D-PREDICT: INTEGRATING GENERATIVE DESIGN AND SURROGATE MODELLING WITH DESIGN ANALYTICS

ESMAEIL MOTTAGHI[1], AHMED M. ABUZURAIQ[2]
AND HALIL ERHAN[3]
[1,2 3] Simon Fraser University, Canada.
[1]ema63@sfu.ca, 0009-0005-6082-9966
[2]aabuzura@sfu.ca, 0000-0002-3604-7623
[3]herhan@sfu.ca, 0000-0002-7630-6351

Abstract. The increasing importance of performance prediction in architecture has driven designers to incorporate computational tools like generative design and building simulations to widen and guide their exploration. However, these tools pose their own challenges; specifically, simulations can be computationally demanding and generative design leads to large design spaces that are hard to navigate. To address those challenges, this paper explores integrating machine learning-based surrogate modelling, interactive data visualisations, and generative design. D-Predict, a prototype, features the generation, management and comparison of design alternatives aided with surrogate models of daylighting and energy.

Keywords. Generative design, building performance assessment, surrogate modelling, machine learning, design analytics.

1. Introduction

Architects have increasingly turned to computational methods, including Generative Design (GD) and building performance simulations, as to develop sustainable built environments. Integrating performance analysis into the design exploration aims to proactively identify and address potential issues as early as possible, ensure sustainability (Iyengar, 2015), align project preferences and constraints with performance objectives (Bernal et al. 2019), and reduce environmental impacts, ultimately contributing to the resilience of built environments. Such integration is more pronounced in GD, where large sets of design alternatives can be rapidly generated.

However, both performance simulations and GD methods pose their own challenges to designers. First, performance simulations, such as for daylight use and energy efficiency, are computationally intensive, mainly when conducted for multiple design alternatives such as those generated through GD. A promising solution is adopting machine learning-based performance assessment methods, including surrogate models. These methods can replace laborious simulations with fast performance predictions, accelerating the exploration of alternatives (Westermann et al., 2019; Yousif and Bolojan, 2022). These methods also enrich design alternatives by

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 1, 455-464.

offering additional layers of building information.

Secondly, performance simulations and GD methods produce large and diverse volumes of data that must be managed and presented well to designers. Innovative interfaces that facilitate practical design data analysis are required to achieve that. Furthermore, exploring design alternatives can be overwhelming, particularly when confronted with a vast design space, leading to the choice overload phenomenon (Erhan et al., 2017). The situation is further complicated when dealing with multiple objectives and conflicting performance goals. To address this issue, architects and designers can rely on data analytics systems (e.g., Chaszar et al., 2016; Garg et al., 2019; DesignExplorer 2, 2023), such as interactive data visualisation, to navigate and assess the data-rich design space, enabling informed decisions while working on multiple alternatives.

In this study, we employ a design study methodology (Sedlmair et al., 2012), which builds on the literature review above and involves architectural design practitioners as collaborators in the research process. The result is D-Predict, a Design Analytics system prototype incorporating GD and machine learning-driven performance prediction and enhances design decision-making through interactive data visualisation. D-Predict focuses on two important but conflicting performance concerns instrumental for sustainable architecture: daylight and energy use. It combines interactive data visualisation, surrogate models, and GD to enhance design decision-making considering performance metrics.

2. Background

Numerous studies have been conducted to explore methods to enhance architects' design decision-making in terms of building performance. These studies have been categorised into three main sections. The first explores integrating the GD and building performance assessment into the design process (Bernal et al., 2019; Anton and Tănase, 2016). Architects used experience, while researchers applied GD principles to optimise solutions for conflicting goals like energy and daylight optimisation. The second category is more relevant to our research investigating how machine learning and surrogate models can enhance building performance prediction. Below we briefly discussed the relevant research on this topic following with research on improving design decision-making when confronted with a large set of design alternatives by employing data analytics interfaces.

