A stochastic model of integrating occupant behaviour into energy simulation with respect to actual energy consumption in high-rise apartment buildings

Hyunju JANG & Jian KANG*

School of Architecture, University of Sheffield, Sheffield S10 2TN, United Kingdom

* Corresponding author

Abstract

Apartment buildings have evolved to be self-sufficient for occupants. Thus, energy use is individually controlled in apartment units, which can be considered as independent thermal zones within buildings. However, this has been disregarded in conventional energy modelling which is mainly applicable for reducing energy demands of buildings with standardised conditions, rather than reflecting actual consumption. This approach has been questioned due to the high levels of uncertainty formed with real buildings. In this study, a model considering occupant random behaviour consuming heating and electricity is developed to reflect variations in actual energy consumption in apartments. Moreover, the effects of various parameters of occupant behaviour in relation to the model were examined. In total 96 apartment blocks in Seoul were used as samples. Gaussian Process Classification was applied to modify occupant random behaviours corresponding to the probability of energy consumption. As a result, it has been found that occupants' general heating controls (25% deviation) are between three and eight hours, with 17 – 20 °C set temperatures. Moreover, the operating hours of electric appliances and lighting are also approximated with the probabilities. This methodology could reduce uncertainties in building simulations, and provide a broader application in buildings with similar development stages.

Keywords

Bayesian inference, Uncertainty, Gaussian Process, Occupant behaviour, Apartment building

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1. Introduction

Apartment buildings are one of the most common types of housing in Asia (Yuen, 2011). Their high capacity of accommodating a large number of residents has attracted the fast grown and growing countries, such as China, South Korea, Hong Kong and Singapore (Yuen, 2011). One of the representative countries for a great number of apartment construction, South Korea, experienced great economic growth in the 1960s, and the country became rapidly urbanised (Chung, 2007). This urbanisation also resulted in a dramatically increased urban population (Chung, 2007). Apartment buildings were introduced to accommodate this increased size of the urban population, particularly for the working class (Lim, 2011). However, the main target for apartment buildings was gradually transferred from the working class, to the "new" middle class that rapidly grew during the economic growth in the 1970s and 1980s (Lett, 2001). This transfer meant that living in apartment buildings became a representative of rising social status (Gelézeau, 2007). For this reason, the proportion of housing that were apartment buildings was much greater (Statistics Korea, 2010a). Seoul was one of the main centres in this significant transformation. In the 1970s and 1980s, 48% and 26% of national apartment construction was concentrated in Seoul, respectively (Statistics Korea, 2010a). They still comprised about 50% of housing in the city (Kim, 2010).

Improving thermal performance in existing buildings has been discussed in many countries (Ouyang et al., 2011) as carbon emissions is an international issue. Refurbishing old existing apartment buildings has been importantly investigated in Asian countries, such as (Yuen et al., 2006; Ouyang et al., 2011). In South Korea, apartment buildings built in the 1970s and 1980s have been highlighted due to their large population, as well as high energy consumption (Kim, 2010), in accordance with the intensified building thermal regulations (Kim et al., 2013). Existing literature (Kim et al., 2006; Lee, 2009; Song, 2009; Son et al., 2010; Kim et al., 2010; Roh, 2012) has focused on reducing the energy demand of apartment buildings in standardised conditions defined by the Energy Performance Index (Ministry of Land, Infrastructure and Transport, 2015a) and Building Energy Efficiency Rating System (Ministry of Land, Infrastructure and Transport, 2015b). These standards have provided deterministic conditions to identify changes in the energy demands of buildings. Thus, they have been used to verify energy efficiency in buildings, and guide buildings to improve their energy performance. However, this approach has been questioned in its relation of real situations. Many studies pointed out the limitations and uncertainties contained in the standard conditions of buildings used in existing literature (Ryan & Sanquist, 2012). One of difficulties in refurbishing existing buildings is the lack of interaction with the occupants (Gholami et al., 2015).

Apartment buildings have evolved to be self-sufficient for occupants despite the unified features of buildings (Gelézeau, 2007). The usage of heating and electricity is individually controlled in each apartment unit, which can be considered as an independent thermal zone in these buildings. Therefore, energy consumption in apartment buildings can significantly vary. Besides, some empirical data in existing studies (Kang et al., 1995; Lee et al., 2012), showed variation in actual energy consumption in apartment buildings despite the similar thermal conditions. However, energy models with standardised conditions in the existing literature are not flexible enough to take into account the possible variations in energy consumption. Furthermore, the results would contain a high amount of uncertainty due to random behaviours of energy consumption.

Existing field studies have indicated how much energy consumption can vary by occupant energy behaviour. One of the existing studies (Galvin, 2013) divided consumers living in the same apartment buildings by the heating consumption levels, due to the normality of the three distributions in the frequency density: lower than 500 kWh, 501 – 3000 kWh and higher than 3000 kWh. Except for the consumption of space heating, electricity consumption could also vary from 50 to 750 kWh among 100 households, and the consumption for standby was between 0 and 1300 kWh per year (Gram-Hanssen, 2013). The monitored usage of electric appliances, apart from the consumption for space heating and hot water, was differed between 35% and 40% depending on the characteristics of the consumers' behaviours (Sidler et al., 2002).

In order to take these variations caused by occupants' controls into building simulations, energy modelling in existing literature has attempted to integrate the variations with a probabilistic approach, rather than deterministic values. One of the probabilistic approaches is to use stochastic models. The concept of stochastic occupants' behaviours considers human behaviour as not deterministic, but complex and unpredictable actions which are represented by a composition of observable states (Virote & Neves-Silva, 2012). Therefore, the stochastic model of occupants' behaviours takes the probability of actions which brings about energy consumption or a change in indoor environment. Virote & Neves-Silva (2012) used the hidden Markov Chain model to integrate observable motivations of occupant behaviour taking the actions consuming energy. Nicol (2001) considered occupants' behaviours as binary – heating on or off – and applied the probit regression analysis for modelling the proportion of occupants' actions in relation to outdoor temperatures. The stochastic models refine the ranges of possible consumption behaviours with the quantified probability. Therefore, the models draw uncertain factors with the more distinctive boundaries in building simulations. However, the limitations of stochastic models can be that they do not provide consistent results that can be directly input in building simulations (Virote & Neves-Silva, 2012), even the results are within the probable ranges.

This study, therefore, aims to develop a probabilistic model of occupant random behaviour consuming heating and electricity, regarding the variation in actual energy consumption for old high-rise apartment buildings. Three objectives are designed: to identify the variation in actual energy consumption in old high-rise apartment buildings built between the 1970s and 1980s; to integrate the variation in actual consumption into energy models; and to identify the possible occupant random behaviours controlling heating and electricity corresponding to the probability of energy consumption.

2. Methods

In order to identify probabilistic occupant random behaviours controlling heating and electricity the procedure was designed in four steps. At first, actual energy consumption in apartment buildings was surveyed, and then its variation was measured. Second, energy models of the random control of heating and electricity were analysed with their uncertainty. Estimated energy consumption of the energy models was optimised to reflect the distribution of the actual usage. Third, the probability of energy consumption was predicted by Gaussian Process Classification. At the same time, the possible ranges of occupant random controls were updated. Last, the probabilistic random behaviour was evaluated.

