Non-Parametric Design: the Inductive Discovery of Parametric Systems

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The earliest and most conceptual phases of a design are difficult to assess, as they happen before requirements are firmly established. This ambiguity leads to ambivalence about the contribution design might have in improving requirements, as exemplified by this quote:

> Engineering designs do not happen by accident; they must satisfy a set of pre-defined set of specifications, even if these specs sometimes get modified as the designer and client both get a better understanding of the design problem and design space. Thus, design is goal oriented. A designer's success is judged by how well his/her design meets desired goals and how well he/she has identified the alternative ways of achieving the those goals.
> [Shah et al., 2003]

In this formulation, the development of requirements is clearly a secondary, even incidental, activity. However, designers know that one of the more powerful aspects of their practice is the choice in how they frame their activities, or in other words the selection of which engineering projects they pursue:

> Competent designers act in a radically different way. They select the elements in a situation that are relevant, and choose a plan to achieve the goals. Problem solving at this level involves the seeking of opportunities, and of building up expectations. In process terms a competent designer is likely to be able to become the creator of the design situation, through strategic thinking. This is a very empowering ability, in contrast to the earlier levels of expertise in which the designer was basically just reacting to design situations as they might occur.
> [Dorst, 2008]

Further, it is often the recognition of an unspecified goal or constraint that is the most important aspect of a design. For example, consider the health care furniture made by Sittris [Sittris Company, 2009]: designed for germ resistance, simple cleaning, caregiver ergonomics, bariatric patient support, and breathability, it competes in terms of health-care specific priorities, establishing its design needs through effective goal discovery. Designers know that exploring, prototyping, and other forms of discovery are critical to their practice, but the articulating a trade-off with unknown benefits is difficult.

Fortunately, engineering design activities may be reorganized to the strategic benefits of discovery. Efforts such as Multidisciplinary Design Optimization (MDO) seek to reorganize the design process to gain information earlier and to retain design freedom longer [MDO Technical Committee, 1991]. If this reorganization is taken further, so that engineering design can proceed concurrently with the requirements gathering process, then contributions can be made to both of these objectives:

- **Design discovers requirements**
  By proceeding down designs that meet a preliminary list of requirements, design processes can adopt goals and requirements from similar projects and assess their feasibility preliminarily. This allows the transfer of considerations from similar projects, avoiding missed stakeholder needs.
- **Design discovers consequences**
  By undertaking designs and analysis speculatively, one can discover outcomes which unavoidably violate constraints prior to further development.
- **Engineering robust to requirements**
  By testing designs under a wide range of potential constraints, the ability to pick designs that will accommodate changes in requirements will be improved.

In short, if design processes are sufficiently flexible as to proceed concurrently with specification, then those processes may become more resistant to the risk of misspecified requirements.

Today, engineering design has done very well in adopting new abstractions. Parametric design allows for multiple designs to be specified together and optimized over, by establishing a set of relationships rather than exact measurements, in its specifications. Let us adopt the following as a definition of parametric design:

> To design parametrically means to design a constrained system that sets up a design space that can be explored through the variations of parameters.
> [Gane and Haymaker, 2012], referencing [Pottmann et al., 2007]

On one hand, this is tremendously valuable, as it allows the systematic evaluation and optimization of a complete family of designs. On the other hand, this means that only designs that can be found through the varying of parameters can be explored. Therefore, it only stands to reason that parametric assessment methods do not assess design activities aimed at discovery, and that parametric methods do not provide direct design guidance to decisions made within the formulation of requirements. This means that the trade-offs involved in the cost of discovering requirements versus the cost of not meeting undiscovered constraints and goals are currently unaddressed.

