

Visualizing Variable Sensitivity in Structural Design

by

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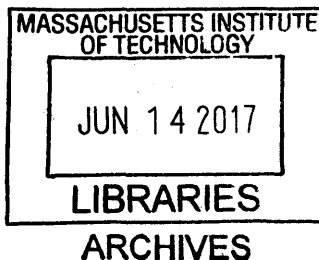
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Abstract

Computational tools allow designers to consider vast amounts of information when designing structures; however, without intuitive ways to visualize and model this data it is of little use in the creative process. In this thesis, the context for the use of computational design tools is established through a brief review of methods of incorporating structural optimization into conceptual design. Then, a novel method of visualizing variable sensitivity is presented in a way that complements established methods of interactive optimization. The technique depends upon local sampling of the design space, which reveals the behavior of quantitative structural and architectural objectives to variations in geometric parameters. Two case studies are given to demonstrate the different forms the visualizations may take and how a designer might choose to interpret those forms. The visualization technique and design approach contribute to modern practices in high-performance structural design by revealing significant behaviors of structures during the conceptual design stage.

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Chapter 1

Introduction

The analysis tools available to the modern structural engineer have almost limitless precision and accuracy to evaluate a finalized concept; however, if most design decisions have been made before the performance of structural system can be analyzed, then the information provided can have little impact. In order for performance information in terms of weight, cost and embodied energy to be fully considered, new techniques and tools are required that generate creative design concepts informed by light-weight performance simulations early on in the process of design. The following work suggests a novel method of incorporating performance information into the conceptual design of structures. This introduction identifies the characteristics of effective structural design tools and describes the aspects of design theory of particular relevance in conceptual structural design problems.

1.1 Effective Structural Design Tools

In order to understand what makes a tool effective in helping a designer incorporate information about structural performance in the design process, it is valuable to look at historical examples. Within the history of structural engineering, two exceptional examples of design tools are graphic statics and the strut-and-tie model. These tools go beyond determining the forces and deflections in a specific structure by also suggesting to the designer how subtle changes in its geometry may impact its

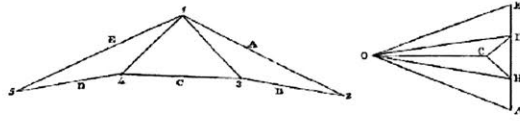


Figure 1-1: The form diagram on the left corresponds to the force diagram on the right [Mueller et al., 2015].

performance.

1.1.1 Graphic Statics

In the 1870's, graphic statics was introduced as a visual method of calculating structural equilibrium. The process involves drawing a series of arrows of relative magnitude to create what is known as a force polygon, see figure 1-1. When complete, the force polygon represents a potential equilibrium state for the structure. By illustrating the forces in the structure in a visual manner the designer can interpret how changes in the magnitude and direction of one force impact the magnitude and direction of the other forces [Mueller et al., 2015].

1.1.2 Strut-and-Tie Models

In the introduction to his original publication of the strut-and-tie model, Schlaich critiques the truss model of cracked reinforce concrete as being inconsistent when addressing discontinuities such as point loads and frame corners. Schlaich continues by asserting that all parts of a structure are of similar importance; therefore, a tool is only useful for a designer when it leads to design concepts that are demonstrably valid for all parts of the structure. Similar to graphic statics, the strut-and-tie provides a rational method of describing the flow of forces through the structure. After presenting the method in detail with several examples, Schlaich goes on to describe the pedagogical value of the strut-and-tie model. Figure 1-2 depicts four common structures that reveal similar strut-and-tie models. Making the connection between the behavior of these distinct applications allows a structural designer to quickly generate performance information for a large range of design concepts [Schlaich et al., 1987].

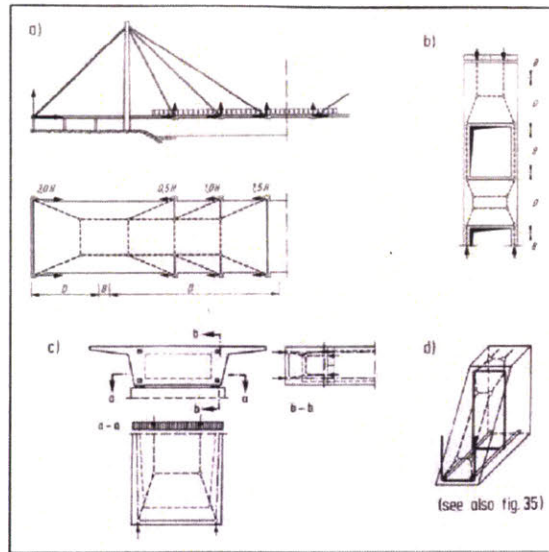


Figure 1-2: The four examples here are different structural systems that can be accurately modeled with similar load paths [Schlaich et al., 1987].

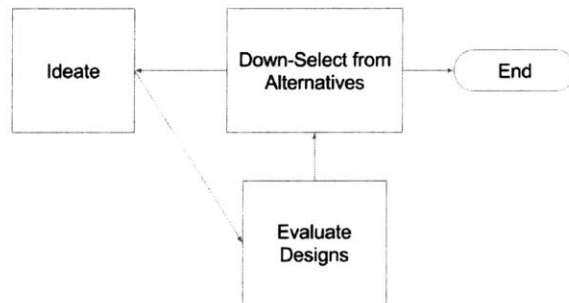
1.1.3 Concerns about Computational Tools in Structural Design

The use of computation in structural engineering has expanded the possibility for structural designers to create predictable high-performance designs. However, over the decades since the introduction of computer-aided finite element analysis and numerical optimization methods, experts in the field have consistently expressed concerns that reliance on such tools obscure the uncertainty generated by modeling assumptions and inhibit the designer's ability to generate innovative solutions. Typically, the precision of the output of a computational tools does not reflect the precision of the input. For example, the moment of inertia of a complex geometric shape can be calculated to tens of significant digits, but that level of precision would not be matched by the support conditions unless there was extensive testing to calculate the spring constant of the points at which the structure is anchored. Concerning creativity, the computational tools often function as black boxes where the user receives no information at the end of the process about the relationship between the input and the output. Understanding these relationships is the basis of the structural intuition that allows designers to quickly and consistently arrive at valid design concepts. The

historical examples of analog structural design tools provide a good baseline comparison when determining whether or not a computational tool is an effective addition to the design process.

1.2 Typical Design Process

In order to understand how a computation tool benefits the design process, the following section addresses the context of designing within the modern practice of structural engineering. There are a wide variety of design processes that have been applied to engineering problems. Rather than enumerating all suggested design processes, the following section combines concepts from design theory and optimization to build up an algorithmic description of interactive optimization within design. The design process proposed in Chapter 3 is a revision and extension of the process presented here.



Typical Design Process

Figure 1-3: A typical iterative design process without explicit optimization.

1.2.1 Closed-Loop Optimization in Design

The typical design process involves ideation, evaluation, down-selection, and, often, iteration of those three steps until a single design is chosen. When using optimization

in design, there is an additional step added to the beginning. Defining the problem statement, more specifically the variables, variable bounds, and objective function, comes before the ideation step. Within optimization there is often an assumption of automated iteration.

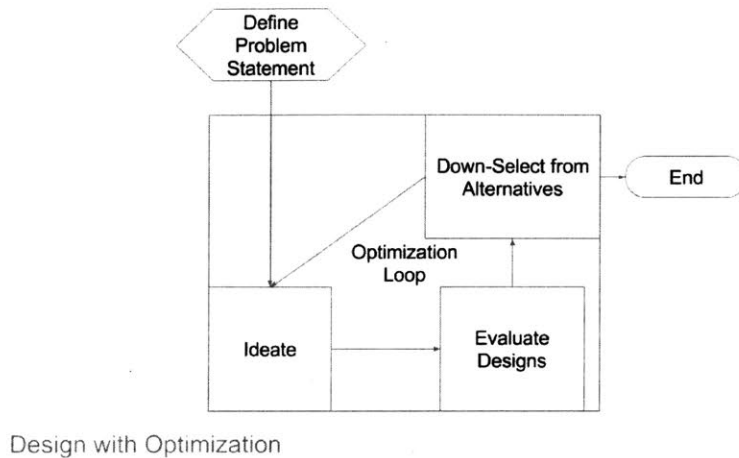
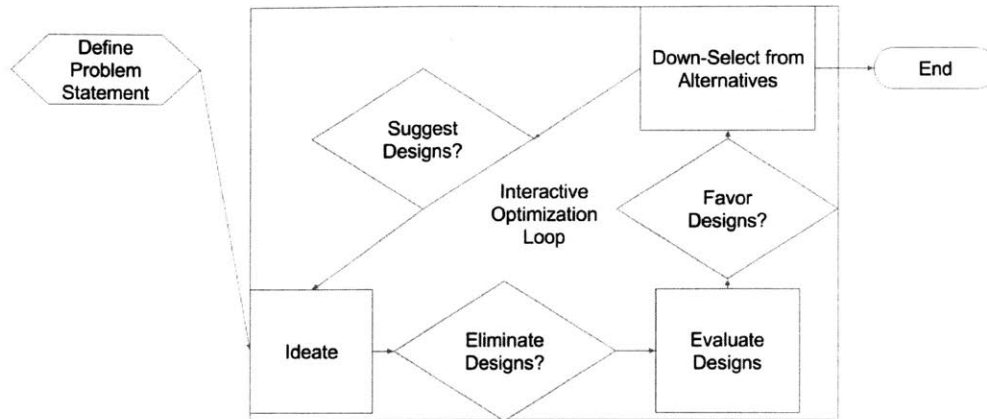


Figure 1-4: A design process that incorporates closed-loop optimization.

1.2.2 Goals of Interactive Optimization

Human-in-the-loop, or interactive, optimization methods for design are proposed for problems that are difficult to define numerically, that are too large to solve in a reasonable amount of time, or that are intended to develop intuition on the part of the designer. Aesthetic criteria in architectural design are an example of objectives that are difficult to quantify. If the initially defined design space is too large, or the evaluation process too slow, human interaction can help to avoid time spent evaluating non-viable solutions reducing the time and computational resources necessary to complete the optimization. The assumption that human interaction is more effective at avoiding non-viable areas of the design space depends on the designer’s understanding of the behavior of the design problem. The development of this understanding depends on the designer’s experience engaging with similar problems. Interaction requires increased engagement on the part of the designer, which in theory should

improve the educational value of experiencing the design process.



Design with Interactive Optimization

Figure 1-5: A design process that incorporates interactive optimization.

1.2.3 Interactive Optimization in Design

Interactive optimization approaches specify that at one or more of the steps within the iterative loop there is the opportunity for the human designer to influence the results of the optimization algorithm. The StructureFit/Stormcloud tool, described in detail in Chapter 2, achieves interactivity by allowing the designer to adjust the evaluation step by selecting preferable designs, effectively updating their objective score to increase the likelihood that similar solutions will appear in later iterations. A neat way to consider this addition to the process is by adding a decision to interact or not at each step within the iteration loop. As the described workflow becomes more complex, the context of the design problem becomes increasingly important.

1.2.4 Modification for Human Experts

Design for engineers necessarily includes an assumption of domain expertise on the part of the designer [Yang, 2005]. Creative design experts have been found to demonstrate specific behaviors that need to be taken into account when proposing a design

tool or method. In particular, there are two features that have an extensive impact on the design process proposed in Chapter 3. Creative designer's frequently identify a "problem frame" and propose a "solution conjecture" [Cross, 2004]. Problem framing consists of gathering information about a problem and prioritizing criteria. A solution conjecture is an early hunch about features of the final design, which the expert develops in parallel with the problem frame.

In terms of the conceptual design process, the solution conjecture might come before the ideation process. In this case, the ideation process would focus on coming up with novel alternatives to the typical design solution. The advantage of the solution conjecture is that the designer explores the edges of a known design space, which is more likely to yield acceptable results in a timely manner.

Problem framing, on the other hand, might come after the evaluation of alternatives where the design process iterates. If all of the alternative designs seem inadequate to the designer, it is within the designer's power to switch cognitive modes and decide to reevaluate the basic assumptions of the model, the choice of criteria, the relative weight of criteria, and the type of changes being made to the design. Situations of reframing may occur when desirable criteria are found to be directly incompatible, when the the assumptions of the model are insensitive or overly sensitive to the criteria, or when there is minimal diversity among the alternatives. It is necessary to not only acknowledge, but to embrace these aspects of human expertise in design when developing a software tool to aid in the design process.

