Modelling of Non-Residential Building Stocks Based on End-Use Consumptions and Bayesian Calibration: A Case Study of South Korea

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Abstract

This paper introduces the development of reference building energy models to represent non-residential building stocks in South Korea. Eight representative stock models were developed: retail, restaurant, accommodation, hospital, non-public office, public office, and education (K-12 and university). In all models, historical revisions of the relevant codes/regulations are reflected in terms of building vintage. Each model was calibrated using a Bayesian technique and compared with end uses (heating, cooling, lighting, service water, electric load, etc.) derived based on national energy consumption statistics. It was shown that percentage differences between the stock models and national statistics in cooling, heating, and total energy consumption were roughly -4.2 – 2.3 %, -6 – 1.8 %, and -2.2– 0.8 % respectively.

The lessons learned from the modeling processes are that not only sensitivity analysis (at the post processing), but also well-prepared national statistics are important, as it helps the modeler infer uncertain inputs at an initial stage, such as equipment or lighting power density. It can alleviate a burden of sensitivity analysis and calibration efforts.

Introduction

Building energy consumption is a major source of the nation's greenhouse gas emissions. In order to analyze the reduction potential in the building sector, representative Building Stock Energy Models (BSEMs) are needed to plan future energy policies for building stocks.

This study aims to develop eight representative BSEMs of non-residential buildings in South Korea: retail, restaurant, accommodation, hospital, non-public office, public office, and education facilities (K-12 and universities). The BSEMs are validated by comparing the stock consumption predictions of the model with national statistics. The national statistics are based on the Total Energy Consumption (TEC), and are subdivided into energy end-use consumptions.

When only the TEC of stocks is needed to be predicted, a black box modeling such as a regression model may be appropriate. The regression model are developed by macro variables such as national GDP, annual energy consumption of the stocks by energy source, weather data (cooling Degree Days and heating Degree Days), building statistics per stock (e.g., total floor area, vintage). This

approach, however, is limited to examine changes in “total amount” (e.g. national greenhouse gas emissions) because it has a limit to provide energy consumptions per each end-use (Kavgic et al., 2010).

The BSEMs can be modeled in detail if the statistics about the end-use consumptions per stock are known (heating, cooling, lighting, service hot water, plug-load, etc.). For these models, all variables related to end-uses (such as average thermal transmittance, density of internal heat gains, lighting or equipment power density, heating and cooling system efficiency) are appropriately lumped and reflected in the model. Many variables of the BSEMs are uncertain, however, some variables can be calibrated or reversely calculated if energy end-use consumption statistics per stock are available. Next, for model validation the model outputs of end-use energy consumptions were compared to national energy consumption dataset. The calibration effort fine-tunes the model output accordingly.

Finally, the developed BSEMs can be used as a supplementary material for the development of future codes and standards (Ballarini et al., 2014; Lee et al., 2015; DOE, 2016), and as a tool when predicting greenhouse gas reduction scenarios by innovative energy conservation technologies (Tommerup and Svendsen 2006; Kurnitskia et al., 2007; Olofsson and Mahlia, 2012).

Figure 1 shows an overview of the development process of this study. First, the energy end-use intensity is calculated by matching the national energy consumption survey and building registry statistics in 2015 for each sector by building activity. The commercial and public sectors are modeled by each activity types, hence eight BSEMs are designed. The standard operation conditions and annual insulation standards over the past years are reflected in each BSEM. Finally, energy end-use intensity of eight BSEMs are compared for calibration and validation.

It is expected that the BSEMs be used as an analysis tool for government investment strategy on retrofit or remodelling for old buildings in terms of end-use savings (heating, cooling, lighting, service water, electric load, etc.). This paper, however, only describes the modeling process and lessons learned from are discussed.

Figure 1: Development overview of building stock energy models.

Types of stock models

The BSEM is an analytical model that represents building group's average conditions. The conditions include the building's thermal physical properties, operational conditions and occupant's activity, and climate region of a building stock. Such "averaging" demands estimation techniques. Estimation techniques may vary depending on aims, expertise, resolution, and availability of statistical data (Kavgic et al., 2010; Corgnati et al., 2013; Ballarini et al., 2014).

Various stock modeling approaches exist. First, the process is classified into twofold: top-down and bottom-up approaches. The top-down approach mainly focuses on the interaction between the energy sector and the economy at large. It can model the relationships between different economic variables and energy demand (Kavgic et al., 2010).