2.1 Evaluating variation in actual energy consumption in apartment buildings constructed in the 1970s – 1980s

2.1.1 Sampling

There are many factors interrelating with energy consumption. Thus, it was important to control effects from unrelated factors in this study. Three sampling units were chosen: 1) locations; 2) physical conditions; 3) data availability. Firstly, the locations of apartment buildings were used to eliminate external effects. Sixteen apartment districts in Seoul were chosen. These districts were mainly developed for apartment constructions under an enforcement decree of the Urban Planning Act since 1976 (Son, 2004). Thus, apartment buildings in these districts were constructed in a similar time frame and near distance, which can minimise the difference in climate effects. Afterwards, these 16 districts were separated by socio-economic factors to avoid the impact of urban segregation in Seoul. Existing literature has identified that the disparities of education levels and occupations are highly correlated to the income levels of residents in Seoul (Yoon, 1998; Lee, 2008; Chung, 2015). Yoon (2011) compared the geographical disparities of various indices related to the socio-economic factors: population, fiscal self-reliance ratio, health and welfare, education, prices of housing and land, industrial structure and transportation. Five boroughs representing relatively better living conditions were chosen from a total of 25 boroughs in Seoul by comparing a standard score of the indices. Residents with high level education were densely populated in these five boroughs. The robust correlation between the high-education residents in these five boroughs and their housing types (apartment buildings) has been found (Zchang, 1994). Sixteen apartment districts are affiliated to these five boroughs. Four of the five boroughs (13 apartment districts), all with apartment buildings constructed in the mid – 1970s and 1980s, were chosen for this study. The residents in the four boroughs, especially those who live in high-rise apartment buildings, were called "new" urban middle class (Lett, 2001; Zchang, 1994). Zchang (1994) described the "old" middle class as small business owners and a higher income than the average. In contrast to the "old" middle class, Lett (2001) discovered the seven categories of occupations in the "new" urban middle class in the four boroughs: scholars, government bureaucrats, corporate salary men, business owners, professionals, religious leaders, nouveaux riches. The life styles of the "new" urban middle class are varied (Lett, 2001; Gelézeau, 2007), but people in this class can afford not to be concerned about energy consumption.

Secondly, the physical conditions of apartment buildings need to be constrained to avoid giving impact on energy consumption. Two of the most influential factors affecting energy consumption, thermal conditions of building envelopes (Kim, 2013) and heating methods (Lee et al., 2004; Moon et al., 2001) were chosen. Therefore, apartment buildings constructed in the 1970s and 1980s were divided into two groups depending on the thermal conditions of building envelopes, which were filtered by construction years. The first group, period A, was comprised of apartment buildings constructed before 1980 when a legislation of building thermal regulations was enacted. The second group, period B, contained buildings built between 1981 and 1988 before the building regulation has a professional form. Therefore, the buildings in both periods need to be refurbished to reduce high energy consumption (Kim, 2010), although buildings in period B can be expected to have relatively advanced thermal conditions compared to buildings in period A. The district heating method was considered only, which was mainly applied to many apartment buildings constructed in the four boroughs.

Lastly, energy bills were collected through the Apartment management information system (Korea Appraisal Board, 2015). The monthly consumption in 2014 was transformed from Won/m^2/year to kWh/m^2/year, according to calculation methods by the Korea District Heating Corporation (2015) and Korea Electric Power Corporation (2014). The bills were separated by heating and electricity. This study only considered energy bills consumed for individual units. Energy bills used for communal purposes were, therefore, excluded even though they were consumed in buildings. In total 96 apartment blocks (44 blocks in period A and 51 blocks in period B) were chosen in this sample study. They occupy 37.1% and 16.3% of apartment buildings built in both periods A and B in Seoul, respectively.

2.1.2 Normality tests

Central limit theorem states that frequencies in empirical populations show bell-shape curves if the number of independent random samples is large enough (Ross, 2002). The collected samples were evaluated for this normality. Firstly, Kolmogorov-Smirnov and Shapiro-Wilk tests were conducted to measure the deviations of the samples from the normal distribution with the same mean and standard deviation. If ρ-values in both tests are not significant ($\rho > 0.05$), then the normality of the samples can be accepted (Ross et al., 2014). Secondly, Q – Q plots were drawn to supplement the limitation of the previous normality tests through visual inspection (Field, 2009). Lastly, skewness and kurtosis were measured to identify how far the sample data is different from the normal distribution; ±1.96 limits were considered as normally distributed (Field, 2009). SPSS (Field, 2009) was used to conduct these tests. The results of normality tests are illustrated in Section 3.1.

2.2 Integrating occupant random behaviour reflecting actual energy consumption into energy modelling

A probabilistic approach was applied to reflect variation in the actual energy consumption in energy models. Energy models were created by the possible behaviours in controlling heating and electricity. The possible energy consumption in the energy models was compared to the variation in the actual energy consumption. The model estimation was optimised to be as similar as possible to the real consumption, which indicates the possible ranges of occupant behaviours determining the variation in the actual consumption.

2.2.1 Energy models of occupant random behaviours controlling heating and electricity

Energy modelling consisted of three parts: building form, thermal properties and energy controls. First, building form was fixed by choosing the most typical unit design (Kim & Kim, 1993; Park, 2003) and building design (fifteen-story and south-facing (Son, 2004; Lim, 2011), as shown in Figure 1. This unit design made up about 80% of apartment buildings built until the 1980s (Kim & Yoon, 2010). The apartment buildings with 15 floors make up the largest proportion, 31.7% (Ministry of Land, Infrastructure and Transport, 2004). Energy models were created with six units: two units on three floors (ground, middle and top floors). The energy consumption in the two units on the middle floor was multiplied to estimate the total amount of energy consumption from the 2nd to 14th floors by using multiplier in EnergyPlus8.0 (EnergyPlus Documentation, 2010). Each room was separately modelled as individual thermal zones to be controlled by different schedules as it occurs in real situations.

Second, thermal properties (U-values) for the two periods (before 1980, and between 1981 and 1988) were identified by reviewing the building thermal regulations and existing literature (Seo, 2012; Kim et al., 2013). The specific applications were also verified by the site survey collecting actual architectural drawings in three apartment blocks. The thermal condition in apartment units is divided into two different areas: unconditioned and conditioned areas (Figure 1). Unconditioned areas mean the bathroom and two balconies, which are directly exposed to the outside without heating facilities, whereas conditioned areas are the main living spaces, which are enclosed by the unconditioned areas to be protected from the outside, apart from the bedroom C. Therefore, thermal protection was focused on the conditioned areas. The profiles of the building envelopes are described in Table 1.

