MAKING A CASE FOR DESIGN ANALYTICS:

Complementing Designers' Toolbox for Data-Informed Creative Decision-Making

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Abstract. "Design Analytics" is a methodological approach for engaging with design form and performance data to guide design space exploration. The goal is to integrate design decision-making with data analytics through interactive visualisations. This paper introduces the approach grounded in three distinct patterns of design exploration: parallel development, solution exploration, and collaboration. These patterns are demonstrated through system case studies developed using a design study method, highlighting diverse opportunities and challenges in using design data. In each case, functional prototypes of the systems are presented. We propose a research agenda for this system-agnostic approach, offering a perspective on restructuring design with new design systems to enhance design computing.

Keywords. data inform creativity, Visual analytics, Design Analytics, data-driven design, design collaboration, design space navigation.

1. Introduction

In this paper, we introduce "Design Analytics" (DA), a research program that focuses on developing methods for leveraging design data to improve decision-making in the specification, generation, and evaluation of design alternatives, especially in the early design phases. Design Analytics integrates design exploration with data analytics, drawing from Visual Analytics techniques (Cook and Thomas, 2005). Our focus is on three related areas of design exploration: parallel development, solution exploration, and collaboration within the context of data. We present three case studies to explore the opportunities and challenges of leveraging design data, following a design study approach (Sedlmeir et al., 2012) and resulting in functional prototypes.

Considering that design representation is digitally created, it is reasonable to assert that a design be treated as data, extending beyond computable descriptions of an artefact. For instance, Building Information Modelling captures layers of design data at varying levels of abstraction, amenable to computing diverse performance factors like sustainability or cost. Although traditionally limited to specifications, contractual documents, and design models, design firms generate more extensive types and

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 1, 515-524.

volumes of data. Therefore, they require enhanced tools to derive valuable insights about their designs (Deutsch, 2015; Loyola, 2018).

Through multiple case studies, we identified and addressed specific gaps around using data to inform different design activities. This includes integrating real-time evaluation and comparative analytics of designs within a modelling environment (D-Flow), navigating through large generative design datasets with interactive data visualisation and analysis (D-Sense, or DesignSense), exploring novel interactions for driving parametric exploration with data (D.Star), collaborating in an asynchronously and data-informed fashion with project stakeholders in the early design stages (D-Art). These cases operate on the premise that most design representations are digitally created, including form and performance data. Such representations encompass geometric and substantial amounts of numeric and textual data in structured and unstructured forms, describing processes and structures. We chose cases as examples to narrow the paper's scope rather than presenting exhaustive system solutions. As part of our contributions, we outline a research agenda for Design Analytics (DA) that positions data as an integral (and system-agnostic) component of different design workflows. We envision the possibility of a new perspective on restructuring design by emphasising the impact of data and data-focused design systems.

2. Developing Design Analytics Interfaces

Designers work on multiple alternatives as a core aspect of their creative process (Woodbury and Borrow, 2006), and this process is increasingly being complemented with data. Developing tools that synergise these two elements—creating multiple design alternatives and data-informed design—is an ongoing endeavour in computational design research. One of the goals of this integration is to enhance designers' ability to navigate and uncover the implicit design space, a concept articulated by Aish and Woodbury (2005). Such tools aim to expand the horizons of design possibilities, allowing designers to explore and realise more performant designs that may not be immediately apparent in the conventional design process. It's instructive to consider how those tools are designed since they are part of the structure of a task environment that influences design problem spaces and, consequently, the strategies designers apply when exploring alternatives (Simon, 1996).

In current design task environments, the computational tools delimit working with alternatives and design data (Kasik, Buxton, and Ferguson, 2005; Terry et al., 2004): they are pressed for features to support the generation and management of multiple solutions with their data collectively (Lunzer and Hornaek, 2008; Schneiderman, 2007; Bilal et al., 2016; Touloupaki and Theodosiou, 2017). While most tools focus on form generation—in architectural design—specification evaluation and collaboration aspects are overlooked for several reasons (Kasik, Buxton, and Ferguson, 2005). For example, generating or selecting the designs based solely on their performance is challenging for two reasons. First, the performance usually reflects only partially and far from a complete set of all the design concerns, even if they are the most critical ones. Second, not all criteria can be easily quantified; some are tacitly known to the designers, such as aesthetics. Making sense of design data requires various visual, logical, and temporal structuring in different types of representations.

