ARCHITECT'S RESPONSES TO PRACTICING GENERATIVE DESIGN FOR FORM FINDING IN THE SCHEMATIC DESIGN STAGE

ARMAN ARISMAN[1], INDAH WIDIASTUTI[2], ASWIN INDRAPRASTHA[3], IWAN SUDRADJAT[4]
[1, 2, 3] *Institut Teknologi Bandung*
[4]*Universitas Katolik Parahyangan*
[1]*arman.wu@gmail.com, 0000-0002-6823-0588*
[2]*indahwidiastuti911@gmail.com, 0000-0001-8176-4739*
[3]*aswinindra@itb.ac.id, 0000-0002-7507-6953*
[4]*iwansudr@gmail.com, 0000-0002-9781-9420*

Abstract. Generative design's future impact on architectural processes relies on its successful integration into the established workflow of architects, as prior experiences indicate that technological innovations struggle when not aligned with existing work cultures. This study examines how architects respond to the challenge of practicing generative design, using the genetic algorithm technique, and focusing on the form-finding process, to achieve optimal design outcomes. The researcher set up an experimental research design involving eight professional architects, whose task is to develop an architectural schematic design based on a given set of algorithms. The interaction between architects and computers as supporting tools during the design process is documented to measure the priority level of given algorithms and time budgeting for every design step. Cognitive reflections of architects are recorded during the experiment, followed by interviews to gather additional insights into their experiences in generative design processes. The findings of this research will provide some insights into the advantages and disadvantages of generative design as an alternative approach to architectural design and the best way to integrate generative design seamlessly into prevailing architects' work culture.

Keywords. Architectural Design, Conceptual Design, Form Finding, Generative Design, Genetic Algorithm, Protocol Analysis.

1. Introduction

Many studies state that generative design has significant potential for utilization in the architectural design process (Azadi & Nourian, 2021; Caetano et al., 2020; Mukkavaara & Sandberg, 2020; Singh & Gu, 2012), but there is still a knowledge gap related to architects' behaviour in responding to new working methods that leverage generative design. Previous studies have explored the technical aspects of generative design, often overlooking human factors and their interaction with generative design tools. This research seeks to address this gap by revealing the cognitive behaviour of

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architects when interacting with generative design tools. In this context, the generative design technique employed is genetic algorithms.

The study utilizes a protocol analysis method involving eight professional architects assigned design tasks to explore architectural forms using generative design tools during the schematic design phase. Interactions between architects and generative design tools are visually and verbally recorded throughout the design process. The data is then analysed to understand the working processes of architects when leveraging generative design. The analysis results will identify the general sequence of activities, the most frequently performed activities, and the total duration of each activity. The findings from this research can serve as a basis for developing generative design algorithms that align with architects' general working processes and thoughts, enabling optimal utilization of generative design in the architectural design process.

2. Literature Review

2.1. GENERATIVE DESIGN FOR ARCHITECTURAL FORM-FINDING

Form-finding is the process of searching for architectural forms conducted by architects. The architect's ability to manipulate architectural forms significantly influences the quality of an architectural work. Forms encompass fundamental elements such as points, lines, surfaces, and spaces (Ching, 2015). Points indicate a position that, when extended, forms a line with a direction. When a line is extended, it creates a plane with surface and orientation. Expanding a plane leads to the creation of space. Architectural design is inseparable from the play of forms, both in two and three dimensions (di Mari & Yoo, 2015). A complex form is essentially a manipulation of simple forms. The manipulation of forms can be achieved in various ways, such as altering their dimensions, changing their orientation, and adding or subtracting elements.

The form-finding process in architectural design typically requires a considerable amount of time. Generative design has the potential to assist in accelerating the form-finding process (Caldas, 2001) . A generative process is also considered as an active space of progressive formation and mutation in the digital design process. One generative design technique that can support this process is genetic algorithms, which is an evolutionary technique inspired by natural evolutionary processes (Singh & Gu, 2012). The computer will be prompted to think and search for the best architectural form solutions based on predetermined genomes and fitness. The genome represents the solution structure, referring in this case to the geometric elements of architectural forms. Meanwhile, fitness is the objective function to evaluate how closely the solutions generated by the computer align with the architect's goals or criteria as the designer. The result of this genetic algorithm process is a population of solutions considered to have optimal quality according to the predefined criteria (Mitchell, 1996; Yang, 2021).

