APPROACH TOWARDS AN IDEAL ENVELOPE SHAPE DESIGN FOR ENERGY EFFICIENCY AND LOW CARBON EMISSION

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Abstract

The building envelope shape is the most salient design characteristic and has a significant influence on energy consumption during the post-occupancy service life and carbon emission. However, during the conceptual design phase, envelope shape finding is defined without considering the energy performance during post-occupancy service life and sustainable characteristics (i.e. low carbon emission). In addition, there is no suitable method for designers to make such calculations. To bridge the post-occupancy service life in efficiency, this research developed an ideal envelope shape finding approach to facilitate the conceptual design phase. The steady-state principle has been used to predict the thermal flow and energy impact on the aspect ratio of various shapes, and compactness. Integrated dynamic simulation and particle swarm optimization method were used to identify the optimal and sub-optimal combinations of envelope shapes for energy consumption and carbon emission. The findings of this research provide a benchmark of energy consumption characteristics of envelope shape and a cut-off range for low carbon emission envelope design. This is one of the simplified design approach facelift the conventional design process to predict post-occupancy energy performances and carbon emission impact.

Keywords: *Energy, Optimization, Envelope, Design, Shape, carbon emission*

1.0 INTRODUCTION

In Malaysia, buildings account for 40% of total energy and 36% of total CO_2 emission (Ahamed et al., 2011). Increasing energy consumption and climate change has drawn the attention of many researchers and practitioners to focus on the methods, ideas, frameworks, and policies to address the challenges in achieving energy efficiency and low carbon emission (Hernandez & Kenny, 2008). The prevailing methods for predicting the energy of buildings during the design stage are rudimentary for design application. However, energy systems (i.e. HVAC) in buildings are relatively complex as building types vary greatly (Zhao & Magoulès, 2012). In such a situation, at the conceptual stage of the design process, designer usually have very little time to explore all the possibilities before making decisions. Hence, existing methods are not very helpful for designers at the early design phase.

The pros and cons of design methods that were intended to reduce post-occupancy energy consumption have been investigated thoroughly. Fabrizio et al. (2010) investigated the optimization of design for building compactness (BCHP system) that saves energy and reduces environmental impact. A model was designed to optimize multi-energy systems in buildings at the design concept stage. Mastny &Mastna (2010) investigated the design of energy systems for low-energy buildings with the support of knowledge technologies. Knudstrup, Hansen, & Brunsgaard (2009) conducted a survey on different types of approaches towards sustainable design. Housing projects have also considered shape for minimizing the use of energy for heating and cooling. Jiang & Tovey (2009) posited a number of new carbon reduction and sustainability strategies that includes technical measures for including effective energy management; adequate measures for energy conservation; renewable energy technologies; awareness raising and behavior change; and offsetting methods, but the carbon emission costs for the implementation of these strategies were not considered.

Sun & Reddy (2006) developed a new approach of building energy system simulation programs suitable for both design and optimal operation. Wan et al. (2004) analyzed the building design and energy end-use characteristics of high-rise office buildings. According to them, design for energy efficiency can be divided into the shape finding and incorporation of sustainable elements. Factors that can affect shape finding mainly include geometry, architectural layout, proportions, size and aspect ratio, envelope elements, and orientation of façade. Sustainable elements include, shape factors, wall window ratio (WWR), energy efficiency glazing proportions, and envelope shading devices. Thermal insulation and envelope characteristics play a pivotal role in the thermal stability and comfort of the indoor environment and reduction of energy consumption during the post-occupancy service life.

However, very few studies have explored the application of particle swarm optimization (PSO) in order to optimize shape and understand carbon emission from building energy consumption. Practical works highly demand multi-faceted analyses with design evaluation. PSO is a technique in computing for finding solutions for optimization. PSO has several advantages: (1) data points are distributed evenly; (2) entire experiments can be understood through analysis. Assuming unchanged project environments, PSO can be used to optimize building envelope design and achieve the lowest carbon emission in the post-occupancy service life (Kennedy & Eberhart, 1995).

This study aimed at developing an optimization approach for building envelope shape design and to identify the lowest energy consumption. The basic principles of heat transfer and the method of calculating building energy consumption were analyzed, including steady-state heat transfer theory and dynamics (Jin, 2008). The classification of factors affecting building energy consumption were then investigated and discussed. Furthermore, based on the basic concept and principles of PSO, a case study was conducted. An energy consumption software was used to calculate the energy consumption identified for various optimal shapes.