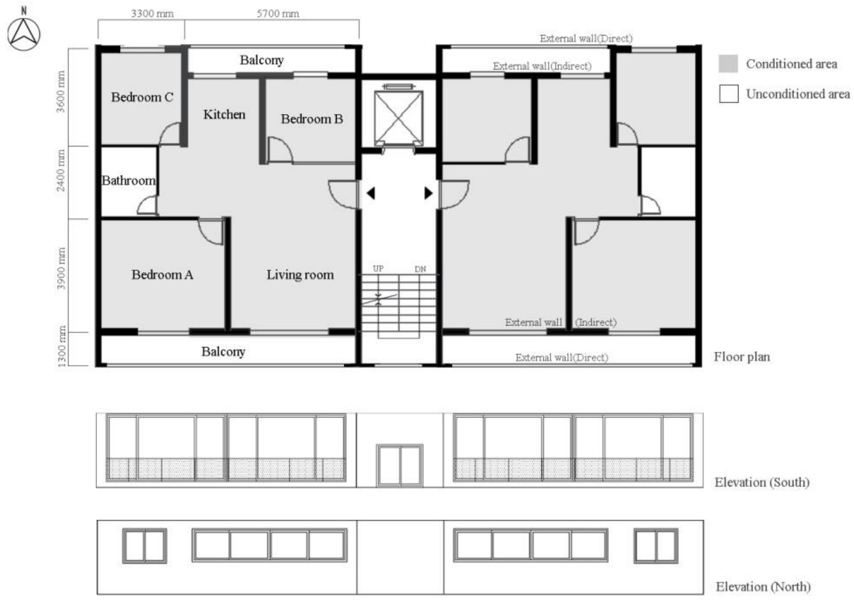


Figure 1 Description of the apartment units

Table 1 Profile of thermal properties in energy models

Location	**Exposure to the outside**	**Materials (mm) (In → out, up → down)** Period A (Before 1980)	**Materials (mm) (In → out, up → down)** Period B (1981 – 1988)	**Thickness (mm)** (Period A/ B)	**Thermal conductivity (W/m.K)**	**Density (kg/m^3)** (Period A/ B)	**Specific heat (J/kg.K)** (Period A/ B)	**U-value (W/m^2K)** Period A	**U-value (W/m^2K)** Period B
External wall	Direct	Mortar	Mortar	18	1.081	1950	921	2.08	2.08
		Cement brick	Cement brick	90	0.605	1700	1550		
		Cavity	Cavity	50	0.15(m^2K/W)	-	-		
		Cement brick	Cement brick	90	0.605	1700	1550		
		Mortar	Mortar	18	1.081	1950	921		
	Indirect	Mortar	Mortar	18	1.081	1950	921	2.08	0.50
		Cement brick	Cement brick	90	0.605	1700	1550		
		Cavity	Insulation	50	0.033	- / 50	- / 838		
		Cement brick	Cement brick	90	0.605	1700	1550		
		Mortar	Mortar	18	1.081	1950	921		
Side wall	Direct	Mortar	Mortar	18	1.081	1950	921	3.24	0.59
		Cement brick	Insulation	90 / 50	0.605	1700 / 50	1550 / 838		
		Concrete	Concrete	200	1.400	2240	879		
			Mortar	18	1.081	- / 1950	- / 921		
Roof	Direct	Mortar	Mortar	24	1.081	1950	921	0.52	0.52
		Concrete	Concrete	200	1.400	2240	879		
		Cavity	Cavity	220	0.18(m^2K/W)	-	-		
		Insulation	Insulation	50	0.033	50	838		
		Plaster board	Plaster board	10	0.209	940	1130		
Floor between ground and underground floors	Indirect	Mortar + Gravels (heating tubes)	Mortar + Gravels (heating tubes)	100	1.081 1.260	1950 1522	921 908	4.36	0.55
		Concrete	Concrete	200	1.400	2240	879		
			Insulation	50	0.033	- / 50	- / 838		
			Plaster board	10	0.209	- / 940	- / 1130		
Window	Direct	Single glazing	Single glazing	3	0.900	-	-	5.89	5.89

Third, heating and electricity controls were set differently depending on uncertainty. Heating supply in each room is controlled by supplying valves, and the controller manipulates set-point temperatures and operations. Heating controls in this study concentrated on the set-point temperatures and operating hours in each room. The possible range of heating set-point temperatures was set between 16 ºC and 22 ºC. The operating hours were gradually increased from three to nine hours per day. In terms of electricity controls, the national surveys investigating behaviours of electricity consumption (Korea Electric Power Corporation, 1990; Korea Electric Power Corporation, 2013) were used to identify the possible range of operations in households. Daily routines of using electric appliances in 500 households were collected in this survey. Lighting and four electric appliances showing variations in their operating hours with higher penetration rates (60%) were chosen: air-conditioner, electric blanket, computer and rice-cooker. Lighting operation was separated by the living room and the bedrooms. The operating hours were increased from 1 to 7 hours per day with maximum 70% fluorescent lights in operation among the 500 households (Korea Electric Power Corporation, 1990). The control of air-conditioners was separated by set-point temperatures and hours. The temperatures were increased from 23ºC to 29ºC. Overall, operating hours of cooling did not exceed more than 32%, which is relatively lower compared to other appliances. The maximum hours of using an air-conditioner was 7 hours in a day with 10% probability. Rice-cookers showed the highest operating hours, with an average of 3800 per year in consuming electricity for warming rice (Korea Electric Power Corporation, 2013). The maximum operating hours was identified to be 16, with about 40% in operation, and the minimum hours was 10, with about 60% in operation. The computer was mainly used at night. The maximum usage is distributed between 7pm and 11pm with about 30% in operation. The electric blanket was generally used between five to six hours per day, but the number of days used in a year indicated more prominent variations from 60 to 120 days. This variation was taken into account in models. In total 19 input parameters were set with the possible range of values (Table 2).

Some appliances, such as the TV, refrigerator, and Kimchi refrigerator, also indicated high electricity consumption, but their operations were much unified: always on for refrigerators and five hours on for the TV, according to the national survey (Korea Electric Power Corporation, 2013). Therefore, they were set in the energy models, but with consistent values. Two air-conditioners were equipped in the living room and the largest bedroom A. Electric blankets for supplementary heating were applied in the living room and two bedrooms. A computer and rice cooker were placed in the living room, including the kitchen. Four occupants were set in each apartment unit, which is the most representative type of household living in apartment buildings (Statistics Korea, 2010b). Electric power for appliances was taken from the average values in the national survey (Korea Electric Power Corporation, 2013): TV (130.6W), refrigerator (40.0W), kimchi refrigerator (22.6W), computer (263.3W), fluorescent light (55.0W in bed rooms, and 165W in the living room), rice-cooker (1022.9W in cooking, and 143.4 in warming). Ventilation rates were set at 0.82ACH for conditioned area and 2.00ACH for unconditioned area (Ministry of Land, Infrastructure and Transport (2015b).