How could we use the methods of parametric design when the parameters are not yet known? One answer is that we can situate parametric design models in an inductive framework, such that we can explore implications of potential constraints, such as those found within previous problems, as well as explore changes that resemble the unexpected surprises found within previous designs. Fortunately, for every parametric framework, there is a non-parametric equivalent. We can find this non-parametric equivalent simply by looking at every kind of input parameter and establishing its concentration in the world, which entails a discovery rate of diminishing returns over various discovery activities, making discovery-based trade-offs analyzable. In this paper we will do exactly this: by looking at a framework for providing metrics to parametric design, we will find ways to measure improvements that come from considering the non-parametric equivalents of parametric frameworks.

The idea of non-parametric models comes from statistics. An extended quote from Jordan [2010] provides a gentle introduction to the idea:

> The word "nonparametrics" needs a bit of explanation. The word does not mean "no parameters"; indeed, many stochastic processes can be usefully viewed in terms of parameters (often, infinite collections of parameters). Rather, it means "not parametric," in the sense that Bayesian nonparametric inference is not restricted to objects whose dimensionality stays fixed as more data is observed. The spirit of Bayesian nonparametrics is that of flexible data structures - representations can grow as needed. Moreover, stochastic processes yield a much broader class of probability distributions than the class of exponential family distributions that is the focus of the graphical model literature. In this sense, Bayesian nonparametric learning is less assumption-laden than classical Bayesian parametric learning.
> [Jordan, 2010]

There, as here, we do not mean that we are talking about design that is not parametric. Instead, we mean that the parametric system for exploring the design space is not fully constrained, but allowed to expand inductively as design processes discover new relevant information[1]. However, the overall process is still constrained by the kind of input parameters the particular parametric methodology can accept. Nonparametric design processes are also limited by the cost of discovery, in that although there may be an infinite number of stakeholders and objectives, we will experience diminishing returns in the number of design activities worth attempting, eventually becoming unlikely that further design activity will be worth its cost. For the purposes of this discussion, let us say that nonparametric approaches address problems with open design spaces, while parametric approaches address closed design spaces.

In order to understand how this might work, let us now look at how to expand the framework of a parametric design assessment methodology to be non-parametric and see what additional modes of analysis that allows.

[1] To use a metaphor from computer science, we conceptualize linked data-structures as arbitrarily large not because we have machines with infinite memory, but because that characterization allows us to more easily manage the data we do have

Expanding Design Assessment

The Design Exploration Assessment Methodology (DEAM) is a methodology for assessing the quality of guidance provided by design processes in parametric design problems [Clevenger et al., 2012]. This framework provides a number of useful definitions and metrics for assessing parametric models with given inputs. By treating these units of analysis as variables instead of as givens, we can directly extend these metrics to assess discovery.

Terminology

Here we look at the terminology of DEAM and make some initial qualifications regarding the use of these terms non-parametrically. Following a similar convention as papers on DEAM, we will highlight words used technically in **bold** font.