2.0 METHOD

According to the basic principles of building heat transfer, the method of calculating building energy consumption includes a simplified algorithm based on the steady-state heat transfer theory and dynamic simulations based on the unsteady heat transfer theory (Xu, 2008). The simplified algorithm of energy consumption mainly includes the temperature–frequency and degree day methods. The temperature–frequency method assumes that envelope load and fresh wind load can be transformed into a linear relationship of outdoor temperature. Using this method, boundary conditions were set based on the project settings (i.e. climatic data). Annual energy consumption can be calculated by the shape aspect ratio (length) and modeling envelope considering shape factors, geometry, WWR, and glazing proportions.

Through this, rate of building energy consumption can be identified for different temperature ranges for shapes. The degree-day method is mainly used for heating analysis of various shapes. Taking the long-term average effect of heat exchange into account, when the average outdoor temperature is at a particular value, the sum of solar radiation energy and interior heat gain offset the room heat loss because indoor load attributed to HVAC performances that are not related only to outdoor temperature (Citherlet et al., 2001).

By comparing several other simulations with dynamic simulations, a more immaculate and accurate calculation of energy consumption can be obtained. Dynamic simulations are mainly used in energy analysis, economic analysis, and optimization of building energy systems and subsystems. They usually use the methods of reaction co-efficient, state space, and cooling load co-efficient for calculation (Davis, Eisenhardt & Bingham, 2007). Figure 1 represents the flow of the design method for guiding designers for envelope shape finding and the dynamic simulation process that explained briefly in section 3.

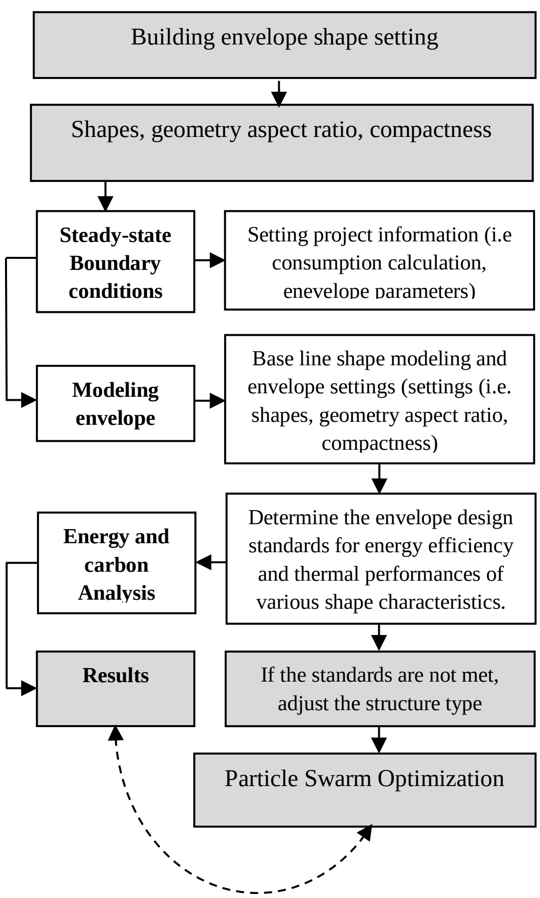

Figure 1: Dynamic simulation and optimization design for envelope shape finding

2.1 Introduction of energy simulation software

There are several approaches to simulate thermal flow and heat transfer. One of the approaches is to explicitly input flow rates by using measured climate data to the model. Because thermal flow depends on the building envelope surface, window, and glazing, practical works usually involve several factors for multi-factor analyses (Tzempelikos, 2007). It is extremely flexible graphical based software focused on assessing the thermal performance of the building.

2.2 Particle Swarm Optimization in envelope shape design

Optimization refers to searching for one or more feasible solutions that correspond to optimal values of one or more parameters. PSO was proposed by Kennedy & Eberhart (1995) to solve optimization problems. PSO is a population-based search algorithm that virtually simulates the social behavior of birds within a flock. It is designed to search for the global best among local best solutions from a randomly initialized swarm of shapes. PSO has been widely applied in solving many real world multi-objective optimizations. This method is appropriate for this research as the optimal and sub-optimal envelope shapes are to be identified from a pool of design alternatives.

Assuming that for the $\boldsymbol{i_0^{th}}$ particles in the $\boldsymbol{t_0^{th}}$ generation of envelope shapes, the position and velocity of the $\boldsymbol{i_0^{th}}$ particles can be denoted as $\boldsymbol{x_t^i}$ — and $\boldsymbol{v_t^i}$, respectively. The position and velocity of the $\boldsymbol{i_0^{th}}$ particles for the next generation $(\boldsymbol{t+1})$ can be expressed as in Clerc & Kennedy (2001); Shi & Eberhart (1998); Zhang & Xing, (2010).

