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A CLASSIFICATION FRAMEWORK FOR PRODUCT DESIGN OPTIMIZATION

Brad M. Brochtrup[1] **Jeffrey W. Herrmann**[2]
Department of Mechanical Engineering
Institute for Systems Research
University of Maryland
College Park, MD 20742

ABSTRACT

Research on design optimization has developed and demonstrated a variety of modeling techniques and solution methods, including techniques for multidisciplinary design optimization, and these approaches are beginning to migrate into product development practice. Software tools are appearing to assist with the optimization task. However, the complexity of the optimization problems being considered continues to increase because changing business strategies stress the importance of concurrent engineering and considering multiple disciplines simultaneously. This paper presents a novel classification framework for design optimization problems. The framework sorts design optimization problems based on the type of variables being considered and the objective functions being optimized. It does not focus on the algorithms used to solve the problems. This classification framework provides a new perspective that can help design engineers use optimization in the most appropriate way.

INTRODUCTION

Product development has been a lively research area over the last few decades especially in system level design optimization. Much work has been done to develop new techniques and frameworks to aid in solving complex optimization problems. Increasing scope and problem complexity accented the major limitations of initial solution techniques thus driving researchers to find alternate approaches [1]. The growing complexity of optimization problems is forcing engineers to depend more on powerful software and computer technology, while improvements in computing technology allow engineers the opportunity to attempt complex problems.

Advancements in computer capabilities and software have helped bridge the gap between research and industrial applications. For example, software such as iSight, MAX, and Smart|Coupling can currently integrate several disciplines into one complete optimization [2, 3]. Third party analysis software such as computational fluid dynamics (CFD), finite element analysis (FEA), spreadsheet simulation, and in house code are currently being integrated through these programs to expand the scope of optimization capabilities. New research in optimization and improvements in software have generated two major shifts in the scope of optimization techniques.

First, a shift from single discipline optimization, e.g. structures, to multiple disciplines within the engineering domain, e.g. performance, structures, and aerodynamics, occurred. As a result, several multidisciplinary design optimization (MDO) techniques such as all-at-once (AAO), individual-discipline feasible (IDF), and multi-discipline feasible (MDF) approaches were developed [4, 5]. Since then, other MDO solution methods including collaborative optimization (CO), concurrent subspace optimization (CSSO), and bi-level integrated system synthesis (BLISS) have been created and demonstrated in example problems [6]. MDO techniques apply various decomposition and coordination methods to facilitate communication between several disciplines while utilizing common optimization solvers to find a solution. Sub-optimization functions can be contained within the subsystems with appropriate coupling variables linking all the systems and subsystems together to ensure a global objective is maintained.

Collaborative optimization (CO) and analytical target cascading (ATC) are two common frameworks used in multidisciplinary optimization that have been demonstrated frequently in the last decade. CO is a bi-level optimization method used for non-hierarchical systems [7-11]. The newer method of ATC, on the other hand, decomposes a hierarchical system into two or more levels [6, 14-17]. ATC is not directly a categorization of an MDO technique because it depends on how the problem is decomposed.

[1] Graduate Student, E-mail: bbrochtr@mail.umd.edu
[2] Corresponding Author, Associate Professor, Department of Mechanical Engineering, University of Maryland, College Park, MD 20742, E-mail: jwh2@umd.edu

The second shift occurred as a result of the growing popularity of decision-based design (DBD). Since Hazelrigg [18] introduced a DBD framework for engineering design, applications have evolved to include decision-making and uncertainty [19-22]. MDO techniques are being applied to the DBD framework in an attempt to handle the added variables from the marketing and manufacturing domains [6,11,16,17]. Many approaches have been developed and tested on example problems; however, the majority of available literature detailing these example problems is organized around modeling techniques and solution methods.

