimental load on several PCs. In coding the program, we avoided evaluating the combinations of N and T_e under Prices where the cost is equal to or bigger than the price.

Given l, m, and n, our computations consist of the following steps:

- Generate all possible combinations of N and T_e.
- For each N and T_e, try all possible prices in the range.
- Compute μ_L and μ_C according to models described in Section 3.3.3 and 3.3.5.
- Compute σ_L and σ_C according to models described in Section 3.3.6 and 3.3.7.
- Perform Monte Carlo Simulation (we use sample size of 200) using μ_L and μ_C and σ_L and σ_C.
- Compute *NPV* and convert it into utility *U*.

4.3 Results

Results of Experiment 1. Table 1 shows the result of Experiment 1. For each value combinations of variables m, n, l, we look for values of number of alternative and evaluation time that leads to the highest value of utility.

Table 1. Result of Experiment 1: various combinations of m, n and l

m	*l*	*n*	*N*	T_e	$N \times T_e$	*Expected Utility*
1.5	2	2	19	4	76	0.747
1.5	2	4	38	2	76	0.834
1.5	2	6	37	2	74	0.884
1.5	5	2	12	5	60	0.797
1.5	5	4	18	3	54	0.870
1.5	5	6	26	2	52	0.907
1.5	10	2	11	5	55	0.815
1.5	10	4	17	3	51	0.884
1.5	10	6	23	2	49	0.916
3	2	2	19	4	76	0.864
3	2	4	38	2	76	0.913
3	2	6	37	2	74	0.940
3	5	2	12	5	60	0.892
3	5	4	18	3	54	0.933
3	5	6	26	2	52	0.952
3	10	2	11	5	55	0.902
3	10	4	17	3	51	0.940
3	10	6	23	2	49	0.957
5	2	2	19	4	76	0.916
5	2	4	38	2	76	0.947
5	2	6	37	2	74	0.963
5	5	2	12	5	60	0.934
5	5	4	18	3	54	0.934
5	5	6	26	2	52	0.971
5	10	2	11	5	55	0.940
5	10	4	17	3	51	0.963
5	10	6	23	2	49	0.974
10	2	2	19	4	76	0.957
10	2	4	38	2	76	0.973
10	2	6	37	2	74	0.981
10	5	2	12	5	60	0.966
10	5	4	18	3	54	0.979
10	5	6	26	2	52	0.985
10	10	2	11	5	55	0.969
10	10	4	17	3	51	0.981
10	10	6	23	2	49	0.987

Discussion: According to the model, NPV (and therefore utility) is determined by accumulated decision-making cost and the accumulated profit earned by selling product in the market window time. Exploring more alternatives will increase the performance, thus the demand will also increase (if the price doesn't increase a lot). But at the same time, exploring more alternatives will reduce the effective market window time. Similarly, spending more evaluation time will reduce the manufacturing cost due to the knowledge of more design details, but it will also reduce the effective market window time. Thus the optimal point (the point that results in the highest value of expected utility) may not simply happen at the extreme point of number of alternatives or evaluation time.

Detailed analysis of data in Table 1 also reveals that optimal values of N, T_e are not sensitive to m. Tables 2.1, 2.2, and 2.3 show the data where l and n are kept constants and m is varied.

Table 2.1. Varying m while fixing l =2 and n =2

m	*N*	T_e	*Expected Utility*
1.5	19	4	0.747
2	19	4	0.803
2.5	19	4	0.839
3	19	4	0.864
3.5	19	4	0.882
4	19	4	0.896
5	19	4	0.916
10	19	4	0.957
1000	19	4	0.999

Table 2.2. Varying m while fixing l =3 and n =4

m	*N*	T_e	*Expected Utility*
1.5	21	3	0.976
2	21	3	0.852
2.5	21	3	0.909
3	21	3	0.923
3.5	21	3	0.934
4	21	3	0.942
5	21	3	0.953
10	21	3	0.976
1000	21	3	0.999