2.1. COMPUTATIONAL BOTTLENECKS AND SURROGATE MODELS

Using simulation processes for building performance assessment is computationally intensive, requiring complete models, particularly when considering multiple performance criteria assessed together. However, a complete model means that designers must prematurely commit some decisions, removing the exploratory opportunities of design from the process. Architects have recently started using surrogate modelling with deep-learning methods to replace simulation methods for reducing the time and required labour when predicting performances in the early stages of design (Westermann et al., 2019; Yousif and Bolojan, 2022; Zorn et al., 2022).

Yousif et al. (2022) proposed an automated performance-driven GD approach aided with surrogate daylighting models to enable the creative and informed exploration of complex floor layouts. In a different study, Zorn et al. (2022) demonstrated the potential of surrogate models (SM) as a novel approach for early-stage design evaluation. Additionally, the authors integrated the SMs into a dashboard presenting several performance indicators, which update in real-time. Westermann et al. (2020) propose a platform (Net-Zero Navigator) for exploring building performance design at the conceptual stage, powered by highly accurate surrogate models for energy that are trained on a dataset of 16 building types over 30 parameters and 20 different climates. The system is available online and features data visualisations, such as parallel coordinates plots, that can filter amongst existing designs or quickly sample designs from select parametric ranges.

The approaches mentioned above focus on surrogate models for either daylighting or energy; furthermore they do not present an interface for interactive design exploration (Yousif and Bolojan, 2022), present a data-only dashboard that does not show design forms (Zorn et al., 2022, Westermann et al., 2020), or an interactive design exploration interface that lacks features of creativity-support (Westermann et al., 2020), as outlined by Shneiderman (2007). Our work is distinguished by attention to daylighting and energy usage as interrelated performance factors. Furthermore, we present a feature-rich prototype that enables generating, evaluating and comparing designs quickly with the support of surrogate models and an emphasis on visualising both design forms and their performance to designers to allow holistic assessment.

2.2. ENHANCING DESIGN BY EMPLOYING DESIGN ANALYTICS

Integrating GD and BPA poses challenges in data management and design decision-making. With the GD approach, architects produce numerous design solutions, and BPA adds layers of information. Consequently, interpreting extensive data to identify the most suitable design alternatives becomes challenging, often leading to an overload of choices (Erhan et al., 2017). In contrast, evidence shows that, in conventional design processes, designers can effectively manage multiple alternatives in large office walls (Woodbury 2010).

This issue requires practical data analysis and decision-making strategies. Architects can use data analysis techniques and interfaces to navigate the design space effectively. These systems facilitate the exploration, analysis, and interpretation of large data sets through data visualisation and analysis, empowering architects to make informed decisions. It’s common to include interactive data visualisations such as parallel coordinates plots (e.g., in Design Explorer 2, 2023 and D.Star), bar charts (e.g., in DANZ by (Garg 2019), and scatterplots (e.g., DreamLens, 2018), which can be used to filter through design alternatives. Accompanying data visualisations are often graphical representations of designs (e.g., a single 2D image, a 3D view, or interactive image galleries), which, combined with visualisations, can help designers judge designs qualitatively and quantitatively.

Supportive techniques like rating, clustering, grouping and annotating designs have also been incorporated into design navigation interfaces. Including those features shows support from studies on designers' behaviour when exploring design spaces under cognitively overloading conditions (Shireen et al., 2017). A longer survey and analysis of design space navigation interfaces can be found in other sources (Abu

Zuraiq, 2020). In addition to the above features, sensitivity analysis (Østergård et al., 2017), clustering and Pareto Frontiers (Brown and Mueller, 2017) can be integrated into design space exploration. Visualising already generated designs helps understand relationships in the design space and filter designs to a few choices. But often, it's also necessary to generate new designs as designers gain new insights about the design problem and their criteria mature. Systems like D-Star (Mohiuddin et al., 2018), the Navigator (Garcia and Leitão, 2022), and the Net-Zero Navigator (Westermann et al., 2020) enable their users to create new alternatives on demand. Finally, each new design project may require bespoke needs in terms of design models or performance analysis. Ritter et al. (2015) introduce a system that connects a parametric modeller like Dynamo to building simulations so that designers can flexibly adapt the parametric model based on their unique needs for each new design task.

