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Architectural Design Optimization—Results from a User Survey

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Abstract

Although there is a substantial body of academic literature on Architectural Design Optimization (ADO), not much is known about actual ADO practices. This paper presents results from a user study of ADO in Grasshopper and compares them with previous studies. Compared to these studies, this anonymous, web-based survey employed a more relevant sample in that all eighteen respondents actually use ADO and in that they represent a mix of students, academics, and professionals. The survey's results highlight the importance of supporting meaningful selections from and better understandings of optimization results and question the ADO literatures' emphasis on evolutionary, multi-objective optimization algorithms. They thus guide future research and development on ADO tools and ultimately contribute to the design of a more resource- and energy-efficient built environment.

Keywords: Architectural Design Optimization, Multi-objective optimization, Performance-informed Design, User Survey, Grasshopper

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1. Introduction

Architectural Design Optimization (ADO) combines parametric design and building performance simulations to automatically find well-performing design options. Although there is a substantial body of academic literature on this topic [7], not much is known about actual ADO practices. This paper discusses survey results from a follow-up study of participants of four conference workshops on ADO the author has conducted between 2016 and 2018 in Switzerland, Germany, Poland, and Mexico. The workshops invited architectural and engineering students, academics, and professionals to bring parametric designs from their practices that were optimizable or that they were optimizing already to the workshops.

While previous interview studies on ADO have included mostly academics [2, 14], this study includes a roughly equal mix of students, academics, and professionals. The study investigates a specific and highly relevant sample in that all respondents use ADO also outside of the workshops, and that all use the visual-programming platform Grasshopper as a platform for simulation and optimization. The survey is more specific

than earlier, larger ones [4, 14] in that it asks about actual rather than hypothetical ADO practices and asks respondents to rank desired features for ADO tools.

2. Survey Methodology

39 former workshop participants were invited by email to participate in the web-based, anonymous survey. Nineteen participants completed the survey, which corresponds to a response rate of 49%. Only one of the respondents replied that they "never" use optimization for their practice and/or research. This sample is excluded from the study. The following subsections present the survey's results and discuss them in comparison with previous studies.

3. Survey Results

3.1. Respondents' Backgrounds

Half of the respondents described their field as architectural design, and another six as computational design. Reflecting the geographical locations of the workshops, most of the respondents came for Europe or North America (Figure 1).

The respondents included four professionals, six academics, and eight students and represented a balanced range of sizes of organizations. (Three respondents worked in organizations with less than ten employees, three in organizations with less than one hundred employees, and two in organizations with more than one hundred employees.) All but one professional worked in their organization's dedicated computational design team.

Twelve of the respondents described their background knowledge on optimization as "moderate", five as "advanced", and one as "basic". This relatively high degree of knowledge likely reflects the workshops' effectiveness in teaching optimization concepts.

3.2. Optimization in Design Processes

Apart from three respondents who use ADO only about once per year, all respondents use ADO several time per year or more (Figure 2). Most use ADO in concept design stages, with only ten respondents using it for developed or technical design stages. This focus on early design stages might initially seem surprising, given that, in ADO,
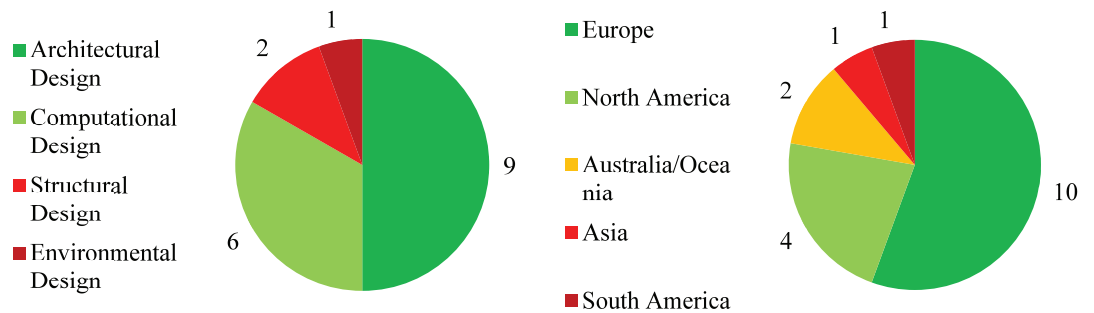
Figure 1: The respondents' fields (left) and continents of residence (right).

