Artificial Intelligence for Engineering Design, Analysis and Manufacturing (2014), *28*, 277–283.

doi:10.1017/S0890060414000225

Generative spatial performance design system

BENJAMIN P. COOREY[1] AND JULIE R. JUPP[2]
[1]School of Architecture, University of Technology, Sydney, Sydney, Australia
[2]School of the Built Environment, University of Technology, Sydney, Sydney, Australia

(RECEIVED March 15, 2013; ACCEPTED February 25, 2014)

Abstract

Architectural spatial design is a wicked problem that can have a multitude of solutions for any given brief. The information needed to resolve architectural design problems is often not readily available during the early conceptual stages, requiring proposals to be evaluated only after an initial solution is reached. This "solution-driven" design approach focuses on the generation of designs as a means to explore the solution space. Generative design can be achieved computationally through parametric and algorithmic processes. However, utilizing a large repertoire of organiational patterns and design precedent knowledge together with the precise criteria of spatial evaluation can present design challenges even to an experienced architect. In the implementation of a parametric design process lies an opportunity to supplement the designer's knowledge with computational decision support that provides real-time spatial feedback during conceptual design. This paper presents an approach based on a generative multiperformance framework, configured for generating and optimizing architectural designs based on a precedent design. The system is constructed using a parametric modeling environment enabling the capture of precedent designs, extraction of spatial analytics, and demonstration of how populations can be used to drive the generation and optimization of alternate spatial solutions. A pilot study implementing the complete workflow of the system is used to illustrate the benefits of coupling parametric modeling with structured precedent analysis and design generation.

Keywords: Generative Design; Parametric Design; Performance Driven Design; Space Syntax; Spatial Analysis

1. INTRODUCTION

A building is more than a list of activities or rooms; it is a pattern of space that abides by conventions that determine the type and number of spaces required, how they are connected, sequenced, and which activities should be grouped together or segregated. Architectural spatial design is a wicked problem that has a multitude of solutions for any given brief. The information needed to resolve architectural design problems is often not readily available during the early conceptual stages, requiring proposals to be evaluated only after an initial solution is reached. This "solution-driven" design approach focuses on the generation of solutions as a means to explore large solution spaces. Generative design can be achieved computationally through parametric and algorithmic processes. This requires the codification of design logic and hence an understanding of the design process.

Kruger and Cross (2006) show that designers rely heavily on preconceptions in solution-driven design. Janssen (2005) differentiates between "limiting preconceptions," which "restrict the freedom of the designer," and "enabling preconceptions," which "give the designer greater freedom." Preconceptions can be in the form of guiding principles, primary generators, or design schemas. The repertoire of organizational patterns and design precedent knowledge as well as the precise criteria and computation of spatial evaluation required for generative exploration is more than what can be expected from the accumulated knowledge of an experienced architect (Schumacher, 2012). There is a need to supplement a designer's knowledge with a computational decision support system that can provide real-time spatial feedback during conceptual design.

This paper presents an exploration of parametric modeling techniques as a mechanism for constructing design logic models, in particular to support spatial feedback during design. The explorations are based around the four mathematical models described in Alfaris and Merello's (2008) generative multiperformance design system (GMPDS) as a conceptual and theoretical starting point for developing a spatial performance design system; the system is implemented through a pilot study to demonstrate how individual parametric logic models can be integrated.

Reprint requests to: Benjamin P. Coorey, School of Architecture, University of Technology Sydney, Sydney, Australia. E-mail: Benjamin.Coorey@uts.edu.au

2. PARAMETRIC DESIGN SYSTEMS

Conceptual design calls for the design of multiple options with a multitude of interdisciplinary criteria at a point where there is limited knowledge on the design problem. To achieve novel solutions, design as exploration (Gero, 1994) is required, and generative systems have the potential to offer computational support for the population and evaluation of solutions. The GMPDS developed by Alfaris and Merello (2008) describes a domain-independent computational framework to generate intelligent variations of an initial design concept using multicriteria evaluation. The GMPDS decomposes a design problem into four mathematical models: synthesis, analysis, evaluation, and optimization. This modularization allows a strategic approach, provides clarity to solving complex design problems, and is particularly suited to parametric modeling. It allows a design problem to be decomposed into parametric submodels. The function of each model is summarized below.