The bottom-up approach is built from data on a hierarchy of disaggregated components that are combined according to their individual impact on energy usage. They can be useful for estimating how various individual

energy conservation measures impact CO_2 emission reduction (Kavgic et al., 2010).

The bottom-up approach are further classified into threefold; (1) building physics models, (2) statistical models, and (3) hybrid models. There are pros and cons to each approach and the modeling methods; the details of these are explained by Kavgic et al. (2010).

It is important to choose such modeling approaches considering the amount of datasets available and the model's capability. In this study, the building-physics based modeling approach was chosen because the BSEMs to be modeled are needed to calculate remodeling benefits such as insulation enhancement and system efficiency improvement.

The next step is to determine a model representativeness of the building physics model. According to Corgnati et al. (2013) and Ballarini et al. (2014), the model representativeness can be distinguished as *Example Building*, *Exemplary Building*, and *Virtual Building* (Table 1).

Example Building and *Exemplary Building* are specific buildings that are selected from actual building stock by expert judgement. As noted in Table 1, these methods are chosen when reliable statistical data are not available. These methods are appropriate only when national statistical data are limited. These methods are often criticized for their subjectivity and narrow generalization caused by an immature or incomplete statistical dataset.

Table 1: Types of bottom-up physical models (Corgnati et al., 2013; Ballarini et al., 2014).

Type	Based on	Information required ^a	Remarks
<i>Example building</i>	Expert judgement	Small	An actual building selected by expert judgement. When reliable statistical data are not available, this method is chosen.
<i>Exemplary building</i>	Expert judgement and basic statistics	Moderate	An actual building selected from the building stock considering its average characteristics. For this method, a well-constructed national building registry is required.
<i>Virtual building</i>	Expert judgement, basic statistics, and building component database	Large	A synthetic building with statistically “average” characteristics. For this method, a detailed national database for building components (e.g., registry of envelope, lighting, materials) is required.

a. The authors added this column considering the time and effort

On the other hand, *Virtual Building* is a synthetic building that is modeled by combining and averaging the statistics of the materials, systems, and building forms. It is only possible when a detailed database for building components (a registry of building envelopes, lighting, materials, etc.) is constructed in a nation-wide scale.

The *Virtual Building* can calculate the energy consumption of building stock of interest (Corgnati et al., 2013). If the validation dataset (e.g. stock’s energy consumption) is available, the model can be calibrated and validated properly. For this reason, it is more rational than *Example Building* or *Exemplary Building*. In other words, one may avoid the criticism of subjectivity. However, its weakness is the fact that it is a composite of virtual elements. It can be said that the better prepared the national stock statistics are, the more rational the model and the results. In this study, the *Virtual Building* approach was chosen.

Data gathering and matching database

Currently, the statistics of energy consumption are managed by Ministry of Trade, Industry and Energy (MOTIE), while statistics of building gross floor area are maintained by Ministry of Land, Infrastructure and Transport (MOLIT) in South Korea. Therefore, a mapping between these two datasets was needed to derive energy end-use intensity for each building type.

MOTIE publishes national energy consumption statistics every three years (KEEI, 2015). In these statistics, the total end-use energy consumption (heating, cooling, service hot water, lighting, plug-load, and building auxiliary) is surveyed for commercial and public sectors except for residential sector. The survey is conducted according to *Standard Industry Classification* rather than *building use type* defined by building registry (Kim et al., 2017).

MOLIT provides annual statistical data on the status of building gross floor area by building use type (EAIS, 2016). The building use types into 29 categories (sales building, office buildings, educational building, etc.) rather than by Standard Industry Classification.

As the categorization criteria of two ministries are different, the matching works for two different statistical data set were carefully conducted. For example, the 29 categories of gross floor area are merged or separated into eight stock type (Table 2) (which based on Standard Industry Classification). Next, when a total amount of energy end-uses of each stock (based on MOTIE, 2015)

Table 2: National end-use intensity (kWh/m²) derived from EAIS (2016) and KEEI (2015) statistics

Sector	Stock type	Total	Heating	Cooling	Lighting	SHW	Plug-load	The rest ^{a)}	Gross floor area (one million m ²)
Commercial	Private office	380.5	118.5	93.6	51.0	12.2	72.7	56.1	174.0
	Retail	358.7	142.0	107.7	39.4	10.0	30.6	40.6	136.5
	Restaurant	591.5	140.8	140.3	87.8	29.6	218.6	198.3	76.7
	Accommodation	337.6	186.3	73.9	37.6	25.7	31.9	29.5	45.8
Public	Hospital	263.8	94.6	68.9	19.5	17.1	61.9	40.2	44.1
	Public office	220.5	75.5	61.0	21.2	7.7	51.8	11.9	28.8
	K-12	164.6	97.0	18.9	15.2	6.7	20.7	20.6	82.9
	University	150.4	51.7	40.2	18.3	6.2	25	19.9	34.8

a) The rest includes building auxiliary devices (e.g. supply and drain pumps), cooking, etc.

is divided by the gross floor area of each stock (based on EAIS, 2015), then energy use intensity for end-uses can be obtained for each BESM respectively. In this study, the BESM were developed and calibrated based on such end-use intensities (Figure 1). The details of data preparation on end-use intensity can be found in Kim et al. (2017).