Table 2 Prior distributions of uncertain parameters in building energy models

Categories	Input parameters	Prior distributions	Optimised distribution Period A	Optimised distribution Period B	Locations	Units	No.
Heating	Set-point temperatures	16 – 22	16– 20 16 – 20	15 – 21 16–21	Living room Bed room A – C	℃(winter)	1 2,3,4
	Operating hours	3 – 9	3–6 -	3 – 9 -	Living room Bed room A – C	Hour/day (winter)	5 6,7,8
Electricity	Air-conditioner (set-point temperatures)	23 – 29	-		Living room Bed room A	℃(summer)	9 10
	Air-conditioner (operating hours)	0 – 7	0 –7		Living room Bed room A	Hour/day (summer)	11 12
	Rice-cooker (operating hours)	10 – 16	7 – 16		Living room (kitchen)	Hour/day	13
	Computer (operating hours)	1 – 4	0.5 – 3.5		Living room	Hour/day	14
	Lighting (operating hours)	1 – 7	0 – 7		Living room Bed rooms	Hour/day	15,16
	Electric Blanket	60 – 120	-		Living room	Day/year (winter)	17,18,19

2.2.2 Optimisation of model estimation reflecting variation in the actual energy consumption

The energy models defined in the previous section were used to estimate the possible ranges of energy consumption. A great number of possible cases were created due to the uncertain controls of heating and electricity. 200 random samples were chosen by Latin Hyper-Cube Sampling (LHS) to conduct the Monte Carlo Method. The LHS method is more robust than other sampling methods (Macdonald, 2009), and has been widely applied to the uncertainty analysis in building simulations such as (Hyun et al., 2008; Silva & Ghisi, 2014). EnergyPlus 8.0 (Crawley et al, 2001) was used to conduct building simulations. Historical weather data for Seoul in 2014, which is provided by White Box Technologies weather data for energy calculations (White Box Technologies, 2014), was applied. Both LHS samplings and simulations were managed by jEPlus (Zchang, 2012). Heating and electricity consumption were separately accumulated. The Probability Density Function (PDF) of the estimated energy consumption was compared to the PDF of the actual energy consumption. The Coefficient of Variation of Root-Mean-Square Deviation (CV RMSE) was used to measure the discrepancy between the model estimation and the actual energy consumption.

The previous occupant random behaviour in energy models could not be specified for the residents living in the old apartment buildings. This can bring about high amounts of discrepancy, compared to the actual energy consumption. This discrepancy was optimised in order to reflect the actual energy consumption. The procedure was divided into two parts. Firstly, multivariate regression analysis was conducted to create linear models of energy consumption only with influential parameters of occupants' random controls. Above all, the linearity was examined by the coefficients of determination (R-squared) and F-ratio values (Field, 2009). Standardised Regression Coefficient (SRC) values were used to determine the influential parameters in the linear models. A stepwise method was applied to create possible linear models automatically. Secondly, the ranges and values of the uncertain parameters were revised for their regenerated random samples to have a similar mean and standard deviation of the actual energy consumption. Random sampling was conducted by uniformly distributed pseudorandom integers in MATLAB 2014a (Hunt et al., 2014). The linear models identified above were used to estimate energy consumption of the regenerated samples. The distribution of the re-estimated energy consumption was compared to the actual energy consumption. CV RMSE was used to evaluate the difference between them. The results are shown in Section 3.2.1.

2.3 Generalisation of probability of occupant random behaviours consuming heating and electricity

Based on the optimised model estimation, this section conducted stochastic processes to identify the probability of energy consumption. Stochastic processes deal with the sets of all possible random parameters (Ross, 2014), and form the generalised probability distributions to functions (Rasmussen and Williams, 2006). In particular, Gaussian Processes easily deal with the many random variables that are approximately considered normally distributed, according to the probability theory (Parzen, 1999). The processes follow Bayes theorem (Rasmussen and Williams, 2006) that modifies prior distributions through observed data to achieve target distributions (Kalbfleisch, 2012). This inference has been used to calibrate parameters of energy models in building simulations, as shown in (Heo et al., 2012). Depending on the types of outputs, either regression or classification is determined in conducting Gaussian processes; regression deals with continuous outputs that deal with real values while classification considers discrete outputs classified by labels (Neal, 1998).

This study focused on classification to predict the probability of heating and electricity in the old apartment buildings, rather than exact calibration case-by-case. The process was divided into three steps. Firstly, the optimised random samples were prepared as training data. The energy consumption was subdivided by 25% deviation. Heating consumption with 25% deviation was defined between 107 and 138 kWh/m^2/year in period A, and between 87 and 112 kWh/m^2/year in period B. The electricity consumption between 30.1 and 33.3 kWh/m^2/year decided the medium class for the both periods.

Secondly, Gaussian Process priors such as covariance functions were formed. Many covariance functions can be applicable. The details of covariance functions were studied by Neal (1997). More than that, the suitable values of hyper-parameters defining covariance functions is more problematic (Rasmussen and Williams, 2006; Neal, 1997). Prior distributions of hyper-parameters are required to be predefined, although the values are optimised during the process. In this study, the Squared Exponential (SE) covariance function, which has been the most widely used (Rasmussen and Williams, 2006), was chosen. This covariance function necessarily requires two hyper-parameters: length-scale and magnitude. The inverse of length-scales demonstrates the relevance of inputs in the process, while magnitude indicates the variances of unknown function values (Neal, 2012). Gaussian distribution was applied for the hyper-parameters in this study.

Thirdly, Gaussian Process models were structured by multinomial probit models with nested Expectation Propagation (nested EP) algorithm (Riihimaki, 2013) to take into account the classes of energy consumption with four to six parameters for heating and electricity consumption. Comparing to MCMC, nested EP algorithm also showed consistent results with small inaccuracy (Riihimaki, 2013), but much less operating time was required. The calculations were conducted by GP-Stuff (Vanhatalo et al., 2013), run by MATLAB 2014a (Hunt et al, 2014). Contour plots were used to draw the predictive probability. The results are illustrated in Section 3.2.2.

2.4 Evaluating estimated energy consumption of probabilistic models

The previous section identified the probability of energy consumption, and the previous identification of behaviours controlling heating and electricity were modified. The updated random behaviours were evaluated to whether or not the predicted energy consumption reflects the variation in the actual energy consumption with reduced uncertainty. 100 random samples were chosen with different probabilities: high probability (50 – 90%) and total probability (0 – 90%). Their estimated energy consumption is compared in Section 3.3.

3. Results

The conventional energy modelling used for high-rise apartment buildings has estimated energy consumption based on the standardised conditions, which are provided from the international or national guidelines. Therefore, the estimation could contain high levels of uncertainties when it is applied to specific types of buildings and groups of occupants. The methodology in this study was designed to reduce the uncertainties, caused by applying the standardised conditions, by identifying the probability of occupant energy behaviour from the national survey and the variation in actual energy consumption. Thus, the result of the probabilistic model can be adjusted for the specific resident group and the conditions of apartment buildings. This section presents the probabilistic model for the "new" urban middle class living in old apartment buildings constructed in the 1970s and 1980s in Seoul. The section is designed in three parts. The first part describes the analysis of variation in actual energy consumption in Section 3.1. The second part illustrates the probability of standardised conditions in Section 3.2. Specifically, the optimisation of estimated energy consumption regarding the actual energy consumption is interpreted in Section 3.2.1, and the results obtained from Gaussian Process Classification are shown in Section 3.2.2. Finally, the estimated energy consumption with the probability of standardised conditions is evaluated in Section 3.3.

3.1 Variation in actual energy consumption in apartment buildings built between the 1970s and 1980s

The results of normality tests demonstrate that the collected samples are normally distributed (Figure 2). The ρ-values in the Kolmogorov-Smirnov tests are unified with 0.200 in the heating and electricity consumption for both periods. Shapiro-Wilk tests also show the ρ-values 0.362 – 0.792, which are not significant. This means that the normality of the samples can be accepted. The Q – Q plots of the samples show slight deviations from the normal distribution at the tails. The deviations are interpreted by Kurtosis and Skewness. The largest Kurtosis is 1.30 in the electricity consumption in period A, while the greatest skewness is found in the heating consumption in period A. However, these deviations are within ±1.96 limits of Kurtosis and Skewness. Therefore, the samples can be regarded as normally distributed, which means that the number of samples is large enough to represent their population.