optimization typically is applied to technical problems. But it confirms the insight from an earlier interview study [3] that practitioners most often use optimization to find starting, rather than end points.

The most-selected reason for using ADO was understanding better what kinds of designs perform well, and why (twelve counts), closely flowed by understanding trade-offs between different objectives (eleven counts), and wanting to find several well-performing designs to choose from (ten counts). The two least important reasons were finding [only] a single well-performing design (eight counts), and convincing colleagues and clients (five counts).

This emphasis on understanding and selection aligns with the author's framework for performance-informed design, which highlights these aspects as key for integrating opti-mization into architectural design processes [20]. (With refinement, i.e., the possibility of adjusting optimization results to ones liking as a third key aspect.) The low emphasis on "rhetorical" uses perhaps assuages the worry that "such analyses sometimes provide functional justifications for seemingly extravagant forms" [13].
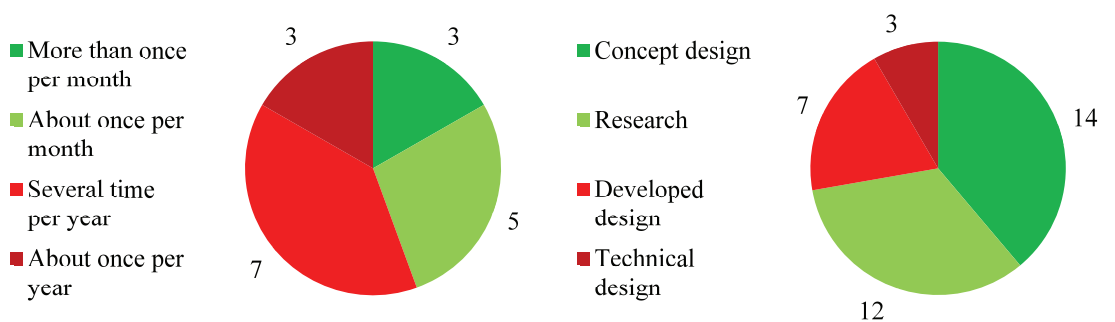

Figure 2: Frequency of using ADO (left), and stages of design processes where respondents use ADO.

3.3. Respondents' Optimization Problems

Respondents indicated that they optimized a variety of optimization objectives, with geometry rationalization, daylight, and solar exposure being named most often (Figure 3). Half of respondents indicated that they typically optimize only a single objective, seven respondents indicated two or three objectives, and two respondents more than three. Of the respondents that optimize multiple objectives, six use penalty functions, five use weighted sums, and only four use multi-objective optimization (MOO) algorithms.

This infrequent use of MOO algorithms appears to contradict the emphasis on understanding tradeoffs found in section 3.2, since MOO results often are presented as Pareto fronts that represent the tradeoffs between objectives [10]. The finding that most respondents do not use MOO algorithms and most often optimize geometry and daylight contrast with the optimization literature: In a review on optimization applied to sustainable design, building energy overwhelmingly is the most studied objective, 39% of surveyed papers employed a MOO algorithm, and only 8% employed weighted sums [7].

