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Decision-Based Design Processes

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DECISION-BASED DESIGN PROCESSES

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This paper studies engineering design decision-making. We show that the decision-based design framework, which seeks to find the most profitable design, can be separated into a sequence of subproblems. This separation is similar to decomposition but does not require a second-level coordination. We identify conditions under which this separation yields an exact solution and other conditions under which the error can be bounded. This separation provides a different way to solve the decision-based design framework and indicates a way to apply the principles of decision-based design to design processes.

1. INTRODUCTION

Organizations that develop products and systems want to create the most valuable design that is feasible. The measurement of value, which depends upon the type of organization, may be profitability, life-cycle cost, or system effectiveness, for example. The value of the product or system that is being designed depends upon the decisions that the design engineer (or development team) makes.

The observation that engineering design requires making decisions has motivated a great deal of research, including work on decision analysis, decision theory, concept generation, modeling customer demand, multi-attribute decision-making, enterprise models, product development processes, and decentralized decision-making [1]. Design organizations can be viewed as a set of loosely-coupled decision-makers [2] that generate and share information in order to generate designs [3, 4]. The ultimate goal is to improve the quality of these decisions and increase the value of product development processes [5].

A variety of decision-making processes have been identified [6]. The two that are most relevant to engineering design are the incremental decision process model and optimization. The incremental decision process model [7] presents a structure in which a major decision is implemented as a series of small decisions. This detailed model involves iterating between the following types of activities: recognition, diagnosis, search, screen, design, judgment, analysis, bargaining, and authorization. Designers will easily recognize the similarities between this process and their own activities.

Design optimization is an important engineering design activity and a difficult mathematical problem. In general, design optimization determines values for design variables such that an objective function is optimized while performance and other constraints are satisfied [8, 9, 10]. Formal design optimization is a useful decision-making process when two conditions hold: (1) there exists enough technical knowledge to formulate a mathematical model that can express the value of a design as a mathematical function of the design variables and (2) there is a consensus on the appropriate objective function [6]. The attributes used to describe a design optimization model can be grouped into four areas: scope, variable set, objective function, and model structure [11].

The difficulty of solving large scale optimization problems and multidisciplinary optimization (MDO) problems, especially in the area of aerospace systems, has motivated various decomposition approaches. In general, these decomposition approaches require multiple iterations to converge to a feasible, optimal solution for a given design optimization model. Model coordination and goal coordination are two common methods for the decomposition of large scale design optimization problems [12, 13]. MDO problems have been the focus of decomposition approaches such as the bi-level integrated system synthesis (BLISS) approach [14], analytical target cascading [15, 16], and collaborative optimization [17].

The decision-based design (DBD) framework [18] is an approach that explicitly addresses the challenge of creating the most profitable design. In this framework, the design problem is to optimize the value of the profit (the expected utility of the profit) by selecting values for all of the design variables and the price. The all-at-once nature of the DBD framework has inspired researchers to develop new design optimization models (called *enterprise models*) that add variables from the marketing and manufacturing domains to models with conceptual design variables and to adapt existing decomposition techniques to solve them [17, 19]. These more extensive design optimization problems reflect the natural desire to handle large, complex problems in an integrated way [20]. However, this recent work does not include detailed design variables in the enterprise models. Thus, they do not completely solve the problem posed by the DBD framework.

This paper introduces an approach to solve design optimization problems by separating them into a sequence of subproblems to form a decision-based design process. In particular, this paper analyzes a version of the DBD framework and identifies conditions under which the separation is exact (the result is optimal) and sufficient conditions for establishing bounds on the quality of a non-optimal solution.

This paper first introduces the concept of separation. We then analyze the DBD framework. Finally, the paper discusses some more general thoughts about engineering design processes.

2. SEPARATION

In this paper we pursue the goal of replacing a large design optimization problem with a sequence of subproblems, solving each subproblem once, and producing a feasible, optimal solution without iterative cycles. We call such an approach *separation*.