- **Stakeholders** are parties with a stake in the selection of **alternatives**. Parametrically, **stakeholders** are known while non-parametrically they need to be discovered.
- **Preferences** are selections between **goals** made by a particular **stakeholder**. One parametric selection is to assign additive weights for each **goal**, while in the most severe parametric case we discover a **preference** for each specific set of **goal impacts** over another.
- **Goals** are declarations of the intended properties of a design solution, specified in terms of a particular **target value**. Departures from **goal targets** are taken to have negative **impacts**. Parametrically, **goals** are given, while non-parametrically they need to be discovered.
- **Constraints** are limits placed on **options** and **impacts**. Parametrically, **constraints** are given, while non-parametrically they need to be discovered. We say that an **alternative** that meets all constraints is **feasible**.
- The **objective** is the all of the **goals** and **constraints** of all **stakeholders** weighted by their **preferences**. Two factors lead to **objectives** not being trivially combinable: not all **stakeholders** legitimately have equal influence, and not all **stakeholders** are prepared to resolve their **preferences** between conflicting **goals**. We say that an **alternative** that satisfies constraints and gives the best available performance along all goals is **optimal**.
- **Variables** are decisions to be made. These decisions can be discrete or continuous, and may have dependencies. In parametric settings, it is the outcome of **variables** that have dependencies, while in non-parametric settings, even the existence of a **variable** may depend on an earlier **variable** selection. Following work on design scenarios [Gane and Haymaker, 2012], let us call a particular set of variables a **design scenario**.
- **Options** are the potential values that can be assigned to **variables**, or in other words the potential outcomes of decisions. Sometimes they may be bounded, but they may also vary non-parametrically (for example, a designer may have to research manufacturing technology to best select a machine to undertake a particular operation).
- An **alternative** is a complete selection of **options** over all **variables** present in the given **design scenario**, yielding a potential design outcome.
- An **impact** is an **alternative's** performance on a particular **goal**. A simplifying assumption is that performance falls off as a percentage deviation from the **goal's target**. Generally, we need to tie particular levels of **goal performance** to particular levels of **stakeholder preference**.
- The **value** of an **alternative** is its net performance in **impact** across all **goals** as a function of **stakeholder preferences**. Non-parametric settings also evaluate **value risk**, or the potential change in the evaluation of **value** if more information was discovered.
- A **challenge** is the set of decisions to be made, encompassing all of the **variables** for which **options** need to be selected to determine an **alternative**. In a non-parametric challenge, the **variables** to be resolved may be partially unknown and discovered in the **exploration** process.
- A **strategy** is a set of steps used to generate the basis for decisions regarding **variables**, which include no advice at all, complete algorithmic specifications, open-ended procedures, guidelines, and heuristics. In a non-parametric setting, a step-by-step procedure may be less complete than a seemingly less guided **strategy**, due to such procedures failing to accommodate discovery.

- An **exploration** is the sequence of **variables** and **options** considered during the course of a **challenge**. A design **exploration** in which multiple **activities** are available should also record these.

- A **design process** is the implementation of a **strategy** leading to a particular **exploration** to be taken in the face of a given **challenge**.

- The **solution** is the **alternative** or **alternatives** selected as a resolution to the **challenge**, ideally being the **alternatives** that best accomplish mutually satisfiable **preferences**. The best **solution** may be no **solution**, if there are no viable **alternatives**.

- **Guidance** is the impact of the **strategy** on the **exploration** undertaken in response to a given **challenge**.

Another facet of parametric problems that is not codified in the DEAM formulation concern **conditions**, which refers to factors of the **challenge** which vary parametrically, but are not controlled by the user. Other work refers to these as 'uncertainties' [Johansson and Krus, 2005], which provides another way to look at these undesigned parameters. Typically, **constraints** must hold in all conditions considered within range in the **challenge** formulation, and the **value** of **goals** might be assessed by their expected value within the **conditions**.

In addition to these terms, it is difficult to talk about non-parametric settings without some additional vocabulary. We've already seen a few of them:

- **Activities** are the various procedures undertaken in the course of a design **exploration**, the purposes of which include discovery, evaluation, and analysis. An open **design process** not only selects **options to analyze**, but also selects **activities** to undertake. Although **activities** themselves are subject to discovery, working from a relatively stationary set of **alternatives** allows for learning which **activities** are most effective.

- A **design scenario** is set of **variables** which, when resolved, lead to an **alternative**. By definition, the choice between **scenarios** itself is a **variable**.

- **Challenge scenarios** are the differing sets of **conditions** in which **alternatives** are evaluated. These allow for overall feasibility, reliability, robustness, optimal average performance, and other nuances when considering **value**. **Challenge scenarios** also need to be discovered. This term reflects the more typical use of the word *scenarios*, but for our purposes when we say **scenarios** we will mean **design scenarios** by default. We say that an **alternative** that remains **feasible** under all **conditions** it might plausibly encounter is **robustly feasible**, if it remains optimal across conditions it is **robustly optimal**, and if it just has consistently good performance across conditions it is **robust**.

