

# TRANSFORMATIVE MODEL OF URBAN BUILDINGS OPTIMIZING ENERGY DEMANDS, SOLAR HARVESTING POTENTIAL, AND INDOOR THERMAL COMFORT

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## ABSTRACT

Cities are requiring more energy by increasing the population. Among urban elements, buildings account for about 40% of energy demands and 30% of carbon dioxide emissions globally. To address the increasing energy demands and environmental responsibility from the population growth, existing buildings should be transformed into high energy efficient forms while satisfying human comfort. This research explores a transformative model optimizing energy balance and indoor thermal comfort based on building forms. The transformative model is built based on analyzing 903 buildings in Sumida-ward, Tokyo, Japan. The result enables city planners to predict urban building performance based on planning or designing building typologies. The model can contribute to planning an optimal urban buildings' retrofitting or redevelopment for future smart and sustainable communities.

**Keywords:** energy resilient urban building planning, transformative model, energy efficiency and security, indoor thermal comfort

## 1. INTRODUCTION

Cities are consuming more energy due to the population growth as expected that about 66% of the world population will live in urban areas by 2050 [1]. The population growth increases energy demands and environmental responsibility of urban areas [2]. Among urban elements, buildings consume about 20-40% of total energy use in developed countries [3]. Corresponded by energy uses, buildings contribute to Selection and peer-review under responsibility of the scientific committee of the 11th Int. Conf. on Applied Energy (ICAE2019).  
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more than 30% of carbon dioxide (CO<sub>2</sub>) emissions [4]. To reduce energy demands and related CO<sub>2</sub> emissions, existing buildings should be reviewed to find the ways of transforming into energy-efficient forms. The transformations should also not compromise indoor human comfort.

In the future, under the framework presented in Fig 1, an integrated urban typology response model should be established by integrating a change model of urban buildings and a change model of urban mobility network. The impacts of urban buildings' transformations are still unrevealed because of their complex and dynamic relationships with multiple performance indicators. Also, buildings contribute to energy efficiency and environmental responsibility of urban area. In this respect, this research focuses on a transformative model for urban buildings for the future smart communities.

This research investigates existing urban buildings to build a change model enabling building forms to be transformed into energy-efficient forms while achieving indoor thermal comfort. Building typology and performance of energy balance and indoor thermal comfort are analyzed by testing 903 buildings located in Kyojima, Sumida-ward, Tokyo, Japan. The transformative model is formed with considering uncertainties in performance indicators and urban building typology through a Bayesian approach. The results of this approach can be referred for planning future urban building typologies by providing how much building forms impact on the energy and comfort performance.

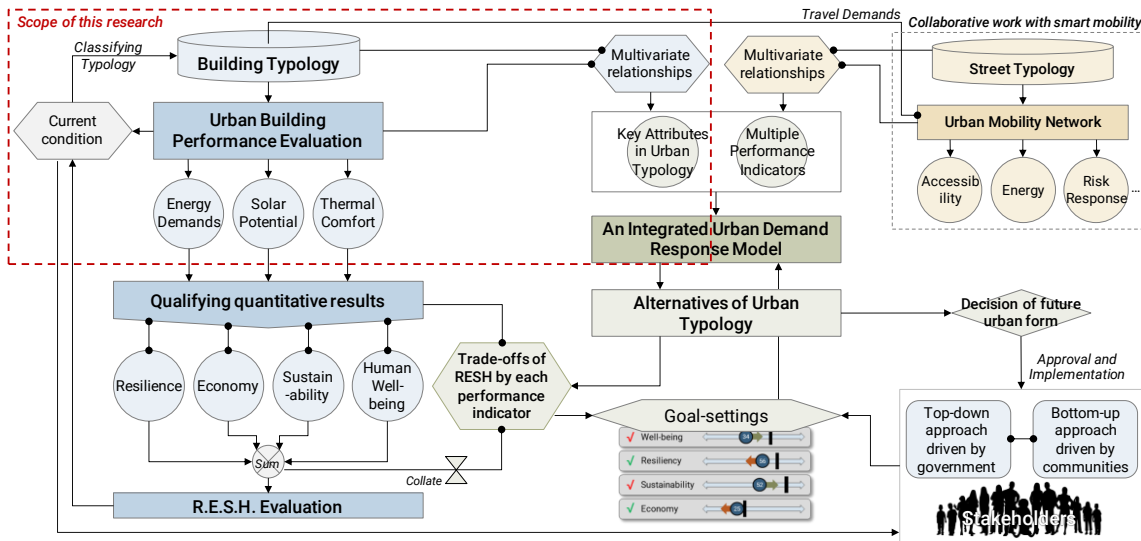


Fig 1 Conceptual framework for transforming urban buildings within urban systems design