1.3 Summary and Scope

The example set by exemplary analog design tools informs the concerns that modern day experts in the practice of structural engineering express about the adoption of computational tools in the engineering design process. Common practice in engineering design demonstrates the great attention that has been paid to the complementary roles of human expertise and computational techniques. The following work reviews computational design tools within structural engineering in Chapter 2, presents a

novel design process within the field of interactive optimization in Chapter 3, and demonstrates through case studies a novel method of visualizing performance information in Chapter 4.

Chapter 2

Literature Review

The literature review places in the context of structural engineering the use of computational design tools. The topics flow from a discussion of the general features of design models to a brief history of modeling techniques in structural design to the most recent tools specifically intended for visualizing design spaces in structural optimization.

2.1 Structural Design Models

Information about complex systems is frequently collected and applied to decision-making through the use of models. Design is a specific type of decision-making process.

2.1.1 Features of a Model

The three essential characteristics of a model are its resolution, its abstraction, and its representation. The representations addressed here are visual and numerical. The level of abstraction is determined by the assumptions necessary to judge structural performance. The resolution will be determined by the speed at which the performance information can be obtained and the flow of the resulting user experience [Gero, 1990]. The following is a review of the types and features of models commonly

used in structural design.

2.1.2 Examples of Structural Modeling Techniques

Three-dimensional physical models have been used in increasingly nuanced ways over time. There are two types of physical models that are particularly important, scale structural models and component models for load testing. A particularly famous example of effective scale modeling is the work of Antoni Gaudi who built high resolution hanging string models of La Sagrada Familia to better understand the distribution of forces [Lirola et al., 2017].

Sketches are useful for both engineering and architectural design of structures; however, the essential qualities of each sketch are distinct. An engineer might sketch the flow of forces and magnified deflection of structural elements on a low resolution model of the geometry. An architect typically would create a higher resolution of the structure's geometry as well as the site on which it is located [Suwa and Tversky, 1997], [Goldschmidt, 1994].

Similar distinctions can be seen in 3D renderings and BIM. BIM contains a significant amount of information about the details and function of the building, while a 3D rendering of the same model would ignore most of the functional details of the structure in favor of displaying the aesthetic impact [Oxman, 2008].

Computers also made parametric design relevant for both architects and engineers. The first CAD program, Sketchpad, developed by Sutherland at MIT actually incorporated parametric features [Sutherland, 1964]. A recent revival of interest in parametric design has led to the development of the open-source, visual programming interfaces, Dynamo and Grasshopper [Arnaud, 2013].

2.2 Optimization in Design

The rise of computers brought about a series of numerical approaches to both structural analysis and optimization. In structural analysis, finite element modeling proved to be a far more efficient method than hand calculations for modeling complex struc-

tural systems. In the field of optimization, numerical approaches allowed for the optimization of objective functions for which there was no analytical form.

2.2.1 Structural Synthesis

Schmit introduced the concept of structural synthesis in the 1960s for applications in aircraft design [Schmit, 1981]. Van der Plaats's review 16 years later, gives a sense of how the field developed from the early introduction of computers to the modern age as computational speed changed drastically [Vanderplaats and Vanderplaats, 1997]. Later, stochastic optimization strategies served to address non-convex objective functions with an acceptable level of accuracy [Xie and Steven, 1997].

2.2.2 Multi-Objective Optimization (MOO)

The field of multi-objective optimization contains another set of terminology important for understanding objective spaces with more than one dimension. Objective weights are numerical values that quantify the designer's preference of criteria. The use of objective weights is an a priori articulation of preferences. Two methods that are better suited for qualitative preferences are a posteriori articulation and progressive articulation. The former involves looking at a set of alternatives selected by the algorithm. The concept of Pareto fronts become relevant when telling the algorithm how to select alternatives. Pareto fronts are sets of designs in which there is no way to change any of the variables that will not worsen its performance in at least one objective [Marler and Arora, 2004]. The final approach to MOO, is progressive articulation. Progressive articulation is the type of optimization best suited for interactive approaches. Two approaches to progressive articulation are the isoperformance method [de Weck and Jones, 2006] and the use of interactive evolutionary optimization [Turrin et al., 2011], [Mueller and Ochsendorf, 2015], [Danhaive, 2015] both of which are described in detail in the next section.

2.2.3 Variable Sensitivity

Another essential concept in practical applications of optimization methods is that of variable sensitivity. Variable sensitivity refers to the partial derivative of an objective function. Sensitivity determines the relevance of the optimization problem to the overarching design goal. If sensitivity is close to zero then a suboptimal value for the variable may be selected without having a significant impact on the performance of the final design. If a variable's sensitivity nears infinity then the distance between its actual value and its optimal value is effectively equivalent to the performance of the design.

The closest existing tools to the method proposed here are StructureFit/Stormcloud, Design Explorer, Tacit.Blue, and the Isoperformance Method.

2.3 Design Space Visualization Tools

The most effective structural design tools combine visual models with numerical simulations to encourage creativity within performance-based design.

2.3.1 State of the Art

StructureFit/Stormcloud and Design Explorer have two distinct approaches to the task of revealing the significant features of the design space.

StructureFit is a user-friendly implementation of a topological and geometric optimization using an interactive evolutionary solver produced by Caitlin Mueller at MIT [Mueller and Ochsendorf, 2013]. Stormcloud, developed as part of a Master's Thesis by Renaud Danhaive, a student of Prof. Mueller, brings the StructureFit functionality into the generic, parametric environment of Grasshopper [Danhaive, 2015]. Both tools use designer interaction with the evolutionary solver to create catalogues of diverse, high-performance designs

Design Explorer was developed by Thornton Tomasetti's CORE studio as an attempt to encourage the consideration of multi-objective optimization approaches

within structural design practice [Howe, 2016]. Design explorer uses a sampling technique to reveal an increasingly selective set of designs as the designer progressively constrains the variables and objectives.

Tacit.Blue developed by Ned Burnell is an alternative to deterministic optimization that encourages interactivity by visualizing the gradient information as arrows [Burnell, 2014]. The gradient connects the location of each node to the objective function. The size of the arrow indicates how steep the objective function is at that specific variable value. The direction of the arrow indicates where the node should move to minimize the objective. The set of plots in the bottom right corner of figure 2-1 that represent single variable sampling in MOO provide very similar information to the arrows in Tacit.Blue, but in a denser format. Each line represents an objective function, while each plot represents a different variable. In this case, the plots include more information about the objective functions than the gradient. The most salient feature is the relative sensitivity of each objective to the same change in the variable value. The relative sensitivity presented in this way is valuable for understanding trade-offs along a Pareto front [Brown and Mueller, 2016b].

De Weck recommends another approach to understanding multi-objective optimization problems, which he calls the isoperformance method [de Weck and Jones, 2006]. In isoperformance, the designer generates alternatives that lie along contours of the design space. The contours represent designs that have equivalent objective scores. De Weck uses the term slack to describe the designer's freedom to choose between alternatives that the isoperformance method has identified.

2.3.2 Limitations

An important distinction that becomes apparent when considering the information given by Tacit.Blue and Design Explorer is the difference between global and local inspection of the design space. Tacit.Blue's gradient-based guidance depends strongly on a good solution conjecture, while Design Explorer depends on a well-framed problem and sufficient computational power. Although there is an element of interactivity within Design Explorer, there is a fundamental difference between the use of surrogate

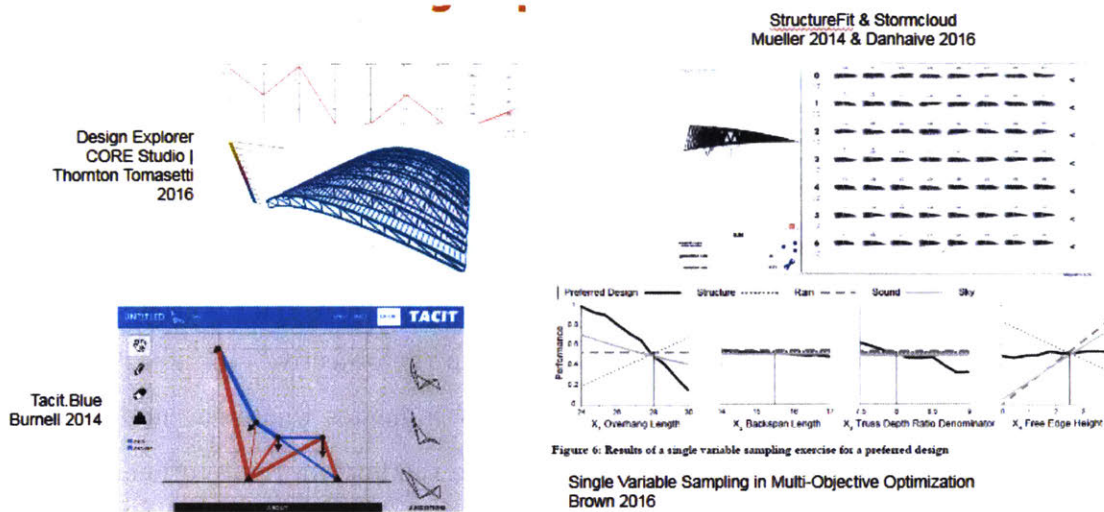


Figure 2-1: A review of the most relevant structural design tools.

modeling and the use of an interactive evolutionary algorithm. The term generative design captures this difference. Design Explorer would not be considered generative design because the evaluated alternatives are fully determined by the choice of variable bounds and sampling method. Interactive optimization strategies have the advantage that they can be stopped and redefined frequently during the time intensive process of evaluating alternatives. A surrogate model that is stopped partway through this time intensive process can provide incomplete or misleading answers. None of these methods for visualizing structural design spaces explicitly describe the contours produced by the isoperformance method described. The single-variable sampling visualization technique, proposed by Brown, is the most applicable, but has not yet made its way into the interactive user interface of a structural design tool.

The method proposed here presents local information that complements global approaches by refocusing computational energy into the most interesting areas of the design space. These interesting areas can be considered synonymous with Cross's solution conjectures. Although both isoperformance and single-variable sampling visualization techniques are promising, the single-variable sampling method is pursued in this work for reasons of computational efficiency, intuitive designer interactions and readability.

2.4 Open Questions

Considering the limitations mentioned previously the most pressing questions that remain open are as follows: How can we provide visual information to designers to give them more performance-based guidance in the conceptual design process? How can a designer use variable sensitivity of parametrically-defined alternatives to revise the definition of the design problem? What type of visualizations clearly display the sensitivity of variables within the design space?

Chapter 3

Methodology

The proposed contributions are a design process, a set of visualization techniques to support the design process, a description of the intended workflow, and example implementations through two case studies. The case studies will be fully discussed in Chapter 4.

3.1 Design Process Overview

This section provides a conceptual overview of the proposed process for performing structural design tasks while making the most effective use of variable sensitivity information.

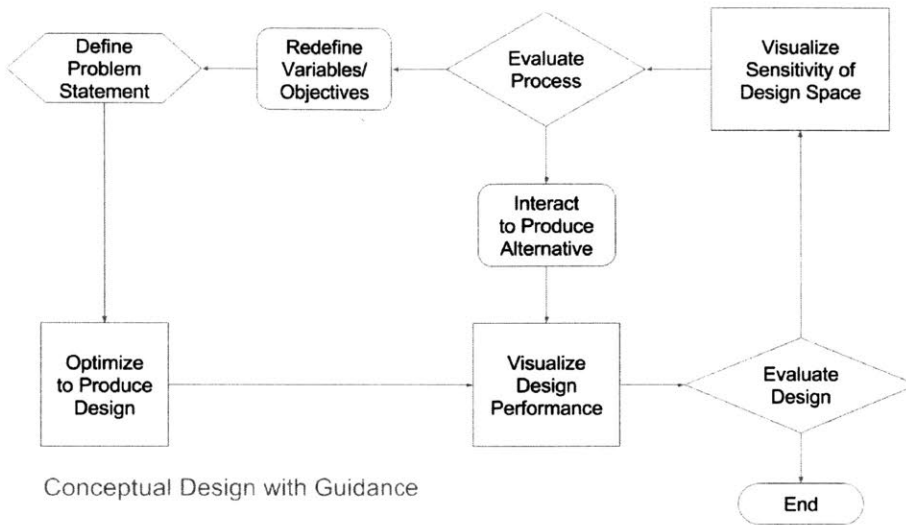


Figure 3-1: The proposed design process for incorporating guidance from variable sensitivity visualizations into an interactive optimization design approach.

3.1.1 Extension of Interactive Optimization

Following the same motivation that fueled the development of interactive optimization approaches, designing with guidance applies to design problems for which the optimization problem is poorly defined. Typically, the problem definition is not within the iteration loop. The proposed design process involves bringing the problem definition into the iteration loop of an interactive optimization approach to design. The critical assumption behind the additional layer of complexity to the process is that information generated during the design process teaches the designer how to improve the problem definition, and sometimes even the algorithm definition.