To the authors' knowledge there have been only two classification schemes related to single product design optimization. The first was a taxonomy for three MDO decomposition approaches developed by Cramer *et al*. [5] resulting in the AAO, IDF, and MDF approaches mentioned previously. The second classification scheme, developed by Balling and Sobieszczanski-Sobieski [9], was a more general and versatile taxonomy for the six fundamental approaches of MDO decomposition. The notation in this taxonomy distinguishes between single and multi-level optimization and whether the analysis is simultaneous or nested at the system and discipline levels. Both of these classification schemes focus on the details of the techniques used to solve multi-discipline problems.

A classification scheme that helped generate ideas for the formulation proposed in this paper was created by Graham *et al*. in 1979 [12]. The three field $\alpha/\beta/\gamma$ notation classifies machine scheduling optimization problems based on various machine environments, job characteristics, and scheduling objectives, respectively [13].

This paper presents a classification framework based on the examination of various design optimization problems from the perspective of information requirements and objectives. We are not directly concerned with decomposition or modeling techniques nor do we limit our classification to MDO problems. The generality of the proposed classification allows even the most basic optimization problems to be classified.

Our goals when developing this classification framework included both scientific and practical ones. First, this classification framework helps us to organize and understand design optimization problems, an important step in any scientific discipline. While this classification framework is not the only conceivable scheme, we believe that it concisely captures the most important attributes while remaining open to including other attributes in the future if so desired. Second, this classification framework provides practical help for design engineers considering design optimization. Using this scheme, a design engineer can locate similar design optimization problems, which can be useful guides for formulating a new problem. Moreover, the set of similar design optimization problems indicates the range of potential solution techniques. Of course, the design engineer must still choose a problem formulation and a solution technique. This classification framework does not replace modeling skill, but it does provide information that can help one develop it. A related task (which the authors are undertaking) is to present examples of design optimization problems that have been solved using a variety of solution techniques and to discuss the tradeoffs involved when selecting a solution technique.

The remainder of the paper proceeds as follows. After defining some key terms used in the paper, we present the classification framework and then use available examples to demonstrate it. A summary concludes the paper.

DEFINITIONS

Many areas within a firm can influence the product development process. Engineering is obviously the basis of design while manufacturing and marketing are a major part of concurrent engineering. The engineering domain represents the perspective of design engineers and concerns about the product design and product performance. The manufacturing domain represents the perspective of manufacturing personnel and concerns about the manufacturing process and the corresponding metrics. The marketing domain represents the perspective of the product manager and concerns about finances, customer preferences, and demand.

Design optimization problems have three primary features: variables, constraints, and objective functions. Our classification framework will consider only variables and global objective functions. Constraints are important because they can influence the choice of an optimization solver based on whether the constraints are linear, nonlinear, equality, or inequality constraints. However, constraints are generally created during the modeling process. Our classification framework is meant to describe the fundamental problem, not the model details.

Due to the nonconformity of terminology in design research, the following definitions are given along with possible synonyms to avoid any confusion.

Product Scope

The classification framework distinguishes between single product design optimization and product family optimization. Definitions for each of the two product types are given for clarity, however, only single-product design problems are treated in this paper. Future work will extend this classification scheme to product families.

Single Product: This is a product that is designed with no regard to similar products. Component sharing and interconnection with other products do not influence the design decisions.

Product Family [23]:

1. A set of common elements, modules, or parts from which a stream of derivative products can be efficiently developed and launched.
2. A collection of common elements, especially the underlying core technology, implemented across a range of products.
3. A collection of assets (i.e., components, processes, knowledge, people and relationships) that are shared by a set of products.

Variables

Variables are sometimes referred to as parameters, design variables, and design parameters [24]. A designer must select the values for variables. Optimization is used to help find appropriate values of variables. The following three definitions refer to more specific types of variables.

Engineering Variables: These are variables specific to the product being designed. Typical engineering variables include product geometry, features, and material selection.

Manufacturing Variables: These are variables specific to the manufacturing domain. Every facility will have different manufacturing variables specific to the machine types and facility layout. Examples include number of machines, time allotment per machine, number of operations per part, force and energy requirements, feed rate, and depth of cut.

