Heuristics for Formulating System Design Optimization Models: Their Uses and Pitfalls

Anand P. Deshmukh*, Deborah L. Thurston† and James T. Allison‡

*Graduate Student, adeshmu2@illinois.edu
†Professor, thurston@illinois.edu
‡Assistant Professor, jtalliso@illinois.edu

Department of Industrial and Enterprise Systems Engineering
University of Illinois at Urbana-Champaign
Urbana, IL 61801

***Abstract*—Modern systems are becoming increasingly complex due to the need to build inherent autonomous decision making abilities in them (e.g. self driving cars, fly-by-wire aircraft systems, automatically controlled wind turbines etc.) and other factors. Like many other new trends, these systems challenge the limits of existing design methods. Traditional normative design optimization methods address objective trade-off issues by employing an organized constraint matrix for quantifying the unavoidable cause and effect relationships between designer choices and product performance. Normative methods can also be used to address subjective tradeoffs under uncertainty with this same degree of analytic rigor. New design trends challenge these and other existing methods by presenting the designer more and more options and tradeoff choices that are well outside the traditional boundaries of analysis. The usual response is to expand the frame of analysis, relying on expert heuristic "rules of thumb" to make the task manageable. However, these heuristics can create unnecessary constraints or lead to cognitive biases. This paper presents a new framework for examining the steps in formulating a design optimization problem, and determining when to keep heuristics for their efficiency and when to replace them with a normative decision approach. An illustrative example employing an automatically controlled wind turbine is provided to demonstrate how a reasonable-seeming heuristic for defining of the design objective can lead to a result that is sub-optimal in terms of satisfying the true system performance objective.**

I. Introduction

Autonomous systems are playing an increasing role in day-to-day life and challenge the limits of existing design methods, presenting the designer with choices, tradeoffs and constraints never before considered. Advances in systems design methodology are often made by expanding the frame of analysis to include new issues [1]. *Normative* design approaches consider these new tradeoffs under uncertainty with the same degree of analytic rigor that was previously applied only to static physical system modelling. While successful, there are times when the cost of normative approaches are too high. This occurs when the effort required to formulate the model, gather data to test hypotheses about the design decision makers' willingness to make tradeoffs, assess their attitude towards risk, and formulate other elements of the analytic model, etc., are simply not worth the effort.

On the other hand, the heuristic 'rules of thumb' employed by design experts, which is a *descriptive* design approach, are faster and more efficient. However, sometimes these heuristics can lead to suboptimal results because of systematic cognitive biases that lead the design choice away from the optimal solution. Heuristics also account for factors in design decisions in a simplified way, also leading to suboptimal decisions. This tension and synergy between normative and descriptive approaches to engineering design is described in [2]. The problem addressed in this paper is that a strictly heuristic design approach can lead to inferior solutions, while strictly normative approach can be too time consuming and costly to implement. This paper presents a set of rules for determining the best combination of both the approaches.

II. Background and Problem Definition

It is not always obvious how and when to consider emerging trends (such as design for autonomy), in the product design process. For example, [3] addressed the relatively new problem of hybrid electric vehicle battery design. They developed a method to address two criteria relevant to cell spacing design; closeness to target temperature and evenness of temperature distribution. Their approach develops the Pareto optimal frontier, and then employs equitable conflicting objective optimization to determine the best location on the Pareto optimal frontier. This computationally intensive approach identifies the optimal cell spacing, but does not yet include consideration of other decision variables such as shape of the battery pack and geometric arrangement of cells.

Analytic methods have brought mathematical modeling rigor to design problem formulation steps that were previously ad-hoc. One such method focuses on determining which attributes should be considered during engineering change evaluation [4]. They formulate a multi-objective optimization problem to quantify the relative importance of feasible attribute sets. The goal is to identify which past design changes should be retrieved (and evaluated) to best evaluate the effect of a proposed design change.

Another approach is the use of Design Structure Matrix (DSM) based methods. A DSM displays the relationships between system components in a compact and analytically useful format [5]. An intuitive next step is then to expand the DSM to include new systems elements. For example, Kasperek et al. [6] propose the expansion of DSM to model systems dynamics, including strategies for simulating several process sequences. While technically sound, this and other matrix-expanding methods can significantly increase level of effort in modeling, data gathering, and matrix size.