3.1.2 The Role of Variable Sensitivity Visualizations

The critical information produced is the variable sensitivity, described in detail in Chapter 2. The relative relationship of the variables with the objective values provides the designer with the ability to infer whether or not further iteration will converge to a meaningful result. In interactive optimization, the designer's direction towards more viable areas of the design space can greatly improve the speed and final result of

the design process. In design with guidance, the designer can choose to redirect the optimization, adjusting the precision of the optimization, or redefine the design space entirely to achieve the same objective of exploring a more viable set of alternative designs. Redirecting the optimization involves changing the objective function in order to improve the down-selection step. Adjusting the precision of the optimization involves changing how the algorithm uses the objective function in order to improve the ideation, generative design, step. In multi-objective optimization problems, the down-selection process frequently involves weighting each of the objectives. Changing the relative weight of the objectives would be considered adjusting the precision of the optimization and not a change to the objective function according to these definitions. Redefining the design space involves changing which parameters are design variables and/or changing the bounds of the design variables.

3.2 User Interaction

The following section describes how to setup a software workflow that allows the user to follow the design process described above.

3.2.1 Setup of Graphs and Dashboard

The first step is to come up with the best tool for creating the necessary graphs. One alternative using Google Sheets and Charts is used in figure 3-2. A second method that relies on Matlab is used for both of the case studies in Chapter 4. Grasshopper provides an exceptional environment for incorporating interactivity within a structural modeling environment. The dashboard for this example is entirely within grasshopper. The values for the design variables are set through the use of slider components. The matrix displays output of raw objective scores as well as the sampled and normalized objective scores. The baseline for the most recently evaluated design is displayed directly below a record of the best performance score so far. The text information is then streamed to a directory, which is read into Matlab to generate the sensitivity plots.

3.2.2 Visualization Techniques

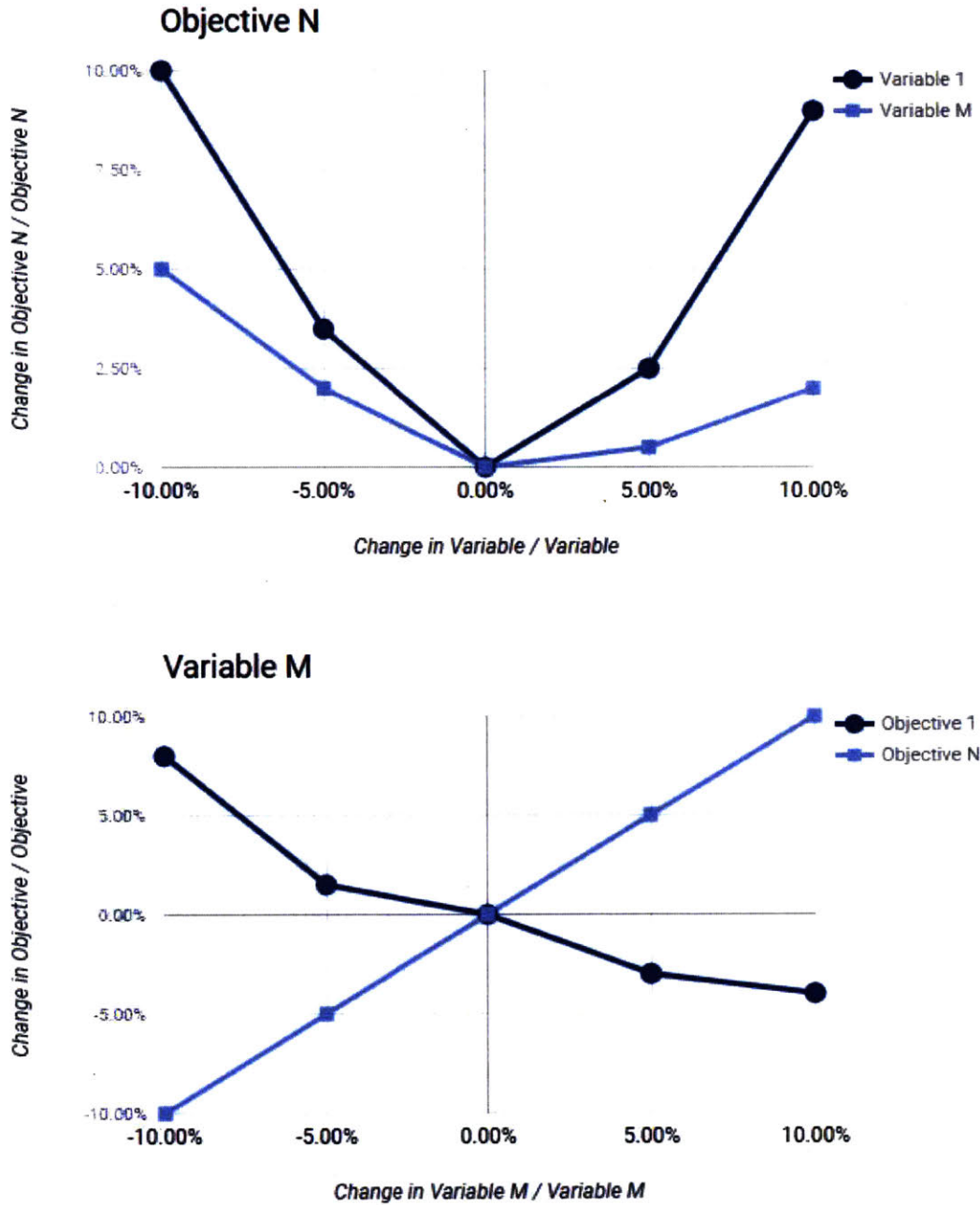


Figure 3-2: The proposed format for visualizing variable sensitivity of multi-objective design spaces.

The clear presentation of design sensitivity information affects the designer's ability to improve the optimization process. The suggested visualization method is shown in 3-2. The top left graph depicts the sensitivity of a single variable to every objective. The bottom right graph depicts the sensitivity of each variable to a single objective. In single objective optimization problems only the bottom right graph is necessary; however, in multi-objective optimization problems the graphs are best presented together. The objective graphs illustrate the relative importance of each variable, allowing the designer to infer whether some variables are unnecessary or too tightly constrained. The variable graphs emphasize the objective trade-offs, allowing the designer to infer whether the problem will converge to an optimal design or generate a set of Pareto optimal designs. The specific behavior demonstrated on the objective graph at the bottom of figure 3-2 can be interpreted as a Pareto optimal design with linear and non-linear behaviors. The specific behavior demonstrated on the variable graph at the top of figure 3-2 can be interpreted as an optima where the shallower curvature of variable m indicates a lower sensitivity than variable one.

3.3 Implementation Details

The process of creating the graph and dashboard can be split into two pieces. The first piece is the creation and evaluation of a series of design vectors. The second piece is the formatting and plotting of the sensitivity of each variable. The full documentation for the case studies in Chapter 4 is provided in the appendix.

3.3.1 Sampling and Evaluating Variables

Similar to the creation of populations in an evolutionary algorithm, the idea behind the sampling is to create a series of alternatives to be evaluated simultaneously. The sampling resolution and extents are set by a series of steps. Each step is defined as the percentage change in the variable. A two variable example of the sampling can be seen in 3-2. The variables are sampled independently (i.e. the second variable is held constant while the first variable steps and vice-versa). For a 2 variable example with

11 sampling steps, there will be a population of 22 design vectors to be evaluated. The objective functions are all produced numerically, not analytically, within the Grasshopper environment using Karamba Structural Analysis. Within Grasshopper, the Hoopsnake component keeps track of the objective scores of each design vector as Karamba evaluates them one by one.

3.3.2 Formatting and Plotting Variable Sensitivity

Once every design vector has been evaluated, the objective values saved within the Hoopsnake component are converted from raw scores into percentage change from the objective value of the initial design. For readability, the percentage change values are truncated to the 0.01%. The percentage change values are serialized as .csv files, which can be read into Matlab to create the objective and variable plots. There will be a separate plot for each variable and each objective. As a result, each data point actually appears twice within the final set of graphs. For the code needed to replicate the implementation described, refer to the appendices.

Chapter 4

Results

The two case studies presented in this chapter are realistic conceptual design problems for architects and structural engineers. The first case focuses on reading the variable sensitivity visualizations and investigates the effect of different sampling approaches. The second case emphasizes the use of the visualizations within a design process by iterating based on the guidance of the variable graphs.

4.1 Cable-Supported Canopy

The task given in this study was the design of a canopy structure for the outdoor seating area of the restaurant figure 4-1. Due to the desire for a free edge and the ability to anchor into the wall above, the hypothetical client asked for a cable-stayed structure. The main topology of the structure is formed by beams that cantilever out from the wall and are supported by a series of cables, which also anchor into the wall. Within this main geometry, participants were allowed to adjust the anchor point spread, height of cable and beam connections, height and horizontal distance to the canopy tip, number of cables, and the curvature of the canopy.

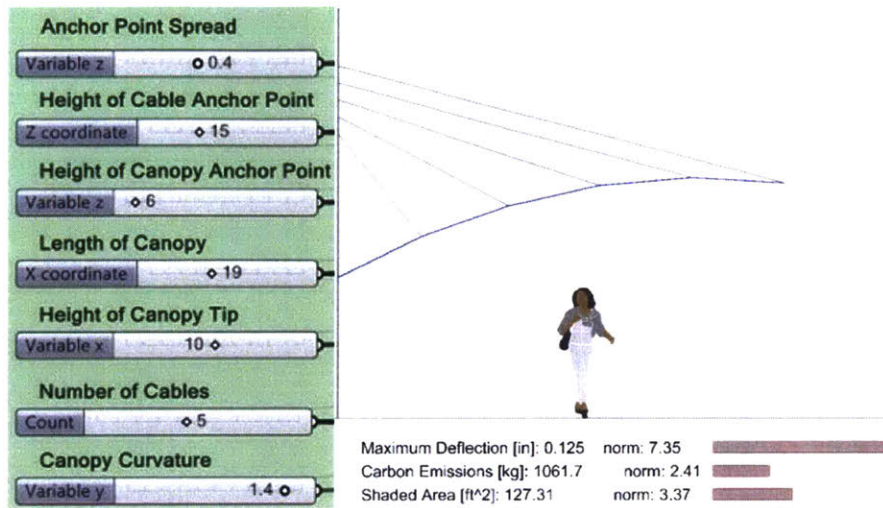


Figure 4-1: The design variables are shown on the left. A representative design in the perspective view is on the right. The objective values are displayed below the image [Brown and Mueller, 2016a].

Variable	Units	Min	Max
Anchor Point Spread		0.0	1.0
Height of (Top) Cable Anchor Point	<i>ft</i>	8	30
Height of Canopy Anchor Point	<i>ft</i>	5	25
Length of Canopy	<i>ft</i>	5	40
Height of Canopy Tip	<i>ft</i>	5	15
Number of Cables		1	10
Curvature		0.5	1.5

Objective	Units	Direction	Evaluation Method
Shaded Area	<i>ft</i> ²	Maximize	50° sun angle
Embodied Carbon	<i>kg CO</i> ₂	Minimize	FEM + Sizer
Maximum Deflection	<i>in</i>	Minimize	FEM

Table 4.1: The variables, variable bounds, and objectives for the structural design of the cable-supported canopy.