## 2. RESEARCH BACKGROUND

Parasonis et al. (2012) has studied relationships between building geometric parameters (i.e., length, envelope area, and internal floor area) and energy demands [5]. The results provide the optimal building envelope area and compactness for reducing energy uses. Premrov et al. (2016) has examined eight building shapes to identify their impacts on energy performance [6]. Rashdi and Embi (2016) have also studied impacts of building shape on cooling loads with constraining floor area, volume, and height [7]. These findings can guide designers to determine the optimal shape for reducing cooling loads. Those research efforts have focused on recognizing relationships between building geometric parameters and energy performance or solar potential. The findings can support to establish urban transformation strategies. However, the methods have tested virtual building shapes, and their parameters have been assumed to increment proportionally. This can limit to reflecting actual building typological characteristics. Also, building typology can influence multiple urban performance including energy demands, indoor thermal comfort, and solar harvesting potential.

Rodriguez-Alvares (2016) investigated current urban fabric for five European cities, and presented energy performance (thermal and lighting loads) of urban buildings [8]. Morganti et al. (2017) tested 14 urban morphologies and identified potential solar irradiation along with three independent variables of the ratio of built area to the site area, the ratio of vertical surface area to floor area, and the sky factor on the façades [9]. The specified results enable urban planners to incorporate energy performance and solar potential at

the preliminary stages of urban planning. Those approaches have isolated the contribution of different parameters individually to understand the influence of factors clearly. However, the isolation can distort the relationships when effects are combined.

To address current challenges, this research tests actual urban building typologies in Tokyo, and considers possible significant variables as regressors collectively.

## 3. RESEARCH METHODOLOGY

This research proposes to establish a change model which enables urban buildings to be transformed with meeting energy security and efficiency and indoor thermal comfort. Fig 2 shows the research methodology integrating parametric modeling and statistical modeling. Parametric modeling evaluates three urban buildings' performance: energy demands, indoor thermal comfort, and solar harvesting potential. Based on current conditions of urban buildings, statistical approach is used to identify relationships between urban building typology and their performance. Bayesian multilevel modeling identifies significant variables and detects the impacts of the important variables on the urban performance indicators. The results of statistical approaches are used to build a change model of transforming urban building typologies, and the model can be used to recognize performance variations along with changes in urban buildings typologies.

### 3.1 Parametric modeling

Parametric modeling using Rhinoceros 3D and Grasshopper plugin is implemented [2,10]. Ladybug plugin for Grasshopper is used to run solar irradiation analysis considering building envelopes of roof and

vertical walls and nearby buildings as shading effects. Honeybee plugin for Grasshopper simulates EnergyPlus for analyzing hourly building energy demands. Based on the indoor environment provided by building energy use, indoor thermal comfort is evaluated using PMV (Predicted Mean Vote) calculator in Ladybug plugin. PMV between -0.5 and +0.5 is considered as comfortable thermal levels [11,12]. In this research, three measures: building energy demands, percentages of indoor thermal comfort, and solar irradiation of building envelopes are evaluated as urban building performance indicators.

### 3.2 Statistical modeling: Bayesian multilevel modeling

Bayesian multilevel modeling is used to consider population effects of building typology parameters as well as group effects of them [13]. After modeling by using all building typology parameters and energy demands, significant parameters minimizing generalization errors to predict energy demands are used to build the change model conducting reliable predictions of urban building performance based on important typology variables. This approach can consider uncertainties by providing confidential intervals of regression coefficients and estimating the posterior distributions of parameters [14].