The problem of unworkably large matrices has been discussed in [7]. They examine several heuristics for decomposing the matrix into a group of workable sets. They find that "In fact all heuristics, even combined, generally fail to decrease the number of combinations to a level that can be handled by the designers, unless the original number of combinations is low." In addition to computational difficulties, having too many choices can lead to the decision maker being unable to make choices, and/or lacking confidence in the result (in part because the designer can see first-hand the range of uncertainty associated with each model parameter). These are just two of several drawbacks to having too many decision options described in [8].

Thus, classic normative approaches (normative multiattribute evaluation under uncertainty, optimization, design for X, etc.) can address many important issues, but can become cumbersome when defining the cognitive frame of the problem becomes more complex than usual. This happens in several instances, including design of automated systems, design of products and procedures for the life cycle, design for complexity, etc.

In autonomous or active systems (e.g., self-driving car, actively controlled automotive suspension system, respectively), sometimes the product is fulfilling a function that would not be possible without automation, or is seeking to automate the actions of a human operator. The initial approach would be to keep the physical configuration the same, and supplement it with some type of automated control system. However, this approach not only imposes unnecessary constraints (operator safety, for example) but also might unnecessarily constrain the frame of the problem. Another example is design of human-operated surveillance aircraft, which requires consideration of safety, reliability, and cost of a large, single aircraft with long service life. Without a human operator, the designer is free to consider the possibility of a completely different configuration, perhaps a number of significantly smaller drones, which presents the designer with a completely different set of attributes to be traded off against one another. The usual solution to these issues is to expand the frame of the analysis to include "X" within the traditional DBD or optimization model, as shown in Figure 1.

On the other hand, the usefulness of heuristics in efficiently capturing new trends and design expertise has been recognized by several researchers. For example, the increasingly heterogeneous marketplace is addressed by [9], where heuristics are developed for use in the earliest stages of design to satisfy a broad range of variation in customer needs. The increased availability of on-line consumer reviews was

Traditional *(Most Normative)*	**New** Decision Variables **Traditional** Objectives
Traditional Decision Variables **New** Objectives	**New** Decision Variables **New** Objectives *(Most Heuristic)*

Fig. 1. Expanded DSM to include objectives and design decision options

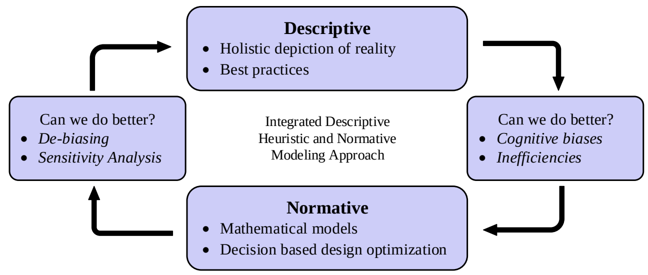

Fig. 2. Method for integrating descriptive heuri1stic and normative modeling approaches

viewed as an opportunity to gain information directly from customers, seeking to gain information in the framework of novel affordances [10], employing a heuristic approach. The heuristic generation process is automated in [11], by applying graph theory to determine a mathematical representation of the functional model.

However, sometimes heuristics can inadvertently include biases, as described by [12]. Several researchers have addressed the issues raised by cognitive biases and how to remedy them [13]–[15]. The problem addressed here is that descriptive heuristic methods for formulating the design optimization problem are fast but can lead to inferior or suboptimal solutions, while strictly normative processes can be too time consuming and costly to implement. The specific problem is that normative "design for trend X" approaches can create a normative optimization model that, while accurate, can incur too much effort to estimate the model parameters. This can also lead to the problem of lack of confidence in the result, as the designer is forced to acknowledge the degree of uncertainty in his or her estimate of model parameters. Ironically, sometimes even heuristics can result in suboptimal solutions in which the decision maker has greater confidence, especially when the "expert" bias comes into play.

III. Proposed Method

The heuristics addressed in this paper are related to the tasks of optimization model formulation shown in Table I. These tasks include identifying the mathematical structure that best reflects the problem (linear, integer, nonlinear, stochastic, dynamic, etc.), and defining the objective function, decision variables, and constraint functions.