4.1.1 Introductory Example

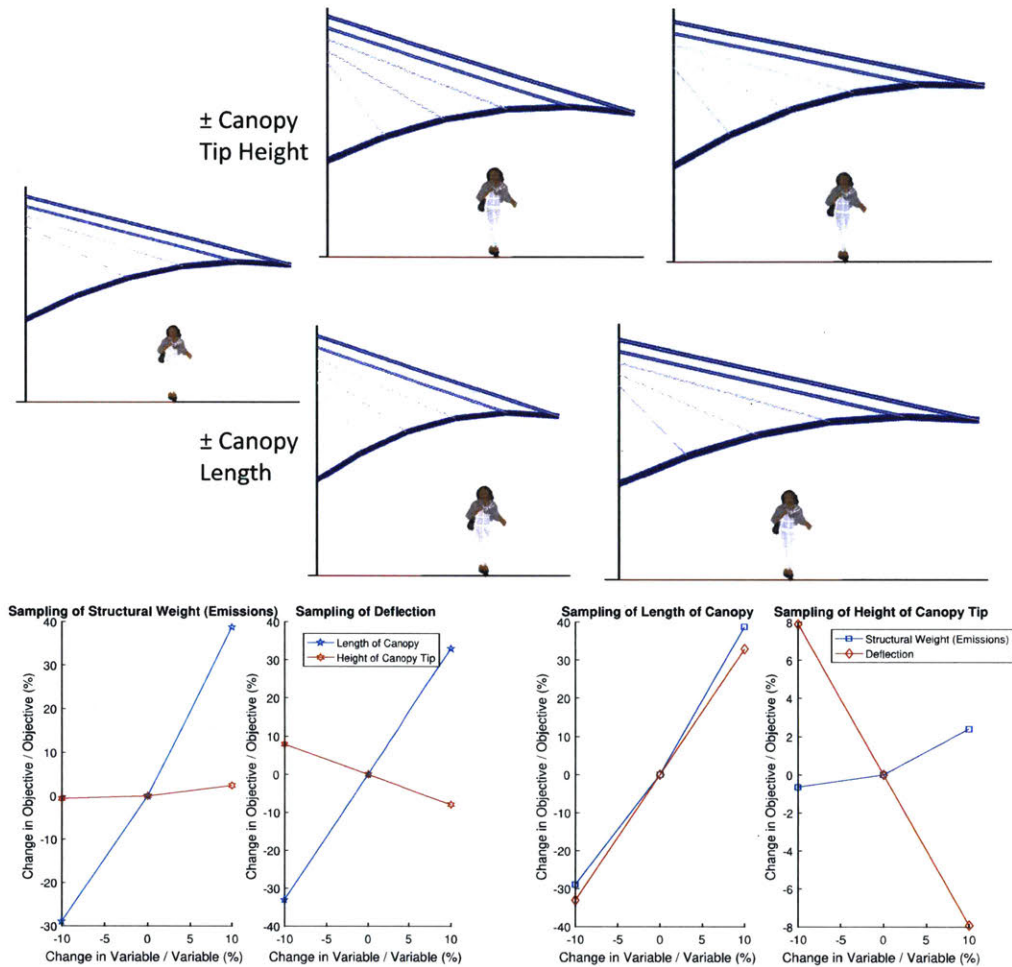


Figure 4-2: The image on the left is the initial design. The images on the top are the sampled designs where the variable height of canopy tip is augmented by -10% and 10%, respectively. The sensitivity of the height of the canopy tip is captured by the line with squares in the objective plots and by the bottom left variable plot. The images on the bottom are the sampled designs for the variable, canopy length. The sensitivity of the canopy length is captured by the lines with diamonds in the objective plots and by the bottom right variable plot.

A simple example to explain the interpretation of the variable sensitivity graphs is shown in figure 4-2. The example depicts two variables, height of canopy tip and canopy length, being stepped once in the positive direction and once in the negative direction. Each of the five designs is evaluated for two objectives, structural weight and shading area. The first objective graph shows that structural weight increases

with both tip height and canopy length; however, the canopy length has a much greater impact as seen by its steeper slope. The designer interprets this behavior as having greater flexibility to vary the height of the canopy tip in order to meet qualitative aesthetic or constructability criteria. The first variable graph shows that increasing canopy length has a similar impact, percentage-wise, on shading area and structural weight. The designer interprets this behavior as an even trade-off where one objective has to be sacrificed, decreasing shading area, in order to improve another objective, making a lighter structure.

4.1.2 Experiment Setup

The following section presents two investigations into the behavior of the variable sensitivity visualizations for the cable-supported canopy. The first investigation adjusts the number, spacing, and extents of the sampling steps. The second investigation begins with an "optimized" design and densely samples select variables to make informed objective trade-offs.

4.1.3 Sampling Investigation

There are four separate series of sampling steps used to evaluate the same design. Each series of sampling steps is defined as the percentage by which the initial value is changed. The general would be $x_o + \delta * (x_{max} - x_{min})$ where x_o is the initial value of the variable, x_{max} and x_{min} are the variable bounds, and δ is the sampling step. The first series steps in 11 uniform, linear increments from -10% to 10%. The second series steps in 6 uniform, linear increments from -10% to 0 and 5 uniform, linear increments from 1% to 9%. The intention of the second series is to see whether asymmetry obscures or reveals different behaviors from symmetric sampling. The third series steps from $-\frac{1}{8}$ to $\frac{1}{8}$ in seven logarithmic steps of base two. The purpose of the third series is to slightly expand the breadth of the design being explored while reducing the resolution. The fourth series steps from -100% to 100% in seven logarithmic steps of base ten. Effectively, the fourth series looks at the variable minimum bound, the

variable maximum bound, at a 10% change in each direction, and at a 1% change in each direction. in figure 4-3 each line of plots corresponds to a different sampling method of the same design, shown in the top right. In figure 4-4, each two line set of seven plots corresponds to a different sampling method of the same design, which is identical to the design shown in figure 4-3.

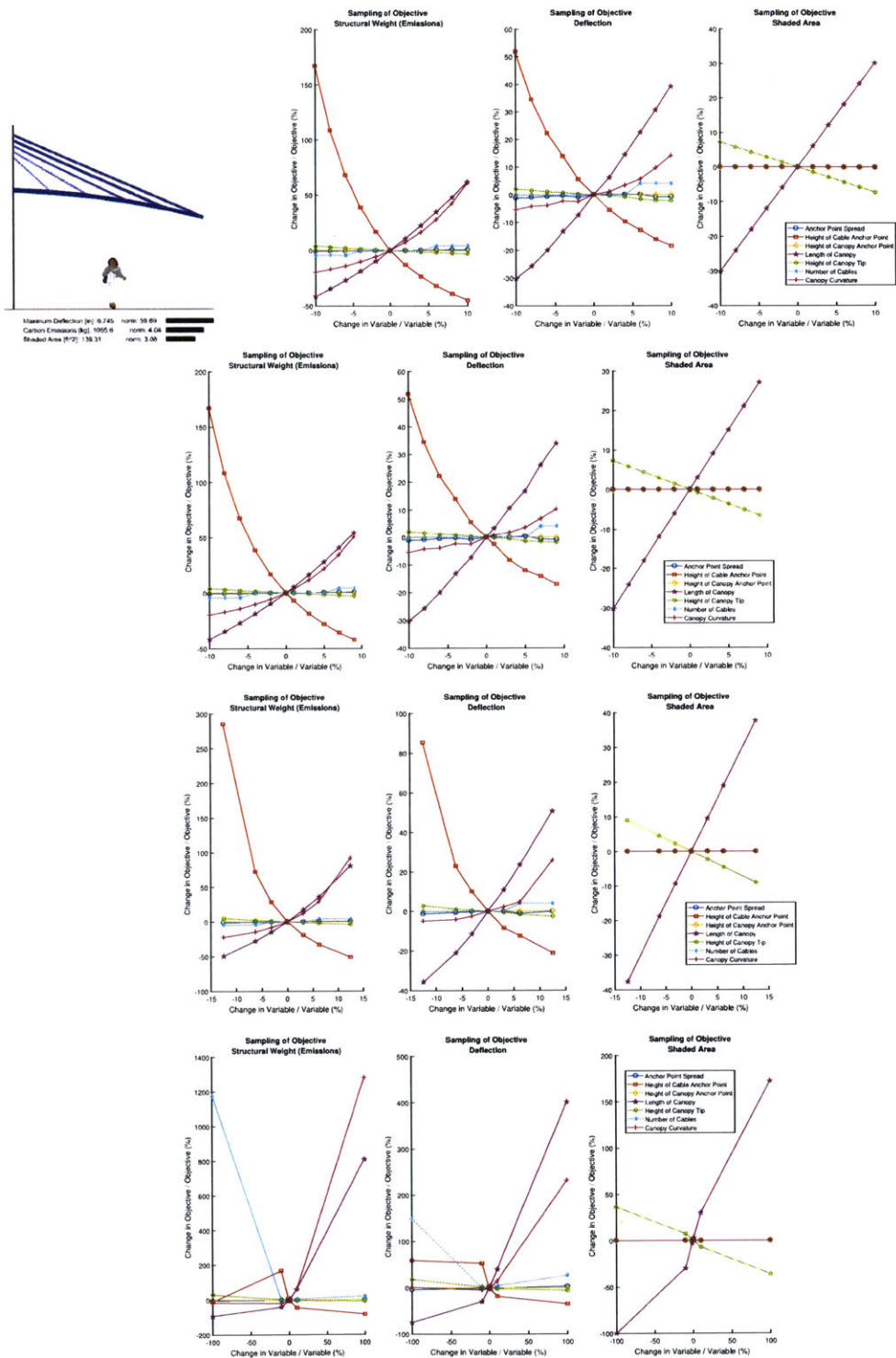


Figure 4-3: Plots of the variable sensitivity for three objectives of the same design using four distinct series for sampling.

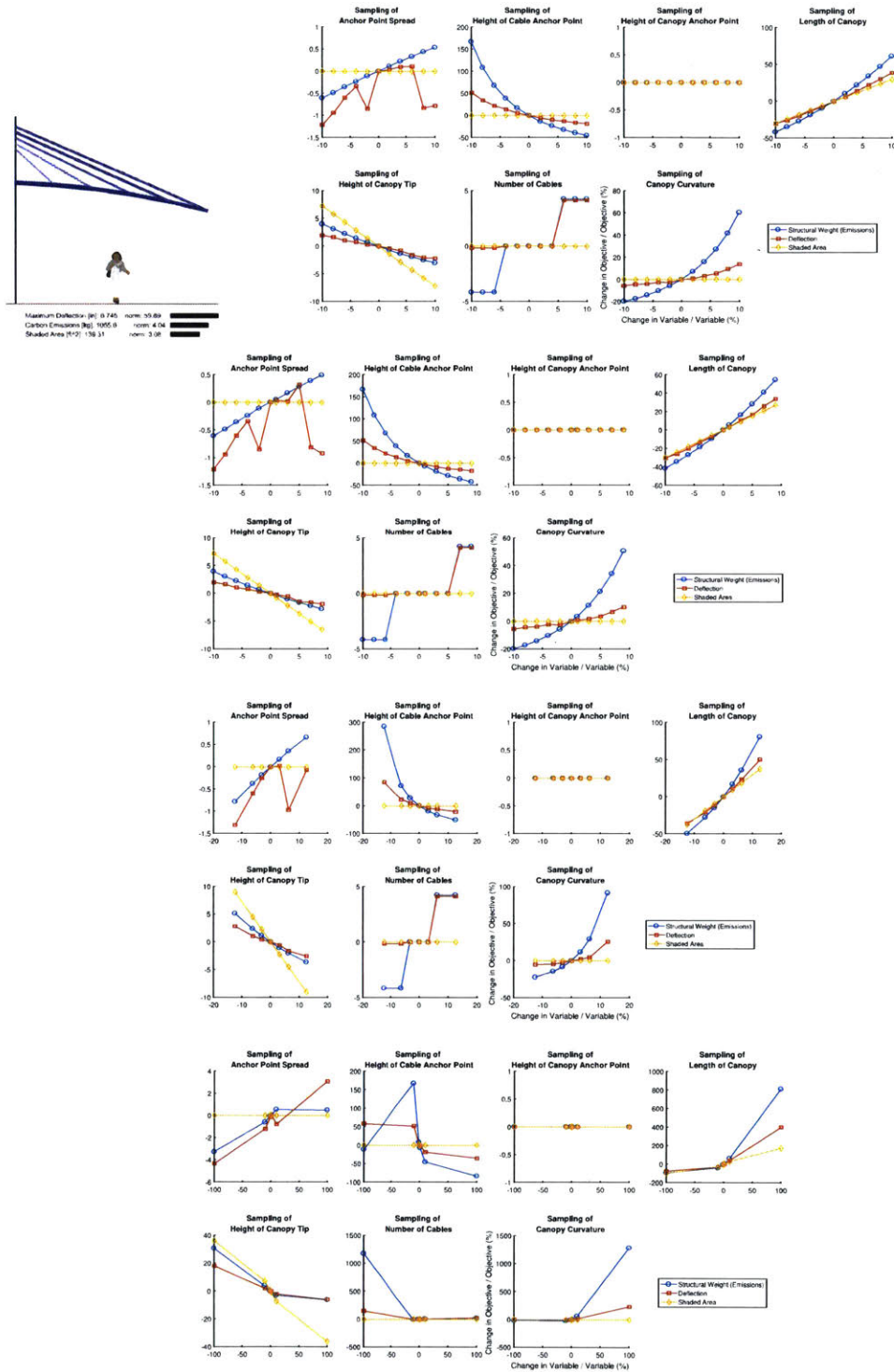


Figure 4-4: Plots of the variable sensitivity for seven variables of the same design using four distinct series for sampling.