2.1. Synthesis models

Synthesis models abstract design intentions into a collection of design parameters, rules, or algorithms. Synthesis models can be constructed via parametric or algorithmic descriptions. Algorithmic models describe design through rules and algorithms, while parametric models describe a design as a series of relationships driven by parameters.

Parametric models have been used to generate design variation (Park et al., 2005; Hernandez, 2006; Almusharaf & Mahjoub, 2010; Coorey, 2010). Because the design is composed as a system of relationships, large populations of design solutions can be generated by varying the parameters. When generative parametric systems comprise analysis, evaluative, and/or optimization models, a significant opportunity arises with the capacity to improve design solutions (Littlefield, 2008; Sakamoto & Ferré, 2008; Gun, 2010; Hensel et al., 2010; Peters, 2010).

2.2. Analysis models

Analysis models determine characteristics from a design solution that are relevant to a specific discipline. Design is often multidisciplinary and requires more than one analysis model. Analysis models are deterministic and should always produce the same result. Depending on the amount of information required, there are low-fidelity or high-fidelity models. Low-fidelity models typically implement observation data, approximations, and heuristics, while high-fidelity models are theoretical models that are either physics based or mathematically derived.

Spatial analytics are typically low-fidelity indicators that can be readily integrated into a parametric model. Space syntax analysis has been used to understand and predict the behavior of urban and interior spaces. Gamma analysis (Hillier & Hanson, 1984) interprets urban space syntax measures for permeability of interior spaces. Ostwald (2011) and Bafna (1999) provide insight into techniques for comparing and identifying spatial patterns within a collection of buildings using gamma analysis. In addition to gamma analysis indicators, which are topological by nature, the parametric model allows the extraction of geometric spatial properties such as area, perimeter, length, width, and spatial proportion. In this way, the range of analytical metrics available from an analytical model forms a multicriteria problem that needs an evaluative model to determine performance. In related work, Heitor et al. (2004) combine shape grammar and space syntax to formulate, generate, and evaluate designs, and Eloy and Duarte (2011) use space syntax to provide a means of describing and evaluating spatial properties to "increase the likelihood of generating solutions that closely correspond to the user's requirements" (Heitor et al., 2004, p. 494).

2.3. Evaluative models

Evaluation models determine how the analytical model is interpreted to allow decision making. This is typically approached by deriving an objective function, commonly referred to as a fitness function. The definition of this function is critical in guiding the search for a solution and with ill-defined multicriteria design problems, often result in conflicting criteria. Evaluation can occur before or after the search for solutions. Preevaluation requires the decision maker to aggregate multiple objectives into a single fitness function. These can be weighted independently to preference certain objectives.

While evaluation models are data driven and not reliant on geometric design software, the advantage for parametric integration lies in the feedback loop that can generate and optimize alternatives in the synthesis model.

2.4. Optimization models

Optimization models enable the search for a solution. This involves cycling through the design space established by the synthesis model and comparing design instances to evaluation criteria in order to identify more feasible solutions. Typically, optimization models can be classified as heuristic or numerical. Heuristic algorithms are nongradient methods such as evolutionary algorithms and simulated annealing, while numerical techniques are gradient based such as Newton's method and steepest descent.

Heuristic algorithms are suited to complex problems associated with the wicked problems typical in design. Developments in parametric modeling software are allowing heuristic optimization methods to be incorporated into the parametric workflow. Heuristic methods are appealing because they can often find a good solution; however, optimality is not guaranteed and a different design solution may be found each time the optimization is run. In saying this, no optimization technique is guaranteed to find the global optimum of a nonlinear, nonconvex problem. Heuristic optimization is akin to a designer's method of solution-driven design.

3. GENERATIVE SPATIAL PERFORMANCE DESIGN SYSTEM (GSPDS)

This section describes a series of spatial parametric logic models that, when combined, enable a performance-based design system, which we have named GSPDS. The following sections will describe the overall conceptual framework and components in more detail. The system consists of the following four models and functions:

1. Synthesis model
    - Construct an abstract parametric rig that represents a spatial configuration.
    - With a parametric rig, reconfigure and generate an alternate solution.
2. Analysis model
    - Calculate spatial analysis metrics through the parametric rig to determine the design spatial properties.
    - Store parametric rig and spatial analytics into a spatial database.
    - Visualize analytical information in real time on design geometry.
3. Evaluation model
    - Evaluate the configuration error of the generated solution.
4. Optimization model
    - Optimize the solution according to the evaluation.