Metrics

With this terminology in place, we can describe various metrics for assessing how well particular strategies yielded effective explorations of particular challenges. These include metrics for assessing the difficulty of the challenge, the coverage of strategies, and the value of the alternatives discovered. Following a similar convention as papers on DEAM, we will use *italics* to delineate metrics, again retaining **bold** for terminology. We will first lookuniformly at each DEAM metric, and then consider what other metrics might be considered for non-parametric design evaluation.

Challenge assessment metrics

Challenge assessment metrics look at the variety of difficulties imposed by the challenge in order to give various strategies a comparative baseline. There are two key reasons for this. First of all, challenge metrics assess the particular character of the difficulty, implying that particular strategies may be more appropriate for the challenges presented. Secondly, less sophisticated strategies may do equally well on uniformly less challenging problems, solving a challenge effectively with less resources. challenge The *Objective Space Size* is taken to be the total number of **goals** and **constraints** considered within the scope of a given exploration. The non-parametric equivalents of this metric would consider the growth of the objective space. For example, the *Goal Concentration* measures the likelihood of discovering a new **goal** in a particular **activity**, which is expected to diminish in rough proportion to how many times that **activity** was undertaken. This can further be decomposed by examining the *Stakeholder Concentration* and the *Goal Per Stakeholder Concentration*. Equivalent discovery concentrations can be proposed for **constraints** (we might expect changes in constraints for areas with scientific or regulatory uncertainty). These rates can be measured in terms of sample count, overall time, or cost. These concentrations reflect the intuition that a **chal-**

lenge becomes more difficult if high-**impact goals** and **constraints** are costly to discover.

Alternative Space Independence is the number of first-order interactions among design **variables** divided by the total number of **variables**. It represents the degree to which coupling between the effect of the **variables** determines **impact** performance. A metric for the of discovering coupling is the *Coupling Concentration*, or the relative commonality of interactions. We might have some domain-specific priors on discovering couplings, such as knowing that certain electrical components cause noise that disrupts the functionality of other components.

Impact Space Complexity is the number of **variables** found to result in performance trade-offs (divergent **impacts**) divided by the total number of **variables**, representing the percentage of **variables** with competing objectives. The *Impact Complexity Concentration* is the concentration given by the number of trade-offs per discovered **variable** and **goal**.

The *Value Space Dominance* is the extent to which performance is dominated by individual **variable** selection. It represents the importance of individual design decisions. Of course, in a **challenge** where **variable** evaluation is contingent upon particular **options**, then the importance of a particular **variable** can have a great deal of consequence. If a **variable** chosen very early in the design is important, it could correspond to an entire **design scenario** being missed. However, if a **variable** in a particular **scenario** (or even worse, a dependent set of **variables**) proves to be the deciding factor, then an **exploration** visiting that branch might not discover its performance amonst the whole decision tree. The *Apparent Scenario Disparity* is the difference between the **value** of the best **alternative** and the best **value** of any **alternative** within the **scenario** with the best average. Other metrics resulting from **design scenarios** include the *Design Scenario Count*, or the overall number of potentially different **variable** sets, and the *Design Scenario Depth*, or the number of decisions needed to resolve a particular set of **variables**.

There are additional parametric assessments not included within DEAM. Many of these are various measures of difficulties caused by varying **conditions**. Fortunately, the difficulty imposed by varying **condition impacts** can be incorporated within the *Alternative Space Independence, Coupling Concentration*, *Impact Space Complexity*, and *Impact Complexity Concentration*.

There are a number of **challenge** metrics with no parametric equivalent. First of all, in an open **challenge**, the pool of relevant **stakeholders** may continue to change, for example through company acquisitions or changes in political leadership. Therefore, the *Stakeholder Concentration* might not decline to zero. However, **explorations** we will also find that some **stakeholders** are legitimately more marginal to the particular **challenge** than others. For example, in a **challenge** centered around creating a new lecture hall at a public university, we may find taxpayers who reject the tax burden of all construction in higher education. While not building a lecture hall is a legitimate design **alternative**, independent observers might assess that these **stakeholders** are in no legitimate position to impose **constraints** and the **goals** they specify might be weighted so lightly as to be negligible to the outcome (though its important not to make this assessment without great care). Therefore, there is a *Stakeholder Strategic Importance*, and like all phenomena where we expect diminishing returns with inquiry, we would also like to characterize a *Stakeholder Importance Concentration* that specifies that, as long as we are discovering **stakeholders** that cause a significant shift in the overall **objectives**, we should keep trying to discover them and accommodate those changes. Even the most discovery-oriented design practitioners find changes in the strategically-important **stakeholders** one of the most difficult issues to manage.