The most significant visual impact of the different variable sampling method comes from the number of sampling points. The fourth method, the five point sampling, shown at the bottom of both figures 4-3 and 4-4, does not have enough degrees of freedom to capture behavior other than smooth exponential or linear behavior. Furthermore, many non-linear behaviors are inaccurately presented as identical to smoothly exponential and linear behaviors, which makes the five point sampling ineffective at identifying the variables that need to be sampled more thoroughly. The anchor point spread variable also demonstrates the weakness of symmetric and low resolution sampling. Its behavior is distinct with each sampling method. The symmetric and asymmetric linear sampling capture similar global behavior, but the local variations from the 3% to 6% range differ significantly in magnitude and the local variations from the 7% to 10% range differ in the direction of the slope. These differences indicate a need for more precise sampling of that variable. The variables with smooth exponential or linear behavior are meaningfully displayed by all sampling methods. Discrete variables such as the number of cables are clearly displayed by the first three sampling methods, but not by the five point sampling. There does not seem to be any significant visual advantage to the third method, seven points of logarithmic sampling of base two, in either the objective or the variable graphs.

4.1.4 MOO Investigation

The example shown here a possible method of applying variable sensitivity to make more informed objective trade-offs. The initial design in figure 4-5 is generated by a single-variable optimization of the sum of the three normalized objectives. Each objective was normalized by dividing its value for this specific design by the minimum possible value for the design space. Ideally, this means the design is on a Pareto front. The variables that demonstrate significant objective trade-offs are the length of the canopy, the height of the tip of the canopy, the number of cables, and the height of the cable anchor point. The design and graphs shown in figure 4-6 are generated by setting the selected variables to a value in the middle of their range and sampling them densely across their entire range. The final design, shown in figure 4-7 is a modified

version of the design in figure 4-5 based on the variable behavior demonstrated in figure 4-6. The canopy length is selected to be at the point where the sensitivity to shaded area and structural weight have equivalent slopes. This value can be found by plotting the slope of both functions and finding where they intersect. Following the same method the canopy tip height is selected to be at intersection of the shaded area and deflection sensitivity slopes. The canopy anchor point height is at its maximum value and the number of cables was held at its mid-range value. The sensitivity results for the final design demonstrate that some of the information gathered by sampling variables individually does not hold true when multiple values change. Of particular note is the height of the cable anchor point. In figure 4-6 the optimal value is at the extrema, while in figure 4-7 its behavior has changed. One conclusion is that the behavior of the cable anchor point is highly correlated to one of the other variables and in order to appropriately predicts its behavior it must be sampled simultaneously with the correlated variable.

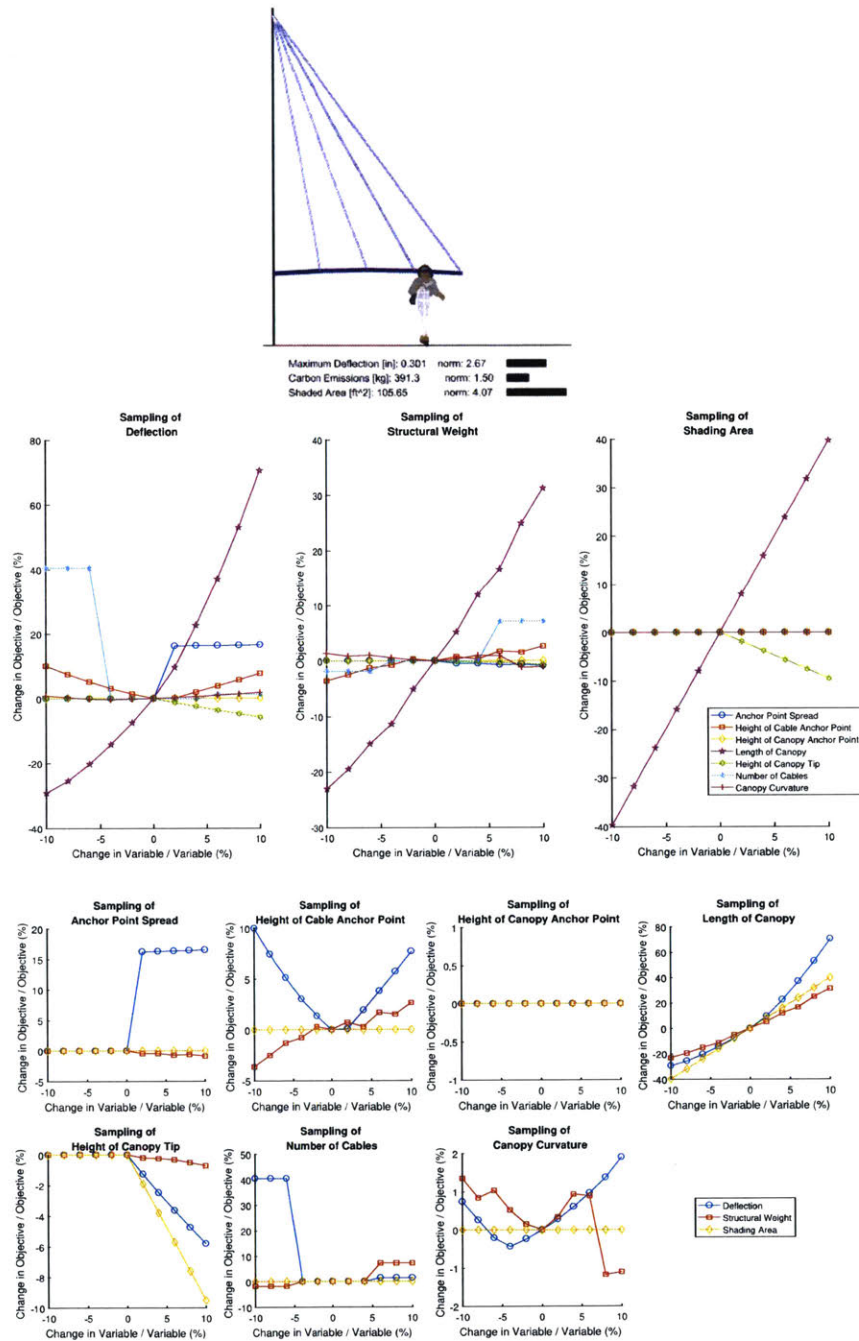


Figure 4-5: The design shown here was generated by applying an evolutionary optimization method where the objective function is the sum of each of the normalized objectives.

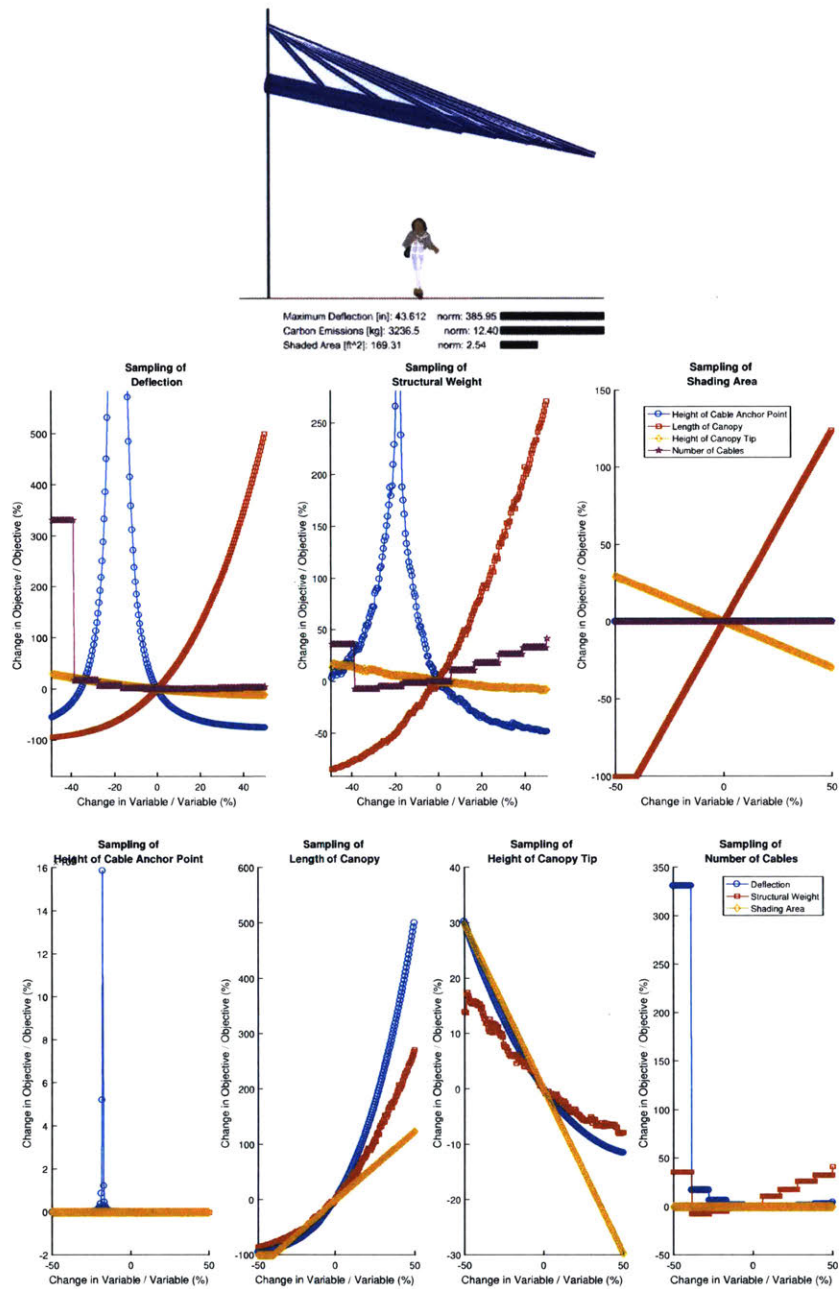


Figure 4-6: The purpose of this design is to observe more closely the most interesting variables from the previous design. The series used for sampling steps by 0.5% from -50% to 50%. A value near the middle of each variable's range was chosen for convenience.

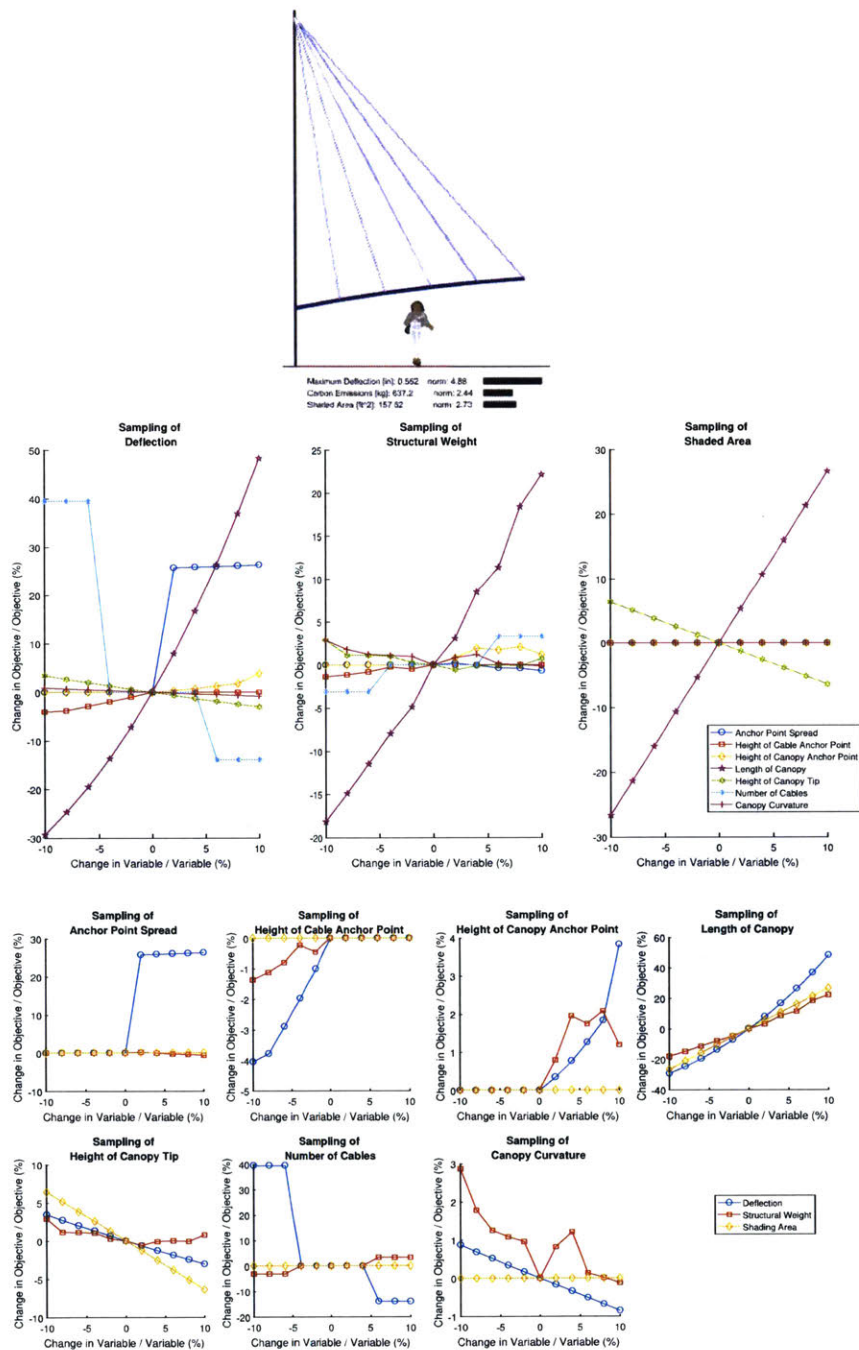


Figure 4-7: The design shown here is adjusted from the design in figure 4-5 based on the information presented in figure 4-6.