Price Variable: This variable is the price of the product or system being designed. Pricing is a critical but complex issue. For a new product, a successful pricing approach first determines the price that customers can be convinced to pay for the product concept, and then the firm designs a satisfactory product that can be manufactured profitably at the expected sales volume [25]. While the initial pricing strategy may be used to set a cost target for the product design, the product price will certainly change over time as the firm's pricing strategy influences their response to market forces. The product development team does not need to make pricing decisions that have not yet arrived. However, optimizing product profitability at the design stage requires understanding what the firm is likely to do. If alternative strategies are feasible (such as skim pricing or penetration pricing), the team may want to evaluate these strategies, since they control future prices.

Objective Functions

Design optimization (especially MDO) can include several sub-problems depending on the system being designed. The classification framework considers only the global objective also known as the system level objective. The classification framework covers single objective as well as multi-objective optimization problems at the system level.

Attribute-based: These objective functions are related to product performance or product characteristics (i.e. attributes). For the purposes of this classification framework an attribute is a quantitative measure related to the object or system being designed. The objective is to maximize or minimize an attribute level, usually a performance measure, based on the product being designed. Although uncommon, it is possible to utilize demand information in the attribute-based objective function but it is not a requirement. Examples: minimize weight, minimize size, minimize stress, and maximize range. Alternatively, the objective may be to minimize the deviation from a target attribute value.

Cost-based: These objective functions are related to the engineering and manufacturing domains. The goal is to minimize the overall cost of the product based on one or more cost models. Generally this type of optimization will be more complex than the attribute-based objective because cost models will be necessary along with the design models. While one can consider a cost objective to be a performance measure equivalent to any attribute-based objective, we treat cost separately because product performance and product cost are fundamentally different and very important objectives, as discussed by Smith and Reinertsen [26]. Therefore it is useful to the designer if a distinction is made between the two types of objectives. Similar to the attribute-based objective function this can include situations where the objective is to minimize the deviation from a cost target. Demand can again be utilized as a weighting method in this objective but is not required.

Profit-based: These objective functions are directly related to the marketing domain. The goal of the optimization is to maximize the design value based on demand information. Although not stated explicitly in the classification it can be assumed that any profit-based objective will require some type of demand model. Another step in complexity is seen through the profit-based models in comparison to the attribute-based and cost-based because more model evaluations are required for this type of optimization. Examples: maximize revenue, maximize profit, maximize expected utility of profit, maximize net present value, and maximize return on investment.

CLASSIFICATION FRAMEWORK

Three main categories become apparent when considering design optimization problems. Our classification framework sorts design optimization problems based on the following three characteristics: problem scope (i.e. single product versus product family), the variables that need to be decided (i.e. engineering, manufacturing, or price), and the primary objective function (or functions) of the optimization problem (i.e. attribute-based, cost-based, or profit-based).

To explain the classification framework, we will begin with the most basic types of deterministic optimization problems involving only a single objective function. Subsequent paragraphs will discuss problems with multiple objectives. After that we will present a modifier to the objective function to describe typical methods of dealing with uncertainty.

The classification framework categorizes design problems using three fields corresponding to the three characteristics mentioned above. The first field notes the number of products. The second field notes the types of variables. The third field notes the type of objective function (or functions). Designing a single product with a single system level objective can include twelve possible optimization framework combinations. Six of the twelve combinations are more likely to be used due to the relationship between the objective function and the variables considered. For example, if the design process includes only engineering variables, then maximizing profit would not be a typical objective function since maximizing profit or the expected utility of profit usually includes the price variable. The twelve combinations for single objective optimization problems are shown in Table 1 with the six most logical in bold lettering.

The product type entry in field one can be either single product (S) or product family (F). Variables present in the optimization, shown in field two, may include engineering variables (E), manufacturing variables (M), or a price variable (P). Field three displays the objective functions for each combination of variables, which include attribute-based objectives (A), cost-based objectives (C), and profit-based objectives (Π).