Computational design tools are creativity-support tools and are expected to enable 'exploratory processes,' facilitate 'collaboration,' manage 'rich history keeping, and be useful for novices and experts (Schneiderman, 2007). In addition, these tools should be 'engaging,' balance 'effort-reward trade-offs,' provide 'transparency' towards achieving tasks and be 'expressive.' For example, the ability to generate solutions creates a need for directly managing, sorting, filtering, and selecting alternatives. Further, evaluating alternatives involves multiple stakeholders with diverse interests, which need means to collaborate and share decisions. Both essentially rely on making design data accessible to decision-makers (Bilal et al., 2016).

3. Adopting a Design Study Methodology

A challenge for DA is to devise approaches and practices for representing, visualising and interacting with design data and workflows. To this end, we use the design study methodology outlined by Sedlmeir et al. (2012), which originates from information visualisation. This methodology is particularly adept at fostering the development of visualisations through an iterative process of design and evaluation. It emphasises a comprehensive approach, starting with analysing real-world problems identified by domain experts and then designing an interactive visualisation system to address these problems. The methodology then moves to validate the design and reflect on the gathered insights to refine guidelines for visualisation design.

The practical advantage of this methodology lies in its structured approach to solution development, allowing us to identify and refine solution features iteratively. It consists of nine stages, distributed across three main phases: the Precondition phase (learning, winnowing, and casting, selecting collaborators), the Core phase (discovery, design, implementation, and deployment), and the final Analysis phase, which involves reflection and evaluation. Each phase is designed with its specific evaluation strategy, ensuring a cohesive and interconnected process throughout all stages. To complement this methodology, we integrated agile and use-case-driven software development. This combination provided a structured yet flexible framework for prototyping, allowing us to develop and refine high-level system requirements in tandem with prototype development. These requirements also served as a basis for the formative evaluations.

Our approach also included extensive research on interactive systems that support data-informed design. In parallel, we engaged with our industry partners to gain insights into their workflows and specific needs in using data in design. This dual approach of theoretical research and practical engagement enabled us to apply learned lessons directly into developing our prototypes, which were enhanced with interactive visualisations to facilitate effective sense-making, as per Cook and Thomas (2005).

Case studies can help with problem characterisation and abstraction, one of the three fundamental contributions of design studies (Sedlmeir et al., 2012). The utility of problem characterisation in the research field lies in its characterisation of patterns for interactive systems requirements on which future efforts can be modelled and, to a lesser extent, the validation of the prototype produced. The cases we present emphasise core stages to provide a structure for research on DA. New technology enables new tasks, altering existing tasks. The discovery and development of these tasks are integral aspects of this problem-driven research. For example, DA should create opportunities for a thorough design evaluation, leading to changes in the approval process.

4. Design Analytics Cases: Generation, Exploration, Collaboration

For structuring the DA case studies, we will follow a workflow consistent with how designs are created in real-world scenarios. In this workflow, the data as input to a design situation is assumed to be given as design constraints or preferences, represented as part of digital models (as parameters or direct input) or implicitly observed by the designers. By taking the risk of simplification for clarity, we divide the workflow into three phases: generation of design alternatives with their form and performance data (both algorithmically and manually), evaluation and filtering of design alternatives, and data-informed collaborative decision-making (Table 1).

Table 1. Design data flow through design exploration and the example tools from practice and research. The tools must be seamlessly connected for data flow coordination and support uninterrupted decision-making.