$$\boldsymbol{v\_id}\,(\boldsymbol{t+1}) = \boldsymbol{w} \times \boldsymbol{v\_(id)}\,(\boldsymbol{t}) + \boldsymbol{c\_1} \times \boldsymbol{Rand} \times [\boldsymbol{P\_(id)}\,(\boldsymbol{t}) - \boldsymbol{x\_id}\,(\boldsymbol{t})] + \boldsymbol{c\_2} \times \boldsymbol{Rand} \times [\boldsymbol{G\_d}\,(\boldsymbol{t}) - \boldsymbol{x\_id}\,(\boldsymbol{t})] \qquad (\mathbf{1})$$

where $\boldsymbol{i}$= 1, 2, 3,….S; S is the swarm size; t =1, 2, 3,….T; T is the generation/iteration number;

c_1 and c_2 are the learning factors: *Rand* … are random numbers belonging to (0, 1). As a result, of the optimal combinations of the various shapes and envelope parameters, minimum energy consumptions and carbon emissions will be searched using PSO.

2.3 Modeling building shapes

A number of different shape clusters were simulated for energy consumption and to identify the optimal solution by PSO. These shape clusters include rectangular, L-shape, T-shape, H-shape, C-shape, and circular shapes as shown Figure-2. Each shape has specific characteristics that are determined by shape compactness and aspect ratio of the bounding rectangle of the building. Other parameters are shape-specific. Different values of the same shape cluster investigated for aspect ratio and shape parameters are shown in Table 1. Parameters were regularized relative to the width or depth of the bounding rectangle

Table 1. Specification for base case benchmarking

Category	Base case office building
Floor area	363 m^2
Floor	Concrete slab 100 mm (R- 6.5[a])
Walls	Brick plastered
Roof and ceiling	Structural insulated with R-2.6 insulation
Window	Single glazed aluminium frames (glazing U-value 2.7 W/m^2 : SHGC =0.65 Vertical shades over E/W/S Glazing area: North 15 m^2 (30%WWR); East 7 m^2 (15%WWR) ; South 15 m^2 (30%WWR); West 15 m^2 (30%WWR);
Ventilation	Normal :0.7 ACH
Infiltration	1 ACH @50 Pa

SHGC- Solar heat gain co-efficient ; Units for R- W/m^2
WWR- Wall window ratio

Figure 2. Selected primitive shapes and variations in clusters of R, L, T, H, U and circular shape

3.0 A CASE STUY OF VARIOUS SHAPES CLUSTERS AND RESULTS

This paper discusses a typical four-storey office building with a total construction area of 343 m^2 in Johor city, Malaysia. The window wall ratio is set 15% in cardinal directions, 30% north and south orientations. Six influencing factors of building envelope to energy performance during the post-occupancy service life were selected: floor area, floor type, wall type, window and glazing, and infiltration. Different scenarios of energy consumption and year round accumulative total consumption were calculated for various shapes by using hourly cooling load. The optimal combination of shape factors and WWR and glazing proportions as well as minimum indoor year round total load were obtained. Larger shape ranges had more influence on the test results. The order of the shape factors results is listed according to the shape ranges as follows: > L-shape > T-shape > H-shape > C-shape > Circular shape. The shape order factor influenced WWR and glazing proportions. For instance, the rectangular shape factor 1:1, 4.62, 0.267 the rate WWR and glazing proportion regulated to 30%. Therefore, shape factor partially determines envelope windows and glazing proportions.

Table 2. Identified optimal and sub optimal envelope for various shape–energy consumption combinations

Dim	Aspect ratio %	Shape Compactness	Co-efficient (m^2/m^3)	Various shape clusters energy consumption (kWh)											
				Rect.		L		T		H		U		Circular	
6	1:1.25	2.71	0.3679	**3080**	R_{11}	1630	L_1	**3315**	T_{11}	**3215**	H_{11}	**2705**	U_7	**3450**	C_{11}
7	1:1	3.06	0.3265	2925	R_{10}	**3050**	L_{10}	**3050**	T_{10}	3120	H_8	**3145**	U_{11}	**2900**	C_{10}
10	1:1.09	3.72	0.2682	**2778**	R_9	2900	L_6	**2705**	T_8	**2995**	H_7	**2850**	U_{10}	**2850**	C_9
13	1:1	4.35	0.2296	**2202**	R_4	**2650**	L_5	**2615**	T_6	**2850**	H_6	2365	U_3	2239	C_3
15	1:1	4.52	0.2208	**2220**	R_5	2150	L_3	**2420**	T_4	**2810**	H_5	**2460**	U_4	**2685**	C_7
18	1:1.13	4.49	0.2224	1846	R_2	2115	L_2	2310	T_3	**2750**	H_4	**2750**	U_9	1935	C_2
20	1:1.10	4.49	0.2224	**2267**	R_7	**2615**	L_4	2290	T_2	2650	H_2	**2500**	U_5	**2383**	C_4
23	1:1.26	4.16	0.2399	2068	R_3	**2920**	L_7	**2505**	T_5	2705	H_3	2350	U_1	**2490**	C_5
26	1:1.24	4.12	0.2423	**2428**	R_6	**3015**	L_9	**2735**	T_9	**3300**	H_{10}	2364	U_2	**2490**	C_6
29	1:1.85	4.28	0.2333	**2555**	R_8	**3015**	L_8	**2668**	T_7	**3175**	H_9	**2600**	U_6	**2750**	C_8
18.5	1:1	4.62	0.2162	1630	R_1	3060	L_{11}	1630	T_1	2050	H_1	**27050**	U_8	1750	C_1