Figure 3 gives the overview of energy consumption in old high-rise apartment buildings constructed between the 1970s and 1980s. The average heating energy consumption in apartment buildings constructed before 1980 (Period A) is 123.2 kWh/m^2/year, while the consumption is reduced to 99.66 kWh/m^2/year in apartment buildings built between 1981 and 1988 (Period B). The comparison of the two average values reveals the significant impacts of thermal conditions of building envelopes on heating consumption. However, the electricity consumption is similar in both periods, A and B, with 31.77 kWh/m^2/year and 31.67 kWh/m^2/year, respectively.

The more interesting aspect is the variation in energy consumption in each period (Figure 3). Heating consumption is deviated 20.6 kWh/m^2/year among buildings in period A, while a greater deviation about 30.1 kWh/m^2/year is identified in period B. Furthermore, the difference between minimum and maximum values in heating consumption is 98.0 kWh/m^2/year in period A, and is enlarged to 128.5 kWh/m^2/year in period B. The relatively lower variation in period A could reveal their desperate need of heating due to the low energy-efficient building conditions. The higher variation in period B would result from the diverse preference in controlling heating by occupants. In electricity consumption, the standard deviation for both periods is about 3.5 kWh/m^2/year, and the minimum and maximum ranges are about 15 – 20 kWh/m^2/year. In general, the actual energy consumption in apartment buildings is 10 –30% deviated from average values. The difference between minimum and maximum consumption is extended up to 50 – 128%.

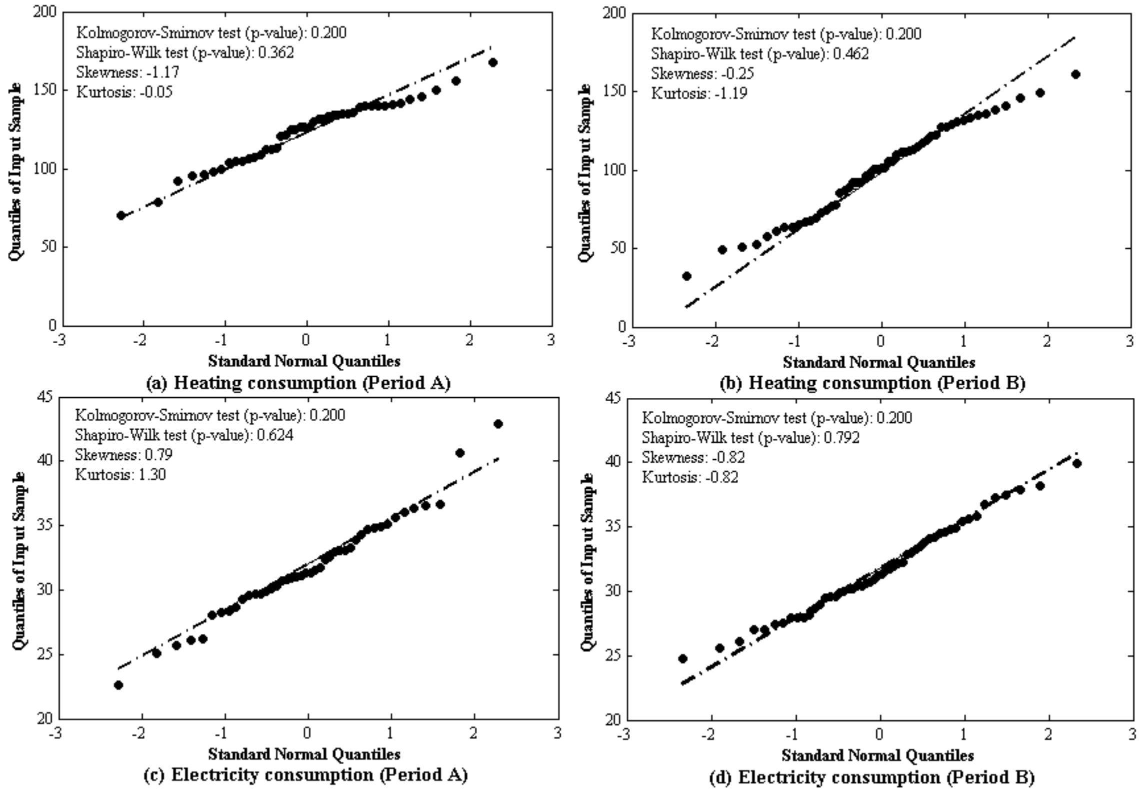


Figure 2 Results of normality tests of actual energy consumption

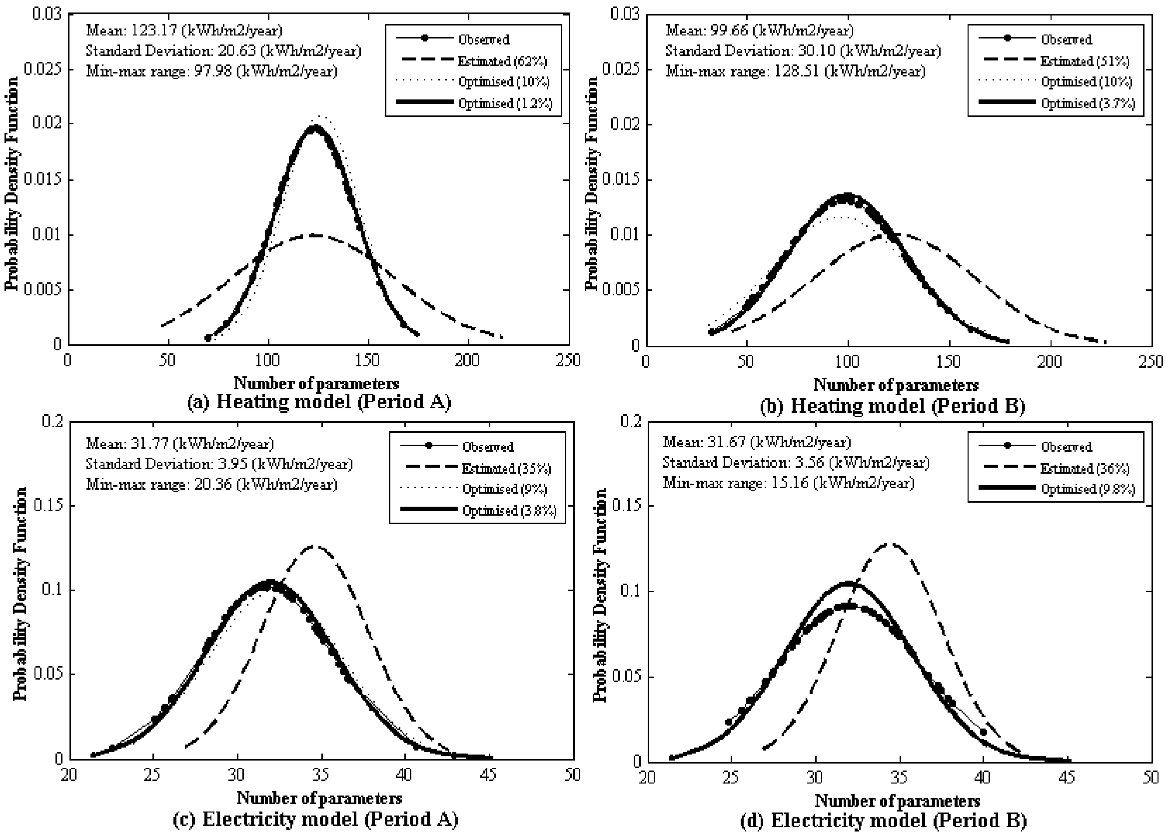


Figure 3 Optimisation of model estimations in comparison to the variation in actual energy consumption

3.2 Probability of standardised conditions regarding variation in actual energy consumption

The probabilistic approach integrating the variation into energy modelling is illustrated in this section. Firstly, energy models with the prior distributions are optimised to reflect the variation in the actual energy consumption in Section 3.2.1. Secondly, the probability of energy consumption is calculated by Gaussian Process Classification. At the same time, the possible ranges of influential parameters are modified. The results are illustrated in Section 3.2.2.