Single Objective					
Field #			Product Type	Variables Included	System Objective
1	2	3			
S	**E**	**A**	**Single**	**Eng.**	**Attribute-based**
S	**E**	**C**	**Single**	**Eng.**	**Cost-based**
S	E	Π	Single	Eng.	Profit-based
S	**EM**	**A**	**Single**	**Eng. & Mfg.**	**Attribute-based**
S	**EM**	**C**	**Single**	**Eng. & Mfg.**	**Cost-based**
S	EM	Π	Single	Eng. & Mfg.	Profit-based
S	EP	A	Single	Eng. & Price	Attribute-based
S	EP	C	Single	Eng. & Price	Cost-based
S	**EP**	**Π**	**Single**	**Eng. & Price**	**Profit-based**
S	EMP	A	Single	Eng., Mfg. & Price	Attribute-based
S	EMP	C	Single	Eng., Mfg. & Price	Cost-based
S	**EMP**	**Π**	**Single**	**Eng., Mfg. & Price**	**Profit-based**

Table 1: Combinations of Single Product Optimization with a Single Objective.

The above classification framework is easy to use and self-explanatory. For instance, if a problem is classified as type S-E-A, one can immediately know that the optimization problem is for a single product, it has only engineering variables, and has an attribute-based objective.

The classification framework also includes multi-objective design optimization problems, resulting in eight more common combinations. The third field of the classification is further divided into two subfields (i.e. positions within the third field). The first subfield will always contain the entry "A" as can be seen in "AA," "AC," or "AΠ." The second field on the other hand can be either "A", "C", or "Π" to distinguish what other objectives are present.

The classification of an optimization problem with two or more attribute-based objectives would contain "AA" in the third field (e.g. S-E-AA or S-EM-AA). If "AC" appears in the third field of the classification then there are two or more attribute-based and cost-based objectives. Similarly, "AΠ" is used for the multi-objective case where attribute-based and profit-based objectives are present. The latter case is common among multidisciplinary design optimization techniques such as ATC and CO when the multi-objective function is to minimize the deviation between attribute targets while maximizing profit [16,17]. Note the specific number of objectives is not specified in the multi-objective case. The formulation of the objective function as well as the choice of optimization program may alter depending on the number of objectives (e.g., two versus four objectives) but from the perspective of the proposed classification scheme these differences are minor. Distinguishing between a single objective optimization and a multi-objective optimization plays a much larger role in selecting a solution technique than the difference between two objectives and four objectives.

A "CΠ" classification is unlikely because cost models are generally inputs to the profit model though this multi-objective problem is technically feasible. The sixteen possible combinations are shown in Table 2 with the eight most typical combinations in bold.

Multi-Objective					
Field #			Product Type	Variables Included	System Objective
1	2	3			
S	**E**	**AA**	**Single**	**Eng.**	**Attribute-based**
S	**E**	**AC**	**Single**	**Eng.**	**Att. & Cost-based**
S	**E**	**CC**	**Single**	**Eng.**	**Cost-based**
S	**EM**	**AA**	**Single**	**Eng. & Mfg.**	**Attribute-based**
S	**EM**	**AC**	**Single**	**Eng. & Mfg.**	**Att. & Cost-based**
S	**EM**	**CC**	**Single**	**Eng. & Mfg.**	**Cost-based**
S	EP	AA	Single	Eng. & Price	Attribute-based
S	EP	AC	Single	Eng. & Price	Att. & Cost-based
S	**EP**	**AΠ**	**Single**	**Eng. & Price**	**Att. & Profit-based**
S	EP	CC	Single	Eng. & Price	Cost-based
S	EP	CΠ	Single	Eng. & Price	Cost & Profit-based
S	EMP	AA	Single	Eng., Mfg. & Price	Attribute-based
S	EMP	AC	Single	Eng., Mfg. & Price	Att. & Cost-based
S	**EMP**	**AΠ**	**Single**	**Eng., Mfg. & Price**	**Att. & Profit-based**
S	EMP	CC	Single	Eng., Mfg. & Price	Cost-based
S	EMP	CΠ	Single	Eng., Mfg. & Price	Cost & Profit-based

Table 2: Combinations of Single Product Optimization with Multiple Objectives.