We present the GSPDS (Fig. 1) as a solution to required objectives. The above system is demonstrated in a pilot study that shows an implementation of the system through a fictional case study.

4. PILOT STUDY

This pilot study demonstrates the capacity of the GSPDS to capture spatial information from a precedent, analyze spatial properties, generate design variations, evaluate a solution according to certain criteria, and optimize for that criteria. The study is demonstrated through the design exploration of a single residential building design. The goal of this study is to demonstrate the appropriateness of parametric modeling techniques in the development of a performative design system. The system is set up to limit designer input to producing a sketch design only. The exploration was conducted using the parametric modeling software Grasshopper, and the various models can be seen through the modularized parametric definitions, visualized in Figure 2. Details of the four parametric models are described in the following sections.

4.1. Synthesis model

The role of the synthesis model is to abstract and capture the core spatial configuration of a building as a parametric model (Fig. 2) that has the capacity to generate alternatives. This is implemented as two design procedures that are illustrated in Figure 3.

The first part of the synthesis model interprets the designer's initial sketch into a "spatial configuration rig" by taking a series of room outlines (closed polylines), a set of relationships between them (lines), and an entry (point) as a set of inputs to produce a network graph consisting of nodes and relationships. Each node represents a space and stores the spatial properties parametrically as an output.

The second part of the synthesis model remaps the spatial configuration rig onto a randomized point cloud (which can be repopulated to produce different starting positions for the rig as a generative mechanism). This reconfigured network can then be optimized to produce alternate solutions. This part randomizes the locations of the spaces while maintaining their topological connection. This allows essentially an infinite amount of variations for space allocation. At this point, they maintain their topological relationships but their geometric spacing is distorted, which is later resolved in the optimization model described in Section 4.4.

4.2. Analysis model

This pilot study is focused on the development of a spatial performance design system and requires spatial analysis of residential buildings. As discussed in Section 2, there are a number of spatial indicators that can be derived from the synthesis model. These include space syntax gamma measures to drive the spatial analytics model, including integration, control, and topological depth as well as geometric measures including area, length, width, and proportion (see Hillier & Hanson, 1984).

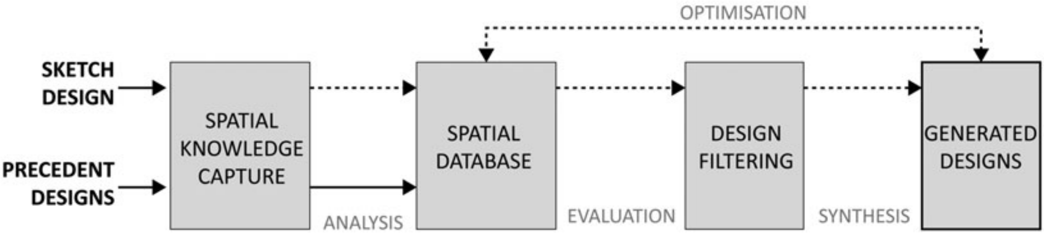

Fig. 1. A model for generative parametric spatial design exploration.