Table 2.3. Varying m while fixing l =10 and n =6

m	*N*	T_e	*Expected Utility*
1.5	23	2	0.916
2	23	2	0.936
2.5	23	2	0.949
3	23	2	0.957
3.5	23	2	0.963
4	23	2	0.967
5	23	2	0.974
10	23	2	0.987
1000	23	2	0.999

As we can see from Table 2.1, 2.2 and 2.3, varying m doesn't influence the values of the output variables. That means that even if the company's risk preference has changed, it should still use the same values of N and T_e. Since expected NPV doesn't change with m, from Table 2, we can see that the point of yielding maximum expected NPV is also the point that yields the maximum expected utility. The plausible explanation to this phenomenon is as following. We are using triangular distributions to describe the randomness of the intermediate variables. Since triangular distributions do not have a long tail, the resulting spread in NPV is limited. Therefore, we are not generating situations in which variations in NPV are significant from one choice to another. Therefore value of m does not change the optimal values of N and T_e.

Another observation is that changing N and T_e, can produce large changes in the values of expected NPV. Figure 9 shows a case in which expected value of NPV varies from negative \$73136 to positive \$476747.

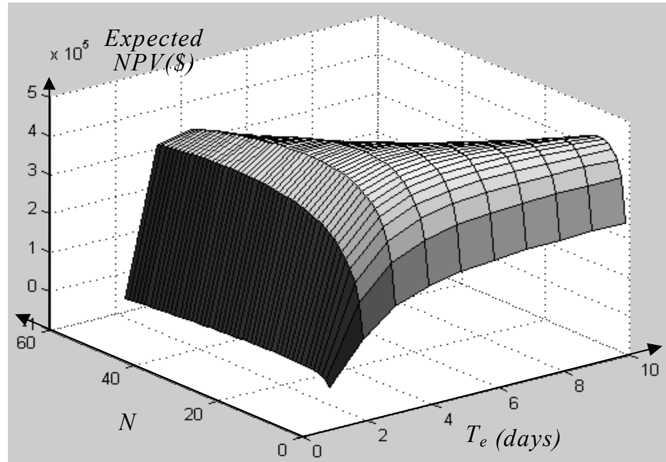


Figure 9: *Expected NPV* vs. N and T_e when m =2, n =2 and l =3

Results of Experiment 2. Table 3 shows the result of Experiment 2. Figure 10 shows the relationships between N and l, and T_e and l. For each value of variables l, we look for values of number of alternatives and evaluation time that lead to the highest value of utility while the values of n and m are fixed.

Table 3: Result of Experiment 2: varying l while fixing m =3 and n =3

l	*N*	T_e	$N \times T_e$	*Expected Utility*
1.5	30	3	90	0.887
2	25	3	75	0.897
2.5	23	3	69	0.904
3	21	3	63	0.908
4	19	3	57	0.914
5	18	3	54	0.918
10	17	3	51	0.926
15	16	3	48	0.928
20	16	3	48	0.929