Another source of additional metrics in open formulations is the additional conditional structure of **scenarios**, both **design scenarios** and **challenge scenarios**. The *Conditional Variable Size* is the number of **variables** that only come into play depending on an **option** selected earlier in the design process.

Just as different **design scenarios** lead to different **variables** and occasionally even different trade-offs between **goals**, **challenge scenarios** lead to different **conditions** and occasionally suggest further **constraints**. The *Challenge Scenario Size* is the number of different **challenge scenarios**, while the *Challenge Scenario Depth* corresponds to the number of factors that need to be resolved in order to specify a particular set of **conditions**. There are a variety of other complexities in discovering and applying **challenge scenarios** that are assessed through the disciplines of strategic foresight [Schwartz, 1991; van der Heijden, 1997] and strategic forecasting. These matters are beyond the scope of this paper. However, these areas also involve the application of activities to discovering the sorts of parameters useful here, and are subject to similar assessments of size, concentration, complexity, and cost.

In open **challenges**, the scale of the **exploration** itself becomes important. In particular, the **challenge** a particular **design process** might mitigate is ongoing in real time, such that **impacts** can expected to befall **stakeholders** without timely intervention. In addition, there may be time and resource **constraints** on the project itself. These **challenge**-specific **constraints** on **exploration** may not be given. The *Real Impact Rate* is the rate at which **impacts** occur.

Strategy assessment metrics

Strategy assessment metrics consider the coverage and efficiency of strategies independent of outcome. However, independence of outcome is not the same as being independent of the challenge. In open problems, the assessment of the challenge is made throughout the execution of the strategy, such that the degree to which the size of the challenge was assessed should also provide metrics for the assessment of the strategy.

Objective Space Quality is the extent to which the **goals** analyzed match the **goals** proposed, as measured by the overall percentage of goal coverage. In a conceptual design space, this would also imply either developing or explicitly ruling out generic guidelines for appropriate goals, including fitness of purpose, total cost of ownership, manufacturability, ecological impact, regulatory compliance, material and energy efficiency, and similar cross-domain concerns. Therefore, *Objective Lookahead Effectiveness* is the degree to which **objectives** assessed prior to establishing **stakeholder preference** come to be established as **objectives** by **stakeholders**.

Alternative Space Sampling is the number of **alternatives** divided by the number of **alternatives** required for a "significant sampling" of the entire **alternative** space. Let us refine this metric a bit, in that what we are not interested in approximating the **value** of all **alternatives**, but rather reducing the risk that an unevaluated **alternative** is of higher **value**. We can rephrase the *Alternative Space Sampling* as the *Alternative Discovery Gap*, or a confidence-weighted expectation of how much new **alternatives** might improve over the best known **alternatives** minus what it is expected to cost to find those **alternatives**. In an open problem with multiple discovery and evaluation **activities**, what we would like is for the risk of not discovering an **alternative** on the Pareto frontier to be minimized. The *Variable Discovery Rate* is the rate at which new **variables** are discovered. This leads to a metric on how confident we will not discover **variables** that contain **alternatives** more valuable than the cost of discovery **activities**, called the *Variable Discovery Gap*. Notice that the *Variable Discovery Gap* is bounded by the *Alternative Discovery Gap*, in that we cannot assess what we know versus what we could discover if we do not know the **value** of what we know.