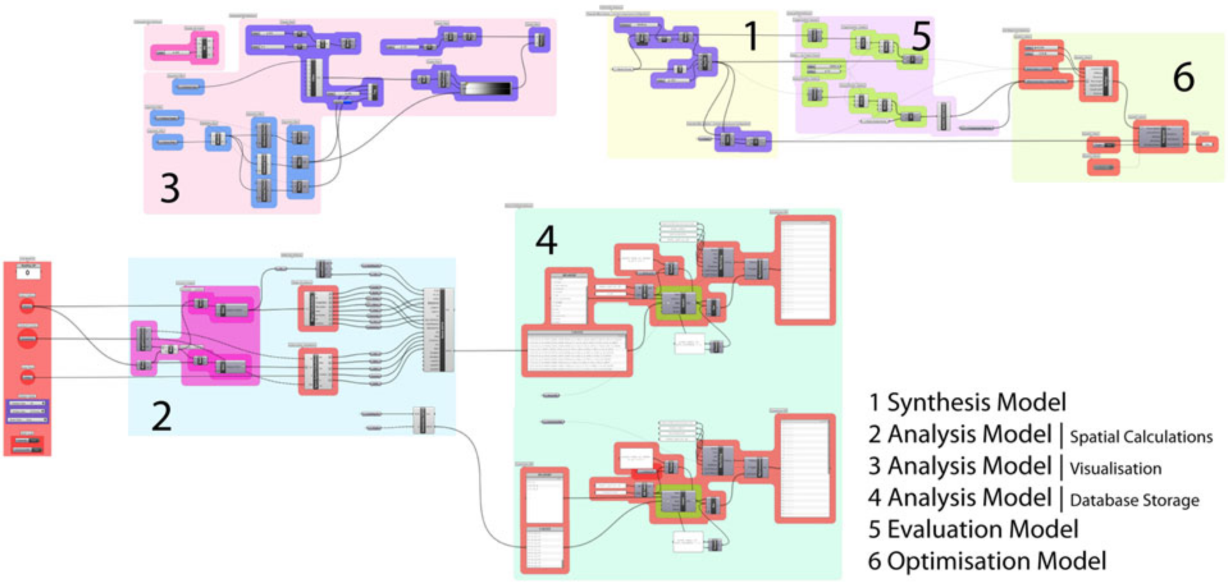

Fig. 2. A parametric definition for the generative spatial performance design system.

The analysis model calculates values directly from the synthesis model in the parametric modeling environment. This provides the benefit of visualizing real-time analysis of the original design geometry.

Topological depth provides a measure to determine the depth distribution of spaces within the building. The measure of *integration* can be understood as how deep or shallow each space is, compared to the limit of how deep or shallow they theoretically could be. This is also known as relative asymmetry and is calculated by averaging the mean depth of the original space to every other space in the system. This provides a number between 0 and 1 for each space, with low values indicating shallow spaces that tend to integrate the network, while high values indicate deep spaces that are segregated. The measure of *control* is a local indicator determining how important a space is in controlling the flow of movement around it. Each space has a number "*n*" of immediate neighbors. Control is calculated by assigning a proportion 1/*n* to each neighboring space. The sum of each receiving space is calculated; spaces that have values > 1 indicate a "strong control," and spaces < 1 indicate a "weak control" of their immediate neighbors.

The analytical data is then used as the input to the visualization procedure, which maps the chosen analytic back onto the individual rooms and colors them according to a black to white gradient field, where a value of 0 is represented as white and a value of 1 is represented as black. An illustration of the different measures can be seen in Figure 4 showing the topological depth, integration, control, and area overlaid onto one of the precedent residential building designs. Once calculated, the analysis can be stored in a spatial database for later retrieval (see Coorey & Jupp, 2013).

4.3. Evaluation model

The evaluation model is required to set a goal for design optimization. While in reality this should be a multicriteria

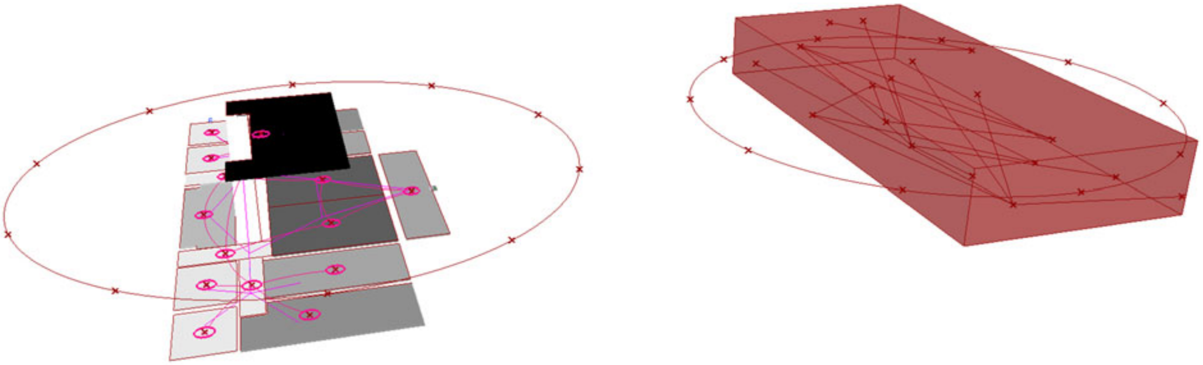

Fig. 3. An interpreted designer's sketch (left) remapped onto a generative point grid (right). Spatial analytical measures. From top left clockwise: topological depth, integration, control, and area.