The concept of separation is similar (but not identical) to the idea of decomposition. Both replace a large design optimization problem with a set of subproblems. In a typical decomposition approach, a second-level problem must be solved to coordinate the subproblem solutions in an iterative manner. (See Figure 1.)

Separation, on the other hand, does not require subsequent coordination. It is a decentralized and sequential approach related to the concept that is called *factorisation* in Pahl and Beitz [21]. A large problem is divided into subproblems. The solution to one subproblem will provide the inputs to subsequent subproblems. However, there is no higher-level problem to coordinate the solution.

The objective functions of the subproblems are surrogates for the original problem's objective function. These surrogates come from substituting simpler performance measures that are correlated with the original one, eliminating components that are not relevant to that subproblem, or from removing variables that will be determined in another subproblem.

It is also important to note that, despite a superficial resemblance, separation is not the same as dynamic programming, which solves subproblems and stores the solutions for later use by other subproblems in a recursive manner. These aspects are not present in separation.

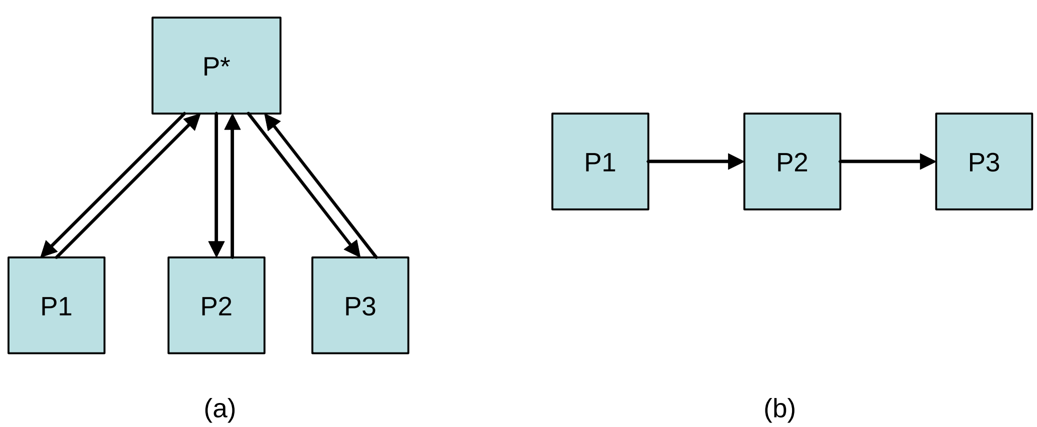

Figure 1. (a) A typical decomposition scheme has multiple first-level subproblems (P1, P2, P3) that receive inputs from a second-level problem (P*), which also coordinates their solutions. (b) Separation yields a sequence of subproblems. Solving one provides the input to the next.

3. SEPARATING A DESIGN OPTIMIZATION PROBLEM

Within a design process, it will be helpful to focus on the decisions that determine the design variables and the relationships between these decisions. This *decision network* view represents the separation of the system design problem. It does not consider details about the individuals making decisions, how they make decisions, or the flow of information between them, unlike the decision production system perspective [3, 4]. We can ignore these details and information processing and project management activities because we are focusing on the essential logic of the separation, not its actual execution. The decisions in the decision network can be seen, in some sense, as the value-adding activities of the decision production system (the design organization), in the same way that the metal cutting and assembly operations (not the material handling and quality assurance tasks) are the value-adding activities in a manufacturing system. In addition, the iteration that might occur if the design process runs into an obstacle is not part of the separation. A separation in which a subproblem has no feasible solution (or the only feasible solutions are unacceptable) is a poor-quality separation. A better one is needed.

We now consider a modified version of the DBD framework [18]. (This version ignores any uncertainties, and the demand affects the manufacturer's total lifecycle cost.) First, we will define the following notation:

m = system configuration. M is the set of all possible configurations.

x = vector of design variables.