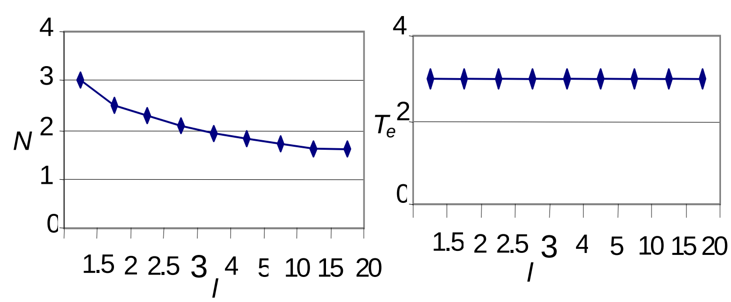


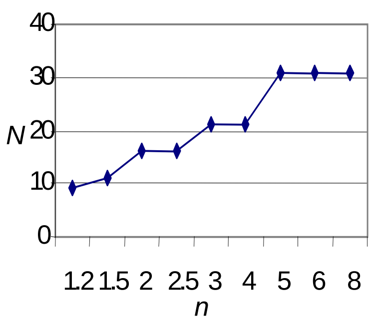
Figure 10. N vs. l and T_e vs. l

Discussion: l is used only in the relationship between μ_L and N. When l increases, for the same N, μ_L increases. However, due to the phenomena of diminishing return, μ_L increases more when N is smaller compared to the case when N is larger. Because μ_L has a positive influence on expected utility, expected utility increases more when N is smaller. For a given $l = l_1$ consider the adjacent area of the optimal point (N, T_e). Expected utilities for points in this area are very close to each other. Let us consider another value of $l = l_2$ ($l_2 > l_1$). The expected utility increases at points with the smaller N are bigger than the optimal point for l_1. Therefore, the optimal point for l_2 has the tendency to shift to points with smaller N. When l is bigger, the diminishing increase phenomenon is stronger. μ_L and expected utility increase in adjacent point are much bigger than the previous optimal point, the distance of shifting is larger. Therefore, we observe larger decrease in N. However, the change of l doesn't changes relationships involving T_e. So the optimal value of T_e doesn't change. Due to decrease in N and constant value of T_e, development time also decreases with the increase in l.

Results of Experiment 3. Table 4 shows the result of Experiment 3. Figure 11 shows the relationships between N and n and T_e and n. For each value of variables n, we look for values of number of alternatives and evaluation time that lead to the highest value of utility while the values of l and m are fixed.

Table 4. Result of Experiment 3: varying n while fixing m =2 and l =3

n	***N***	***T_e***	***$N^* T_e$***	***Expected Utility***
1.2	9	8	72	0.786283
1.5	11	6	66	0.799562
2	16	4	64	0.825243
2.5	16	4	64	0.846735
3	21	3	63	0.866347
4	21	3	63	0.887511
5	31	2	62	0.906880
6	31	2	62	0.920469
8	31	2	62	0.931076



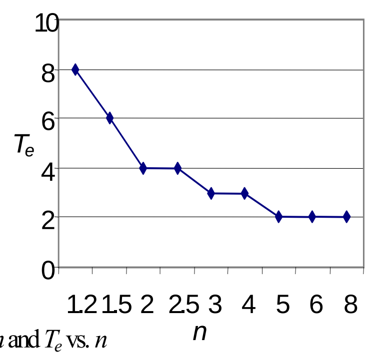


Figure 11. N vs. n and T_e vs. n

Discussion: The diminishing return n is used in the relationships between μ_C and T_e, σ_L and T_e, and σ_C and T_e. For a given value of T_e, increasing n reduces μ_C and σ_C simultaneously. Reduction in manufacturing cost leads to the increase of NPV and expected utility. However, due to the phenomena of diminishing return, μ_C and σ_C decrease more when T_e is small compared to the case when T_e is larger. Because μ_C and σ_C have negative influence on expected utility, expected utility increases more when T_e is smaller compared to case when T_e is larger. For a given $n = n_1$, consider the adjacent area of the optimal point (N, T_e). Expected utilities for points in this area are very close to each other. Let us consider another value of $n = n_2$ ($n_2 > n_1$). The expected utility increases at points with the smaller T_e are bigger than the optimal point for n_1. Therefore the optimal point for n_2 has the tendency to shift to a point with smaller T_e. When n is bigger, the diminishing increase phenomenon is stronger. μ_C, σ_C and expected utility increase in adjacent point are much bigger than the previous optimal point; therefore the distance of shifting is larger. Hence we observe larger decrease in T_e. However, currently we cannot predict the nature of change in N.

5 CONCLUSIONS

5.1 Summary

This paper describs a model for estimating the optimal number of alternatives to be explored and the optimal evaluation time for each alternative by incorporating cost of decision-making in the overall design decision model. We investigated how characteristics of the design task influence the optimal number of alternatives and the optimal evaluation time using a simple design case study. We draw the following conclusions based on the experiment conducted above.

1. The number of alternatives explored and the evaluation time significantly influences NPV-based utility. The optimal number of alternatives to be explored and the optimal evaluation time cannot be guessed intuitively. Optimal values of these parameters are dependant on the characteristics of the design task. Determining optimal values of these parameters requires constructing a detailed quantitative model of the design process and studying effects of these parameters on design team's utility via simulation.