Phase	Design Analytics	Tool
Generation of design alternatives	Designers generate solutions algorithmically, manually (e.g., by a directly interactive, or mixed, initiative CAD tools). The solutions consist of form and performance data at various levels of abstraction.	D-FlowUI (Erhan et al. 2020) directly interactive modelling and D-CAT (Zarei, 2021) for comparative data analysis D.Star (Mohiuddin and Woodbury, 2020) generative design in a design gallery interface.
Evaluation and Filtering	Generated design alternatives are explored by considering their form and performance metrics. Data used to assess model integrity.	D-Sense by Abuzuraiq (2020), Design Explorer by Thornton Tomasetti (2019) or DreamLens by Matejka et al. (2018)
Collaborative Decision-Making	Curated alternatives are shared with design stakeholders to initiate data-informed discussion and maintain synchronous or asynchronous collaboration	D-ART (Osama and Erhan, 2022) collaborative design-data analytics considering form and performance data presented on interactive data visualizations.

4.1. GENERATION OF DESIGN ALTERNATIVES

Design generation has been widely studied since the availability of computational methods to designers. Detailed reviews of generative or algorithmic design methods can be found in other literature, e.g., (Woodbury, 2010; Krish, 2011; Caetano, Santos and Leitão, 2020). The common characteristic of these methods is their capability to use a parametric description of a design model to generate a large set of alternative solutions. Most such techniques focus on developing ‘form’ with some degree of optimisation considering design criteria. Design generation using parametric models can also occur using design data directly instead of geometry or changing parametric definitions. For example, D.Star by Mohiuddin and Woodbury (2020) uses a parallel coordinate interface (Figure 1) serving two purposes: visualise input and output parameters and generate variations by using the graphs or tracing data points directly on the interface. The form and additional design data are computed and visualised on data graphs. D.Star interfaces combine both DA and design exploration tasks.

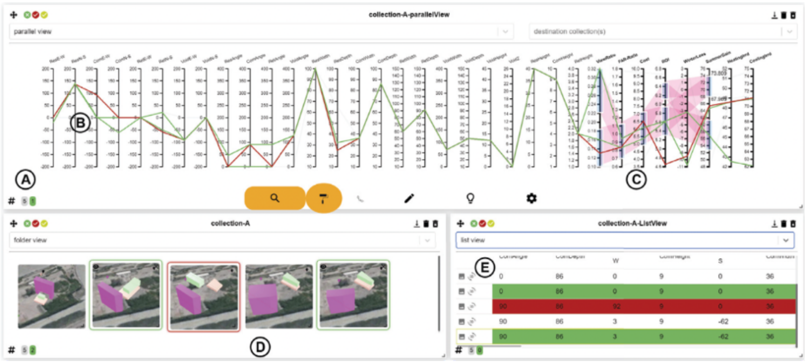

Figure 1. D.Star generates designs (A) on parallel coordinates to assign values and control ranges (B and C). Alternatives are displayed as 3D forms (D) and in a tabular layout (E).

Setting up parametric systems is labour-intensive and cannot be cost-effective in every design case. As a more common method, directly interactive modelling focuses on single-state designs that are amenable to refinement more than exploration, hence the lack of support for the parallel creation of solutions as demonstrated by expert designers (Woodbury, 2010; Erhan, Salmasi, Woodbury, 2010; Kolaric, Erhan, Woodbury, 2017). Design data should be assessed and inform decision-making in design exploration. D-FlowUI provides interfaces for interactively exploring design solutions (Figure 2-left) and D-CAT with D-FlowUI (Figure 2-right) to enable comparative DA (Erhan et al., 2020; Zarei et al., 2021). They are built on a combination of an actively used CAD tool, Rhino, and its add-on for parametric design, Grasshopper. The data visualisations demonstrate close-to-real-time design data, particularly in the concept development phases.