2.2. DESIGN COGNITION IN GENERATIVE DESIGN

Design process determine the quality of an architectural work (Jordanous, 2016; Lee et al., 2015). The fact is that architectural design work often proceeds in non-linear process in terms of analysis, synthesis and evaluation (Yu et al., 2021). The media or work environment has a significant impact on the architectural design process. At the same time, the use of generative design in the architectural design process also has its own challenges, especially those related to behavior and thought processes. Several studies do show that there are changes in cognitive behavior in design processes that utilize computational design (Lee et al., 2015; Maher & Tang, 2003; Yu et al., 2021).

Generative design, as part of computational design, has the concept of harnessing the thinking capabilities of computers. The thought process traditionally rest entirely on the individual of architects is partially delegated to computers. In this context, computers do not "think" in the true sense, but they possess the ability to perform calculations quickly and accurately. Utilizing computers for this thinking process poses its challenges. Generative design needs to be adapted to be accepted by architects as the primary actors in the design process. Design cognition in architectural design utilizing generative design needs to be studied to understand the characteristics of generative design tools when interact with the general cognitive behaviour of architects. One formal method for studying design cognition is through the use of protocol analysis (Gero & Milovanovic, 2020; Lee et al., 2020; Yu et al., 2021).

3. Method

3.1. PROTOCOL ANALYSIS

The main method used in this research is protocol analysis, a popular cognitive research technique for analysing the design process through the recording of actions, behaviours, verbal responses, or written information strictly and repetitively (Lee et al., 2020). The analysis process is conducted on the results of audio and video recordings from an experiment conducted using protocols. The recorded data will be segmented based on a coding scheme to facilitate organization and classification. The coding scheme for this research divides activity categories into four levels adopted from various coding schemes in previous studies and based on four creativity levels in design: Representation, Perceptual, Functional, and Conceptual (Suwa et al., 1998).

The Representation category involves activities that are directly related to creating a physical model. The Perceptual category includes the architect's activities when examining the visuospatial features of the model. The Functional category includes actions related to understanding non-visual information, where the architect checks whether the resulting visuospatial elements and features are able to convey information well. The Conceptual category involves cognitive actions that are not directly driven by the physical or visuospatial features of an element. Each category is further divided into several sub-categories which are the codifications of activities. They can be listed as shown in Table 1.

Table 1 Coding scheme

Category	Code	Description
Representation	R-Genome	Set genomes (parameters that affect fitness)
	R-Parameter	Adjust parameters
Perceptual	P-Brief	Attend to design brief
	P-Generate	Attend to the generation process
	P-Geometry	Attend to geometry
Functional	F-Fitness	Set fitness (value to be optimized)
	F-Information	Attend to non-geometry information
Conceptual	C-Alternative	Compare alternatives
	C-Evaluate	Evaluate generation results
	C-Write	Write idea

3.2. EXPERIMENT SETTING

This experiment involved 8 participants who are graduates of architectural education with work experience ranging from 1 to 6 years. All participants work as design architects and have been directly involved in the architectural design process at the schematic design stage. The experiment was conducted alternately in the same setting, in a closed workspace of approximately 12 sqm. Each experiment lasted for 40 minutes on a workday within the time range of 8:00 AM and 12:00 PM.

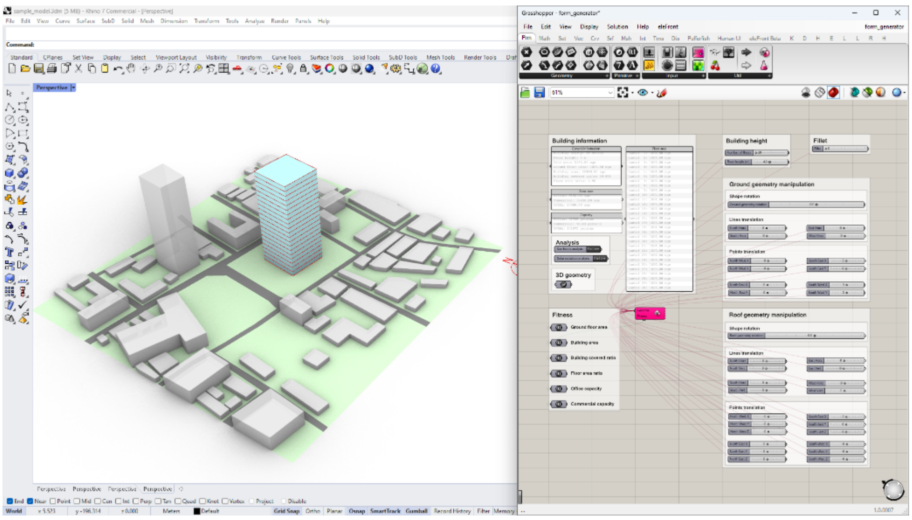

Figure 1 The user interface of generative design tools used

Each participant was assigned the same design task using Rhino, Grasshopper, and Galapagos. The generative design algorithm for the building to be designed was provided by the researcher. Participants received the same base model with certain parameters, as shown in Figure 1, to be developed into a schematic mass form with office and commercial functions, aiming to serve as a landmark for a city. The final design had to meet specific criteria, including having an area of approximately 3,000 sqm with a total of 20-30 floors.