3.2.1 Optimisation of the estimated energy consumption in energy modelling

The model estimation with the prior distribution of input parameters (thick dashed lines in Figure 3) is dissimilar from the distribution of the actual energy consumption (solid lines with dots). At first, the average values of the model estimation are greater than the actual values, apart from the heating estimation for period A. The average values of heating consumption in period B is overestimated by about 23 kWh/m^2/year with the prior distribution, while a nearly 3 kWh/m^2/year reduction is required in the average value of electricity consumption. Second, the distribution of the estimated heating consumption is far greater than the one of actual consumption: 62% discrepancy in period A (Figure 3 – a) and 51% in period B (Figure 3 – b). This wider distribution of the estimated heating consumption indicates that the ranges of occupants' random controls would be wider than the actual usage, which needs to be narrowed down. On the contrary, the ranges of the parameters for electricity consumption are required to be wider to reduce the about 35% discrepancy from the variation in the actual use (Figure 3 – c and d). This opposite trend of estimation, compared to the actual use, implies that different parameters respectively affect heating and electricity, and their modification needs to be different.

Multivariate regression analysis is used to choose the most rigid linear models with less residual. In the results of the R-squared values (Figure 4 – a and b), the highest R-squared values of more than 0.7 are generally achieved by increasing the number of parameters. However, the increasing of R-squared values in heating models becomes significantly steady after the fourth model (0.84 and 0.70 for period A and B), while the sixth model (0.94 and 0.78 for period A and B) in electricity models. These models also show higher F-ratios with less numbers of input parameters: 256.2 in period A and 114.6 in period B for heating (degree of freedom: 4), and 554.4 in period A and 112.2 in period B for electricity (degree of freedom: 6) (Figure 4 – c and d). Hence, they are chosen as the most fitted models.

These linear models for heating and electricity consumption are respectively comprised of four and six parameters, as shown in Table 3. In the heating models, set-point temperature is the most significant factor, followed by operating hours. Specifically, the volume of space determines their impacts on heating consumption. Thus, set-point temperature in the living room presents the highest SRC of 0.587 and 0.526 in periods A and B. Their operating hours has the second highest SRC, which are 0.504 and

0.469 for period A and B, respectively. The third parameter is set-point temperatures in the bedroom A with SRC of 0.320 and 0.271 for both periods A and B. This is because the bedroom A is the largest bedroom. The fourth parameter is set-point temperatures in the bedroom C with SRC of 0.285 and 0.260 for both periods A and B, which is the bedroom directly exposed to the outside.

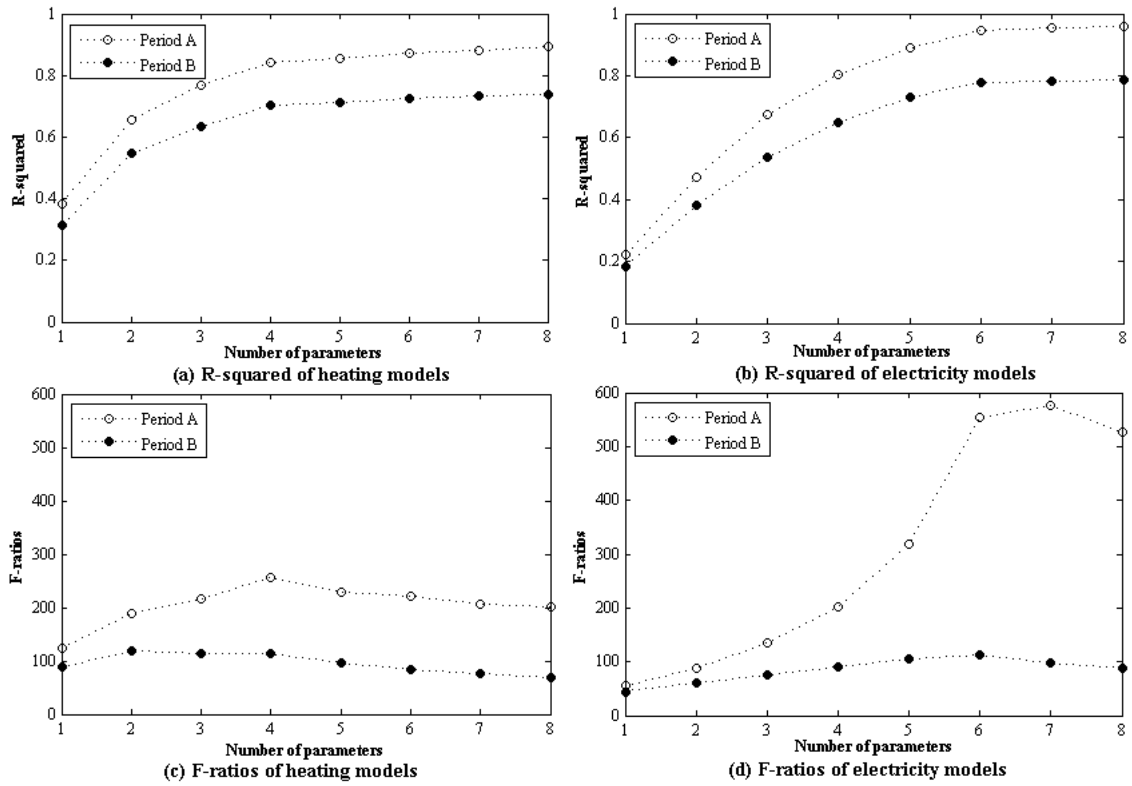


Figure 4 Changes in the coefficient of determination (R-squared) and F-ratios of energy models

Electricity models are structured by operating hours of six parameters that can be categorised by three groups: lighting, appliances used in daily routines and cooling. The most influential factors are the operating hours of lighting in the bedrooms (SRC 0.527 and 0.475 in periods A and B) and living room (SRC 0.475 and 0.433). The operating hours of rice-cookers and computers show the fourth and fifth highest SRC of 0.343 and 0.339 in period A, and 0.336 and 0.329 in period B. In terms of the seasonal devices, cooling hours is the most influential compared to the other factors, including cooling set-point temperatures. Their impact on electricity consumption is determined by the size of volume. Thus, cooling hours in the living room have SRC of 0.459 and 0.383 in periods A and B, while cooling operation in the bed room show SRC 0.239 and 0.220 in the two periods, respectively.