3. Developing D-PREDICT: Methods

We employed the design study approach as a problem-oriented research methodology. It involves "analysis of a specific real-world problem faced by domain experts, designing a visualisation system that supports solving this problem, validating the design, and reflecting about lessons learned to refine visualisation design guidelines." (Sedlmair et al. 2012). Below, we summarised the initial high-level requirements for a design analytics system combining performance evaluation with GD, which are derived from a literature review:

R1. Support exploration generated design alternatives (Shneiderman 2007).

R2. Facilitate user-friendly, engaging interactions with design models and surrogate models for performance analysis, catering for designers with varying levels of expertise (Shneiderman 2007).

R3. Guide selecting parameters and make their sensitivity on design generation transparent (Hamby 1994; Bernal et al. 2020).

R4. Support collecting and retrieving design (Shneiderman 2007).

R5. Keep a history of choices within the GD (Shneiderman 2007).

R6. Support the different design exploration methods and styles ("wide walls") while providing advanced data visualisation techniques for those who can use them (Shneiderman 2007; Abu Zuraiq 2020).

We present D-Predict as a low-fidelity design analytics tool for design decision-making. D-Predict can be classified as a Creative Support Tool (CST) (Shniderman, 2007), offering design generation, exploration, and comparison capabilities. D-Predict is developed as a prototype to provide insights into the GD, analysis of alternatives using surrogate models, and their comparative evaluation. The prototype serves as an integral part of the design exploration process. D-Predict can connect with surrogate model-driven performance prediction systems. Its prototype includes functionalities that demonstrate possible solutions rather than being a usable system.

4. D-Predict System Design

D-Predict adopts a specify-generate-evaluate cycle in GD (Figure 1). Central to the workflow, design analytics interfaces combine GD and performance prediction using data visualisations. The building performance prediction layer generates data by selecting surrogate models for performance concerns. After merging data from GD and performance prediction, designers explore the potential of each solution or set of solutions using coordinated views.

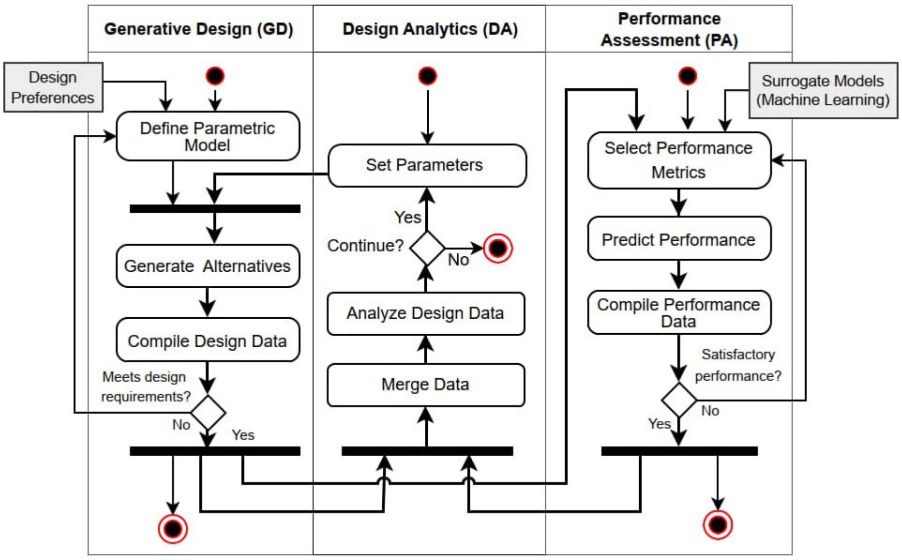

Figure 1. The proposed workflow integrates Design Analytics interfaces as a central data flow control between GD and performance prediction. The design alternatives are evaluated through such interfaces for their potential; then, they can be used for performance prediction. A design alternative can be directly used for performance prediction and evaluation. Therefore, the flow makes the design decision-making as flexible as possible.

4.1. D-PREDICT INTERFACES

D-Predict interfaces comprise three primary views: setup, data generation, and comparison views (Figure 2). In the Setup View, architects can establish a modelling environment in D-Predict by connecting it to a parametric model in a building modelling system, such as Grasshopper. This feature enables architects to leverage their parameters, previously crafted in the source software, and adjust parameters.

