Optimization of Freeform Building Shape Using Genetic Algorithm

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ABSTRACT

This paper proposes an optimization algorithm for envelope design during an early stage freeform building design. This study performs geometric modeling using a three-dimensional (3D) design tool called Rhino, which designs examples of freeform buildings with a parametric design method, i.e., a 3D design technique for freeform building design. This method proceeds by mesh generation for the freeform building base using finite element analysis (FEM; a finite design method). The design variables from the thermal load prediction model are transformed based on the geometric information. This study used a genetic algorithm (GA) to minimize the envelope thermal load of freeform buildings. The results of the optimization process, which were applied to freeform building, indicated a 23.6–52.3% discrepancy between the initial and the optimized forms. We found that the optimized form consumed 23.6–52.3% less energy than the initial buildings produced by the parametric design method, which was facilitated by tuning each parameter for energy-conserving freeform buildings.

KEYWORDS

Freeform building, Rhino, Different climates, Regression models, Design of experiment

INTRODUCTION

Freeform building aspires to realize exceptional freedom in terms of building shapes and structural formats, which are very different from conventional buildings. The complex physical shapes of freeform buildings indicate that the prediction of thermal characteristics

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using detailed building energy simulation tools may incur greater time and costs compared with more conventional buildings. Thus, there is an increasing need for a prompt and reliable energy performance prediction tool for freeform buildings, which should be applicable during the early stage of the design phase. The rapid estimation of thermal performance is critical for identifying the best or optimum design solution for an energy-efficient freeform building within a reasonable time. Significant time and effort is required to apply a conventional tool for estimating the thermal performance of freeform building and for determining the optimal design. It is inefficient to analyze all of the design alternatives and select the best solution using a dynamic building energy simulation program from the initial design phase.

Recently, studies have been performed to achieve shape optimization during an early stage of design based on the relationship among the thermal load and parameters that affect the envelope geometry of buildings. However, most of these studies have dealt with standard building designs with only limited consideration of the physical properties of freeform buildings, if any (Wang et al. 2005, Jaffal et al, 2009, Tuhus-Dubrow et al. 2010, Yi et al. 2009). In the current study, we developed a simple thermal characteristic prediction model and an optimization process that applied a genetic algorithm (GA) to freeform buildings, which can also be used for conventional buildings.

PARAMETRIC DESIGN METHOD

To perform envelope optimization for freeform buildings, we used a parametric design method based on a configurable envelope generation technique for constructing the envelope of freeform buildings. The envelope was designed using the NURBS-based three-dimensional (3D) design program, Rhino, with a Rhino plugin module, Grasshopper. The parametric design method used 3D digital technology to parameterize the elements (line, point, spline, curve, surface, and solid) that affect the configuration design. We corrected the parameter values in the basic configuration system, which were normally corrected automatically, and finally, we produced the shape very rapidly. The building design process demonstrated how changes in the shape depended on the parameters used (Borning, 1981).

REFERENCE BUILDING

The reference building used in this study was parameterized as follows: a polygonal-shaped roof plane (top polygon type), the side length of the roof plane (top length), a polygonal-shaped lower floor plane (bottom polygon type), the side length of the lower floor plane (bottom length), and the height of the building (height). To reflect planes with variable azimuths and tilted designs, which are characteristics of freeform buildings, we also selected the normal vector tilt of the roof plane and floor plane (tilt angle), the twist angle of the roof plane and floor plane (twist angle), the azimuthal angle of the building (azimuth angle). In total, eight parameters defined the configuration of the reference building (Fig. 1).