The generative design technique employed is genetic algorithms, with the location, land boundaries, and surrounding buildings as its static inputs. These static inputs are provided as existing data and cannot be altered. The parameters used for the form-finding process include building height, ground floor geometry, and roof geometry. Each parameter has sub-parameters used as genomes in this genetic algorithm. The parameters and sub-parameters can be seen in Figure 2. Meanwhile, the performance indicators include building area, building covered ratio, floor area ratio, and building capacity, used as criteria for fitness evaluation.

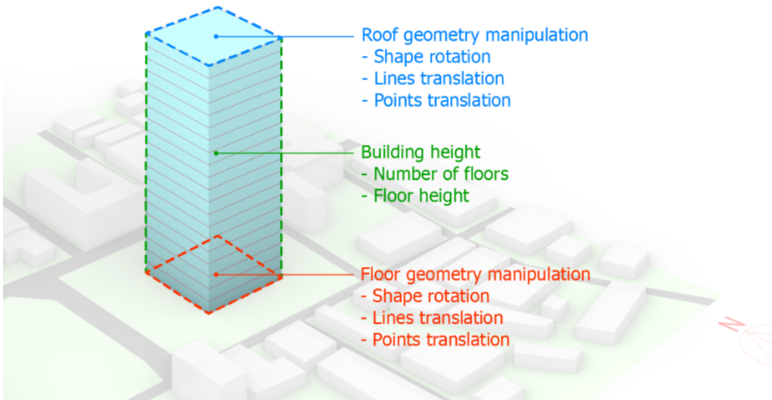

Figure 2 Parameters and sub-parameters for the form-finding process

Each participant was asked to verbally narrate what they are doing and thinking during the design process using generative design tools. The design results from the participants can be seen in Figure 3. Each session will be recorded using two cameras for video recording, a microphone for audio recording, and OBS Studio software to capture the laptop screen in use. The recording results in 2 video files from the cameras, 1 audio file from the microphone, and 1 screen recording file from OBS Studio. After the experiment concludes, participants will be interviewed to share their experiences in designing using the provided generative design tools, especially to reveal the advantages and disadvantages of employing generative design in architectural design.

4. Result

4.1. TIME ALLOCATION FOR EACH ACTIVITY

The segmented activity results from each participant are utilized to obtain data on the time allocation used by the participants per activity code and per activity category. Based on this data, the overall time allocation in the generative design process can be observed. Data related to the participant's behaviour in allocating their time can be seen in Table 2 and Table 3.

Based on Table 2, it can be observed that the activity with the largest overall time allocation is P-Generate at 21.37%, followed by C-Evaluate at 19.81%, and R-Parameter at 16.69%. P-Generate and C-Evaluate are the main activities in this experiment, hence it is reasonable that they receive a significant time allocation. P-Generate is an activity when participants observe the generation process conducted by the computer. C-Evaluate is an activity when participants evaluate the outcomes of the generation process. R-Parameter is an activity where participants directly adjust forms by changing the parameters that affect those forms. R-Parameter indicates that participants tend to be dissatisfied with the generation results produced by the computer. They tend to directly intervene in the forms generated by the computer, even though they were chosen by the participants themselves. While the generated forms by the generative design tool may be aesthetically pleasing and favoured, participants still feel the need for direct adjustments. Therefore, features related to R-Parameter need to be carefully considered when creating a generative design algorithm.

Another noteable finding is the small-time allocation for P-Brief at 2.10% and F-Information at 6.21%. It appears that participants are not overly concerned with various non-geometric information displayed, including the design brief. Participants spend more time observing and engaging in visually related geometric activities. This finding is important as it highlights the need for design tools to align more closely with architects' workflows and preferences, particularly the emphasis on visual and geometric aspects of design over textual or non-geometric information.