Model development

Table 1 shows eight BESMs developed. These models represent the commercial and public building sectors: retail, accommodation, restaurant, private office, public office, hospital, K-12, and university.

Table 3: Eight types of building stock energy models developed

Sector	Stock activity
Commercial	Retail, accommodations, restaurant, private office
Public	Public office, hospital, university, K-12

In this study, simplified zoning was applied due to limitations of zone-level statistics. The developed stock models may reflect the representative operational schedule of occupancy, lighting, equipment, and HVAC.

As mentioned in the Introduction, the stock modeling method are determined depending on the available information. Considering model requirements (Table 4). In this study, EnergyPlus 8.1 (Crawley et al., 2001) was chosen, which is a representative whole-building simulation tool. This tool has merit to analysis for Energy Conservation Measures (ECMs) analysis in detail.

Table 4: Building stock energy model requirements

Model should reflect	Input (averaged)	Output
Level of envelope thermal resistance and airtightness	U-value, SHGC, and ACH, referring codes and standards revisions	Heating and cooling
Amount of service hot water, level of system efficiency	Service hot water consumption rate (L/m ² /day)	SHW
Level of lighting system efficiency and operational hours	LPD (W/m ²) and operational hours	Lighting
Level of Electric power density and operational hours	Equipment power density (W/m ²) and operational hours	Plug-load

One difficulty of developing BSEMs is the preparation of averaged or representative stock input values, such as the average heat source of the stock, type of air conditioning system, efficiency of the system, appropriate amount of hot water supply, appropriate Lighting Power Density (LPD), and appropriate plug-load. All inputs are not the values of individual buildings, but “averaged” (or abstract) values for a group of buildings.

Likewise, the shapes (zoning) of individual buildings also be averaged into representative one.

Even though the uncertain input values were well calibrated once, but the calibration have to be done again 7if the shape (or zoning) of the BSEM are changed. It shows low explanatory power (or generalization) of the model. One method to avoid is calibrate the model after an agreement on the shape is made, but this issue is not discussed here because it is beyond the scope of this study.

Uncertain input variables

In general, many variables are uncertain when a BSEM is modeled. Major uncertain variables include the infiltration and ventilation rates, the thermal properties of building envelopes, and occupant-related variables (operation of equipment and lighting). Fortunately, some variables can be inversely determined by a simple calculation. Furthermore, the appropriate level for insulation can be determined referring the revision history of insulation standards over the years.

The uncertain variables can be classified into three fold: physical, operational, and morphological. Physical variables include efficiency and envelope properties.

Some physical variables were referred to Korean national codes and/or standards or similar ones. However, some physical variables (Table 5) have to be estimated because they simply describe the stock’s macro behavior using the notion of “overall” or “averaged.” Even worse, no common reference data exists.

Table 5: Uncertainty types of input variables of BESMs

Type	Inputs	Remarks
Physical	Averaged inputs: cooling/heating system overall efficiency, setpoint temperature, ACH, and SHGC.	The variables including the notion of “overall” or “averaged” are uncertain due to abstraction of the physical phenomena
	Envelope thermal properties (U-value, etc.)	Logically defensible by referring to national codes and standards
Operational	Occupant density	Fundamentally uncertain
	Operational hours of LPD and equipment	Logically defensible by referring to similar countries’ reports and surveys (Deru et al., 2011)
	LPD, EPD, SHW consumption rate	Logically defensible by inverse calculation based on statistics of end uses and gross area
Morphological	Averaged building form, height, WWR, and zoning	Logically defensible using “mean shape” analysis (Kim et al., 2016) or expert judgement

Some operational variables were inversely determined by simple calculation by referring the end-use statistics. For example, the energy end-use intensity (Lighting Power

Density [LPD], Equipment Power Density [EPD]) in kWh/m² of each model were inversely calculated based on the dataset from national statistics.