https://doi.org/10.1017/S0890060414000225

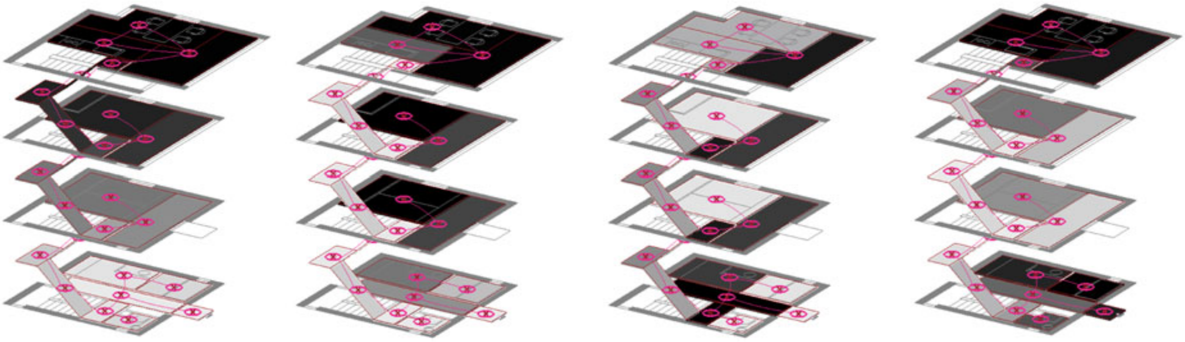

Fig. 4. Spatial analytical measures. From top left clockwise: topological depth, integration, control, and area.

evaluation problem, this case study demonstrates the logic by considering one evaluation criteria: spatial proximity. This model determines the validity of a generated solution by comparing the generated solution's spatial proximity distances to the original specification in the spatial configuration rig. The evaluation model can then determine the configuration error for each spatial relationship and, through a simple aggregation procedure, determine the average configuration error for the generated design. Optimization of this criterion will produce alternate design configurations that are reconfigured with the exact same three-dimensional spatial proximity as per the original design, which we will call "optimized" designs.

To explore the ability to generate novel topologies, a hybridization procedure was developed. Two existing designs were hybridized by connecting similar spaces from one design to another to form a novel configuration to evaluate against. The hybrid network is then used to map a new sketch design onto a target design through alignment of programmatic spaces. Each design can differ in the number and type of spaces. The hybrid network takes this into account by bifurcating or collapsing programs into each other. For example, if one building has one bedroom and the other has three, three connections will be drawn from the single bedroom to the three bedrooms. With the different programs mapped, the designer can choose the configuration from existing buildings "A" or "B" to be mapped onto the hybrid network. This will maintain the base topology of the chosen building; however, it will add in additional links to any bifurcated spatial programs using the same method of hybridization described above. An equally weighted hybrid network between two houses can be seen in Figure 5, which can then be used as an evaluation source to provide novel typologies.

4.4. Optimization model

The pilot study concludes with an optimization module that attempts to take the generated configuration, with a configuration error determined by the evaluation model, and optimize the solution to reduce that error, creating an optimized design. The optimization model achieves this through the parametric plugin Kangaroo (Piker, 2013), which is a physics-based "springs system." Each spatial relationship is represented by a "spring." Each spring has a rest length, which is the desired spatial proximity to its neighbor. The evaluation model determines the configuration error, and the spring system iteratively reduces this error by expanding or contracting until the whole system resolves, that is, the configuration error is minimized.