TABLE I
DESIGN OPTIMIZATION FORMULATION TASKS, THEIR DIFFICULTY AND HEURISTICS EMPLOYED

Design Task	**Why is it difficult?**	**How the design task is accomplished?**
Determine Type of Model (linear, integer, non-linear, dynamic, stochastic etc.)	• No single model can include everything • Some models require extensive data gathering effort • Some models pose computational difficulties	• Framing • Computational ease
Define Objective Function	• Preference functions can be time consuming to assess, especially with need to make trade-offs under uncertainty • Trade-offs can be outside of designer's realm of expertise	• Sequential Task Ordering • Setting targets • Use of proxy estimators
Define Decision Variable Set	• Need to first envision configuration, materials used, geometry, manufacturing and assembly process employed, etc.	• Framing • Availability • Anchoring
Define Constraint Equations	• Need to first envision configuration, materials used, geometry, manufacturing and assembly process employed, etc.	• Framing • Availability • Anchoring • Use of proxy estimators
Determine Stopping Point and Take Action	• Defining "good enough" is difficult when the designer does not know what is possible	• Satisficing • Expert opinion

The objective is typically defined first, and includes design attributes that are important in terms of performance and how alternative designs are evaluated and compared. One might reasonably define the objective function to include only those things that will make a difference in design decisions. The goal is to not to waste modeling effort in gathering data that will not change the rank ordering of alternatives, either because the differences among the alternatives is small, and/or the designers willingness to make tradeoffs is small. Other heuristics for defining the objective function are to include only those elements that the designer can estimate and control through design decisions.

The framing heuristic is used to define the boundaries of the design problem. Framing defines the boundaries between what will be considered by the designer and what is considered to be outside the designer's responsibility and/or expertise.

For the design task of defining decision variables, the designer must specify which parameters he or she can control directly. Examples of independent decision variables include material choice, configuration, geometry, manufacturing and assembly methods, etc. The heuristic of catalog search can be employed, where the designer reviews how previous designs accomplished a similar objective before. This heuristic can lead to a cognitive bias called "fixation". Several have studied the negative influence of fixation, which can result from using the anchoring and adjustment heuristic [16], [17]. Designers often employ this heuristic during the product configuration stage by starting with examples of previous, similar products, or components found during catalog search. The fixation bias is that instead of using the "available" example simply as a starting point for innovation, the designer becomes "fixated" on the example, and becomes less able to create innovative concepts.

For the design task of defining the constraint equations, technical engineering expertise is employed. This is where the predictive models to estimate various aspects of design performance and failure modes are used. These might include equations to estimate weight as a function of material choice and component geometry, to estimate cost as a function of design configuration and manufacturing process parameters,

TABLE II
RULES FOR CHOOSING DESCRIPTIVE HEURISTICS VS. NORMATIVE DESIGN APPROACH

Use *descriptive* heuristics when the heuristic,	Replace Heuristics with *normative* approach when the heuristic,
• Embodies expert domain knowledge efficiently, where efficiency means that the model formulation process is fast	• Inadvertently embodies cognitive biases that systematically take the designer away from the best solution
• Eliminates the need for costly and time consuming data gathering efforts that the normative approach would require. This can include estimating model parameters, outcomes, probabilities or utility functions	• Does not include consideration of new materials, manufacturing processes and/or control systems resulting in possible decision variables remain unexploited
• Results in a design problem formulation that does not pose computational difficulties in arriving at the optimal solution	• Unnecessarily constrains the feasible region. This might be due to outdated expertise that does not include information about the set of desirable tradeoffs available when newer materials, manufacturing methods and automated control systems are employed
• Results in a design process that is fast and an efficient use of the resources of time and money	• Results in systematic cognitive biases that lead to inaccurate estimates of optimization model parameters, including probabilities, objectives outcomes
• Results in is "good enough" design (satisficing)	• Creates a lack of confidence in result because it can lead to counter-intuitive results that cannot be explained
• Avoids the designed being overwhelmed by too many choices	
• Increases confidence in result, enabling the designer to take action and move on to the next task	

energy as a function of configuration and operating parameters, etc. A reasonable heuristic might be to include only those constraint equations with which the designer can estimate design performance with a reasonable degree of accuracy. This would include the ease with which the designer can control performance via the design decision variables, and also the degree of uncertainty associated with the result.