Alternative Space Flexibility is the average number of **option** changes between any two **alternatives** divided by the number of **variables** modeled. This metric indicates the variety of **alternatives** that were explored in a given **exploration**. In a non-parametric **challenge**, we are interested in the average number of different **variables** modeled, divided by the average number of **variables** modeled per **alternative**. Given that different sets of **variables** correspond to different **scenarios**, we can call this metric the *Scenario Space Flexibility*.

Given the DEAM metrics, let us now consider some strategy metrics that appear when we expand to look at open problems. First, we'll look at metrics that assess the quality of the **activities** undertaken, and then we will consider to assess how well a given **design process** characterizes the underlying **challenge**.

The most simple metric for assessing **activities** is the *Average Activity Cost*. If a given set of **activities** can produce the same discoveries and evaluations as another set for fewer resources, then those **activities** are superior.

Clearly, the total **activity** cost is contingent on the determination that **activities** do not need to be undertaken. Working through an idealized model or interviewing certain **stakeholders** may reveal that certain **options** lead to infeasible or highly suboptimal **alternatives**. In the event that some **activities** render others unnecessary, we reduce the activities that we need to undertake.

The *Activity Reduction Effectiveness* is the degree to which the outcomes from one **activity** can prevent the need to undertake other **activities**, measured as one minus the cost of the undertaken activities divided by the cost of downstream activities that would need to been undertaken to make a similar assessment. Even more strongly, when **activities** are undertaken prematurely, their results can be entirely undermined by the findings from other **activities**, rendering them ineffective. Therefore, this metric can return negative values.

There is a downside to **activity** reduction, namely that the approximation or idealization employed incorrectly analyzes the true behavior of the design, eliminating good designs spuriously. This *Activity Reduction Risk* looks at the potential error caused in both neglecting valuable **alternatives** and in pursuing spurious **alternatives** due to mistakes.

We can only assess if the **activities** of an **exploration** have found valuable **alternatives** that merit their cost if the **challenge** has been sufficiently well articulated. The metrics we have already seen for assessing this include the *Alternative Discovery Gap*, the *Variable Discovery Gap*, and the *Option Discovery Gap*. The *Stakeholder Discovery Rate*, *Stakeholder Importance Rate*, *Goal per Stakeholder Rate* give rise to the *Preference Discovery Gap*, or the expected difference in **value** caused by newly discovered **criteria**, **stakeholders**, **preferences**, **goals**, and **criteria** versus the cost to discover them. The *Challenge Discovery Gap* similarly looks at assessing the potential for undiscovered **challenge spaces** in invalidating the **value** of **alternatives** addressing the overall **objectives**.

In short, for every parametric input, there is an underlying non-parametric concentration which generates a discovery rate, leading to a decision-theoretic assessment of the loss caused by neglecting undiscovered inputs, which we call the discovery gap.

Exploration assessment metrics

Exploration metrics examine the value of the **solution**, or how well the particular application of the **strategy** met the **challenge. The exploration** of an open **challenge** may discover several distinctly satisfiable **objectives**, and therefore should be assessed for the fidentifyingull variety of **solutions** produced.

The *Value Space Average* is the mean **value** of the set of **alternatives** analyzed, while *Value Space Range* measures the dispersion, the standard deviation serving well for this purpose. If the **design process** discovers distinctly pursuable sets of **objectives**, each of those **alternatives** is assessed only with respect to the **value** of **alternatives** according to the set of **objectives** that were being pursued. One can distinguish separable set of **objectives** by a subset of the **stakeholders** are indifferent to that **alternative**. Therefore, open problems allow *Value Space Averages* and *Value Space Ranges*.

Value Space Maximum is the top **value** of the **alternatives** generated in a design **exploration**. Given that open **challenges** might provide multiple preferred **solutions**, we instead assess the *Value Space Maxima* of the **exploration**.