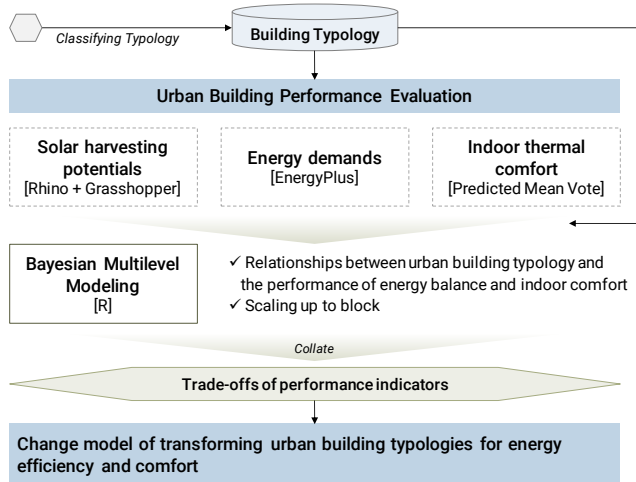


Fig 2 Research methodology

## 4. STUDY AREA AND ANALYSIS

Buildings in a superblock (Cho-cho-moku) located in Kyojima 1-chome, Sumida-ward, Tokyo, Japan is analyzed. Out of all buildings, three buildings are megastructure of concave geometry, and parametric modeling of energy simulation keeps providing errors to form thermal zones. Except the three buildings, 903 buildings out of 906 buildings are analyzed.

### 4.1 Parametric modeling results

Parametric modeling inputs are building geometry (floor area, height, etc.), building structure (wood, concrete, or steel), and building land use (residential, office, commercial, mixed, or special). All buildings' window-wall ratio is assumed to be fixed values of 40% of north, 25% of east, and 20% of south and west. This enables us to compare energy demands of building typologies under controlling building parameters rather than typology. Based on predicted energy (Fig 3 left) required to form the certain indoor environment (the setpoint of cooling is 23.9°C and the setpoint of heating is 21.1°C), indoor thermal comfort is calculated using PMV metrics. The percentage of comfort time is detected in Fig 3 (right). In that solar irradiation is influenced by surrounding context, the solar irradiations on façades in a block is averaged and projected in Fig 3 (middle).



Fig 3 Parametric modeling results

### 4.2 Relationships between typology and performance

Building typology parameters: structure, number of floors, number of rooms, number of each room type (household, office, vacancy, and other), percentages of households, offices, vacancies, or others in each building (denoted as S\_HH, S\_OFF, S\_VAC, and S\_OTH, respectively), height, stories, floor area, total floor area, total floor area of the space type, average area of the space type (total floor area of a room type divided by the number of the room type), land use, rise type, use (single or mixed use), and projected building population, are detected. Performance indicators of energy use intensity, solar irradiation potential, and indoor thermal comfort are considered. The relationships between urban building parameters and each performance indicator are discussed in the following sections.

#### 4.2.1 Building typology and energy predictions

Among building parameters, structure, height, stories, floor area, land use, S\_HH, S\_OFF, S\_VAC, S\_OTH, rise type, use (single or mixed use) can explain the energy predictions with minimized generalization error. Those

variables are used to predict energy demands by using Bayesian multilevel additive regression model.

Rise type is categorized based on building heights. Above ground level height is used to transform height to stories every 4 meters for building height less than 8 meters [15] and every 3 meters for building height equal to or greater than 8 meters [16]. Six rise types are identified: Single Story (1 story), Low rise (2 to 7), Mid Rise (8 to 20), High Rise (21 to 130), Super High Rise (130 to 200), and Mega High Rise (200 or more). Land use variables are simplified five types: office, residential, commercial, retail, and mixed. Use variable means single or mixed use of buildings.

(i) Population effects for continuous variables (Height, stories, and floor area), (ii) non-linear interaction effects for S\_HH, S\_OFF, S\_VAC, and S\_OTH, and (iii) group effects for categorical variables (structure, rise type, land use, and use) are assumed.

$$y_{ij} = \sum_{j=1}^J \alpha_j + \sum_{k=1}^K x_{ij,k} \beta_k + \sum_{q=1}^Q f_q(z_{ij,q}) + \varepsilon_{ij}$$

where  $i$  denotes the index of the measurement interval;  $j$  denotes structure, land use, rise type, or use of the measurement ( $J=4$ );  $y_{ij}$  is the explained variable;  $\alpha_j$  is the random intercept for the structure, land use, rise type, or use, and is assumed to come from a normally distribution with mean zero and unknown variance;  $x_{ij,k}$  are the regressors from height, stories, floor area ( $K=3$ );  $\beta_k$  are the fixed regression coefficient including the fixed intercept;  $z_{i,q}$  are the regressors from S\_HH, S\_OFF, S\_VAC, and S\_OTH ( $Q=4$ ) whose impact on  $y_i$  are possibly non-linear;  $f_q(\cdot)$  are the smoothing spline function as which we used the bivariate tensor spline function recently developed by Wood et al. (2013) for modeling the non-linear impact [17],  $\varepsilon_{ij}$  are the mean zero and unknown variance normally distributed disturbance.