Figure 2. Three main views of D-Predict: The setup view for linking parametric from a model to initiate the interaction in the generate-predict-evaluate cycle.

4.2. DESIGN GENERATION VIEW

The design generation view is composed of two dynamic sidebars. The left sidebar is dedicated to architectural modelling, allowing designers to adjust parameters (R1) (Figure 3A). On the right one, the surrogate models are selected for performance prediction (Figure 3B). In the same panel, the repository panel stores visited alternatives (Figure 3E). Two vertical panels in the centre feature a parallel coordinate chart (Figure 3C) displaying the parameters and performance data. Simultaneously, the lower panel includes the 3D model, akin to the views in 3D software (Figure 3D).

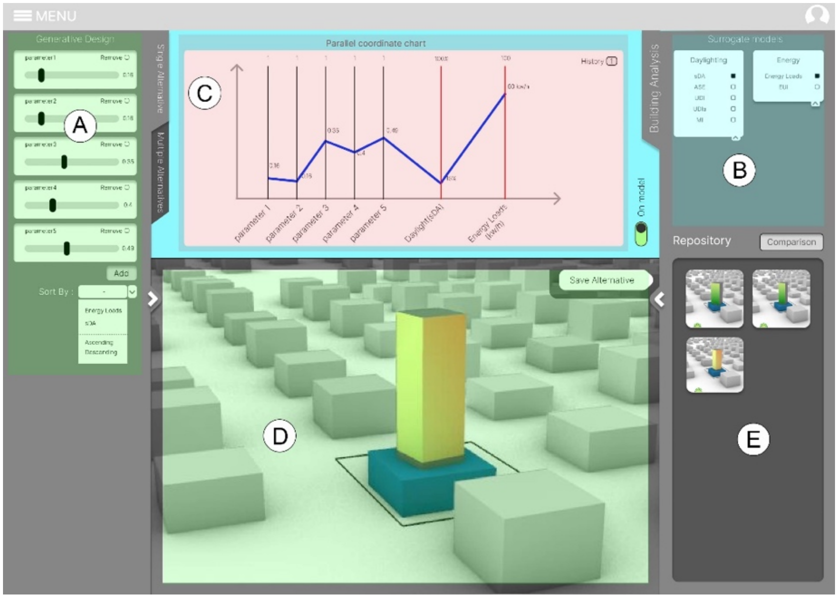

Figure 3. The generation comprises five views: (A) GD view to create multiple alternatives; (B) Surrogate Models to define performance metrics and select surrogate models; (C) Parallel coordinates displaying input and output parameters; (D) 3D View providing a visual representation of the form generated and used for performance analysis; (E) Repository view serving as a visualisation of visited alternatives and allowing persistent storage and retrieval on-demand.

The parameters from the CAD modeller are viewed to enable the generation of alternatives (R1). The users can add or remove parameters and modify the building configuration and material by adjusting the parameters. Once the form is defined, the users can choose one or multiple surrogate models to perform performance prediction, in which the results are viewed on the 2D parallel coordinate and the 3D model view (R2). The surrogate models' panel is designed explicitly for daylighting and energy load metrics, encompassing sDA (spatial daylight autonomy), ASE (annual sunlight exposure), UDI (useful daylight illuminance), and MI (mean illuminance) for daylight, as well as EUI (energy use intensity) and energy load for energy analysis. The repository enables storing preferred designs based on architectural concerns.

4.2.1. History tracking

One of the main features of D-Predict is history tracking (R5), allowing designers to monitor their past decisions. On the top-right corner of the parallel coordinate chart is a space for specifying the number of previous actions the designer wishes to revisit. By defining this number, the designer can see and retrieve the previous values for each parameter either on the parameter slider or the chart. (Figure 4).