The *Value Space Iterations* metric is the number of **alternatives** generated before the highest **value** is reached. Nominally, reducing this number is the efficiency of the **exploration**. In an open **exploration**, there are two important milestones for efficiency. The most direct analog to *Value Space Iterations* is *Cost to Value Maxima*, which reflects the actual cost of **activities** to reach a peak **value** alternative. However, the more important efficiency metric might be the *Cost to Cost/Risk Equilibrium*, which is the cost to determine that further **activities** would not likely be effective in discovering further **objectives** or **valuable alternatives**. In other words, this is the effectiveness of the **design strategy** in correctly determining the **exploration** is completed. It may be that a given **exploration** did not find this equilibrium, at which point we can still assess a *Cost to Cost/Risk Gap Margin*, though it may be difficult to compare **explorations** that stopped with different margins.

Heuristics

There are several consequences of these metrics that provide heuristics for design exploration. First of all, designers use high-volume, low-cost, low-quality methods to generate ideas, such as brainstorming, in the early stages of a problem, their way to a solution. These allow for potentially high rates of discovery at low cost, and are effective when subject to careful selection. The process of selection is developed by a careful study of needs and context, often through ethnographic approaches. These studies of the problem in context assures that relevant dependencies are given their appropriate salience.

Next, divergent trade-offs between stakeholder goals may have several different consequences. If the trade-offs are over the same physical resource, some kind of dispute resolution may be necessary. However, if these specifications describe outcomes that can pertain to different resources, then those resources can be separately configured to independently meet these needs, creating product families or even separate enterprises. Therefore, understanding the nature of trade-offs and developing activities that support them is useful.

The designer is also the consumer of trade-offs. In particular, a family of potential components and component assemblies might be available, that while not exactly optimizing the need fill the role economically.

Finally, the arrangement of activities to avoid costs leads to a variety of models and idealizations designed to coarsely determine the suitability of alternatives for various goals and constraints. Prominent in engineering design are metamodeling measures [Wang and Shan, 2007], which look at ways to reduce extensively modeling design alternatives when they might already be disqualified by similar alternatives that are already modeled.

Non-Parametric Optimization

Given that we now have a variety of metrics, how do we improve design processes to optimize them? Non-Parametric Design Optimization (NDO) is the theory that parameters do not need to be known exactly for optimization techniques to aide the design process if the processes for discovering parameters are sufficiently well understood, as this implies statistical descriptions are available for the current state of the design investigation and that the risk of conceptual model changes that can yet been avoided by further inquires can be roughly characterized. The trade-off being optimized by NDO is to find exactly when the expected risk due to undiscovered factors is tolerably less than the discovery activity cost, where cost is broadly interpreted to include resources such as time[2]. Future work will develop a mathematical formalism for NDO.

Conclusion

This paper introduced a non-parametric design, an approach for creating an inductive system of parametric designs, allowing for the analysis of conceptual design. First, it explained how parametric analysis necessarily leaves a certain amount of risk on the table by taking its inputs for granted. Next, it took an existing parametric design assessment methodology and extended it to account for non-parametric effects, both through new terminology and through new metrics. From there, it showed how certain heuristics about the design process, common among designers, stem naturally from respecting non-parametric assessments. Finally, it briefly articulated how improvement according to these metrics may allow a kind of engineering optimization for conceptual design.

What we now understand is that for every kind of input to a design problem, it is possible to characterize the members of that kind as unknowns with a discovery concentration. By establishing this concentration, we can determine the discovery gap, or whether the risk reduction of discovering more inputs outweighs the cost of discovery. From here, we can look to the overall effectiveness of discovery procedures, which minimizes the cost to correctly discover the necessary design elements and to correctly determine that no further exploration is merited. With this beginning, the next matter at hand is how to formalize non-parametric design so designers can be provided with analytical tools and processes that assist the conceptual discovery which already drives their work.

[2] Or, in other words, to minimize the *Cost to Cost/Risk Equilibrium*. As realistic problems undergo changing circumstances, it is also useful to think about *the Cost/Risk Equilibrium Maintenance Cost Rate*.

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