Table 2 The percentage of coding results by activity code

Code	E01	E02	E03	E04	E05	E06	E07	E08	Mean
R-Genome	6.94	10.99	4.02	0.00	8.07	1.45	4.72	6.01	5.27
R-Parameter	4.57	18.45	18.16	22.04	9.11	41.62	19.03	0.58	16.69
P-Brief	2.45	1.86	2.47	0.00	4.74	4.59	0.00	0.71	2.10
P-Generate	11.02	17.57	10.00	24.43	24.20	7.77	45.68	30.32	21.37
P-Geometry	14.94	5.12	16.44	11.60	19.38	5.13	8.44	10.68	11.47
F-Fitness	6.49	2.58	1.34	1.44	2.95	1.00	1.29	1.88	2.37
F-Information	9.58	5.91	13.93	12.10	6.61	7.27	0.00	6.21	7.70
C-Evaluate	37.96	19.56	19.58	21.32	15.59	9.04	13.54	21.85	19.81
C-Write	6.04	17.97	14.06	7.05	9.36	22.13	7.30	21.77	13.21

Table 3 shows that the activity categories with the most time allocation are Perceptual at 34.94% and Conceptual at 33.01%. Both have a very small difference, making them fairly balanced. Meanwhile, the category with the least time allocation is Functional at 10.07%. From these results, participants spend more time on conceptual thinking and observing geometric information. The Functional aspect is not as emphasized at this stage. However, the functional aspect is crucial in architectural design. With this tendency, features, and algorithms supporting the functional category should still be incorporated into the algorithm as a basis for generating good designs, although the information may not need to be visually highlighted too much. Architects are likely to focus more on the visual form. Even if there are low-performance indicators after selection and they match the chosen form, architects tend to adjust them later after achieving the desired form.

Table 3 The percentage of coding results by activity category

Category	E01	E02	E03	E04	E05	E06	E07	E08	Mean
Representation	11.51	29.43	22.18	22.04	17.17	43.07	23.75	6.59	21.97
Perceptual	28.42	24.55	28.91	36.04	48.32	17.49	54.12	41.70	34.94
Functional	16.08	8.49	15.27	13.55	9.56	8.27	1.29	8.09	10.07
Conceptual	44.00	37.52	33.64	28.37	24.95	31.17	20.84	43.62	33.01

4.2. GENERAL WORKFLOW

The segmentation results also reveal the sequence of each activity conducted by the participants from start to finish. Based on this data, activity sequences for each participant were created. Many repetitions between two consecutive activities occurred. The number of repetitions for each pair of different activities was then calculated for each participant. For example, one participant repeated the P-Generate activity followed by C-Evaluate 5 times in one session, while another participant repeated it 2 times. If such repetitions occurred multiple times, the sequence between these two activities is likely a common tendency. Therefore, the researcher attempted to map such repetitions.

Two sequential activities that occur only once will not be counted. Two sequential activities that repeat with a percentage below 20% will also not be counted. Such a low percentage is considered not representative of the overall workflow. This sequence is only performed by one or two participants. Meanwhile, a high percentage indicates that the sequence occurs frequently and is likely performed by the majority of participants, making it categorizable as a common behavioural sequence.

Table 4 The percentage of the occurrence of two activities sequentially

Previous Activity	Following Activities	n	%
P-Brief	C-Write	1	11.1
	R-Parameter	1	11.1
	F-Information	4	44.4
	P-Geometry	1	11.1
	F-Fitness	1	11.1
	P-Generate	1	11.1
F-Information	R-Genome	2	22.2
	P-Brief	2	22.2
	R-Parameter	3	33.3
	P-Generate	1	11.1
	P-Geometry	1	11.1
R-Parameter	F-Information	4	13.3
	P-Geometry	11	36.7
	F-Fitness	6	20.0
	P-Brief	1	3.3
	R-Genome	5	16.7
	C-Write	2	6.7
	P-Generate	1	3.3
P-Geometry	R-Genome	4	10.3
	R-Parameter	22	56.4
	F-Fitness	4	10.3
	F-Information	4	10.3
	C-Write	5	12.8

Previous Activity	Following Activities	n	%
C-Write	R-Parameter	2	18.2
	P-Geometry	5	45.5
	F-Information	4	36.4
R-Genome	F-Fitness	9	36.0
	P-Generate	12	48.0
	P-Geometry	1	4.0
	P-Brief	2	8.0
	R-Parameter	1	4.0
P-Generate	C-Evaluate	35	87.5
	P-Geometry	2	5.0
	R-Genome	2	5.0
	F-Fitness	1	2.5
C-Evaluate	P-Geometry	17	51.5
	C-Write	1	3.0
	F-Information	5	15.2
	R-Parameter	4	12.1
	R-Genome	2	6.1
	P-Generate	4	12.1
F-Fitness	R-Genome	6	27.3
	P-Generate	15	68.2
	F-Information	1	4.5