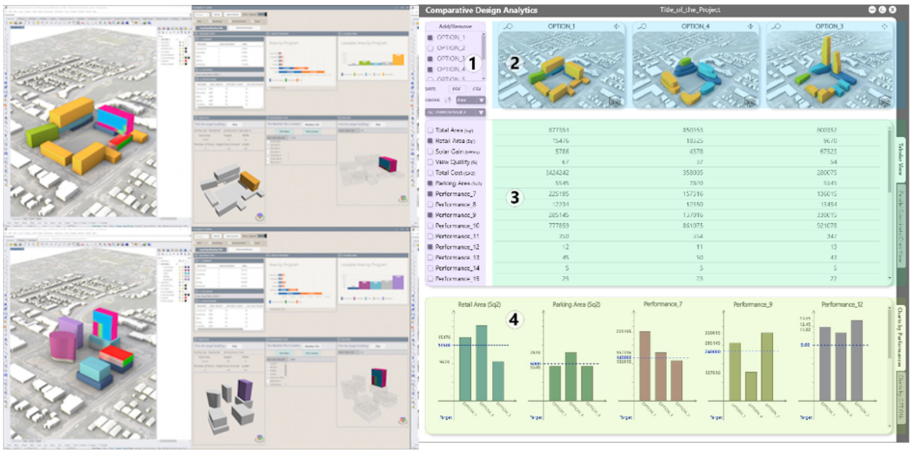

Figure 2. D-FlowUI shows two alternatives to a mixed-use building complex (Top). D-CAT (bottom) proposes interactive data visualisations to focus on performance criteria.

4.2. REVIEW, SELECT, SORT, AND FILTER WITH DATA

Tools for sifting through the generated solutions have been proposed, e.g., Design Explorer by Thornton Tomasetti (2019) and Dream Lens (2018). We developed D-Sense to navigate design space through coordinated and interactive data visualisations. Unlike the others, D-Sense can perform similarity- and set-based interactions (Abuzuraiq, 2020; Abuzuraiq and Erhan, 2020) (Figure 3).

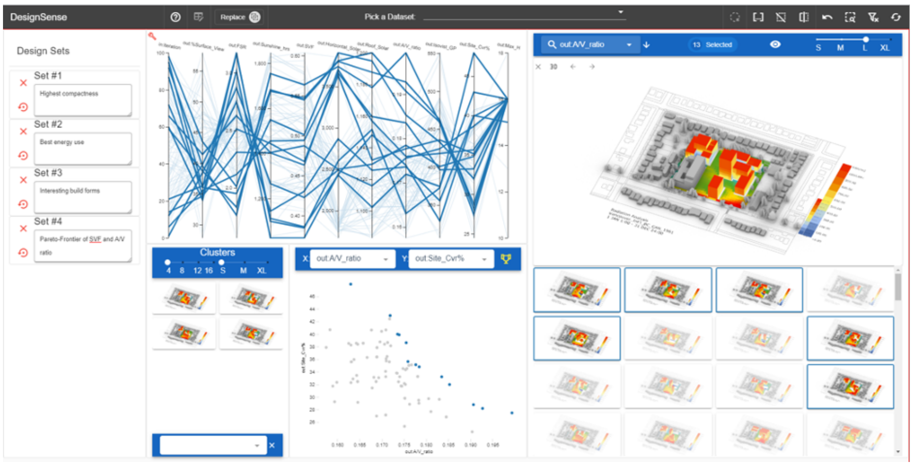

Figure 3. D-Sense (or Design Sense) is an interactive DA dashboard that can adapt any design data type (including form data and images) for exploring alternatives (Abuzuiraq, 2020).

A typical generative design dataset is multi-dimensional, including the input and performance metrics. Both are often quantitative, maybe occasionally categorical or ordinal. 2D images and 3D geometry models represent form. Other images can also be used to visualise the results of performance simulations, such as heatmap colouring to indicate how much sunlight is received. Generated alternatives must be evaluated in a performance-driven process (Erhan, Wang, Shireen, 2014; Anton and Tanase, 2016). The performance computation expects specific geometric fidelity in particular data structures; any inaccuracy, incompleteness, or error will result in unreliable or invalid design data. Considering these, the developers and users of parametric models should be aware of the importance of building reliable, scalable, and reusable models. Therefore, the design models and their parametric descriptions should be tested for their readiness for analysis (Figure 4).

Given the challenges for a large-scale generation of solutions through algorithmic methods, data visualisations can reveal form-performance inconsistencies, avoiding premature commitment. For example, we analysed ten different versions of the parametric tower designs in a workshop. After creating visualisations of the initial 250 designs in Tableau (2022) and using our custom analysis tools, we discovered unexpected patterns in building performance (Figure 5). Exploration involves design space segmentation and simplification for finding satisficing solutions by deciding on trade-offs and recording insights for sharing design decisions. In D-Sense, designers can compose sets of alternatives to reduce, eliminate or mark solutions for further analysis. Selections can be kept as a subset of solutions to be revisited or used for detailed analysis with set operations (e.g., the intersection of two sets of alternatives).