Deterministic models are preferred by engineers due to the simplicity of formulating and solving them. Unfortunately, it is a well known fact that the real world is not deterministic. Therefore, it is important to include uncertainty in the classification framework. An objective function subclass, including five methods of dealing with uncertainty, categorizes and clarifies optimization problems further. The first method of dealing with uncertainty is ignoring it, thus the problem is a deterministic optimization problem. Four other common methods include expected value (EV), expected utility (EU), worst-case (WC), and probability of satisfaction

(PS). Although there are variations to the methods mentioned above (such as the Hurwicz criteria and maximum likelihood criteria), we believe the most common forms are accounted for.

The classification framework represents the uncertainty subclass using a subscript on the objective function terms in the third field. Deterministic objective functions would have no subscript in the third field while the four common methods for dealing with uncertainty described above would include a subscript of EV, EU, WC, or PS respectively. For example, the classification S-E-A_{WC} is used for problems that address a single product, have engineering variables, and optimize the worst-case performance.

The framework is deployed in the next section to classify available examples. Engineers will be able to use available examples to perform a case-based search and find design problems that are similar based on the three fields of the classification scheme and compare the different solution techniques previous designers used in solving the problem.

EXAMPLES

Available examples of various optimization problems, including MDO problems, will be classified using the proposed framework. The MDO problems used for demonstrating the framework were solved using either ATC or CO techniques.

An S-E-A type optimization is the most basic because it involves only the engineering domain. Therefore, the equations used to model this type of optimization rely only on principles of engineering science. First a general optimization problem is discussed followed by another example that employs one of the afore-mentioned MDO techniques.

A simple single discipline example of designing a fingernail clipper can be found in Otto and Wood [27]. In this example a model is formulated to represent finger force. The variables included in this model are finger force, cutting force at the blade, length of lever arm, distance to the blades, nail thickness, shear strength of nail material, width of blade, and blade height. The deterministic attribute-based objective chosen in designing the fingernail clipper is to minimize the finger force required subject to stress and dimension constraints. It can easily be seen by looking at the variables involved that only engineering variables are included for the design of a single fingernail clipper. Thus, this problem can be classified as type S-E-A. Cost and manufacturing concerns are not present in the formulation although it is possible to extend this problem to include such domains.

Kroo *et al.* [8] present a system level aircraft design problem. The global objective function is to maximize range under the influence of an aerodynamics subsystem, a structures subsystem, and a performance subsystem. Range is an attribute of the system to be designed, which corresponds to the "A" in the classification. The variables in this problem are all related to the plane's design and include wing geometry, wing weight, twist angle, aspect ratio, gust loading, and lift-to-drag ratio, all of which affect range. This is a deterministic S-E-A problem because no distributions are applied to the input variables. Figure 1 shows the CO framework applied to solve this aircraft design problem.

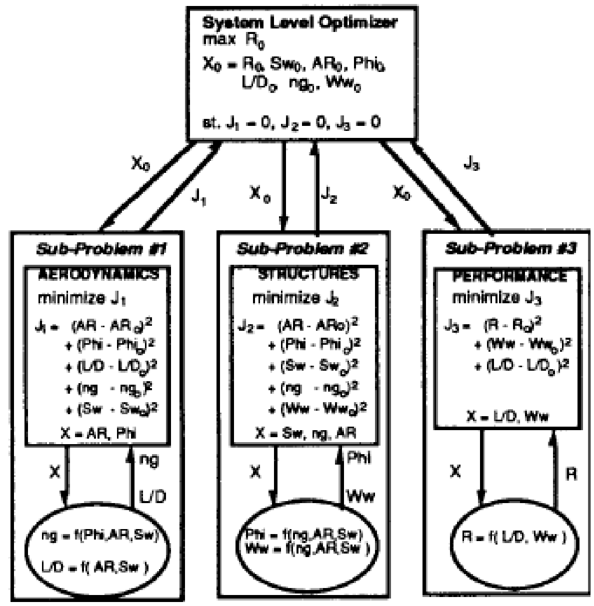

Figure 1: CO Framework for Aircraft Design [8].