This result likely is partially due to the workshops, which presented penalty functions, weighted sums, and weighted products as methods to combine multiple performance criteria into a single objective to reduce the optimization problems' difficulty. (This difficulty increases exponentially with the number of objectives.)
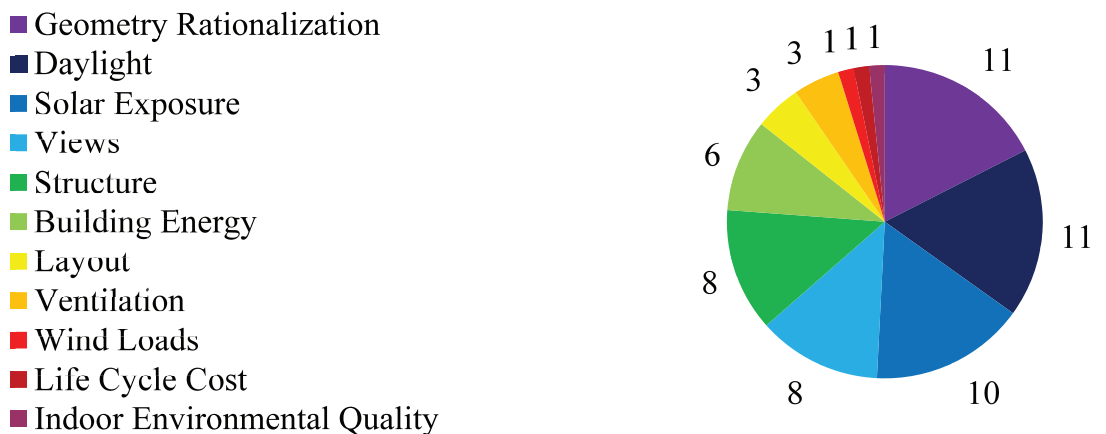
- Geometry Rationalization
- Daylight
- Solar Exposure
- Views
- Structure
- Building Energy
- Layout
- Ventilation
- Wind Loads
- Life Cycle Cost
- Indoor Environmental Quality

Figure 3: Objectives optimized by the respondents.

3.4. Opportunities and Challenges for Using ADO

The survey asked respondents about potential opportunities and challenges for using optimization in their design processes. In general, respondents were positive about using optimization: Most agreed that their designs' performance was important, that that they knew which aspects of designs to optimize, that optimization enhances their design creativity, that optimization tools find solutions fast enough, and that it is easy to understand and interpret optimization results (Figure 4).

The two largest challenges identified by the respondents were ease-of-use of simulation and optimization tools and the translation from qualitative design intentions to quantitative objective (i.e., fitness) functions and simulations results. The last challenge is unsurprising insofar the difficulty of formulating objective functions also was raised in all of the workshops.

These results contrast with a similar study of more skeptical "early adopters" of ADO for building energy reduction [14]: In this study, almost 90% of respondents agree that "long calculations times" are a hindrance to the adoption of ADO, and about 60% agree that ease-of-use ("lack of a user-friendly interface") is a hindrance as well.

In another interview study with 28 "experts on building performance optimization" from mostly academia [2], 24 experts identified long simulation times as an obstacle. Sixteen identified a lack of platforms "integrating and linking simulation and optimization", and twelve identified difficulties in formulating objective functions.

The fact that the other two studies find a larger challenge in finding solutions fast enough could be related to their respondents' likely use of less-efficient optimization algorithms, such as evolutionary ones [18]. According to several benchmark studies [5, 16, 18], RBFOpt often is the fastest algorithms when only a small number of simulations can be performed. Opossum, an optimization plug-in developed by the author and used in the optimization workshops, includes the RBFOpt algorithm [5], and is used often by the respondents (section 3.5).