In such a scenario, D-Sense enables the selection of data dimensions and segments them into clusters based on their similarity. The evaluation of design alternatives generates design data as assumed earlier; each design act, whether related to specification, generation, or evaluation, is part of DSE.

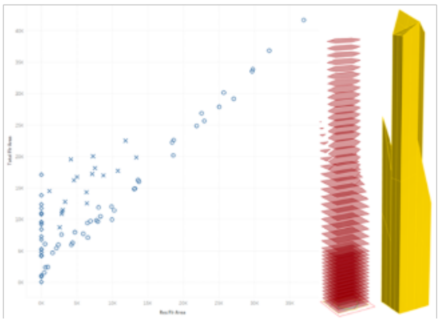

Figure 4. Left: Scatter plot of Total Floor Area vs. Residential Floor Area. Crosses show unexpected outliers. The vertical strip (diamonds) on the marks on the vertical axis are alternatives with no residential floors. Right: Floor planes with random segmentation or orphan floor plates.

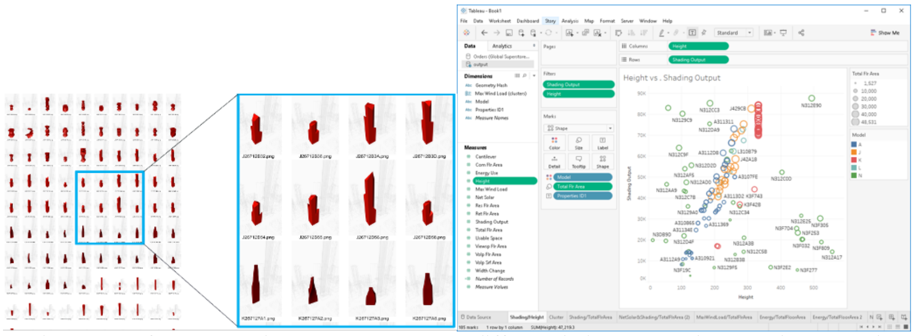

Figure 5. Performance and geometry present two different design aspects that complement each other. Evaluations capture only a fraction of the criteria that may be in action, while geometry at low fidelity can be misleading without details.

4.3. DATA-INFORMED COLLABORATIVE DESIGN-EVALUATION

Evaluating designs, as an integral part of the design process, involves multiple stakeholders with diverse backgrounds. Although there are computational systems for supporting evaluation tasks, they are either highly specialised for designers or configured for a particular workflow with limited functions. There may be a need to share relevant design data to inform collaborative decision-making. Also, stakeholders' feedback creates another layer of design data as input to the design.

To support stakeholders in reviewing a set of curated design alternatives, interacting with each other, and providing feedback, we propose the Design Alternatives Reporting Tool (D-ART) is a design data dashboard akin to a social web app. It aims to complete the data-informed design decision cycle (Alsalman and Erhan, 2022) (Figure 6). It aims to enable the presentation of each design alternative with personal visualisations of data while engaging stakeholders in conversation and feedback sharing. The stakeholders can visually compare and provide input on design alternatives to their data. Being an online platform decouples it from the design systems to manage the interface complexity and to accommodate different stakeholders with different interests and backgrounds. The stakeholders can interact with each other when they compare design alternatives.