For the design task of estimating uncertainty associated with design outcomes such as cost, efficiency, etc., the heuristics of availability, representativeness, anchoring, and adjustment have proven quite useful. However, they simultaneously present potential for incurring cognitive biases that make it difficult to estimate event probabilities accurately, as described in Ref. [12].

The solution proposed here goes beyond simply expanding the design decision matrix. As shown in Figure 2, the solution is to examine the descriptive heuristics as they are employed in design optimization formulation, and determine what to keep and what to toss. Figure 2 shows that the descriptive heuristics often embody a holistic depiction of design expertise and best practices. These heuristics are then examined to determine if it is possible to do better by employing a more normative, mathematical modeling approach. If the heuristic results in cognitive biases or inefficiencies, the designer should consider using quantitative mathematical models and/or decision based design and optimization methods. Moving from the bottom to the left side of Figure 2 occurs when new issues test the limits of the current design method. Rather than simply expanding the mathematical model or relying solely on heuristics to deal with new technological developments, the designer should consider which design considerations are best addressed with heuristics, and which are best addressed with mathematical models. A hybrid approach might involve the use of descriptive heuristics to guide the normative decision process in a more structured way. For example, in [18], multiple heuristics are employed in a generative design abstraction that implicitly structures and simplifies the design space. One set of heuristics ensure that certain challenging constraints are satisfied automatically for any design candidate considered, and another set of heuristics biases the search toward higher-performance designs. This hybrid strategy reduces design space dimension and computational expense significantly, while still supporting identification of exceptionally high-performance designs.

To that end, we propose two sets of rules in Table II for when to use descriptive heuristics and when to replace them include in the expanded matrix and what to leave intact as a heuristic.

IV. ILLUSTRATIVE EXAMPLE - WIND TURBINE SYSTEM DESIGN

This section presents a wind turbine system design example, in which we analyze designers' decision process and demonstrate how the use of a seemingly reasonable heuristic for objective function definition can lead to a result that is sub-optimal in terms of satisfying the true system performance objective. We then discuss how the approach described in Table II could have mitigated this issue.

The example presented here is based on the simultaneous design of the wind turbine artifact and its automatic control system [19]–[22]. In the subsequent subsections we present the decision process adopted by designers (who are same as authors for this work) and follow it up with analysis of this decision process in the context of rule set presented in Table II.

A. Choice of Design Objective

Choice of design objective is key during the design of wind turbines. There exist three possible primary metrics that can be suitable candidates for a design objective. They are listed as follows:

1. Peak Power (P_w): It is defined as the peak (maximum) power that the wind turbine can produce over the time horizon in consideration.

2. Annualized Energy Production (AEP): It is the cumulative energy produced over a year while accounting for the annual variability in wind speed.

3. Cost of Energy (CoE): It is defined as the cost ($$) per unit of energy.

We (the designers) chose AEP for our study due to its ability to account for wind speed variability over the year. AEP provides a more comprehensive picture of turbine performance compared to P_w. Maximizing P_w might result in a large spike in power over a small period followed by lower power production thus eventually producing lower energy over a longer time horizon. Finally, we did not use CoE as our objective due to unavailability of accurate models of future energy costs. Given the opportunity it is advisable to use CoE as the design objective due to its ability to capture cost vs. benefit trade-off for wind turbine design. The cost functions however are not always smooth (even discontinuous at times) thereby introducing additional complexities in the design optimization problem.

B. Selection of Design Decision Variables

After the design objective is identified, we then move on to the selection of design decision variables. To that end, we look at the formulae for power production of wind turbines and associated AEP. The power produced by a wind turbine for wind speed v is given by:

$$P_w(v) = \frac{1}{2} C_p(\lambda, \beta) \rho \pi R^2 v^3 \tag{1}$$

where $C_p(\lambda, \beta)$ is the power coefficient which is a nonlinear function of blade tip speed ratio (the ratio of blade tip speed and wind speed: $\lambda = \omega R/v$) and blade pitch angle β. The air density is ρ, R is the rotor radius, ω is the rotor speed and v is the wind speed (assumed here to be uniform over the entire swept rotor area). For a given physical turbine design and wind speed, the power capture maximization problem reduces to tracking the optimal power coefficient ($C_{p_{opt}}$), by controlling the blade-tip speed ratio (via generator torque) and blade pitch angle.