Morphological variables include the building shape, window-wall-ratio, zoning, etc. In this paper, all models developed are cube-like shape and have averaged window-wall-ratio. However, it cannot be said that such morphological variables are represent the stock modeled.

Morphological uncertainty is not easy to quantify. For example, what is the average shape of a building stock? The answer is not easy. Statistical shape analysis may provide a logical alternative (Kim et al., 2016), but the relevant data are limited. This topic is beyond the scope of this study and not discussed in detail.

Parameter screening

Uncertain variables still remain even after the aforementioned work. In this case, model calibration should be performed after first selecting variables with high influence. For this purpose, the Morris method was used, which is often used to select variables with high influence (Saltelli et al., 2004).

Figure 2 shows the results of sensitivity analysis by the Morris method with regard to the EnergyPlus model. As mentioned above, the purpose of sensitivity analysis is to screen some parameters that have significant effects. In this study, the top seven parameters (within top 33%) among the twelve variables were regarded as the parameters with high influence.

Regarding the heating energy, (1) overall heating system efficiency, (2) heating setpoint temperature, and (3) infiltration/ventilation rate (ACH) were found to have relatively high sensitivity in all the eight models. For the cooling energy, (4) overall cooling system efficiency, (5) cooling setpoint temperature, (6) fenestration SHGC, and (7) occupant density were found to have high sensitivity for all building types.

Finally, seven parameters that are sensitive to heating and cooling energy consumption for all building types were selected: (1) overall cooling system efficiency, (2) cooling setpoint temperature, (3) overall heating system efficiency, (4) heating setpoint temperature, (5) infiltration rate (ACH), (6) occupant density, and (7) fenestration SHGC. Then, Bayesian calibration was performed for the cooling and heating energy consumption.

(a) Heating energy

(b) Cooling energy

Figure 2. An example of Morris analysis for private offices.

Calibration results

In this study, Bayesian calibration was used. The Bayesian calibration sets the uncertainties of input variables by probability distribution and finds the posterior probability distribution that minimizes errors. For sampling, an adaptive metropolis algorithm (Haario et al., 2001), an MCMC algorithm, was used in this study (Equation 1).

$$Y_{n+1} \sim N(X_n, \lambda \Sigma_n) \quad (1)$$

where,

Y_{n+1} : proposal distribution used at next period (n+1)

N : multivariate Gaussian distribution

X_n : posterior samples

λ : scaling factor (= 2.38 / parameter dimensions)

Σ_n : covariance matrix of subsamples

n (subscript): Current posterior sampling period

This algorithm is a variation of the random walk metropolis algorithm and improves convergence by updating the covariance matrix (Σ_n) of the subsamples generated at regular update intervals in the whole sampling process and updating it ($\lambda \Sigma_n$). In this study, 50,000 MCMC samples (burn-in samples: 25,000, posterior samples: 25,000, regular update intervals: 5,000) were generated, and the posterior was derived by the Gaussian kernel density estimation with the MCMC samples. Burn-in refers to discarding an initial portion of a Markov chain sample so that the effect of initial values on the posterior inference is minimized.

As shown in Table 6, the errors in the cooling and heating consumption before calibration are large. The values in italics indicate that the ratio of the actual values to prediction exceeds ± 0.10 from the criterion of 1.0.

In particular, the output ratios of the before models for Private office, Public office, and K-12 are around 0.45-0.69, indicating that initial predicted values are significantly higher than the national statistics (Table 2). The main causes seem to be underestimation of the average heating and cooling system efficiencies, heating and cooling setpoint temperatures, and low infiltration (ventilation included) rates. For example, CL SOEs are increased more than 20% and HT SOEs are increased more than 10% compared to others. The range of SPTs are more wider and ACHs decreases.

In contrast, the ratios of Restaurant and University are approximately 1.2-1.3, indicating that initial predicted values are relatively lower than the national statistics. The

main reasons are the overestimated CL and HT SOEs, the loose HT and CL SPT ranges, and low ACHs. Hence, most of the parameters were adjusted to increase predicted energy uses. Table 7 shows the calibration results (mean and standard deviation). The results after calibration (Table 6) show that the ratio differences decreased to approximately less than 0.1. Detailed descriptions about prior and posterior distributions for Bayesian calibration are omitted due to the lack of space in this paper.

Table 6: Comparison of model output ratio of actual value (Table 2) to prediction.