Diverse ranges of the input parameters in the linear models are examined for their estimation to be as close as the distribution of the actual energy consumption. As a result, the discrepancy is significantly declined with the new sets of random samples, as depicted by 'optimised' in Figure 3. The lowest discrepancy is achieved: 1.2% of the heating energy model for period A and 3.7% for period B. The modified electricity consumption in period A shows 3.8% discrepancy. The discrepancy became higher to 9.8% for period B by applying the same set of the modified samples used for period A. In comparison to the previous distribution (Table 2), the large discrepancy in annual energy consumption is reduced by little change in daily routines. In the heating models, the range of set-point temperatures is reduced from 16 – 22 ºC to 16 – 20 ºC, and the operating hours are also reduced from 3 – 9 hours to 3 – 6 hours in the heating models for period A. For period B, the range of set-point temperatures is moved to 15 – 21 ºC in the living room, and reduced to 16 – 21 ºC in the bedroom A and C. In the electricity model, the possible ranges of operating hours of lighting and rice-cooker are extended by about 1 – 3 hours. The range of the computer is moved to 0.5 – 3.5 hours. Overall, the changes in set temperatures are within 2 ºC, while operating hours are revised within 3 hours from the previous distributions.

Table 3 Result of multivariate regression analysis

		Period A (Before 1980)			Period B (1981 – 1988)		
		Unstandardised Coefficients		Standardised Coefficients (p-value)	Unstandardised Coefficients		Standardised Coefficients (p-value)
		B	Std. Error		B	Std. Error	
Heating	Set temperatures in living room	-303.777	16.520	(0.000)	-346.219	26.161	-(0.000)
	Heating hours in living room	10.070	0.500	0.587 (0.000)	10.444	0.792	0.526 (0.000)
	Set temperatures in bedroomA	8.669	0.497	0.504 (0.000)	9.347	0.787	0.469 (0.000)
	Set temperatures in bedroomC	5.470	0.495	0.320 (0.000)	5.651	0.784	0.285 (0.000)
	Set temperatures in living room	4.649	0.492	0.271 (0.000)	5.157	0.779	0.260 (0.000)
Electricity	(Constant)	15.134	8.036	(0.000)	16.546	15.921	(0.000)
	Lighting in bedrooms	0.835	0.027	0.527 (0.000)	0.740	0.053	0.475 (0.000)
	Lighting in living room	0.755	0.027	0.475 (0.000)	0.676	0.053	0.433 (0.000)
	Cooling hours in living room	0.729	0.027	0.459 (0.000)	0.597	0.054	0.383 (0.000)
	Operating hours of rice-cooker	0.544	0.027	0.343 (0.000)	0.523	0.054	0.336 (0.000)
	Operating hours of computer	1.079	0.055	0.339 (0.000)	1.028	0.109	0.329 (0.000)
	Cooling hours in bedroom A	0.378	0.027	0.239 (0.000)	0.343	0.054	0.220 (0.000)

3.2.2 Probability of energy consumption with Gaussian Process Classification

Figures 5 and 6 show that the probability of energy consumption with 25% deviation (medium class) is formed by various combinations of the influential parameters. In other words, the definition of standardised conditions can also be varied by the probability of energy consumption. All parameters linearly effect energy consumption, but they are paired depending on the relevance and the order of coefficient values for the presentation. Pairs of the parameters can be organised in different ways. However, each parameter interacts in an inverse proportion in determining the probability of energy consumption. For instance, the operating hours of the living room is reduced, while the set-point temperature is increased. Hence, the distribution taken from the actual consumption can be maintained. At the same time, this interaction allows the standardised conditions flexible in determining the probability of energy consumption. In addition, impacts of the parameters shift the probability of energy consumption. This is shown by the dispersion of contour lines. Thus, wider dispersion reveals that the parameters are not significantly relevant to determine the probability of energy consumption as found in heating set-point temperatures in the bedroom A and C (Figure 5 – b) and cooling hours (Figure 6 – c).

The 90% probability of the medium class (25% deviation) is overall formed by the range of heating set-point temperature from about 17 to 20 ºC (Figure 5). Heating operating hours are about 3 – 6 hours for period A, and 5 – 8 hours for period B: three hours (19:00 – 22:00), four hours (19:00 – 23:00), five hours (19:00 – 24:00), six hours (18:00 – 24:00), seven hours (18:00 – 01:00) and eight hours (18:00 – 02:00). This range is lower than the conventional standardised conditions that include 20 or 24 ºC set temperatures and its operation controlled by the set temperatures. Furthermore, the possible deterministic value of heating set temperature can be closer to 18 ºC by regarding the actual energy consumption rather than the 20 ºC mostly used in existing literature. The conventional conditions in calculating energy demands are not perfectly out of range, but heating energy consumption can be overestimated.

Interestingly, the probability in heating consumption for period A (Figure 5 – a and b) is formed by the slightly lower values of set temperatures and operating hours, than the values for period B (Figure 5 – c and d), despite higher heating consumption in period A. This can be interpreted by realistic compromise, possibly due to the cost of energy. The medium class for period A consumes about 107 – 138 kWh/m^2/year by the possible setting identified above. However, the medium class for period B spends less heating energy, between 87 and 112 kWh/m^2/year with the setting above because of their relatively advanced thermal conditions, compared to period A. This reveals that occupants in period A would tactically suppress their heating controls despite the significant heat loss through building envelopes.

Electricity consumption with 90% probability is generally derived from diverse ranges in operation (Figure 6). Specifically, lighting is possibly used from 1 to 5 hours. The rice-cooker can be operated about 9 – 14 hours in warming rice, and the computer is operated for 0.5 – 3.5 hours per day. The air-conditioner can be used for up to 6 hours during summer. The results provide more realistic operations for the appliances with intermittent operations by linking between the actual energy consumption and the national survey about using electrical appliances.