In case of AEP we need to consider a probability distribution of wind speed over the year. Wind speed typically follows a two-parameter Weibull distribution as follows:

$$p(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \tag{2}$$

where v is the wind speed and k and c are the Weibull parameters. Based on the distribution, the annualized energy production (AEP) in kWh/yr, can be quantified as:

$$f_1 = AEP = 8760 \times \int_{v_i}^{v_o} P_w(v) p(v) dv \tag{3}$$

where v_i is the cut-in wind speed (minimum operational speed) and v_o is the cut-out wind speed (maximum operational speed). Looking at Equations (1) and (3), it can be observed that the rotor radius R has direct impact on AEP, hence it is an obvious first choice as a design decision variable. Secondly, it is well known that the wind speed monotonically increases with the increase in turbine tower height H, hence that is chosen as a second design variable. Next, the hub diameter D_h also affects the power production (and hence AEP) through some non-intuitive aerodynamic interactions. These aerodynamic interactions between rotor blades and wind are captured for this case study through the simulation software (FAST) [23]. Finally, as described earlier, the AEP is affected indirectly by the power coefficient $C_p(\cdot)$, which in turn is influenced by the blade-tip speed ratio (controlled via generator torque) and blade pitch angle (controlled directly). We used generator torque as the control design variable here (not shown in the formulation here for brevity). We assign the symbol f_1 to represent the AEP objective and define the design decision variable set for this problem as:

$$[X_1, X_2, X_3] = [R, H, D_h] \tag{4}$$

It should be noted that all the design variables chosen for this example are either based on some engineering judgment or subject matter expertise. A more sophisticated approach might involve the selection of design variables based on their individual sensitivities. Let's now examine the heuristic that was employed earlier to define the objective function:

"*… we did not use CoE as our objective due to unavailability of accurate models of future energy costs. Given the opportunity it is advisable to use CoE as the design objective due to its ability to capture cost vs. benefit trade-off for wind turbine design. The cost functions however are not always smooth (even discontinuous at times) thereby introducing additional complexities in the design optimization problem.*"

It is a necessary, useful, and reasonable heuristic to define an objective function for which the designer can provide reasonably accurate parameter estimates, instead of one where the designer cannot. However, the purpose of generating power is to sell it at a profit, and lower costs result in higher profits.

Now, the design task is to ask the question "Have we reached a stopping point? Can we do better?" Acknowledging that cost minimization is the real objective, the analyst might seek to determine where the solution can be improved by considering cost more directly. First, cost must be estimated, either directly or indirectly. The typical Cost of Energy (CoE) is defined as the cost per unit (kWh) of energy.

$$CoE = \frac{\text{Total Cost}}{AEP} \quad (5)$$

Total Cost in turn includes both capital and operating cost of the turbine. Since we don't have the exact total cost models available, we use a proxy for CoE function. The proxy function is defined as the ratio of total mass and annualized energy production (AEP).

$$f_2 = \text{Proxy for } CoE = \frac{\text{Total Mass}}{AEP} \quad (6)$$

This is a reasonable heuristic assumption since the total cost is typically proportional to mass of the turbine. We assign symbol f_2 to this objective function.

Table III shows the results of the previous optimization problem where maximizing f_1 was the objective function, with the last line of the table showing the value of f_2 for that solution. The value shown is 71.26.

Now, if the original optimization problem, which maximized f_1, is replaced with one that minimizes the f_2 using Equation 6, the optimal solution is different. Table IV shows that using f_2 as the objective function results in a 3% improvement (71.26 – 69.26)/71.26. As expected, replacing f_1 as the objective function with the f_2 results in a 30% decrease in f_1 ((3231.5 – 2260)/3231.5).