$X(m)$ is the set of designs that are feasible for a given configuration m.

p = selling price per unit.

a = vector of product attributes.

D = total demand over the product lifecycle (units).

C = lifecycle cost to manufacturer.

The following functions are given:

$a(x)$ relates the attributes to the design variables.

$D = q(a, p)$ relates the demand to the attributes and the price.

$C(x, D)$ relates the lifecycle cost to the design variables and the demand.

u = utility of profit. Note that u is monotonically increasing.

Problem P is to choose m, x, and p to maximize the utility of the profit:

$$\begin{aligned} \max \quad & u\left(Dp - C\left(x, D\right)\right) \\ \text{s.t.} \quad & D = q(a(x), p) \\ & m \in M \\ & x \in X\left(m\right) \\ & p \geq 0 \end{aligned}$$

To separate this problem, the designer should define A, the set of all feasible attribute combinations, and $\hat{c}\left(a, D\right)$, the life cycle cost if the demand is D and the product attributes are a. Then, let the profitability Π be the surrogate objective function:

$$\Pi\left(a, p\right) = q\left(a, p\right) p - \hat{c}\left(a, q\left(a, p\right)\right)$$

Solve the following Problem P1 to get a^*, p^*:

$$\begin{aligned} \max \quad & \Pi\left(a, p\right) \\ \text{s.t.} \quad & a \in A \\ & p \geq 0 \end{aligned}$$

Let $D^* = q\left(a^*, p^*\right)$. Then solve Problem P2 to get $m^* \in M$ and $x^* \in X(m^*)$:

$$\begin{aligned} \min \quad & C\left(x, D^*\right) \\ \text{s.t.} \quad & a\left(x\right) = a^* \\ & m \in M \\ & x \in X(m) \end{aligned}$$

The quality of this separation is determined by the set A and the function $\hat{c}\left(a, D\right)$. Let $A(m)$ be the set of attribute combinations that are feasible for a given configuration m in M:

$$A(m) = \{a(x) : x \in X(m)\}$$

If $A = \bigcup_{m \in M} A(m)$ and $\hat{c}(a,D) = \min_{m \in M, x \in X(m)} \{C(x,D) : a(x) = a\}$, then this is an exact separation. To show this, we need to show that *m**, *x**, and *p** are an optimal solution to Problem P.

Suppose not. Then there exists $m' \in M$ and $x' \in X(m')$ and $p' \geq 0$ such that *a'* = *a*(*x'*), *D'* = *q*(*a'*, *p'*), and *u*(*D'p'*-*C*(*x'*,*D'*)) > *u*(*D*p**-*C*(*x**,*D**)).

Because *u* is monotonically increasing, *D'p'*-*C*(*x'*,*D'*) > *D*p**-*C*(*x**,*D**). By the definition of *m** and *x**, $C(x^*, D^*) = \hat{c}(a^*, D^*)$. Then, because $\hat{c}(a', D') \leq C(x', D')$:

$$\begin{aligned}\Pi(a', p') &\geq D' p' - C(x', D') \\ &> D^* p^* - C(x^*, D^*) \\ &= D^* p^* - \hat{c}(a^*, D^*) \\ &= \Pi(a^*, p^*)\end{aligned}$$

This contradicts the optimality (from P1) of *a**, *p**. Therefore, *m**, *x**, and *p** are an optimal solution to Problem P. QED.

Now suppose that the cost function is not exact but we have the following bound on the cost function error:

$$\left| \hat{c}(a,D) - \min_{m \in M, x \in X(m)} \{C(x,D) : a(x) = a\} \right| < \varepsilon$$

Then we can show that the profitability of *m**, *x**, and *p** must be within 2ε of the optimal profitability.

We will use a graph-like figure to represent a separation. This decision network figure has nodes that correspond to subproblems. An arc from a subproblem node indicates the variables whose values are determined by that subproblem. An arc leading into a node indicates the variables whose values are required by that subproblem.