4.2 Bus Station Canopy

The task given in this study is a canopy for a bus station, based off of an actual structure built in Hamburg, and recreated as a design problem by Caitlin Mueller and Renaud Danhaive for a course taught at MIT in the fall of 2016. The basic requirements of the design are to provide commuters with shelter from the rain and to serve as an artistic piece celebrating engineering. The main topology of the structure is a series of columns that branch at the top to support the mid span of transversal beams that meet at the structure's spine. Longitudinal beams connect the tips of the transversal beams and run parallel to the spine. See figure 4-8 for an example design. The design performance objectives under consideration are the area covered by structure, strain energy, maximum deflection, and structural weight.

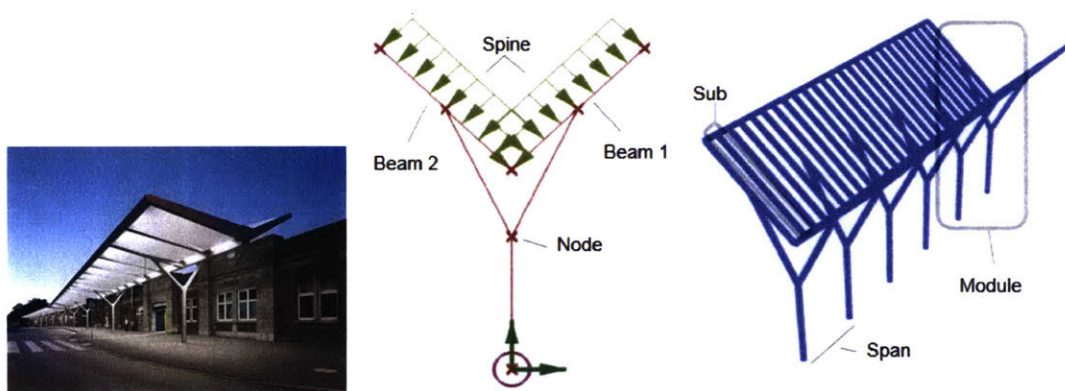


Figure 4-8: The bus station in Hamburg that inspired the design problem is shown on the left [Temme Obermeier, 2012]. The analytical model for structural modeling is shown in the center. The perspective view of the 3D model is on the right.

Variable	Units	Min	Max
Node Height	<i>ft</i>	0.0	12.0
Spine Height	<i>ft</i>	6.0	12.0
Overhang Width 1	<i>ft</i>	1.0	10.0
Vertical Translation 1	<i>ft</i>	1.0	10.0
Overhang Width 2	<i>ft</i>	1.0	10.0
Vertical Translation 2	<i>ft</i>	1.0	10.0
Node Location on Beam 1		0.0	1.0
Node Location on Beam 2		0.0	1.0
Number of Modules		1	10
Span Between Columns	<i>ft</i>	1	10
Number of Subs		1	10

Objective	Units	Direction	Evaluation Method
Projected Area	<i>ft²</i>	Maximize	Geometric
Embodied Carbon	<i>kg CO₂</i>	Minimize	FEM + Sizer
Maximum Deflection	<i>in</i>	Minimize	FEM
Strain Energy	<i>lb – ft</i>	Minimize	FEM

Table 4.2: The variables, variable bounds, and objectives for the structural design of a bus station.

4.2.1 Design Priorities for Free Exploration

The intention of this case study is to explore the impact that performance information has on free exploration of the design space. The results will be a record of the designs evaluated for variable sensitivity, the designer’s interpretation of the variable sensitivity visuals and an explanation of intended changes for the next iteration.

4.2.2 Annotated Free Exploration

A design setting all variables to the middle of their range and then iterated once is shown in figure 4-9. The variable sensitivity visualizations demonstrated local optima for most variables. The node height was raised to produce a more visually interesting effect. The spine height was lowered and the number of subdivisions was decreased to reduce embodied carbon without sacrificing projected area. As seen in table 4.3, the resulting structure decreased in embodied carbon and maximum deflection without a change in projected area.

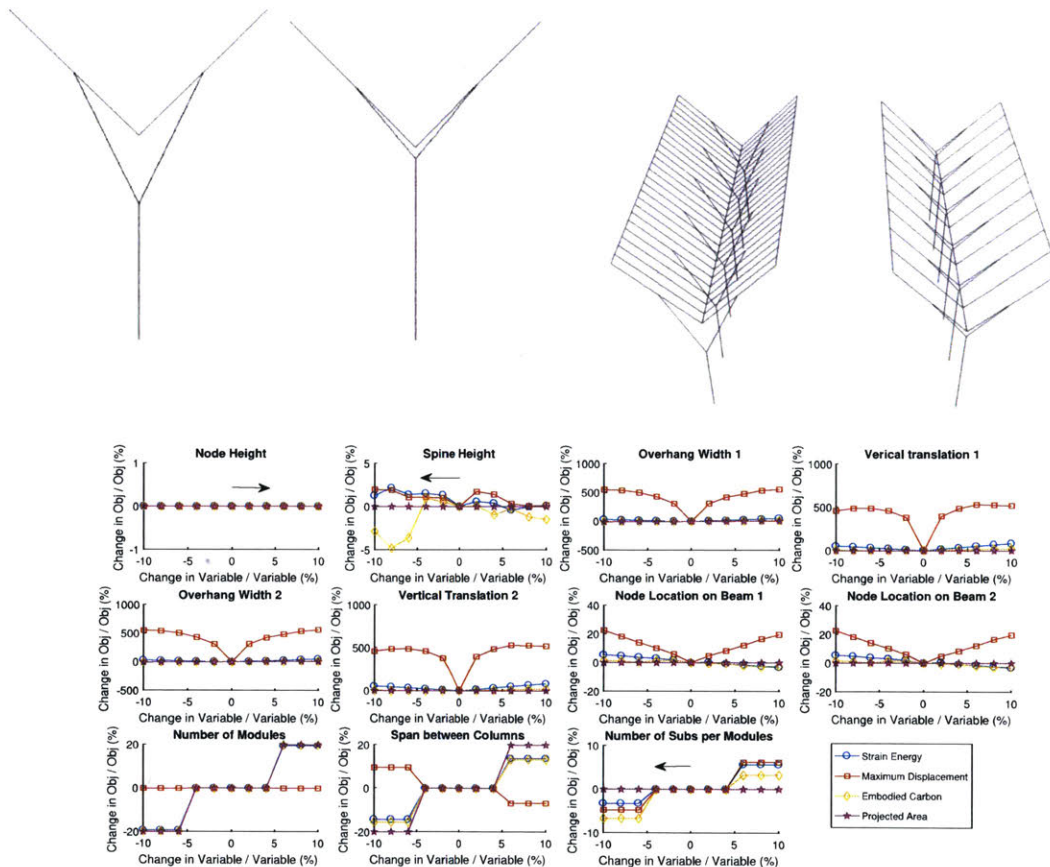


Figure 4-9: A symmetric design [left], its variable sensitivity plots, and another design iteration [right] based on the interpretation of the plots.

	Initial	Iteration	Comparison	Notes
Projected Area (ft^2)	275	275	100%	equal area
Embodied Carbon ($kg CO_2$)	348.8	267	77%	lower embodied carbon
Deflection (in)	0.303	0.298	98%	lower max deflection
Strain Energy ($lb - ft$)	2.1	2.4	113%	greater total deflection

Table 4.3: Comparison of the designs shown in figure 4-9.

A second arbitrarily chosen asymmetric design and its iteration are shown in 4-10. The node height is raised because the designer sees that it will have minimal impact on the performance and decided to leave more room for seating beneath the canopy. The designer chose to reduce the number of subdivisions while simultaneously increase the span and number of modules in the hopes that these trade-offs would improve the ratio of area covered to structural weight. Finally, the designer decided to move the node locations on beam 1 and 2 in order to minimize all three structural objectives because they can improve performance without impacting the projected area. The iteration of the asymmetric design increases in projected area, decreases in embodied carbon, decreases in maximum deflection and increases in strain energy. The results shown in table 4.4 show that the changes informed by the sensitivity graphs improve performance. The most interesting result might be that the strain energy increases while the material used and maximum deflection are reduced which implies that the changing geometry offsets the structural impact of the increased load by distributing deflection more evenly along the structure.

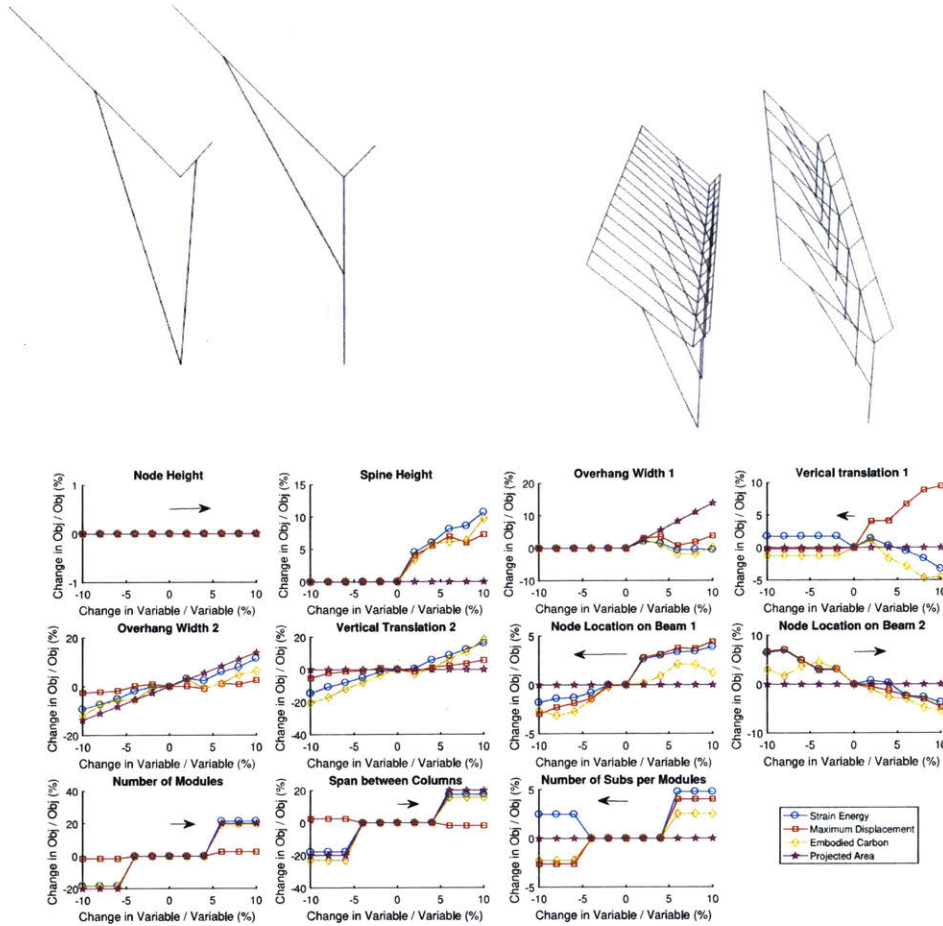


Figure 4-10: An arbitrary asymmetric design [left], its variable sensitivity plots, and another design iteration [right] based on the interpretation of the plots.

	Initial	Iteration	Comparison	Notes
Projected Area (ft^2)	162.5	234.0	144%	greater area
Embodied Carbon ($kg CO_2$)	283.4	233.8	83%	lower embodied carbon
Deflection (in)	0.49	0.46	95%	lower maximum deflection
Strain Energy ($lb - ft$)	2.6	3.9	151%	greater total deflection

Table 4.4: Comparison of the designs shown in figure 4-10.