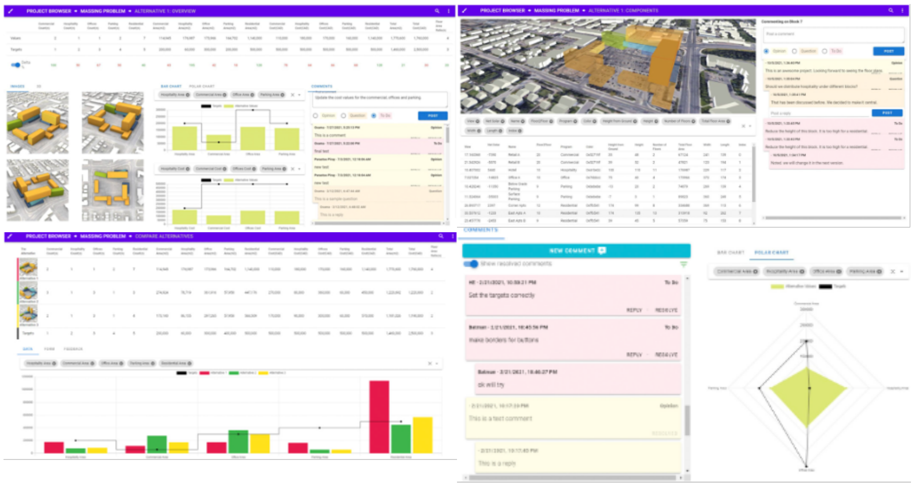

Figure 6. D-ART presents design data in alternatives, component, and comparison views.

5. Discussion and Conclusions

Design Analytics aims to engage in data-informed decision-making on interactive visualisations throughout the design decision-making lifecycle. With the decision-making cases and the tools we proposed, we demonstrated several ways for how DA can better serve in design workflow and create better-built environments with the caveat that neither the cases nor the tools are complete nor may be ideal. In this position paper, we also presented a set of tools and a conceptual process workflow that centres DA as a core activity in data-informed design beyond the conventional approaches with limited interactivity between the data, designers, and design stakeholders.

An example design workflow is presented in Figure 7, where a parametric model is specified to set the design constraints and preferences. Once the model is adequately defined, the system can help generate design alternatives. The designer employs DA to evaluate the alternatives and selects a subset that aligns with the predefined goals. At this stage, the designer can either regenerate additional alternatives or continue working with the existing ones. If the decision is to proceed and the designer deems the alternatives promising, it is necessary to choose metrics for performance assessment, e.g. using simulation or surrogate models. The designer can select plausible alternatives for further consideration upon aggregating the performance data with their design data counterparts. If the performance of the alternatives necessitates improvement, the system regenerates additional alternatives. Conversely, if the performance is deemed satisfactory, the system archives the selections in a repository, which can also serve as a training model. This can lead to generating similar or exploring entirely distinct design possibilities. Through the design study method, each of the presented tools went through several iterations of formative evaluation to better answer the question of what the other cases are or how such tools can improve the design workflow. However, we predict that there will be emerging issues as such tools become part of the real world.

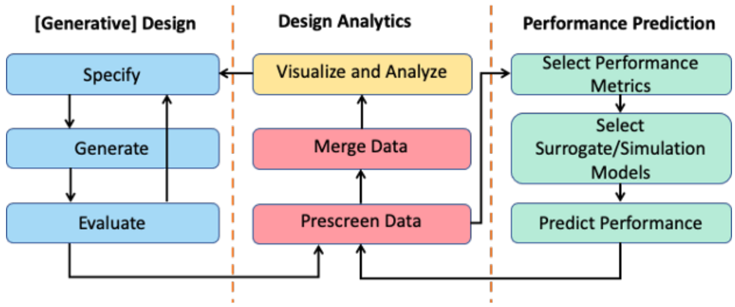

Figure 7. A conceptual model of DA in generative design and performance prediction.

We envision two salient obstacles. The first is about the difficulty of disrupting the established processes or changing beliefs. In time, the demonstration of effective use of design data can gradually trigger changes. The second is developing suitable tools for design tasks considering human-cognitive capabilities. Design-data dashboards can become quickly overpopulated with data visualisation and complex interaction techniques that can affect visual encoding. For example, while D-Sense is highly specialised and affords complex operations on design data, its capability should be revisited to understand how it can scale to respond to different design scenarios with varying levels of abstraction. D-ART presents opportunities for design-data democratisation for projects involving the public or input from different communities. Although the dashboard view may be simplified, transitioning from one view to another requires focused attention. We recommend striving for simplicity and clarity while making DA accessible to different stakeholders.

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