Stock type	Calibration	Cooling	Heating	Total
Private office ^{a)}	Before	0.40	0.58	0.45
	After	0.99	1.01	1.00
Retail	Before	1.09	1.11	1.08
	After	1.04	1.01	1.02
Restaurant ^{b)}	Before	1.19	1.26	1.29
	After	1.02	1.06	1.01
Accommodation	Before	1.06	0.90	1.01
	After	1.01	1.01	1.00
Hospital	Before	1.13	1.05	1.02
	After	1.00	1.02	1.01
Public office ^{a)}	Before	0.80	0.65	0.69
	After	0.98	1.00	1.00
K-12 ^{a)}	Before	0.97	0.48	0.54
	After	0.99	0.98	0.99
University ^{b)}	Before	1.21	1.71	1.26
	After	1.03	1.03	1.02

a) The predictions of the initial model are too large than the actual values.

b) The predictions of the initial model are too small than the actual values.

Limitations and Conclusion

One of the considerations in our study is whether the stock model input variables, how can estimate aggregated states of building stock's properties. Hence, at first, national energy consumption survey dataset was reprocessed into end-energy uses (heating, service hot water, cooling, lighting, plug-load, and the rest). Next, the representative operation hours of each end use were determined based on the literature and expert judgement. Finally, the model inputs, comprising the aggregated state (e.g., densities of lighting and plug-load power) were derived. Such approach reduces a burden for handling uncertain variables at an initial stage. In other words, a well-prepared national statistical dataset is important for alleviating uncertain stock model inputs. The remaining uncertain variables were determined by sensitivity analysis and Bayesian calibration. It is the main difference between our study and others.

It was shown that the overall percentage differences of the total energy-use intensity of the corrected models were approximately -2.2–0.8%. The percentage differences of the cooling and heating energy were -4.2–2.3% and -6.0–1.8%, respectively.

One of the limitation of the study is that it is difficult to judge the estimated inputs are correct or not. Because these are abstract (not physical) values, i.e. the values are “averaged” in accordance with the model structure. For these abstract values to be meaningful, a further study on giving meanings to them is required, but such study has not been conducted yet as far as the authors know. Lastly, a further study is required to check whether our approach is properly applied to new dataset (the next publication of the energy consumption survey) or not.

Table 7: Bayesian calibration results (mean and standard deviation) of uncertain inputs

Stock type	Calibration	CL SOE	CL SPT	HT SOE	HT SPT	ACH	Occ D	SHGC
Private office	Before	2	24	0.77	21	0.99	0.64	0.72
	After	2.95 (0.05)	27.5 (0.445)	0.89 (0.005)	19.26 (0.305)	0.52 (0.013)	0.55 (0.024)	0.57 (0.013)
Retail	Before	2	24	0.77	19	0.69	0.92	0.72
	After	2.06 (0.044)	24.74 (0.26)	0.88 (0.005)	19.72 (0.221)	0.67 (0.021)	0.92 (0.023)	0.63 (0.012)
Restaurant	Before	2	24	0.77	19	2.36	0.83	0.72
	After	2.14 (0.044)	24.37 (0.235)	0.73 (0.005)	20.21 (0.209)	2.29 (0.043)	0.77 (0.014)	0.62 (0.015)
Accommodation	Before	2	24	0.77	20	0.99	0.65	0.72
	After	2.15 (0.027)	25.45 (0.313)	0.79 (0.005)	20.08 (0.201)	0.88 (0.018)	0.71 (0.031)	0.64 (0.021)
Hospital	Before	2	24	0.77	20	0.35	0.35	0.72
	After	2.18 (0.026)	26.25 (0.31)	0.79 (0.005)	19.76 (0.196)	0.44 (0.013)	0.57 (0.023)	0.62 (0.021)
Public office	Before	2	25	0.77	19	0.85	0.38	0.72
	After	2.4 (0.015)	27.03 (0.291)	0.9 (0.005)	17.8 (0.216)	0.66 (0.022)	0.47 (0.02)	0.61 (0.013)
K-12	Before	2	24	0.77	20	0.9	0.18	0.72
	After	2.53 (0.049)	25.98 (0.572)	0.87 (0.005)	17.6 (0.498)	0.64 (0.047)	0.39 (0.042)	0.59 (0.025)
University	Before	2	24	0.77	20	0.46	0.51	0.72
	After	1.86 (0.044)	25.17 (0.241)	0.65 (0.005)	20.54 (0.242)	0.56 (0.017)	0.68 (0.023)	0.65 (0.025)

CL: cooling; HT: heating; SOE: overall system efficiency; SPT: set point temperature, ACH: air change per hour, Occ D: occupant density in person/m², SHGC: solar heat gain coefficient

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