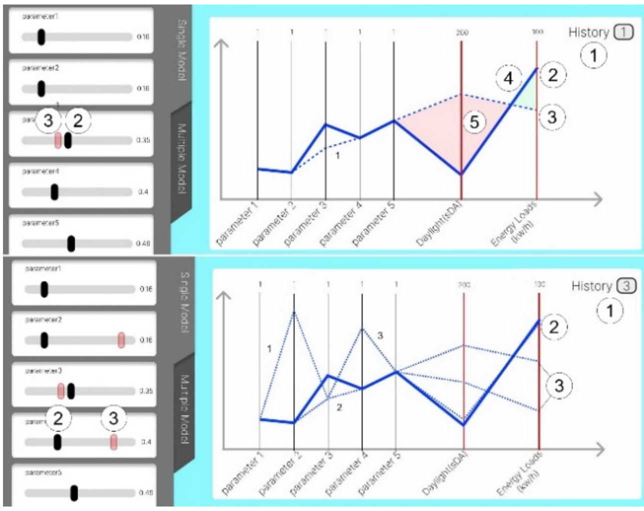

Figure 4. History tracking functionality allows monitoring and retrieving previous actions. (1) Defines the number of previous actions. (2) Displays the current state. (3) Displays the previous states. (4) The green area depicts an increase in value compared to the previous alternative. (5) The red area depicts a decrease in value compared to the previous alternative.

4.2.2. Alternative generation options

To generate alternatives, we have proposed three methods (Figure 5): single alternative generation by adjusting parameter values individually, multiple alternative generation by setting multiple discrete values for each parameter, and multiple alternative generation by value ranges. Subsequently, design forms are generated and used for performance prediction. The potential solutions can be stored in the repository for further investigation or revisiting later.

4.2.3. Sensitivity analysis

The impact of different parameters on each performance metric varies. Sensitivity analysis helps designers predict which parameters enhance or decrease performance more significantly. D-Predict offers a feature to view the impact of each parameter in two ways (R3). First, designers can rank the parameters based on their influence on a specific metric. This shows the relative importance of each parameter in achieving an expected outcome. The second visualises the results of a specific building performance metric, considering different values of one parameter while keeping the values of other parameters unchanged (Figure 6).

Figure 5. Three different methods to generate design alternatives: (left) single alternative by values, (middle) multiple alternatives by discrete values, and (right) multiple alternatives by value range.

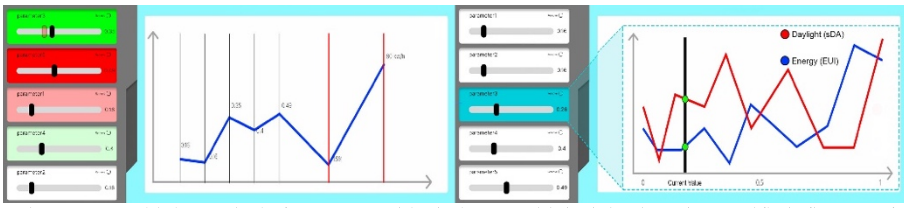

Figure 6. Sensitivity analysis features provide designers with insights into the specific influence of design parameters on performance metrics in two ways: (left) sorting the parameters based on their impacts and (right) displaying the effect of each parameter on overall performance.

4.2.4. Comparison View

The repository allows reexploring visited alternatives. By applying specific filtering techniques (Figure 7), designers can navigate a large set of alternatives and sort them to find potential designs by narrowing the search space. In this view, designers can create multiple subsets within the repository.

5. Conclusion

D-Predict represents an example towards making progress in sustainable architectural design by integrating GD, performance prediction, and interactive data visualisation. The discussion concerns overcoming computational challenges by adopting surrogate models, providing a quick alternative to laborious performance simulations. This approach aims to accelerate the design space exploration process and enrich potential by introducing additional layers of building information. D-Predict's interfaces, particularly the Comparison view, address the complexity of handling extensive data, offering architects mechanisms to navigate the design space and make data-informed decisions. The design study methodology ensures building a practical tool shaped by the insights and needs of design practitioners. As a part of this study, we identified high-level requirements for such systems.