The decision networks corresponding to the integrated model and the separation are shown in Figure 2. This separation corresponds to a simple design process in which marketing experts determine the product's price and the attribute combination that the product should have; then the engineers have to find the lowest cost design that can satisfy these attributes.

The analysis shows that the quality of this separation depends upon the marketing group's ability to identify feasible attribute combinations and to estimate costs. If marketing selects an infeasible attribute combination, then it will be impossible to design a satisfactory product. If the cost estimates are inaccurate, then the resulting product will be suboptimal.

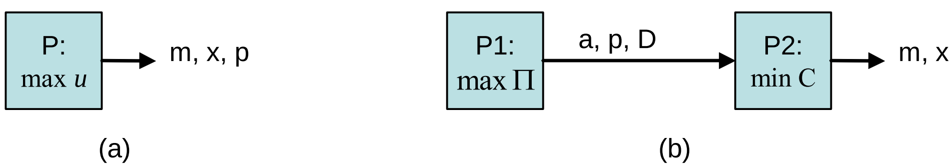

Figure 2. (a) The decision network for the integrated design optimization model.
(b) The decision network for the separation.

We can further separate Problem P2 into two subproblems: the first chooses the configuration *m*, and the second determines, for that configuration, values for the design variables *x*.

To separate this problem, the designer should define $\bar{C}(m, D)$, the life cycle cost if the demand is *D* and the product configuration is *m*, and $\bar{A}(m)$, the set of all attribute combinations that product configuration *m* can achieve.

Solve the following Problem P2.1 to get *m**:

$$\begin{aligned} \min \quad & \bar{C}(m, D^*) \\ \text{s.t.} \quad & a^* \in \bar{A}(m) \\ & m \in M \end{aligned}$$

Solve the following Problem P2.2 to get x^*:

$$\begin{aligned} \min \quad & C(x, D^*) \\ \text{s.t.} \quad & a(x) = a^* \\ & x \in X(m^*) \end{aligned}$$

Before analyzing this separation, we need to introduce the following definition: Let x and y be vectors in spaces E_1 and E_2 with $S \subset E_1 \times E_2$. Consider a real-valued objective function $f(x, y)$ defined over the set S and a real-valued function $g(x)$ defined over the set E_1. If $g(x_1) < g(x_2)$ if and only if $\min\{f(x_1, y) : (x_1, y) \in S\} < \min\{f(x_2, y) : (x_2, y) \in S\}$, then we will call $g(x)$ a *correlated surrogate*.

Now, define $C_{\min}(m, D) = \min\{C(x, D) : x \in X(m)\}$. If $\bar{A}(m) = A(m)$ and $\bar{C}(m, D)$ is a correlated surrogate for $C_{\min}(m, D)$, then P2.1 and P2.2 form an exact separation of P2. That is, the resulting m^* and x^* are optimal solutions to P2. The proof follows directly from the definition of a correlated surrogate.

In the following case, we can form an approximate separation for P2. Suppose that $\bar{A}(m) = A(m)$ and we have the following bound on the cost function error:

$$\left| \bar{C}(m, D) - C_{\min}(m, D) \right| < \varepsilon$$

Let m' be the configuration that minimizes $C_{\min}(m, D^*)$ and x' be a solution in $X(m')$ that minimizes $C(x, D^*)$. This m' and x' are the optimal solutions to P2. Then, we have the following bound on the separation penalty:

$$\begin{aligned} C_{\min}(m^*, D^*) &< \bar{C}(m^*, D^*) + \varepsilon \\ &\le \bar{C}(m', D^*) + \varepsilon \\ &< C_{\min}(m', D^*) + 2\varepsilon \end{aligned}$$

Thus, under this condition, this separation has a separation penalty of 2ε. The cost of the solution is less than 2ε from the optimal cost.