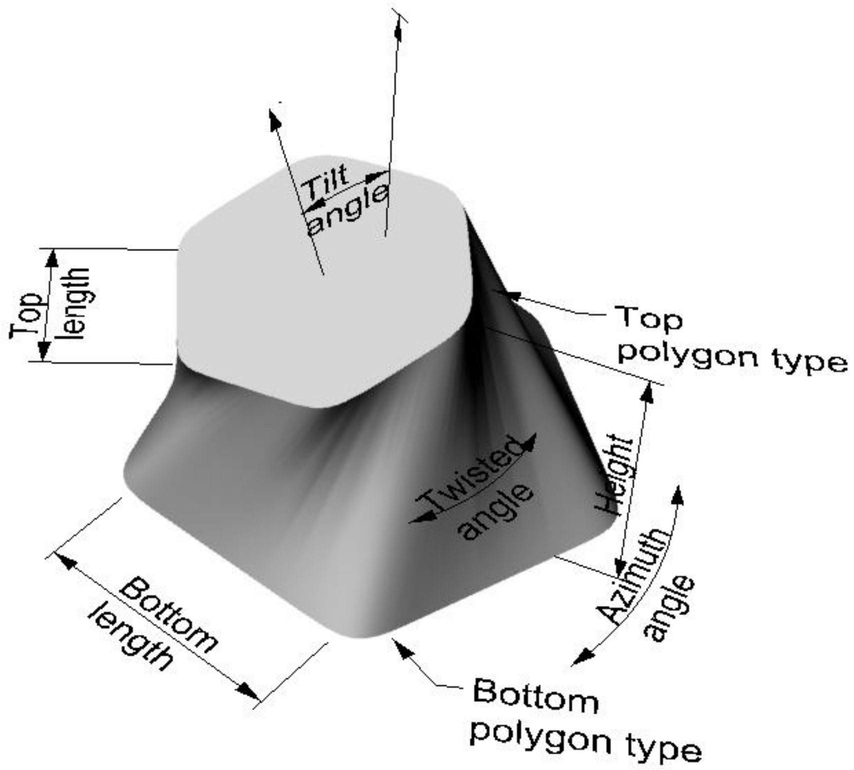


Figure 1. *Design parameters of the reference building*

Table 1. *Parameters of the reference building*

Parameter name	Parameter type	Min.	Default	Max.
Top polygon type	Dynamic	4	6	8
Top length (m)	Dynamic	4.0	6.0	8.0
Bottom polygon type	Static	-	5	-
Bottom length (m)	Static	-	10	-
Height (m)	Dynamic	8.0	10.0	12.0
Tilt angle (°)	Dynamic	0	15	30
Twist angle (°)	Dynamic	0	90	180
Azimuth angle (°)	Dynamic	0	180	360

To design the initial shape of the reference building, the parameters used to define the shape were classified as static and dynamic parameters, and the ranges and standard values of the parameters were defined. Based on the parameters defined in Table 1, the Rhino plugin module Grasshopper was used to construct the design components for the reference building and the initial shape of the reference building was designed using the base value for each parameter (Fig. 2).