2. Degree of decreasing return with respect to alternatives explored (n) and degree of decreasing return with respect to evaluation time (l) significantly influence the optimal values of number of alternatives and evaluation time. Therefore engineers must proactively collect data from prior projects to estimate n and l.

5.2 Limitations of The Study and Ideas for Further Research

In this paper we developed and studied models for a design task with one design parameter in a finite design space. In order to apply our models to more complex design tasks, the following extension is needed:

1. *Extend to More Comprehensive Decision Models*: Complex design tasks usually have multiple design parameters. The model must be extended to handle multiple design parameters. Furthermore, we assume the same degree of diminishing return in different models to simplify the computation. This coupling should also be relaxed. We assume that the mean value of performance is only affected by the number of alternatives explored and mean value of manufacturing cost is only affected by the evaluation time. Actually, in some design tasks, the mean value of manufacturing cost is also affected by number of alternatives explored. Therefore models should be extended to include this possibility. We use triangular distribution to describe the uncertainty in performance and manufacturing cost. In some design situations, other types of distribution may be more appropriate.

2. *Incorporating Procedural Models:* In the approach presented in this paper, we use closed form functions to model various relationships. Our rationale behind using these functions is to develop a better understanding of the underlying models. In complex design tasks, constructing closed form functions may be difficult. Fitting a function to large amount of data usually results in (1) either poor fit, or (2) ill-behaved functions. In such cases, a better alternative might be to utilize procedural models that can find the appropriate data from database and perform required interpolation/extrapolation locally.

3. *Extending Models to Support Hierarchical Evaluation.* The design task investigated in this paper has only one design parameter, thus the design space has a flat structure. Determining the optimal values of number of alternatives has to enumerate all its possible values. However, complex design tasks usually have hierarchical structured design space (e.g., design concept, system design, subsystem design, component design). In such a design space, the evaluation could also be done hierarchically. For example, we may first decide how many alternatives in the first level to explore and then the second level and so on. In this way, the optimal numbers of alternatives need to be determined at each level.

4. *Extending Models to Support Evolutionary Design Spaces.* In our models, we assume the design space is known to us before starting the evaluation. However, sometimes the design space is not known in the beginning. It develops as the design proceeds. This is especially typical in new product development. In this case, we may need to employ some forecasting mechanism to estimate the possible growth of the design space and update the models after the design space has evolved.

5. *Extending Models to Support Product Evolution.* Due to product evolution, different versions of the same product are launched over a period of time. We may know the design space at the beginning, but since the product is evolving, the design space is also evolving due to the emergence of new technology, part obsolescence, or changes in supply chain. In this case our metric needs to be changed to maximize the overall expected utility of several product launches. In this sense, our models may be used to decide how many product launches are needed and how many alternatives are to be explored in each product launch. For example, we may explore a small number of alternatives so that we can launch the first version quickly to get a big market share. Then we explore a lot of alternatives to develop a fine-tuned version.

6. *Improving Computational Performance*: Since we need to consider many possible values of number of alternatives and evaluation time with Monte Carlo simulation, the computation load is expected to be very large when the changes to models in above items have been incorporated. In such cases, more sophisticated pruning algorithm can be used to improve the computational performance.

NOMENCLATURE

T_e: evaluation time for each alternative (days)
N: number of alternatives to be explored
P: price ($)
C_d: decision-making cost rate ($/day)
r: discount rate
t_d: decision-making time (days)
t_m: market window (years)
D: demand (number of product units)
U: utility
V: net present value ($)
L_S: service life (months)
μ_L: mean value of service life (months)
σ_L: standard deviation of service life (months)
C: manufacturing cost ($)
μ_C: mean value of manufacturing cost ($)
σ_C: standard deviation of manufacturing cost ($)
m: degree of risk averseness
l: degree of diminishing return of μ_L with respect to N
n: degree of diminishing return of μ_C , σ_L or σ_C with respect to T_e
ki: scaling constants
ai: auxiliary constants

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