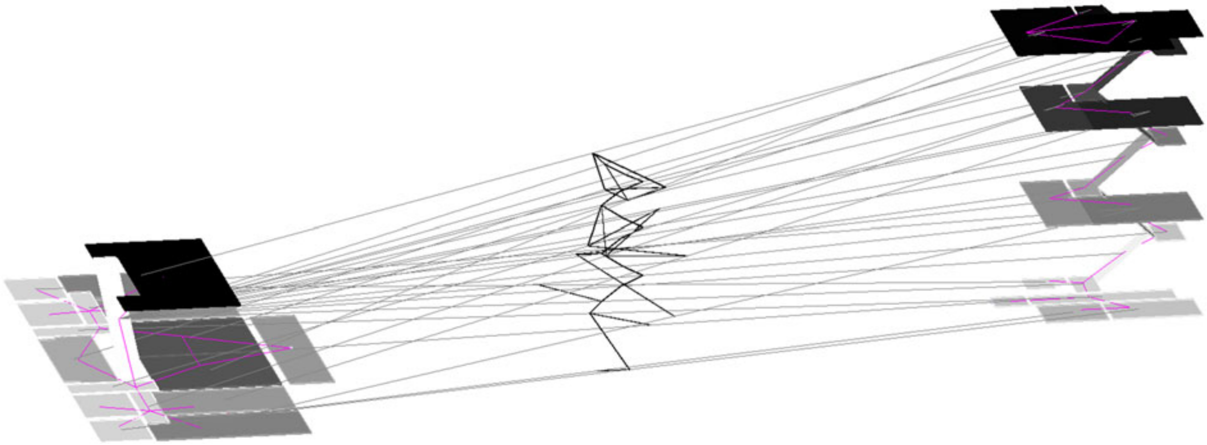

Fig. 5. The hybrid network.

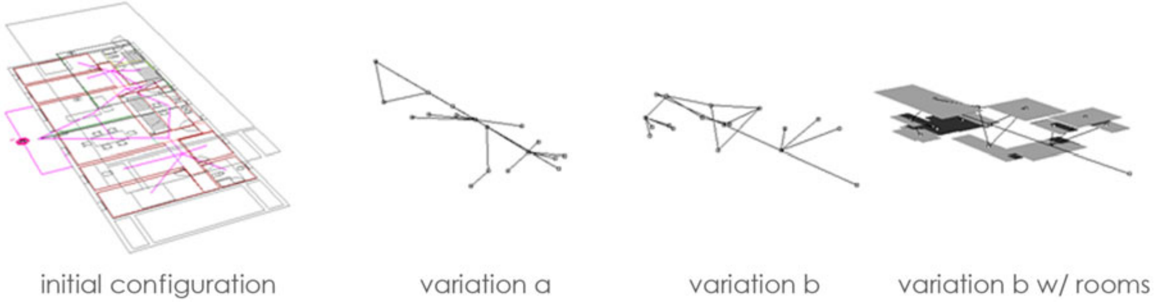

Fig. 6. Generated spatial design variations.

Physics-based systems have been used to generate spatial configurations (Arvin & House, 2002) and were explored for suitability in the parametric environment. The desired distances are inputs from the original design or hybrid design, and the optimization model attempts to resolve those relationships. Figure 6 shows an original network, with two alternate generated network solutions and the mapping of the original spaces onto the new network.

5. CONCLUSION

This paper presented the GSPDS, which integrates a series of parametric logic models into a system for design exploration. The main contribution of this paper is a demonstration of workflow that allows the modularization of design logic that can be modeled parametrically for integration into a design decision support system. The system presented here is configured for the specific and significant architectural problem of residential spatial design. In the pilot study, the demonstrated workflow highlights the computational power and flexibility of coupling generative parametric design with precedent analysis for optimizing design solutions. While this study validates the conceptual framework, the resultant optimization is a single criterion proximity optimization and not necessarily an optimization of a spatial network according to multiple spatial analysis principles as per the initial goal.

However, the system demonstrates the advantages of using parametric modeling for the development of a design system, namely, the ability to modularize a design problem, achieve real-time analytical feedback, and work in a visual programming environment that provides instant feedback for design logic development. The limitations of such a system are in the capacity to compose a fitness value that integrates a series of spatial criteria in a manner that allows the assessment of the solution's spatial performance. Ongoing research is addressing this limitation.

Future research requires further analysis of the generated outcomes, especially in terms of the validity of the generated spatial program. This may be enhanced by introducing additional goals for the evaluation model that provide better control over the variables of the optimization process. This will enable the development of design solutions that have a more integrated spatial rationale. While the system was configured to limit the designer's input, it would be beneficial to allow designer input for influencing the optimization process. Finally, the spatial analytical data was able to be captured into a spatial database; however, the evaluation and optimization models were not developed to utilize this precedent knowledge. Future work will explore the determination of evaluation rules as compared to the parameters captured and controlled by a precedent database.

REFERENCES

Alfaris, A., & Merello, R. (2008). The generative multi-performance design system. *Proc. Silicon+ Skin: Biological Processes and Computation* (28th ACADIA), Minneapolis.

Almusharaf, M., & Mahjoub, E. (2010). A performance-based design approach for early tall building form development. In *CAAD|Cities|Sustainability: 5th Int. Conf. Proc. Arab Society for Computer Aided Architectural Design*, pp. 39–50. Fez, Morocco: Arab Society for Computer Aided Architectural Design.