The CO framework in this example clearly shows what variables are present during the optimization as well as the disciplines influencing the system level design. Notice the classification framework is not directly related to how the problem is divided or what disciplines within engineering are included. Sobieski and Kroo [10], Kim *et al.* [14, 15], Otto and Wood [27], and McAllister and Simpson [28] demonstrate other examples of S-E-A type optimization problems.

Although a fingernail clipper and aircraft design problem in the above examples intuitively seem very different, the difficulty in solving them is not all that different. The fingernail clipper is a detailed design problem while the aircraft wing is more conceptual. The aircraft design problem could have been formulated and solved as an AAO instead of using the collaborative optimization, in which case the two examples would appear to have a greater similarity. When a problem can be decomposed and modeled in different ways, a design engineer would probably want to see examples of several different methods to find the most appropriate one. There is no specific cutoff based on the complexity of the problem to determine when an MDO technique is more effective than a distributed approach such as AAO, IDF, or MDF. Therefore, multiple examples of techniques based on similar problems seem more useful especially when dealing with a somewhat complex design problem.

Next, an example of an S-EP-Π type optimization problem is examined. Gu *et al.* [11] details an aircraft concept-sizing problem to maximize profit under the influence of engineering variables and a price variable. The authors chose to assume the utility of profit to be profit itself thus treating it as a deterministic problem for calculation purposes. If uncertainty were accounted for through a utility function this problem would be classified as S-EP-Π_{EU}. Figure 2 shows the general layout of the decision-based collaborative optimization approach.

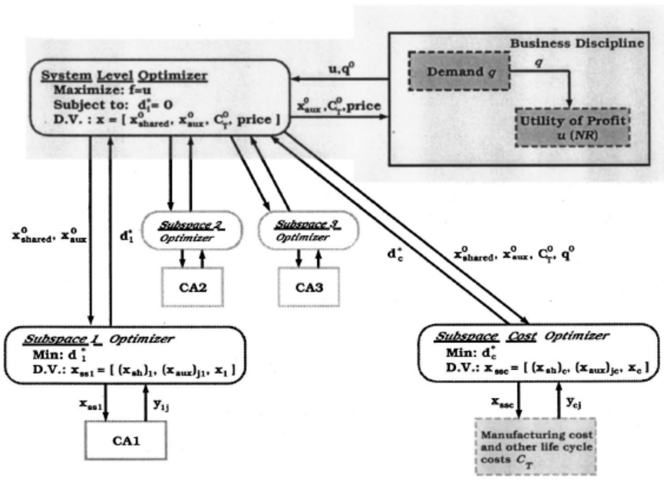

Figure 2: A General Decision-based CO Framework [11].

The engineering variables included in this single aircraft optimization example consist of aspect ratio, wing area, fuselage length, density of air at cruise altitude, cruise speed, and fuel weight. The price variable is also part of the optimization problem. In a profit-based optimization problem the cost models are present as inputs to a profit function but do not affect the classification framework because it is not a system level objective. The cost model term is present in the classification framework only for systems with a cost-based objective. Another example of a type S-EP-Π optimization can be found in Kumar *et al*. [6].

