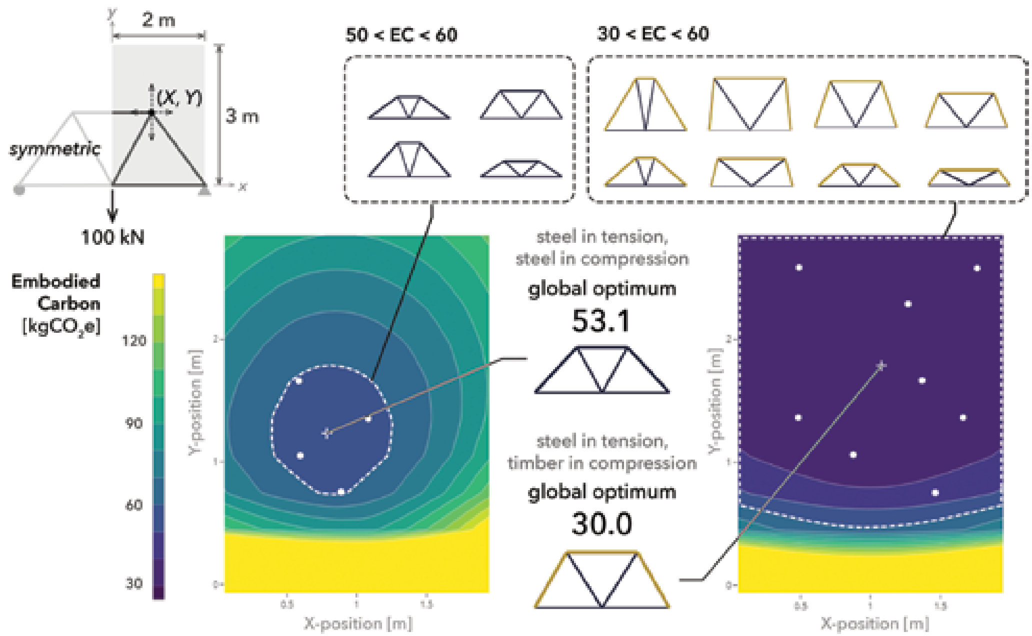
Parametric Structural Design for High-Performance Buildings

By Demi Fang and Caitlin Mueller, Ph.D.



Parametric design space visualized for a three-panel truss, showing embodied carbon associated with various options across geometries and materials.

The climate crisis has shifted priorities in all sectors. For structural engineers, improving performance, such as reducing emissions embodied in structural materials, can improve low-carbon building design. Parametric design can enhance current structural design methods by enabling designers to more readily explore the design space, the space of available design solutions, and optimize within it for single or multiple objectives. This exploration can reveal high-performance or optimal structural solutions that may otherwise have been overlooked. While many architects have started using parametric design methods in recent years, there are untapped opportunities for structural engineers to use such approaches to enhance collaborations with architects and play a more active role in the design process. This article presents both theoretical background and practical tips for structural engineers to implement parametric design in their work.

Parametric Design and Implementation

Parametric design is a framework that allows a design to vary along different quantitative parameters, called **design variables**. Ideally, these design variables capture the extent of all possible solutions, also known as the **design space**. For example, given a building massing, the column grid spacings of a structure may be parameters, with each design variable bounded by feasible spans. These variables may be continuous, such as any angle between 20 and 45 degrees, or discrete, such as the integer number of panels in a truss.

The value of a parametric framework in engineering is systematically comparing design alternatives according to one or more performance metrics. For example, performance metrics can include occupancy, air flow rate, or energy loads in building design. In addition, specific structural metrics for material efficiency might include volume or embodied carbon of materials used.

Typical engineering workflows already incorporate some degree of parametric design. For example, most spreadsheets of engineering calculations follow a parametric framework. The cells that the user updates with project data are the design variables, while the rest of the spreadsheet may use formulas to calculate the single engineering solution associated with the input variables. The user can manually explore the design space by changing the design variables within the bounds of the problem.