The larger importance placed by the other two studies on user interfaces and integration between simulation and optimization tools likely stems from the respondents' use of different platforms: All respondents of this survey use Grasshopper [12], which seamlessly integrates simulation and optimization platforms and whose visual interface arguably is easier to use than the programming interface of, for example, GenOpt [17]. GenOpt is a popular optimization package in the building energy optimization community [2]. This contrast suggests the larger suitability of Grasshopper for ADO

compared to other platforms. Indeed, Grasshopper is regarded as the most popular platform for ADO among architects [4].
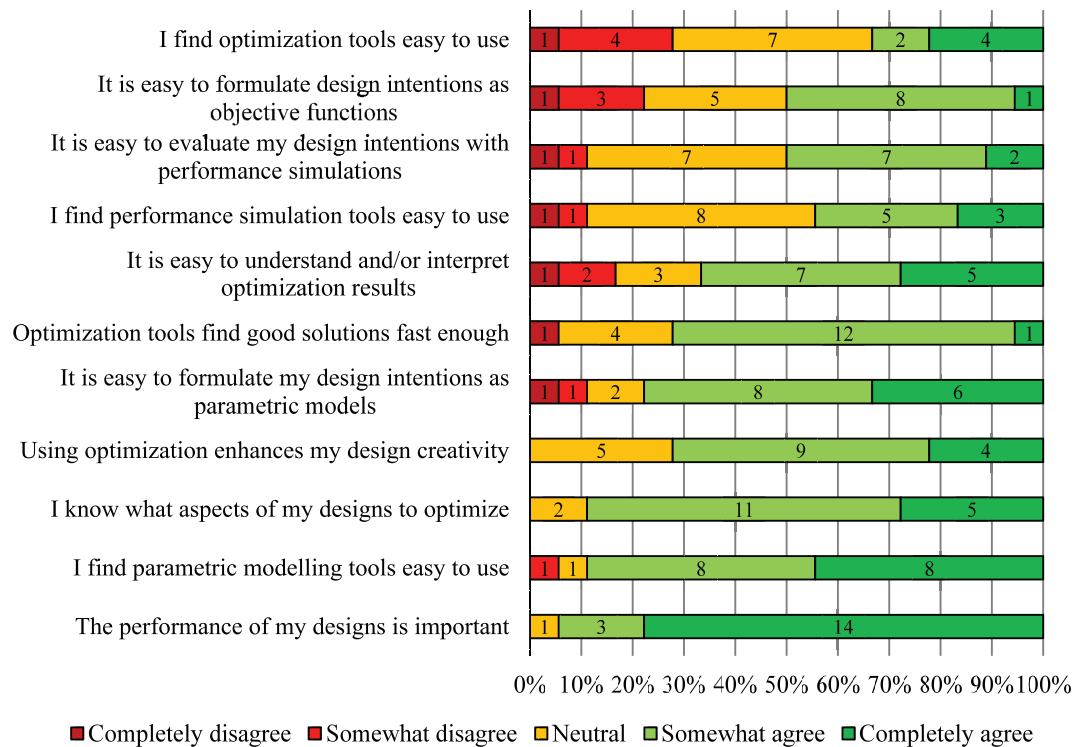

Figure 4: Responses to opportunities and challenges for ADO.

But, despite Grasshopper's seamless integration and visual interface, some respondents find optimization tools difficult to use. The results in [4] suggest that this difficulty might be due to a desire to understand more about the underlying algorithms. Another results that appears to contradict the conventional wisdom of ADO sceptics [13] is that most respondents experience ADO as creativity-enhancing.

3.5. ADO Tools used by Respondents

The two most popular optimization tools among respondents were Galapagos [11], which implements a genetic algorithm (GA) and simulated annealing (SA)—and Opossum [19], whose development is led by the author and which offers the machine-learning-related RBFOpt algorithm [5] (Figure 5).

Some respondents also regularly use Octopus [15], which offers two multiobjective algorithms and a three-dimensional visualization of optimization results, and Goat [8].