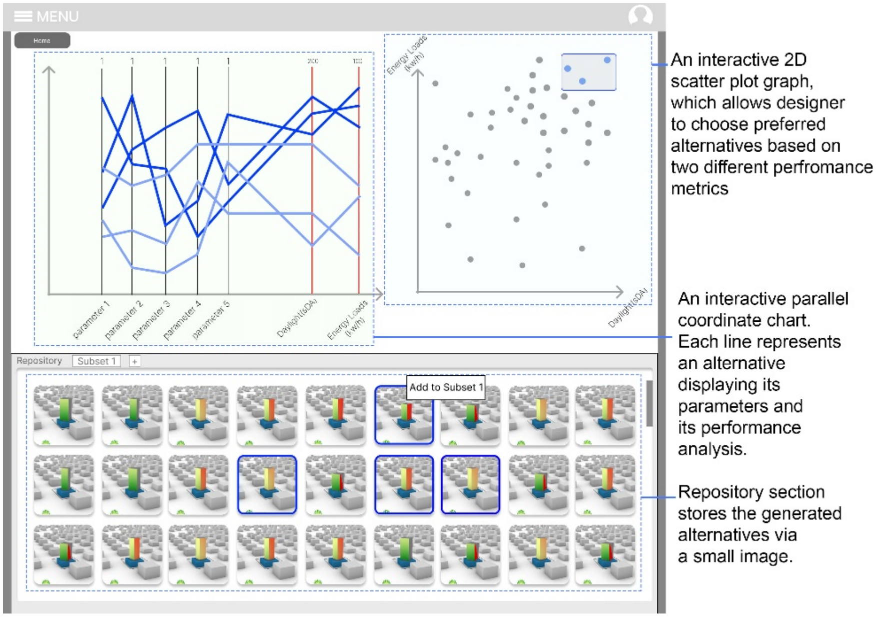

Figure 7. The comparison view enables evaluating sets of the generated design alternatives.

Based on the first version of the prototype, we developed a partial implementation of D-Predict as a Rhino plug-in. It integrates parametric design with machine learning-based analysis of daylight and energy load assessment (Figure 8). Our ongoing efforts involve conducting a user study with domain experts to evaluate the utility and adaptability of the system in practice. The Initial feedback has been positive and motivating. We will publish the updated system and the user study at a future venue.

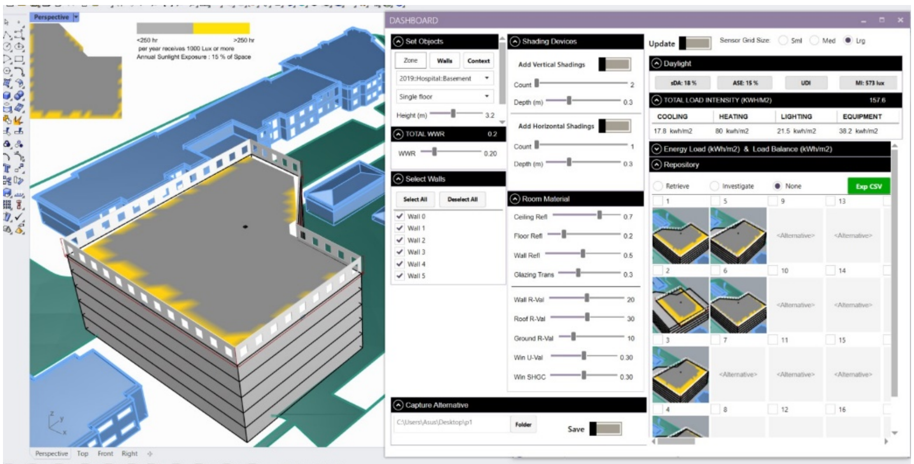

Figure 8. D-Predict's partial implementation on Rhino.

References

Abu Zuraiq, A. (2020). DesignSense: A Visual Analytics Interface for Navigating Generated Design Spaces. Retrieved December 13, 2023, from https://summit.sfu.ca/item/34308

Anton, I., & Tănase, D. (2016). Informed Geometries: Parametric Modelling and Energy Analysis in Early Stages of Design. Energy Procedia, 85.

Bernal, M., Marshall, T., Okhoya, V., Chen, C., & Haymaker, J. (2019). Parametric Analysis versus Intuition - Assessment of the Effectiveness of Design Expertise.