Architects are increasingly utilizing tools like Grasshopper for Rhino 3D or Dynamo for Revit to create parametric models directly into the stages of design and modeling. Both Grasshopper and Dynamo are visual programming tools that enable users to define geometries based on quantitative parameters and rules. In addition, both tools can connect directly to structural analysis software to compute metrics. By gaining proficiency in these parametric tools, structural engineers can enhance early-stage collaborations and design decisions with the architects who use them.

Parametric Design and Optimization

The parametric design space also offers opportunities for automated optimization, which returns the best combination of design variables according to specified performance metrics, called **objectives** in optimization frameworks. Established structural optimization methods include member size, shape, and topology optimization, but parametric design and optimization can generally be applied to a range of building problem types.

It is not always practical to select the theoretically optimal design. There may be qualitative or hard-to-quantify considerations not accounted for in the objective functions, such as the visual preference of the architectural designers. And, the theoretically optimal solution may not be compatible with current manufacturing or construction methods. Because of these inevitable limitations, navigating the design space offers a powerful way to flexibly consider a collection of better-performing designs in a less automated way. In addition, navigation methods can account for multiple objectives, as in multi-objective optimization, and offer ways for human engineers and designers to interact with generative algorithms.

This is practical because designs within a comparable range of the optimal solutions are often still valuable engineering solutions. The *Figure* shows the design space of a 3-panel steel truss loaded at its midpoint; despite determining a geometry that attains minimal emissions, the design space reveals various designs that perform within 15% of the global optimum. Furthermore, if alternate materials are considered during early-stage design, one can see that substituting timber for compression members results in even more options that outperform the optimal steel design. This exploration could be made more realistic by adding a model for economic and environmental cost of connections, but the latter is typically small relative to the rest of the structure.

Navigating the Design Space

How do you find the regions of high performance in the design space? For low-dimensional problems, this can be done by plotting a solution's objective score against different sets of design variables and finding regions of variable settings that result in higher performance, as the figure shows.

For more complex problems, more advanced tools for exploring the design space are available. One such tool is a plug-in developed by the MIT Digital Structures Research Group for Grasshopper, called Design Space Exploration (DSE). Given a parametric model in Grasshopper, components of DSE can be used to sample and record solutions in the design space, create approximate surrogate models, evaluate variable importance, and find optimal solutions with automated, interactive, and multi-objective approaches. This tool is available free and open-source (see online *References*). More recent academic research seeks to enhance these methods with new advances in computing, including VR and sketch interfaces, incorporation of historical design data, and deep learning of relationships between variables and performance (see online *References*).

The Power of Parametric Design

For climate-conscious structural engineering, an understanding of performance in conceptual building design is critical. Parametric design space exploration enables engineers to discover comparably high-performing solutions systematically that may not have been previously considered. In addition, the ability to offer multiple solutions in collaborative early-stage design is not only an asset to structural engineers everywhere but can also enhance the structural engineering field at large.▪

References are included in the PDF version of the article at **STRUCTUREmag.org**.

Demi Fang is a Ph.D. candidate in Building Technology at MIT's Department of Architecture. (dfang@mit.edu)

Caitlin Mueller is an Associate Professor at MIT in the Building Technology Program within the Architecture and Civil and Environmental Engineering departments. She directs the Digital Structures Research Group, whose work focuses on new computational methods for designing and constructing innovative structures in the built environment.

ADVERTISEMENT–For Advertiser Information, visit STRUCTUREmag.org

References

Fang, D. (2020). *Timber joinery in modern construction: Mechanical behavior of wood-wood connections*. M.S., Massachusetts Institute of Technology, Cambridge, MA, USA, 2020. **https://dspace.mit.edu/handle/1721.1/127868**

www.food4rhino.com/app/design-space-exploration

Brown, N. C., & Mueller, C. T. (2019). Design variable analysis and generation for performance-based parametric modeling in architecture. *International Journal of Architectural Computing*, 17(1), 36-52.

Danhaive, R. A. and Mueller, C. T. (2021). Design subspace learning: structural design space exploration using performance-conditioned generative modeling. *Automation in Construction*, 127. **https://doi.org/10.1016/j.autcon.2021.103664**