Goat is an interface to the nonlinear optimization library NLopt [9], which, among other algorithms, offers DIRECT, a deterministic algorithm that always results in the
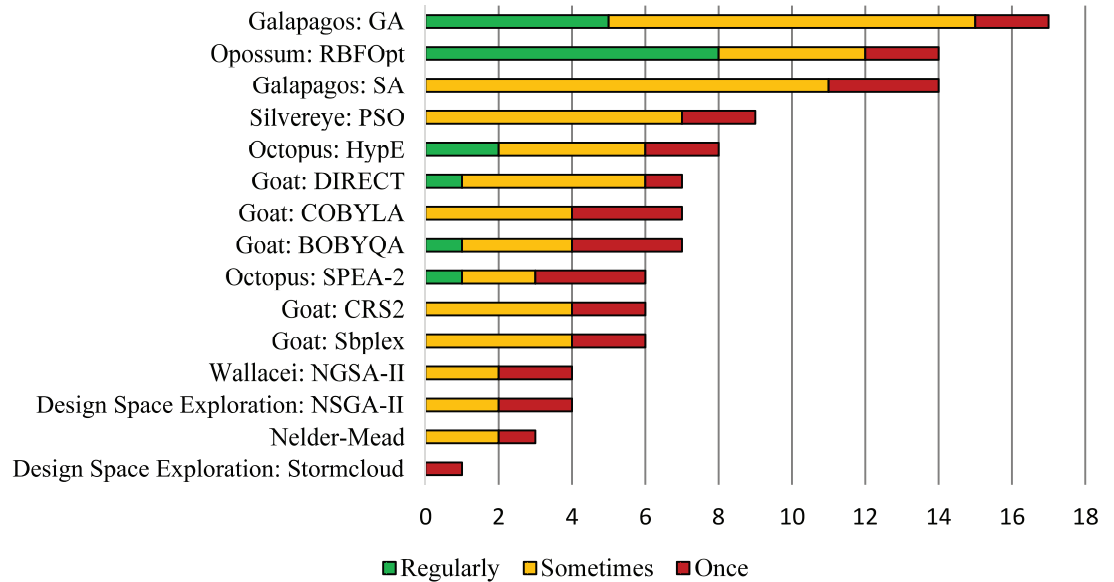
Figure 5: Frequency of use of optimization tools and algorithms indicated by the respondents.

same result and that works well for problems with small numbers of variables [18], and local algorithms (COBYLA and BOBYQA) that can improve results found by other algorithms by "finetuning" parameter values.

This result is unsurprising insofar Galapagos is inbuilt in Grasshopper, genetic algorithms are the most popular in the ADO literature [18], and the author's workshops recommend Opossum and Goat as good first choices, based on benchmark results [16, 18].

In these benchmarks, the Galapagos SA sometimes does well for certain problems, although its results exhibit a larger variability than RBFOpt. Using the Galapagos GA cannot be recommended due to the large variability of its results. (In other words, it is unlikely that the Galapagos GA will achieve a similar quality of results on repeated runs on the same problem.) This high variability, which is problematic for practical use, is shared by other evolutionary algorithms [16].

DesignBuilder [21], a commercial BIM software with simulation and optimization capabilities, GenOpt [17], a free optimization library, modeFrontier [22], a commercial optimization and visualization software, and Optimo for Dynamo [1], are optimization tools outside of Grasshopper that the respondents said to use more than once.

3.6. Desirability of Features for ADO Tools

The survey asked respondents to rank five potential features/characteristics of optimization tools in terms of desirability: (1) Efficiency, i.e., finding better performing designs

more quickly, (2) multiple objectives, (3) choice, i.e., presenting several designs with meaningful differences, (4) overview, i.e., providing a visualization of all possible designs, and (5) interactivity, i.e., influencing optimization processes.

Efficiency implies providing more efficient optimization algorithms, and multiple objectives providing multi-objective algorithms. Clustering methods that sort design candidates into groups are a popular method to support choice, while multivariate visualizations provide overviews of all design candidates. Stormcloud is an example of an interactive, genetic algorithm that allows users to choose the design variants that are recombined to form the next generation [6].