4. DISCUSSION: ENGINEERING DESIGN PROCESSES

The analysis above shows that a design optimization problem can be replaced by a sequence of subproblems. The first benefit is that the separation approach provides a way to model a decision-making process in which a decision does not determine a specific design but instead selects a set of similar designs (e.g., those that provide the same functionality), which is an important aspect of real-world engineering design decision-making.

We now turn to engineering design processes and discuss how separation provides us with a new way to consider engineering design processes. In particular, we can consider them as ways to solve the problem of finding the most valuable design and use separation as a model for a certain class of engineering design processes.

We will use the term *progressive design process* to describe an engineering design process that creates a product or system design through a series of phases. The phases generate intermediate results by making decisions about different aspects of the design and generating increasingly detailed information. (The name reflects the similarity to a progressive die, which makes an increasingly complex part through a series of punches.) Pahl and Beitz [21], Asimow [22], Ullman [23], and Ulrich and Eppinger [24] are among those presenting progressive design processes.

Progressive design processes emphasize the movement from one phase to another and the intermediate results that are generated. A progressive design process can be viewed as a heuristic for the value optimization problem discussed at the opening of this paper. For instance, if we consider the design process presented by Pahl and Beitz [21], one part of the process is described as optimizing the principle (or concept); another optimizes the layout, form, and material; and another optimizes the production. Moreover, the process is based on a general problem-solving process and ends with a "solution." It seems clear that the entire process is concerned with optimizing the system design; it is a way to find a good solution to this problem (though optimality is not guaranteed). In particular, Simon [2] describes the separation needed to design a battleship. He emphasizes that the battleship design decision is a "composite decision" that is made by making decisions about different subsystems.

Previous research has developed models of design processes that focus on the activities that need to be done, as in Gantt charts, the PERT and critical path methods, IDEF, the design structure matrix, Petri nets, and signposting [25]. Such models have been used to estimate the cost and duration of design processes [26-30]. The approach taken in this paper provides a way to consider the quality of the design process: how good is the solution that it creates? Answering this question would seem to be a way to extend the principles of decision-based design (including the idea that design should find the most valuable product) from a single decision to a design process.

The result above, though at a high level of abstraction, shows how to evaluate the quality of a progressive design process by modeling it as a separation of a design optimization problem. The separation of the DBD framework presented here provides a general guideline for how to do this. Moreover, it indicates mathematically that a progressive design process is a reasonable way to design a product or system, provided that the subproblems are appropriately formulated. It is not necessary to formulate and solve the problem as an integrated whole. Ongoing work is evaluating separations for specific design optimization problems [31].

This discussion is not meant to justify all heuristic design methods. Instead, it highlights the need to evaluate engineering design processes as a whole and to validate individual design tools and methods by considering their role as heuristics for subproblems in the separation of the design optimization problem. They can be evaluated properly only in the context of the design process in which they are used. Otherwise, they may be finding excellent solutions to the wrong problem.

5. CONCLUSIONS

This paper introduces an approach for solving design optimization problems by replacing them with a sequence of subproblems, which we call a separation. The separation approach provides a way to model a decision-making process in which a decision does not determine a specific design but instead selects a set of similar designs. Separation also provides a different way to solve design optimization problems. However, a separation must be carefully designed to provide a good solution. This paper has shown how separation can be used to solve the decision-based design framework. If the subproblems are correctly formulated, the separation yields an optimal solution. In the future perhaps we will see a careful analysis of various design methods that considers their usefulness as part of a design process and the quality of the solutions that are generated.

Adopting a general concept of optimization as a way to view progressive design processes places this paper among other work that views design as a mathematical problem-solving process or a rational decision-making process. However, there is also value in other perspectives, including those that view design as a creative process, a cognitive process with divergent and convergent thinking, or a social process involving teams and various languages or representations for communication. (See, for example, Dym *et al*. [32] for more about these other perspectives.) Future research will need to study the relationships between these perspectives and the one taken in this paper.

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