Arvin, S.A., & House, D.H. (2002). Modeling architectural design objectives in physically based space planning. *Automation in Construction 11(2)*, 213–225.

Bafna, S. (1999). The morphology of early modernist residential plans: geometry and genotypical trends in Mies van der Rohe's designs. *Proc. Space Syntax-II Int. Symposium*, Brasilia.

Coorey, B. (2010). Scalability: parametric strategies from exoskeletons to the city. In *New Frontiers: Proc. 15th Conf. Computer Aided Architectural Design Research in Asia* (Dave, B., Li, A.I., Gu, N., & Park, H.-J., Eds.), Hong Kong, April 7–10.

Coorey, B., & Jupp, J. (2013). A schema for capturing and comparing parametric spatial data. *Open Systems: Proc. 18th Conf. Computer Aided Architectural Design Research in Asia (CAADRIA)* (Stouffs, R., Janssen, P.H.T., Roudavski, S., & Tunçer, B., Eds.), Singapore, May 15–17.

Eloy, S., & Duarte, J.P. (2011). Transformation grammar for housing rehabilitation. *Nexus Network Journal 13(1)*, 49–71.

Gero, J.S. (1994). Towards a model of exploration in computer-aided design. In *Formal Design Methods for CAD* (Gero, J.S., & Tyugu, E., Eds.), pp. 315–336. Amsterdam: North-Holland.

Gun, O. (2010). Geometric gestures. In *Elements of Parametric Design* (Woodbury, R., Ed.). London: Routledge.

Heitor, T.V., Duarte, J.P., & Rafaela, M. (2004). Combining grammars and space syntax: formulating, generating and evaluating designs. *International Journal of Architectural Computing 2(4)*, 492–515.

Hensel, M., Menges, A., & Weinstock, M. (2010). *Emergent Technologies and Design*. New York: Routledge.

Hernandez, C. (2006). Thinking parametric design: introducing parametric Gaudi. *Design Studies 27(3)*, 309–324.

Hillier, B., & Hanson, J. (1984). *The Social Logic of Space*. Cambridge: Cambridge University Press.

Janssen, P.H.T. (2005). *A design method and computational architecture for generating and evolving building designs*. PhD Thesis, Hong Kong Polytechnic University.

Kruger, C., & Cross, N. (2006). Solution driven versus problem driven design: strategies and outcomes, *Design Studies 27(5)*, 527–548.

Littlefield, D. (2008). *Space Craft: Developments in Architectural Computing*. Marylebone: Royal Institute of British Architects.

Ostwald, M.J. (2011). A justified plan graph analysis of the early houses (1975–1982) of Glenn Murcutt. *Nexus Network Journal 13(3)*, 737–762.

Park, S.M., Elnimeiri, M., Sharpe, D.C., & Krawczyk, R.J. (2005). *Tall Building Form Generation by Parametric Design Process*. Chicago: Illinois Institute of Technology.

Peters, B. (2010). The new Elephant House. In *Elements of Parametric Design* (Woodbury, R., Ed.). London: Routledge.

Piker, Daniel. (2013). Kangaroo Plugin for Grasshopper [Computer Software]. Accessed at http://www.grasshopper3d.com/group/kangaroo October 1, 2013.

Sakamoto, T., & Ferré, A. (2008). *From Control to Design: Parametric/Algorithmic Architecture*. Barcelona: Actar-D.

Schumacher, P. (Ed.). (2012). *The Autopoiesis of Architecture: A New Framework for Architecture*, Vol. 2. Chichester: Wiley.

Benjamin P. Coorey is a Lecturer in the School of Architecture at the University of Technology, Sydney. He specializes in parametric and computational design. His expertise includes parametric modeling, building information modeling, and architectural systems design. His research focuses on the integration of generative, analytical, and evaluative techniques for performative-based design.

Julie R. Jupp is an Associate Professor in the School of Built Environment at the University of Technology, Sydney. She specializes in design and construction technologies in the built environment. Her expertise covers areas related to building information modeling, parametric modeling, and knowledge and information management through life. Her research thus encompasses key areas such as technological requirements of digital modeling, analysis, and simulation, information technology and implementation issues, and governance mechanisms relative to contractual, relational, data.