In performance-informed design, choice is important to present designers with options instead of a single, high-performing design candidate, and overview is important to help designers understand the relationships between design parameters and objectives [20].
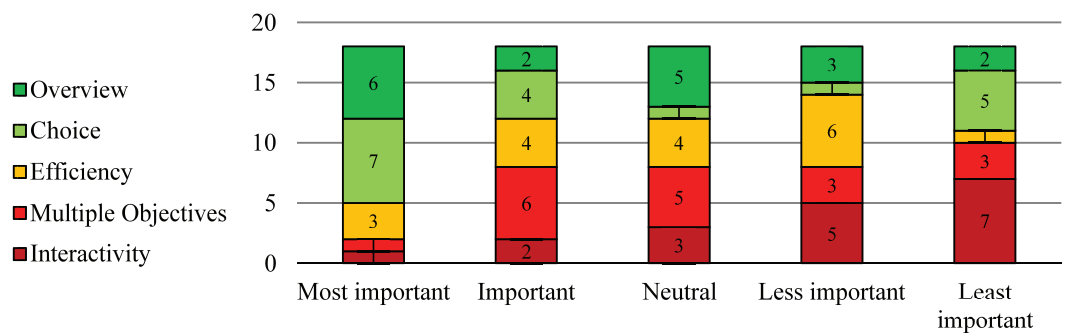

Figure 6: Ranking of desired features for optimization tools.

The author proposed performance-informed design based on the results from a user test with thirty participants. This survey confirms the results from that test in that respondents ranked overview and choice as the most important features (both scored 61 when adding the chosen ranks), followed by efficiency (56) and multiple objectives (53). Respondents ranked interactivity as the least important feature (39) (Figure 6).

In the survey by Cichocka et al. [4], 91% of respondents desired to influence optimization processes (i.e., interactivity), 82% desired "a few high-quality solutions" as an optimization outcome (i.e., choice), and 78% desired to optimize "many features (multi-objective optimization)". (The latter question did not distinguish using a multi-objective algorithm from using penalty functions, weighted sums or weighted products with a single-objective algorithm.) In terms of efficiency, 30% of respondents were willing to wait five minutes for the optimization results, 36% up to one hour, 31% up to one day, and 3% up to one week.

That survey's design did not ask respondents to rank their desired features. In other words, respondents did not consider potential trade-offs between, for example, being willing to wait for only five minutes and wanting to optimize many objectives. This survey design makes it problematic to compare the results from [4] with this survey.

However, apparently there is a clear difference in the desirability of interactive optimization between the two surveys. This difference might again be due to different groups of respondents: While all respondents in this survey actually use optimization in practice and/or research, [4] did not distinguish between potential and actual users of ADO. In other words, interactivity possibly appears more attractive in theory than practice.

4. Limitations and Future Work

The sample size from a specific population (i.e., Grasshopper users that attend conference workshops on optimization) limits the survey's generalizability, but is comparable to similar studies of "expert" users of ADO [2, 14]. The comparisons with results from these studies and with [4] are limited by differences between populations and differences in study design.

A future survey based on the current study aims at a much larger sample size of a broader population by soliciting responses via relevant social networks, through the author's contacts in the ADO community, and from users of Opossum. This future survey aims to clarify the ease-of-use problems faced by this study's respondents. This future study

5. Conclusion

This survey has provided guidance on how to support the increasing integration of ADO into architectural design processes, to ultimately create a more resource- and energy-efficient built environment. This increasing integration is aided by visual-programming platforms such as Grasshopper that solve or mitigate problems of user interfaces and interoperability. Nevertheless, ease-of-use remains a challenge.

According to the survey, MOO is less popular than suggested by other studies and the ADO literature. This lesser popularity motivates a need for more efficient MOO algorithms and a shift of focus towards topics such as formulating objective functions, presenting meaningful options, and visualizing optimization results.

The respondents' reasons for using ADO (section 3.2) and desired features (section 3.6) illustrate the relevance of selection and understanding as important concerns of performance-informed design and deemphasize the need for interactive optimization.

Conflict of Interest

The author has no conflict of interest to declare.

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