The first order sensitivities of the design variables are computed for both the f_1 and f_2 objective functions. The results are listed in Table V. These approximate sensitivities are obtained by perturbing each design variable by 0.5 units while keeping other design variables fixed. The sensitivity s_i of the design variable X_i is then obtained as:

$$s_i = \frac{f(X_i + 0.5) - f(X_i)}{0.5} \quad (7)$$

It should be noted here that the sensitivities across the objective functions are of different magnitudes because the objective function values themselves are magnitudes of order different. However, when we look at the individual sensitivities of design decision variables in case of f_1 objective, it appears that the variable X_1 (i.e. rotor radius, R) clearly has highest effect on the f_1 objective. In case of f_2 objective, this distinction is less clear, since all the design variables appear to have sensitivities that are not too far apart from each other. This demonstrates the effect of objective on the choice of design decision variables.

It can be seen from Figure 3 that optimal design decision variables for f_2 are smaller compared to those for f_1. This is expected since f_2 includes mass, and smaller mass roughly corresponds to smaller turbine geometry.

The next step would be to examine some of the other heuristics employed in the original formulation of the model. The "Sequential Task Ordering" heuristic is demonstrated in the statement:

"*After the design objective is identified, we then move on to the selection of design variables for this problem.*"

TABLE III

OPTIMAL SOLUTION WITH f_1 AS AN OBJECTIVE FUNCTION (f_2 IS PROVIDED FOR COMPARISON)

X_*	Co-Design
X_1	34.75
X_2	76.66
X_3	2.33
f_1	3231.5
f_2	71.26

TABLE IV

OPTIMAL SOLUTION WITH f_2 AS AN OBJECTIVE FUNCTION (f_1 IS PROVIDED FOR COMPARISON)

X_*	Co-Design
X_1	30.00
X_2	75.88
X_3	2.49
f_2	69.26
f_1	2260.0

The "Ease of Estimating Model Parameters" heuristic was employed to define the design decision variable:

"*It should be noted here that all the design variables chosen for this case study are either based on some engineering judgment or subject matter expertise. A more sophisticated approach might involve the selection of design variables based on their individual sensitivities.*"

The "Ease of Controlling the Model Parameters" heuristic was also employed to define the decision variable set:

"*Looking at equations (1) and (3) it can be observed that the rotor radius R has direct impact on AEP, hence it is an obvious first choice as a design variable.*"

"*AEP is affected indirectly by the power Coefficient C_p which in turn can be affected by controlling the blade-tip speed ratio (via generator torque) and blade pitch angle. We used generator torque as the control design variable in this case*

TABLE V

APPROXIMATE SENSITIVES OF DESIGN VARIABLES TO THE f_1 AND f_2 OBJECTIVE FUNCTION

X	Sensitivity (f_1)	Sensitivity (f_2)
X_1	56	0.33
X_2	16	0.46
X_3	-16	-0.33

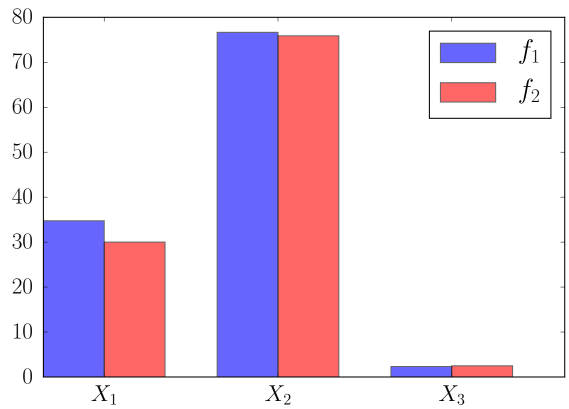

Fig. 3. Comparison of optimal decision variables for two different objectives: f_1 and f_2

study."

V. Discussion

This paper addressed a problem that can occur when new trends in technology test the limits of design methods. The problem is that simply expanding the design optimization formulation to include these new issues can make the analytic problem too big, requiring significant data gathering and modeling efforts. On the other hand, more efficient heuristic approaches pose their own problems of unnecessarily constraining the design space, or creating cognitive biases that lead to erroneous results.

A description of steps involved in design optimization formulation and the heuristics commonly employed was presented. A method for analyzing these heuristics was described, to determine when it is best to rely on expert descriptive heuristics and when it is best to take a normative approach. An illustrative example of wind turbine design was presented. The approach determines how to redirect holistic human design expertise when situation calls for it, and when cognitive biases result in inferior designs or design processes. The goal is that both the design process itself and the end product are improved because the design process will take less time and be more efficient since data gathering and analytic effort is focused where the payoff is greatest.

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