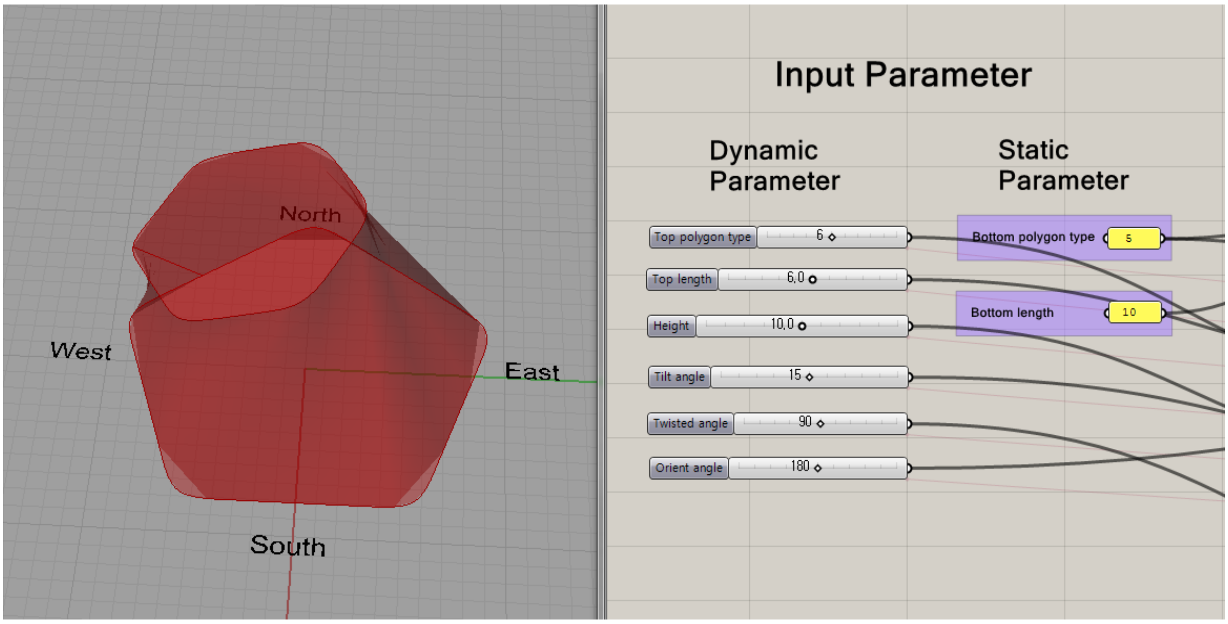


Figure 2. *Initial design of the reference building using Grasshopper*

THERMAL LOAD PREDICTION MODEL

To statistically derive polynomial models to determine the thermal performance of a freeform building, we initially selected the design variables with high effects on the building envelope load. Next, we estimated the envelope loads after changing each design variable of the freeform building, before comparing the loads with those for the conventional building defined in this research. TRNSYS 16 (Klein et al. 2007), a building energy simulation program, was used to estimate the envelope loads for the freeform and conventional buildings. The ratio of the envelope load of the freeform building to that of the conventional building (i.e., the envelope load ratio) was calculated after changing each design parameter, and a database of envelope load ratio prediction models was generated. The design of experiments (DOE) approach was used to derive a highly reliable prediction model with the minimum number of thermal performance data. A commercial equation solver program, EES (Klein et al. 2004), was used to derive linear equations based on the established database to predict the variation in the envelope load ratio for the freeform building compared with the reference building with each change in the design variables. The design variables that affected the thermal load of a building were categorized into two types: uncontrollable and controllable parameters (Bouchlaghem 2000). Tables 2 and 3 list the parameters considered in this study. AR of a certain azimuth is defined as the ratio of the envelope area facing the given azimuth to the total building envelope area. Similarly, WWR is the ratio of the window area to the envelope area with a given azimuth. In addition, the tilt of an envelope component is also a controllable design factor that affects the solar heat gain. The impact of the envelope tilt on the solar heat gain was considered using a view factor (VF) in this study. VF is a function of the tilt (θ), i.e., the angle between the ground normal and the envelope normal (Khoury et al. 2005).

Table 2. *Controllable design parameters: Geometric information*

Azimuth	N	NE	E	SE	S	SW	W	NW	H
AR	AR_1	AR_2	AR_3	AR_4	AR_5	AR_6	AR_7	AR_8	AR_9
WWR	WWR	WWR_2	WWR_3	WWR_4	WWR_5	WWR_6	WWR_7	WWR_8	WWR_9
VF	VF_1	VF_2	VF_3	VF_4	VF_5	VF_6	VF_7	VF_8	VF_9

Table 3. *Controllable design parameters: Thermal properties*

Design variable	Name	Physical property
U_{wall}	Overall thermal transmission coefficient of the walls	Heat transfer through the walls
U_{roof}	Overall thermal transmission coefficient of the roof	Heat transfer through the roof
U_{win}	Overall thermal transmission coefficient of the windows	Heat transfer through the windows
$SHGC$	Solar heat gain coefficient	Solar radiation heat transfer though the windows

OPTIMIZATION PROCESS BASED ON GENETIC ALGORITHM

There are many different optimization methods, including simple and gradient methods, but it is very difficult to apply those methods when a building is complex and many calculations need to be dealt with. However, GA is different from other optimization algorithms because it requires no skilled mathematical knowledge and is easy to apply. Therefore, we used a GA to perform envelope optimization for freeform buildings. GA aims to obtain superior genes via multiple generations, which is similar to a biological evolutionary process. Thus, a superior gene provides a more optimal shape and generates a minimal envelope thermal load. The dynamic parameters used in the initial shape definition of the reference building are defined as genetic traits and the optimization is performed using the GA, so the optimum dynamic parameters produce the minimum envelope thermal load. Figure 3 shows the GA-based envelope optimization process for freeform buildings, which was established using the 3D design program Rhino with the Rhino plugin module Grasshopper. After considering the parameters that define the configuration of a freeform building, the genetic traits define the effective range of each parameter. The first-generation parameters were selected randomly from the range of maximum and minimum values listed in Table 1. The first generation involves the process of reproduction, crossover, and mutation of genes after separating the superior genetic traits using a fitness test. The next generation reproduces and many generations are conducted until the objective function converges to a specific optimum value set.