4.3 Discussion

The first case study demonstrates that the choice of sampling is critical to the readability of the design sensitivity visualizations. The most effective visualizations seem to balance number of variables with the range and resolution of the sampling. When beginning a design problem with a large design vector, it may be best to sample with a large range and a low resolution. After reducing the problem to a smaller set of variables that demonstrate objective trade-offs, a smaller range and greater resolution are valuable in fine-tuning geometry.

The second case study demonstrates that the design sensitivity visualizations can be used to improve arbitrary designs in a manner similar to an interactive optimization algorithm. Additionally, the impact of the initial design is clearly shown by the appearance of local optima for the symmetric, but not the asymmetric case. The arbitrary starting point within the design space of the asymmetric design encourages the designer to explore different variables than in the symmetric case.

One critical disadvantage demonstrated by both case studies is the embedded assumption of variable independence. By only sampling a single variable at a time, the interaction of variables remains hidden. The clearest example of this behavior is noted in the MOO investigation section 4.1.4 where the cable anchor point variable significantly changes its behavior in the second design iteration even though the anchor point value itself does not change.

Another disadvantage is that it is quite easy for the designer to find a local optima and disregard a more thorough search for the globally optimal approach. As a result, the variable sensitivity visualizations should be used in tandem with some form of global, or stochastic, optimization technique in order to scan the design space and become aware of diverse designs that may have significantly better performance than the initial design.

Chapter 5

Conclusion

The variable sensitivity visualizations presented here are an important step in making structural performance a critical, usable criteria in the conceptual design process. The graphical format of variable sensitivity information along with examples of their interpretation effectively reveal behavior of realistic design spaces.

5.1 Summary of Contributions

The two contributions presented and demonstrated through case studies are a computer-aided design process that accommodates the observed behavior of expert structural designers and a graphical format for visualizing variable sensitivity of multi-objective design spaces. Although graphs of single-variable sampling have been introduced previously as a method of understanding MOO problems in structural design, the workflow incorporating these visualizations within a specific design process is a novel contribution. Another distinction between the visualizations demonstrated previously and those shown here is the combination of objective graphs and variable graphs. The single-variable sampling in previous work has presented a single graph for each variable, while in this work there is a single graph for each variable as well as a single graph for each objective. The combination allows a designer to switch back and forth between considering the impact of changing a specific variable and considering which variable would have the most significant impact on a specific objective. In a simi-

lar manner, the additional loop within the novel design process allows the designer to switch back and forth between deciding which alternatives to generate within a specific design space and deciding whether or not to reframe the design space itself by changing variables, variable bounds, or objective functions. The intentional act of moving between problem framing and analysis of a solution conjecture during the design process is grounded in the protocol studies of expert designers referenced in Chapter 1.

5.2 Potential Impact

The incorporation of variable sensitivity considerations in both practical and educational scenarios will improve the intelligent application of optimization techniques within the field of structural design. A design process that encourages the designer to question the design space in which they apply optimization methods should serve to reduce the misuse of computational design tools, while simultaneously increasing their adoption and further development. As designers become more comfortable at integrating computational tools in their methods without threatening their own creative contribution, they will become more effective at integrating the enormous amount of information produced by increasingly nuanced performance simulations.

5.3 Future Work

The most pressing future work is to create a more seamless transition between interaction with the model's variables and visualizing their sensitivity. The simultaneous development of additional case studies and a catalogue of observed behaviors will improve the quick interpretation of design guidance provided by the visualizations. The coupling of variables in the sampling method should improve the reliability of the design guidance. For example, the cable anchor point issue presented in 4.1.4 could possibly be resolved in three ways. The first would be to create a coupled sampling approach that steps height of the cable anchor point at the same time as

another variable both in the positive direction, then both in the negative and then a third and fourth time where the variables are stepped in opposing directions. The second would be to replace the height of the cable anchor point and the height of the canopy anchor point with a new variable that describes the distance between the anchor points. If it is the case that these two variables are only correlated with each other then the behavior of the new variable would appear consistent as the other variables change. A third, more algorithmic method, might use a statistical test to check for independence of all of the variables; however, the computational cost would need to be taken into consideration. If variables prove to be dependent, then the computational tool may suggest that the designer reframe the problem to separate those variables.

5.4 Concluding Remarks

The desire to understand the sensitivity of the variables in a structural design problem is a quality that designers need to develop in order to make the most effective use of the suite of computational tools available to them. The pursuit of performance information is a valuable educational experience regardless of the specific method used to gather such information. As a result, the author hopes to continue to see the development of innovative approaches to gathering and displaying such information within the field of structural design.

Appendix A

Canopy Implementation

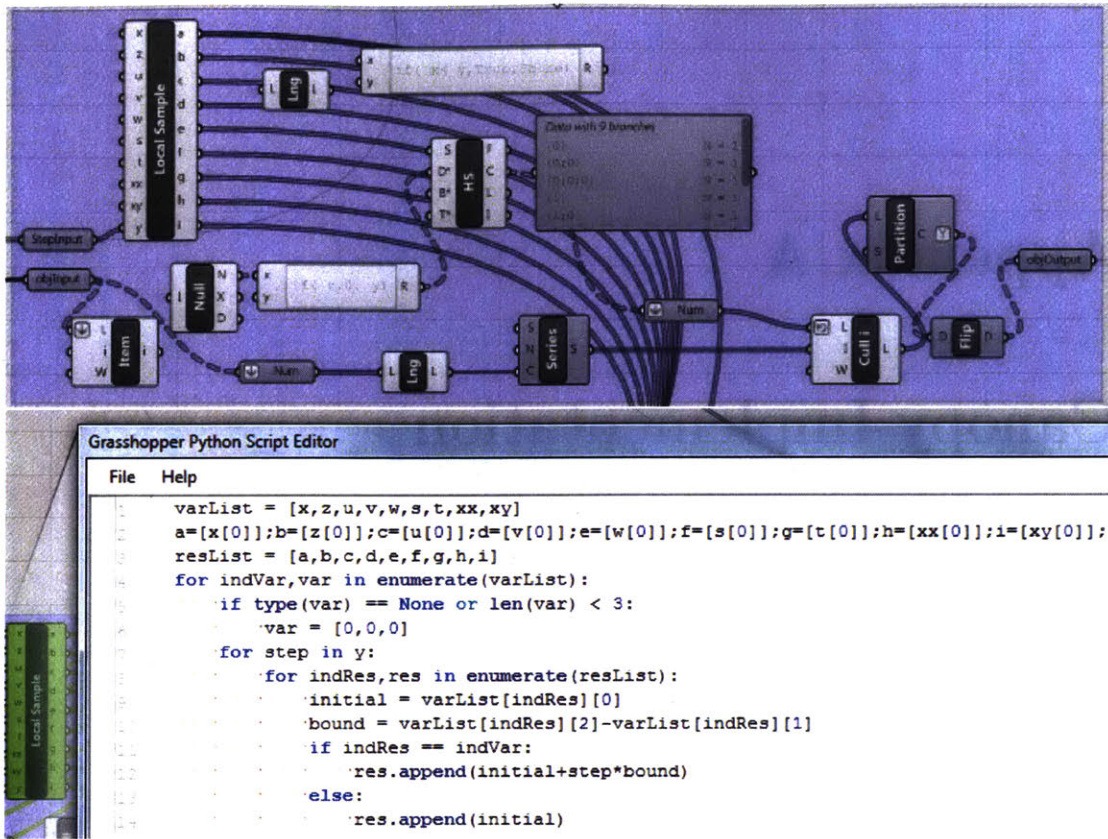


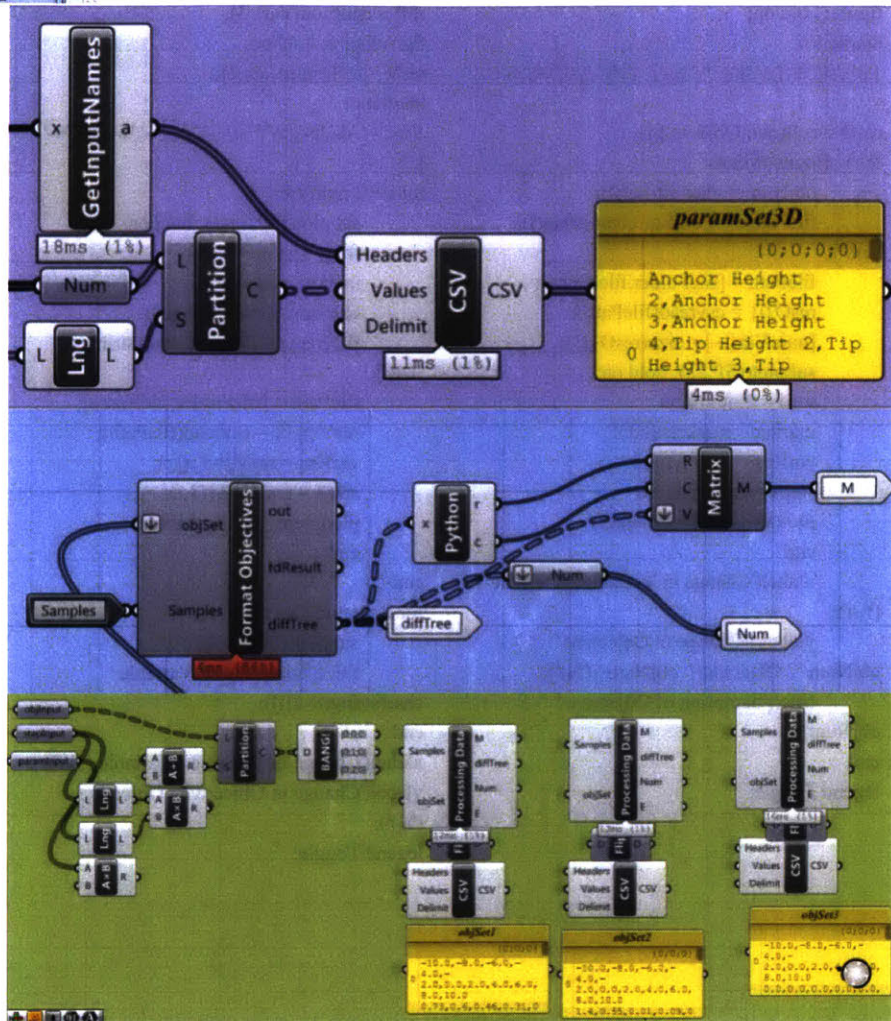
Figure A-1: The grasshopper and Python code used to sample the variables.

```

Grasshopper Python Script Editor
File Help
import Grasshopper as G

baseLine = objSet.pop(0)
weightedDL = [int((val - baseLine)/baseLine*10000)/100.0 for val in objSet]
verboseOutputList = ["Parameter (0) Objective 1: (1)\n".format(i+1,weightedDL[i]) for i in range(len(weightedDL))]
verboseOutput = ["\n".join(vo) for vo in verboseOutputList]
fdResult = "Change in objective as a percentage of the baseline\n\n"+ "\n".join(verboseOutput)
diffTree = G.DataTree[float]()
print len(weightedDL)
for ind,newVal in enumerate(weightedDL):
    indAdj = ind/Samples
    diffTree.EnsurePath(indAdj)
    path = diffTree.Path(indAdj)
    diffTree.Add(newVal,path)
print diffTree

```



objSet1	4/27/2017 7:04 AM	Microsoft Office E...	1 KB
objSet2	4/27/2017 7:04 AM	Microsoft Office E...	1 KB
objSet3	4/27/2017 7:04 AM	Microsoft Office E...	1 KB
paramSet	4/27/2017 7:04 AM	Microsoft Office E...	6 KB

Figure A-2: The grasshopper and Python code used to format the objective scores for each design, serialize and stream them in the .csv format.

```

%%Streaming from csv output of GH
fileFolder =
'C:\Users\abmchugh\Documents\Streaming
GH\Mar302017\';
numObjSets = 3;
rSP = ceil(numObjSets/2);
figure; hold on;
markers =
{'o-','s-','d-','p-','h-','*-','+-','-x','^-','v-','>-','<-'}
};
resO = cell(numObjSets,1);
for j=1:numObjSets
    objNum = char(string(j));
    fileName = ['objSet' char(string(j))
'.csv'];
    filePath = [fileFolder,fileName];
    resO{j} = csvread(filePath);
    [numVars,~] = size(resO{j});
    subplot(rSP,2,j); hold on;
    for i = 2:numVars
        marker = markers {i-1};
        varRes = resO{j}(i,:);
        steps = resO{j}(1,:);
        plot(steps,varRes,marker)
    end
    xlabel('Change in Variable / Variable
(%));
    ylabel(['Change in Objective '
objNum ' / Objective ' objNum ' (%)']);
    title(['Sampling of Objective '
objNum]);
end
legend Toggle;

%%
fileFolder =
'C:\Users\abmchugh\Documents\Streaming
GH\Mar302017\';
numVars = 7;
numObjSets = 3;
rSP = ceil(numVars/3);
fig = figure; hold on;
resV = cell(numVars,1);
markers =
{'o-','s-','d-','p-','h-','*-','+-','-x','^-','v-','>-','<-'}
};
for i = 2:numVars+1
    subplot(rSP,3,i-1); hold on;
    for j=1:numObjSets
        marker = markers {j};
        objNum = char(string(j));
        fileName = ['objSet' char(string(j))
'.csv'];
        filePath = [fileFolder,fileName];
        resV {i-1} = csvread(filePath);
        varRes = resV {i-1}(i,:);
        steps = resV {i-1}(1,:);
        plot(steps,varRes,marker)
    end
end
for k=2:numVars+1
    subplot(rSP,3,k-1);
    title(['Sampling of Variable '
char(string(k-1))]);
end
xlabel('Change in Variable / Variable (%)');
ylabel('Change in Objective / Objective
(%));
legend Toggle;

```

Figure A-3: The Matlab code used to read the .csv files and create the objective and variable plots.