Next, an example is taken from Sues *et al*. [30] to demonstrate the uncertainty sub-class within the classification framework. This shape optimization of an airplane wing includes seven engineering variables related to the wing geometry. Values for aspect ratio, taper ratio, semispan wingtip incidence, structure skin thickness, structure span thickness, and wing sweep all need to be decided. The global objective of this single wing shape optimization is to maximize expected cruise range. Uncertainty appears through random distributions on all of the design variables to account for inconsistencies in the manufacturing processes. This example can be classified as type S-E-A_{EV}. Several other examples dealing with uncertainty can be found in Sues *et al.* [30]. An example of type S-EP-Π_{EU} can be found in [29].

Finally, a multi-objective optimization example will be classified using the framework. Azarm and Narayanan [31] discuss a multi-objective example regarding the design of a fleet of ships. The objectives of this example include minimizing construction and operating costs and maximizing the cargo capacity. The engineering variables present in the model of this optimization include: breadth, depth, deadweight, length, number of ships, draft, utilization factor, speed, and displacement. Due to the conceptual nature of this optimization problem, specific manufacturing construction variables were not considered. Manufacturing costs, however, were accounted for in the cost models. This problem can be classified as type S-E-AC. The "A" denotes the presence of an attribute-based objective (maximize cargo capacity) while the "C" denotes the presence of a cost-base objective (minimize construction and operating costs). Tappeta and Renaud [32] present an aircraft concept-sizing problem that can be classified as S-E-AA. The problem has two attribute-based objective functions: minimize mass and maximize range.

CONCLUSIONS

A novel classification framework for design optimization problems has been presented. The classification framework offers a new perspective on design optimization problems. Several examples of design optimization problems (including multidisciplinary design optimization problems) were considered to show the versatility and usefulness of the classification framework. Software and hardware capabilities make the deployment of optimization techniques more practical than ever. Designers can use this classification framework and the reference examples as a starting point for considering the scope of the design optimization problem and reviewing relevant examples before working on the details of the problem formulation and programming the optimization software.

The classification framework does not cover every characteristic of design optimization problems. For instance, the classification framework does not cover qualitative but important measures such as safety and environmental impact unless a specific objective function can be found. It does not consider important issues such as the linear (or nonlinear) nature of the constraints and objective functions. It does not distinguish between optimization problems used in different phases of product design (e.g., conceptual design or detailed design).

The first contribution of the classification framework is to begin organizing the ever-increasing variety of design optimization problems using characteristics that are relevant to design engineers. Its second, related, contribution is to provide guidance to design engineers and product development teams who want to use design optimization.

A set of design optimization problems that receive the same classification may cover a range of formulations, solved using a variety of techniques. This diversity is useful since it provides a range of relevant examples so that the designer (or design team) can find one that is most appropriate for their situation and their abilities.

In addition, the classification framework provokes the designer (or design team) to consider a broader perspective of the entire process. Abstraction early in the design phase allows a designer to focus on the high level understanding of the problem at hand before getting immersed in the details. Second, a methodical review of what the major goals and decisions for the project are can clarify and guide the process.

More generally, effectively incorporating design optimization into the product development process requires a solid understanding of the problem objectives and design variables. A designer that understands the design problem well enough to classify it will likely understand it well enough to develop an appropriate problem formulation.

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APPENDIX

Classification	Reference #	Description
S-E-A	1	Launch Vehicle Design
S-E-A	2	Aircraft Engine
S-E-A	8	Aircraft Design
S-E-A	10	Aircraft Wing Design
S-E-A	14	Chassis Design
S-E-A	15	Chassis Design
S-E-A	27	Finger Nail Clipper
S-E-A_{EV}	30	Airplane Wing
S-E-C	1	Launch Vehicle Design
S-E-C	2	Aircraft Engine
S-EP-Π	11	Aircraft Concept Sizing
S-EP-Π_{EU}	6	Suspension Design
S-EP-Π_{EU}	29	Universal Motor Design
S-E-AA	32	Aircraft Concept Sizing
S-E-AC	31	Fleet of Ships
S-EP-AΠ	16	Weight Scale

Table A.1 Classified Examples from Reference Papers