Dim-dimension; PSO Results of R-rectangle shape; L-shape; T-shape; H-shape; U-shape ; C-circular shape

The optimal shape was selected according to the shape compactness index and also year-round accumulative total load. For year round accumulative total load, smaller shape factors were found to be better: $R_1 < R_2 < R_3 < R_4 < R_5 < R_6 < R_7 < R_8 < R_9 < R_{10} < R_{11}$ for rectangular shape; $L_1 < L_2 < L_3 < L_4 < L_5 < L_6 < L_7 < L_8 < L_9 < L_{10} < L_{11}$ for L-shape; $T_1 < T_2 < T_3 < T_4 < T_5 < T_6 < T_7 < T_8 < T_9 < T_{10} < T_{11}$ for T-shape; $H_1 < H_2 < H_3 < H_4 < H_5 < H_6 < H_7 < H_8 < H_9 < H_{10} < T_{11}$ for H-shape; $U_1 < U_2 < U_3 < U_4 < U_5 < U_6 < U_7 < U_8 < U_9 < U_{10} < U_{11}$ for U-shape; and $C_1 < C_2 < C_3 < C_4 < C_5 < C_6 < C_7 < C_8 < C_9 < C_{10} < C_{11}$ for circular shape (see table 2). We could obtain the optimal energy consumption only for larger shape compactness. Comparing shape groups for shape compactness, WWR and glazing proportions the values of the each factors such as aspect ratio, compactness and co-efficient reaches (i.e. 1:1, 4.62, 0.216) optimal values, and the values with the smallest absolute difference were considered sub optimal for energy consumptions. After comparing the optimal energy performances of shape characteristics the absolute differences, the smallest groups were R, L, T, H, U, and C. Therefore the optimal shape combinations are R_1,R_2,R_3,; L_1,L_2,L_3; T_1,T_2,T_3; H_1,H_2,H_3; U_1,U_2,U_3; and C_1,C_2,C_3.

4.0 CARBON EMISSION FOR OPTIMIZED SHAPE

Carbon dioxide emissions during the post-occupancy service life of buildings are mainly determined by energy consumption [20]. The formula for carbon emission during post-occupancy service life is

$$Q_u = U.\sum_{i-1}^{n} E_{ui} \qquad (2)$$

$Q_u -$ carbon dioxide emission
$E_{ui} -$ energy use during service life
$U -$ conversion coefficient
The formula was used based on equation 2

$$Q_u = 0.322\ X\ E_u \qquad (3)$$

Dynamic energy consumption was applied to calculate the optimal and sub-optimal envelope shape carbon emission. Table 3 shows the identified carbon emissions for optimal envelope shapes.

Table 3. Optimal shape combination carbon emission

Optimal shape	Carbon dioxide emission (T)
R_1	11.18
R_2	13.05
R_3	14
L_1	13.7
L_2,	15.9
L_3	17
T_1	12.8
T_2	13.9
T_3	16
H_1	14
H_2	16.9
H_3	18
U_1	11.96
U_2	14.8
U_3	16.08
C_1	10.58
C_2	11.97
C_3	13.05

5.0 CONCLUSION

This research is the first of its kind to investigate various shape clusters for energy performance during the post-occupancy service life and carbon emission cut-off range during the conceptual design phase. Firstly, this study reviewed the strengths and weaknesses of various energy prediction and optimization methods. Envelope parameters that influence energy performance, such as shape factors, wall window ratio, and glazing proportion, were classified, excluding physical attributes of the envelope. Furthermore, based on the basic principles of the steady-state theory, various shapes, thermal transfer, and heat flow performances were analysed using dynamic simulations. Optimal shape energy performance characteristics were determined by PSO based on year round accumulated cooling load. The identified optimized shape combinations were found to be R_1,R_2,$R_{3,}$; L_1,L_2,L_3; T_1,T_2,T_3; H_1,H_2,H_3; U_1,U_2,U_3; and C_1,C_2,C_3. Lastly, this research also quantified the carbon emission cut-off range for shapes that have been used by designers. This research provides an approach that integrates dynamic simulations and optimization method to design energy-responsive envelope shape designs. In addition, the process facelifts the conceptual design process by suggesting appropriate envelope combinations and their optimal energy performances during post-occupancy service life.

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