Brown, N., & Mueller, C. (2017). Designing with Data: Moving beyond the design space catalog. Proceedings Catalog of the 37th Annual ACADIA 2017 (pp. 154–163).

Chaszar, A., von Buelow, P., & Turrin, M. (2016). Multivariate interactive visualization of data in generative design. Proc. of SimAUD, 16.

Erhan, H., Abuzuraiq, A., Zarei, M., AlSalman, O., Woodbury, R., & Dill, J. (2020). What Do Design Data Say About Your Model? - A Case Study on Reliability and Validity. Proceedings of the 25th CAADRIA Conference. pp. 557-567

Erhan, H., Chan, J., Fung, G., Shireen, N., & Wang, I. (2017). Understanding Cognitive Overload in Generative Design - An Epistemic Action Analysis. Protocols, flows and glitches. p 127Protocols, Flows, and Glitches, CAADRIA 2017.

Garcia, S., & Leitão, A. (2022). Navigating Design Spaces: Finding Designs, Design Collections, and Design Subspaces. Int. J. of Architectural Computing, 20(2), 176–195.

Garg, A., & Erhan, H. (2019). Use of Data in Design Exploration: Design Analyzer. In J.-H. Lee (Ed.), Hello, Culture! (pp. 399–411). CUMINCAD.

Hamby, D. M. (1994). A Review of Techniques for Parameter Sensitivity Analysis of Environmental Models. Environmental Monitoring and Assessment, 32(2), 135–154.

Iyengar, K. (2015). Sustainable Architectural Design: An Overview.

Matejka, J., Glueck, M., Bradner, E., Hashemi, A., Grossman, T., & Fitzmaurice, G. (2018). Dream Lens: Exploration and Visualization of Large-Scale Generative Design Datasets. In Proceedings of the Conf. on Human Factors in Comp. Sys. (pp. 1–12). ACM.

Mohiuddin, A., Ashtari, N., & Woodbury, R. (2018). Directly Interactive Design Gallery Systems: Interaction Terms and Concepts. Comp. on Cultural V. and Heredity (pp. 15–32)

Østergård, T., Jensen, R. L., & Maagaard, S. E. (2017). Early Building Design: Informed Decision-Making by Exploring Multidimensional Design Space Using Sensitivity Analysis. Energy and Buildings, 142, 8–22.

Ritter, F., Geyer, P., & Borrmann, A. (2015). Simulation-based Decision-making in Early Design Stages. In Proceedings of the 32nd International Conference of CIB W78, Eindhoven, The Netherlands, 27-29 October (pp. 657-666).

Sedlmair, M., Meyer, M., & Munzner, T. (2012). Design Study Methodology: Reflections from the Trenches and the Stacks. IEEE T. on Vis. and Comp. Grph., 18(12), 2431–2440.

Shireen, N., Erhan, H., Woodbury, R., & Wang, I. (2017). Making Sense of Design Space - What Designers Do with Large Numbers of Alternatives?, 17th Int. CAAD Futures 2017.

Shneiderman, B. (2007). Creativity Support Tools - Accelerating Discovery and Innovation. Communications of the ACM, 50, 20–32.

CORE Studio. (2023). Design Explorer 2. https://tt-acm.github.io/DesignExplorer/

Westermann, P., & Evins, R. (2019). Surrogate Modelling for Sustainable Building Design – A Review. Energy and Buildings, 198, 170–186.

Westermann, P., Rulff, D., Cant, K., Faure, G., & Evins, R. (2020). Net-Zero Navigator: A Platform for Interactive Net-Zero Building Design Using Surrogate Modelling.

Woodbury, R. (2010). Elements of Parametric Design. London; New York, NY: Routledge.

Yousif, S., & Bolojan, D. (2022). Deep Learning-Based Surrogate Modeling for Performance-Driven Generative Design Systems. In Proc of the 27th CAADRIA (pp. 363–372).

Zorn, M., et al. (2022). Replacing energy simulations with surrogate models for design space exploration. Bauphysik, 44(6), 311–316.