Table 1 shows relationships between performance indicators of energy demands, solar irradiation, and indoor thermal comfort and building typologies. Based on the significance of the parameters, the model predicting energy demands can be simplified to have building parameters of floor area, structure, land use, rise type, use, and combined effect of percentages of households, of offices, of vacancies, and of others. We checked the convergence of the all coefficients in the Bayesian model by Gelman and Rubin (1992)'s methods [18].

#### 4.2.2 Urban building typology and solar irradiation

Solar irradiation considers radiation reached on each façade to represent solar harvesting potential. Since the solar irradiation is influenced by shading effects, this research scales up the solar potential in block levels to consider urban context. Block numbers are provided to the response variable of solar radiation as an additional information to define the data [19].

#### 4.2.3 Building typology and indoor thermal comfort

In Table 1, building stories have a linear positive relationship on the indoor thermal comfort. The non-linear combined effects for percentages of space types are significantly influencing the indoor thermal comfort. Also, the comfort indicator will be different in different groups of structure, land use, rise type, and use.

#### 4.3 The transformative model optimizing trade-offs

According to the results of Bayesian multilevel modeling for each performance indicator and building typology in Table 1, increasing the floor area of buildings can reduce energy demands per unit area and increase solar irradiation. Although the height of buildings is not statistically significant to energy predictions or solar

Table 1 Relationships between urban building performance indicators and building typologies

Responses		Energy predictions	Solar irradiation	Indoor thermal comfort
Effects	Predictors	Mean (95% CI) Significance*		
(i) Linear Population effect	Height	-0.31 (-0.93, 0.27)	-0.23 (-0.49, 0.02)	0.04 (-0.04, 0.12)
	Stories	-0.83 (-2.57, 1.02)	-0.37 (-1.09, 0.40)	0.77 (0.52, 1.01) *
	Floor Area	-0.04 (-0.06, -0.03) *	0.01 (0.00, 0.01) *	0.00 (0.00, 0.00)
(ii) Non-linear Combined effect	f(S_HH, S_OFF, S_VAC, S_OTH)	Non-linearity assumed *		
(iii) Linear Group effect	Structure	22.23 (6.79, 63.13) *	3.04 (0.07, 12.60) *	1.65 (0.05, 8.55) *
	Land Use	17.00 (5.65, 39.58) *	4.84 (0.47, 12.09) *	6.53 (3.09, 13.93) *
	Rise Type	38.59 (15.32, 83.94) *	4.37 (0.14, 14.82) *	6.01 (1.98, 14.11) *
	Use	17.19 (0.49, 62.94) *	13.03 (3.75, 34.57) *	4.32 (0.05, 16.44) *

irradiation, the tendency of decreasing predicted energy demands (kWh/m<sup>2</sup>) or solar irradiation can be observed when increasing buildings' height (Fig 4). On the other, increasing building heights can improve the percentages of comfortable time (Fig 4). When floor area increases, predicted energy demands per unit area decrease (Fig 5). This finding is also aligned the finding from previous research conducted by Rodriguez-Alvarez [8]. Non-linearity assumption of combinations of room type holds for all performance indicators.

Group effects (structure, land use, rise type, and use) are all significantly influencing performance indicators, and trade-offs by group effects are observed as below.

- While comfort level or solar irradiations are achieved similar levels across the structure, concrete-structured buildings outperform for reducing energy demands.
- Operations by office schedule can reduce building energy, and operations by residential schedule can secure comfort levels (Fig 6 left).

- Regardless of their land use, about 95% of buildings can achieve more than 125 kWh/m<sup>2</sup> of solar harvesting potential during June 1<sup>st</sup> to August 31<sup>st</sup>.
- Midrise type is the best for energy demand reductions, and about 97.5% of single-story buildings demand more energy than about 90% of midrise buildings. Low-rise type is better for comfort than midrise type. Solar irradiation is similarly distributed across rise types.
- Mixed used buildings are better for three performance indicators than single used buildings.