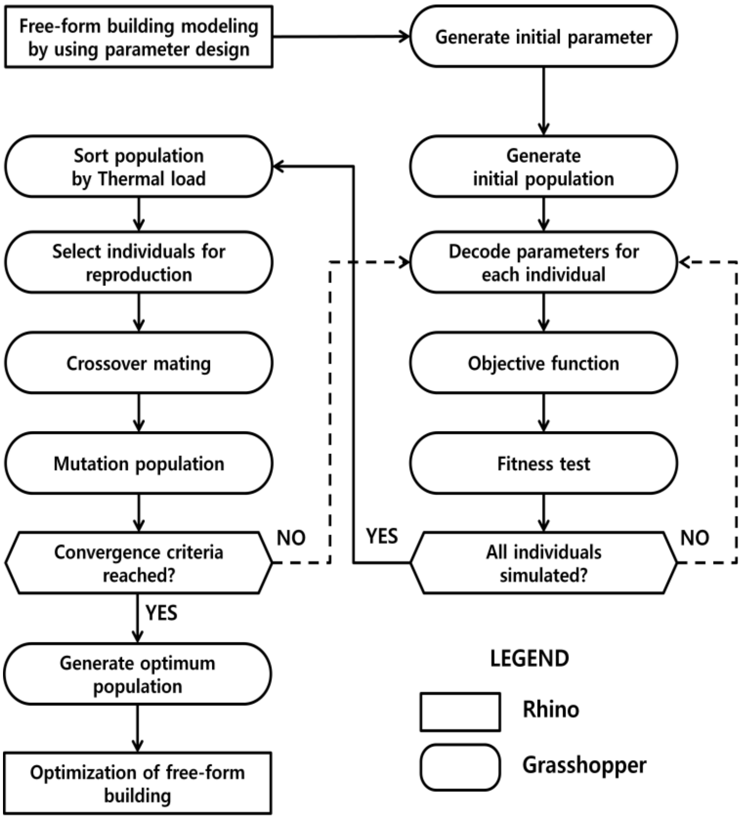


Figure 3. *Flowchart of the optimization process*

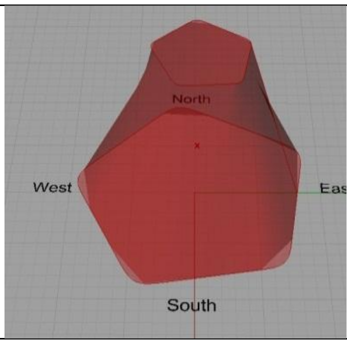
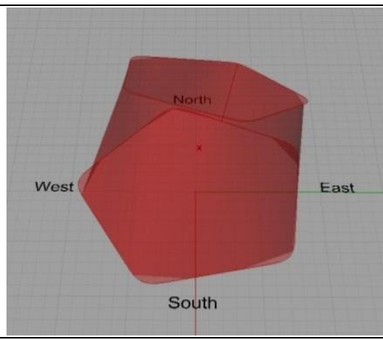
Table 4 lists the main conditions for executing the optimization process. During optimization with the GA, the population size in one generation was set to 50 and the number of species in the initial parent generation was set to 100, which was double the number in one generation. In addition, 5% of superior genes had a reproduction probability, 75% had a crossover probability, and a 5% mutation probability was assumed for one mutation in each generation. The final parameters were determined when the optimum objective function was generated. The GA was complete when the objective function converged to a constant number and the parameter values at that time were confirmed as the solution of the optimization.

Table 4. *Genetic algorithm options*

Option name	Option value
Number of individual in each generation	50
Number of individuals in the initial parent generation	100
Reproduction rate	5%

Crossover rate	75%
Mutation rate	5%
Convergence condition: generation	50

Table 5. *Optimum form and parameters*

	Shanghai	Hong Kong
Optimization form		
Initial value	1.183	1.256
Optimum value	0.904	0.599
Convergence generation	94	254
Top polygon type	5	8
Top length (m)	4.0	8.0
Height (m)	12.0	8.0
Tilt angle (°)	3	24
Twist angle (°)	70	40
Orient angle (°)	45	120

OPTIMIZATION RESULTS

After executing the GA-based configuration optimization process for Shanghai and Hong Kong in China, the initial shape (Fig. 2) was optimized to produce the final configuration. The optimum time, value, and parameters are listed in Table 5.

Table 5 shows that the Shanghai region converged at the 94^{th} generation from the initial shape object function value of 1.183 to the optimum of 0.904, whereas the Hong Kong region converged at the 254^{th} generation from the initial shape object function value of 1.256 to an optimum of 0.599. Finally, the configurations of the buildings were defined using the parameters in Table 5. The objective values were decreased by 23.6% in the Shanghai region and by 52.3% in the Hong Kong region. Thus, the loads of the envelopes of the reference buildings were decreased by 23.6% in the Shanghai region and by 52.3% in the Hong Kong region after GA-based optimization.

CONCLUSIONS

In this study, we applied envelope thermal performance optimization during the early stage of design by applying a GA to freeform buildings designed using a parametric design method. The envelope performance of freeform buildings designed using a parameter design method was evaluated using thermal load prediction model, and the thermal load change rate was predicted rapidly when the parameters were varied. Thus, the results reflected the changing design. The parameter conditions (maximum value, minimum value, etc.) were set when freeform buildings were designed and they had a very important role in the exploration of the optimal solution. If the optimization process is accomplished using the optimization algorithm suggested in this study, it may be possible to optimize the envelope thermal performance of freeform buildings to reflect the climate and characteristics of each city.

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