The data in Table 4 is then consolidated into a workflow diagram as shown in Figure 4. This diagram is also created based on the data in Table 2 to illustrate the time allocation for each activity. Each activity is depicted as a bubble with different shapes, font sizes, and colours. Larger shapes and fonts, as well as darker colours, indicate that the activity has a longer time allocation compared to bubbles with smaller shapes, fonts, and lighter colours. Each bubble is connected by arrows with varying thicknesses. The thicker the arrow, the more repetitions occur between the two activities.

Figure 3, demonstrate a trend that respondent tended to start with reading the design brief (P-Brief activity). However they did it very quickly. Meanwhile, the most frequently performed sequence of activities is P-Generate followed by C-Evaluate. Both of these activities are the two with the largest time allocation. It is crucial for a generative design tool to support this workflow trend. Observing the generation process and evaluating the results are key aspects of creating a generative design algorithm.

This diagram in Figure 3 can serve as a foundation for developing a generative design algorithm, ensuring that generative design aligns with the general behaviour of architects. The algorithm and user interface are designed to enable architects to utilize generative design tools optimally in the architectural design process.

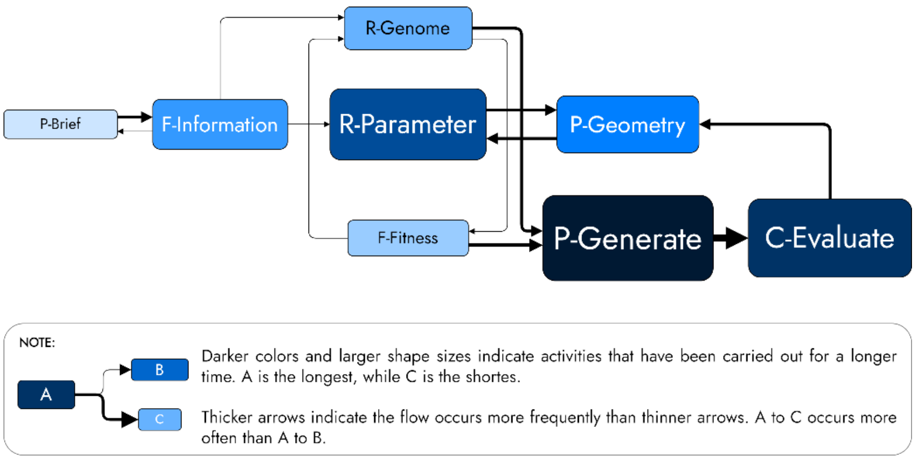

Figure 3 The workflow in general based on activity codes

5. Discussion

The cognitive behaviour of architects during the schematic design phase tends to be more focused on visually related aspects of building geometry. Generative design tools need to adapt to this condition. Generative design tools should facilitate architects in observing the generation process, evaluating its results, and refining those outcomes. Generative design will become more readily accepted when it can accommodate the needs and align with work culture of architects. This necessitates the provision of user-friendly operational features in generative design tools. Several participants mentioned that they need to adjust to the way the generative design tool works.

Architects, as designers, tend to actively engage in a process and not merely wait for results. Designing architects must have access to intervene in the models they are creating. This is evident from a significant allocation of time to modify the geometry of the model generated by generative design by adjusting various parameters. Designing architects are not satisfied with merely choosing from among the models generated. Their experience and knowledge lead them to identify shortcomings in the generated models, requiring the flexibility to further refine them. This finding is supported by the results from post-experiment interviews with the participants. Most of them mentioned that they always had the desire to directly change the form of the generated result. Therefore, even if they had chosen one of the forms produced by the computer, they had a tendency to improve that form.

A generative design tool needs to provide robust features to enable architects to intervene in the generated models. While computers can generate a large quantity rapidly, it is crucial for designing architects to continue adjusting their models and not passively accept the generated results. The active involvement of architects in interacting with generative design tools can influence computers to produce variations that better align with the preferences of designing architects. Simultaneously, architects' involvement in interacting with generated models provides them with the opportunity to refine them to match their envisioned ideas.

Based on the findings from this study, there are several promising areas for future research. Experiments can be conducted at other stages, such as during the design development. Experiments can also be conducted on different participant criteria. For example, involving participants from different work environments. Additionally, focus can be given to tasks other than form finding. Or the same experiment can be conducted but using different operations and parameters.

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