## 5. CONCLUSIONS

This research explored relationships between urban building typologies and performance of energy balance (energy demands and solar potential) and indoor thermal comfort for 903 buildings in Kyojima, Tokyo, Japan. While increasing building heights for energy use intensity and indoor thermal comfort, the average heights in a block should be moderate for including the considerations of solar irradiation. It can indicate the imbalance of energy self-sufficient rate of individual

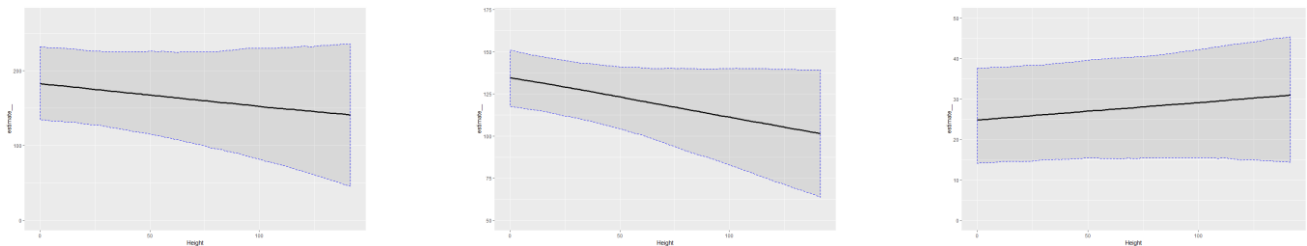


Fig 4 Population effects of height: X-coordinate all represents building height and Y-coordinate represents predicted energy demands (left), solar irradiation (middle), and indoor thermal comfort (right)

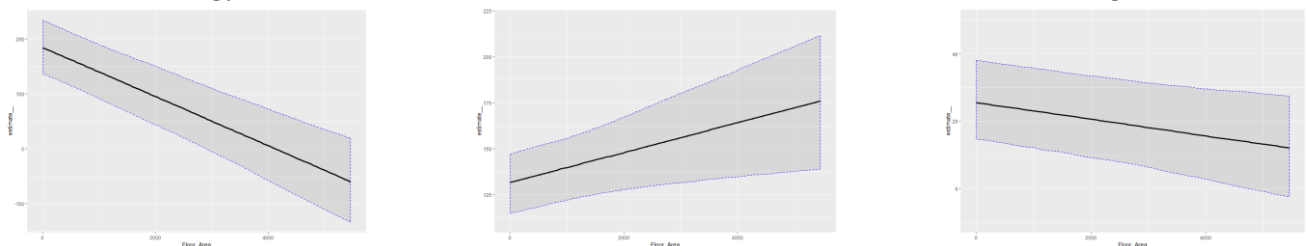


Fig 5 Population effects of floor area: X-coordinate all represents building floor area and Y-coordinate represents predicted energy demands (left), solar irradiation (middle), and indoor thermal comfort (right)

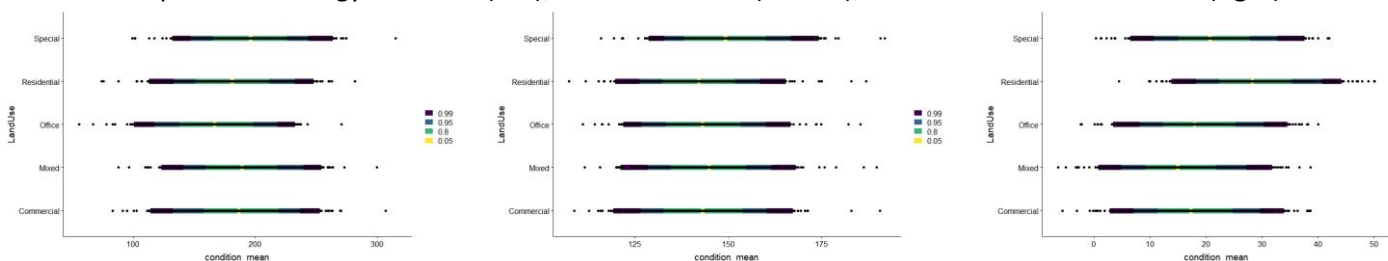


Fig 6 Group effects of land use type: X-coordinate represents predicted energy demands (left), solar irradiation (middle), and indoor thermal comfort (right), and Y-coordinate represents land use; special, residential, office, mixed, commercial (from the top to the bottom)

buildings. In this respect, sharing energy generations can be discussed in a block level.

The results provide a transformative model to recognize changes in urban performance along with changes in urban building parameters. This will provide city planners or designers with potential impacts of retrofitting or redeveloping urban buildings. Also, this information can be referred to establishing new category of urban buildings to manage performance-based planning of communities and urban buildings.

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