Appendix B

Station Implementation

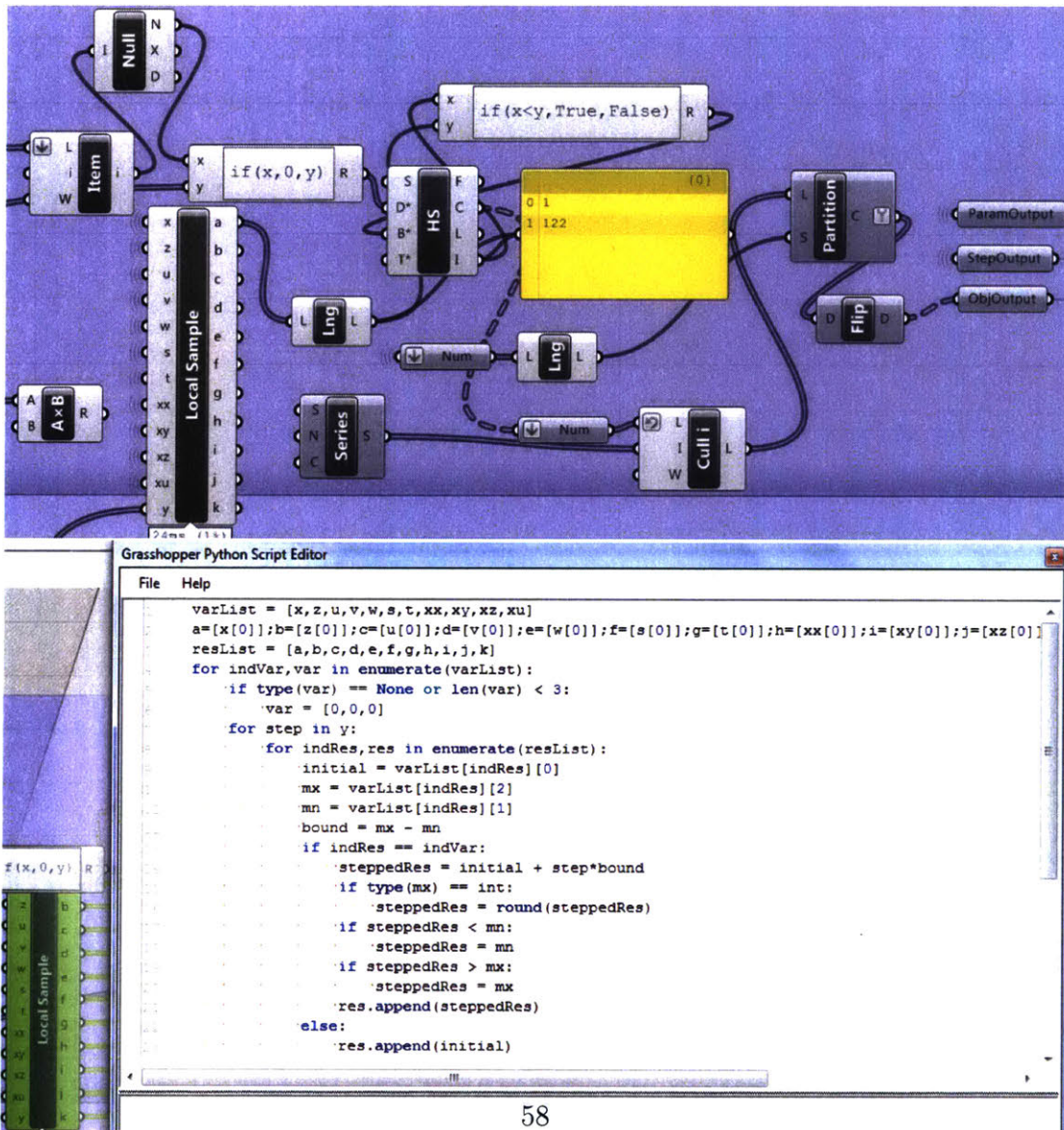


Figure B-1: The grasshopper and Python code used to sample the variables.

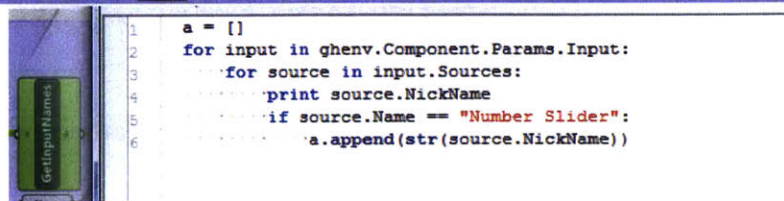
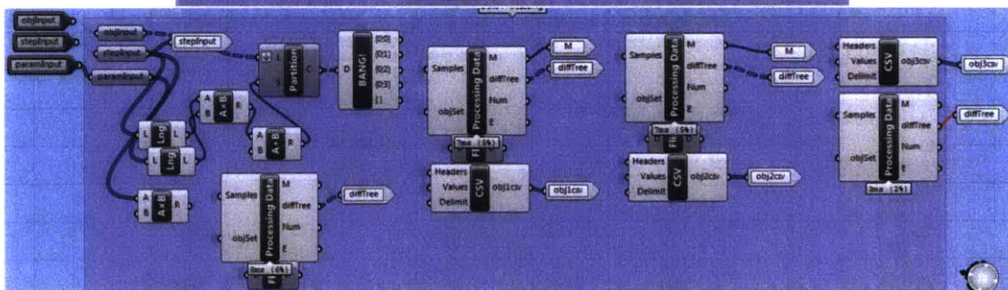
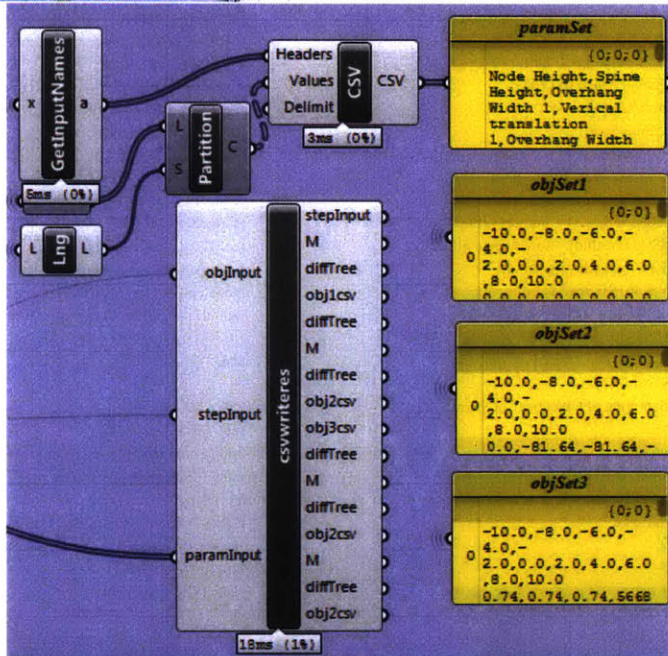
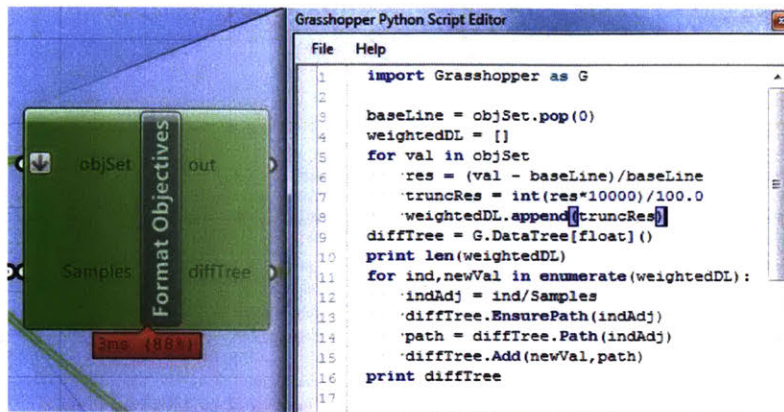


Figure B-2: The grasshopper and Python code used to format the objective scores for each design, serialize and stream them in the .csv format.

```

%%Streaming from csv output of GH
fileFolder =
'C:\Users\abmchugh\Documents\StreamingGH\StationApr1
72017\FreeExploreShortBackspan';
numObjSets = 3;
rSP = ceil(numObjSets/2);
figure; hold on;
markers = {'o-','s-','d-','p-','h-','*','+','-x','^-','v-','>-','<-'};
resO = cell(numObjSets,1);
for j=1:numObjSets
    j
    objNum = char(string(j));
    fileName = ['objSet' char(string(j)) '.csv'];
    filePath = [fileFolder,fileName];
    resO{j} = csvread(filePath);
    [numVars,~] = size(resO{j});
    subplot(rSP,2,j); hold on;
    for i = 2:numVars
        marker = markers{i-1};
        varRes = resO{j}(i,:);
        steps = resO{j}(1,:);
        [culledRes,cullInd,~] = unique(varRes);
        [sortedSteps,sortInd] = sort(steps(cullInd));
        sortedRes = culledRes(sortInd);
        plot(steps,varRes,marker)
    end
    xlabel('Change in Variable / Variable (%)');
    ylabel(['Change in Objective ' objNum ' /
Objective ' objNum ' (%)']);
    title(['Sampling of Objective ' objNum]);
end
fileName = 'paramSet.csv';
%fileName = 'ParamSet3D.csv';
filePath = [fileFolder,fileName];
fileID = fopen(filePath);
parse = '';
for k=1:numVars
    parse = [parse '%s'];
end
C = textscan(fileID,parse,...
'Delimiter',';');
fclose(fileID);
[~,n] = size(C);
paramNames = C{1}(1);
for l = 2:n-1
    paramNames = [paramNames C{l}(1)];
end
legend(paramNames);

%%
fileFolder =
'C:\Users\abmchugh\Documents\StreamingGH\StationApr1
72017\FreeExploreShortBackspan';
numVars = 11;
numObjSets = 3;
rSP = ceil(numVars/3);
fig = figure; hold on;
resV = cell(numVars,1);
markers = {'o-','s-','d-','p-','h-','*','+','-x','^-','v-','>-','<-'};
for i = 2:numVars+1
    subplot(rSP,3,i-1); hold on;
    for j=1:numObjSets
        marker = markers{j};
        objNum = char(string(j));
        fileName = ['objSet' char(string(j)) '.csv'];
        filePath = [fileFolder,fileName];
        resV{i-1} = csvread(filePath);
        varRes = resV{i-1}(i,:);
        steps = resV{i-1}(1,:);
        [culledRes,cullInd,~] = unique(varRes);
        [sortedSteps,sortInd] = sort(steps(cullInd));
        sortedRes = culledRes(sortInd);
        %plot(sortedSteps,sortedRes,'o-')
        plot(steps,varRes,marker)
        %plot(1:length(steps),varRes,'o-') %log plot bad
    xlabel
    end
end
for k=2:numVars+1
    subplot(rSP,3,k-1);
    title(['Sampling of ' paramNames{k-1}])
    %title(['Sampling of Variable '
char(string(k-1))]);
    xlabel(['Change in Variable / Variable (%)']);
    %xlabel(['Change in Variable ' char(string(k-1)) '
/ Variable (%)']);
    ylabel('Change in Obj / Obj (%)');
end
C = {'Embodied Carbon' 'Maximum Displacement'
'Energy'};
[~,n] = size(C);
objNames = C{1}(1);
for l = 2:n
    objNames = [objNames C{l}(1)];
end
legend(paramNames);
legend(objNames);

```

Figure B-3: The Matlab code used to read the .csv files and create the objective and variable plots.

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