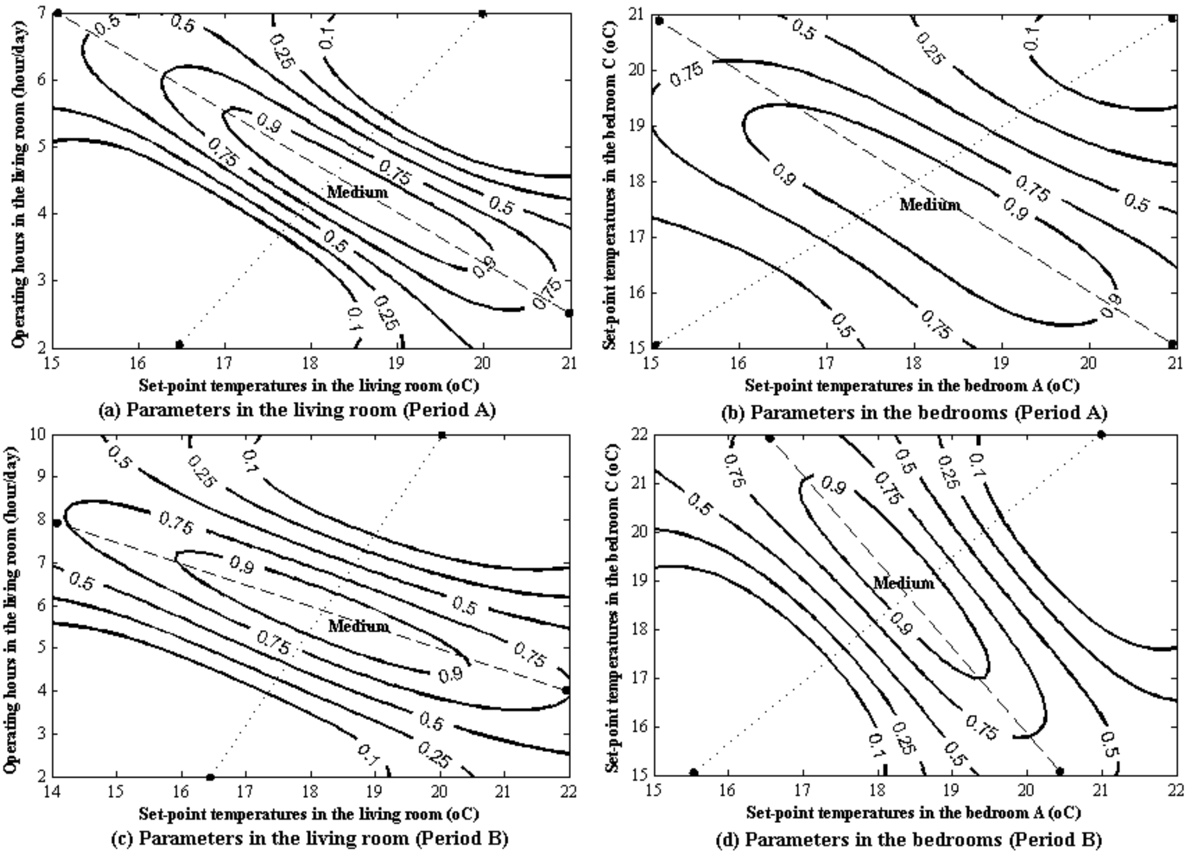


Figure 5 Results of Gaussian Process Classification for heating consumption

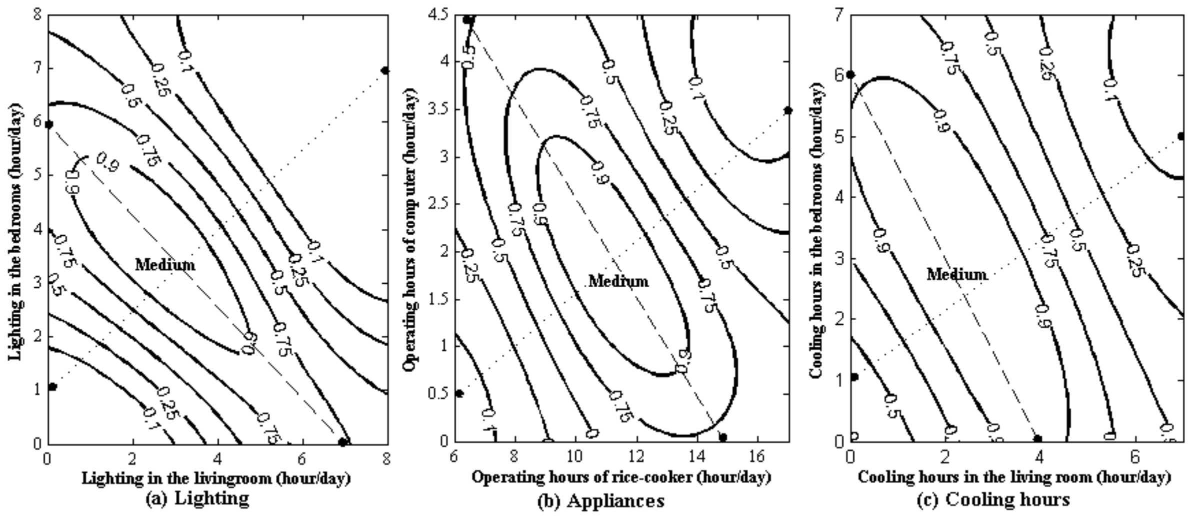
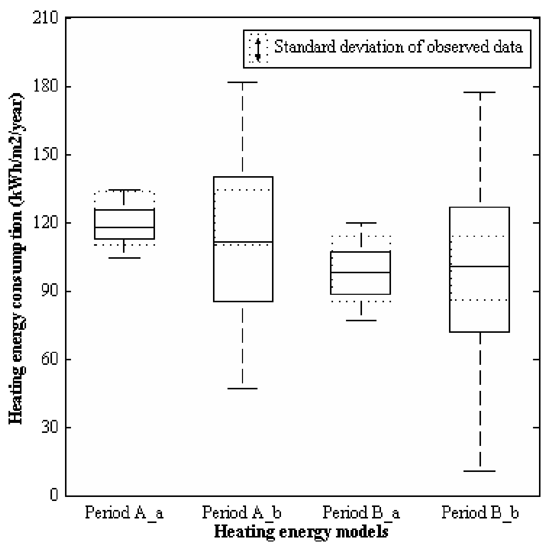


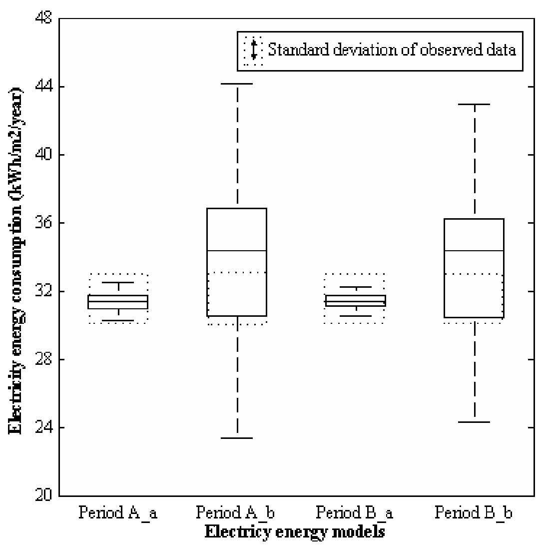
Figure 6 Results of Gaussian Process Classification for electricity consumption

3.3 Evaluation of estimating energy consumption with the probability of the standardised conditions

Energy consumption is estimated by 100 random samples with different probability: high (50 – 90%), and total probability (0 – 90%). Figure 7 demonstrates the comparison between the two different probabilities. The random samples with high probability (on the long-dashed lines in Figure 5 and 6) result in a much lower distribution compared to the samples with total probability (on the dotted lines). The estimated heating consumption of the samples with high probability is distributed from 104 kWh/m^2/year to 136 kWh/m^2/year for period A (Period A_a in Figure 7), while the estimation for period B is from 76 kWh/m^2/year to 119 kWh/m^2/year (Period B_a). In contrast, the samples chosen with total possibility create a much extended distribution, 46 – 195 kWh/m^2/year heating consumption for period A (Period A_b) and 23 – 179 kWh/m^2/year for period B (Period B_b). In terms of electricity consumption, the samples with a high probability estimate electricity consumption between 30 and 32 kWh/m^2/year for both periods (Period A_a and Period B_a). The distribution of estimation is enlarged with total probability from about 24 to 44 kWh/m^2/year. Depending on the form of the probability, combinations of random samples can be diverse, and their estimation can be different each other. However, the estimation with high probability closely represents the standard deviation identified in the actual energy consumption in each period, while the estimated consumption with total probability reflects the minimum and maximum range of the actual energy consumption.



(a) Estimated heating energy consumption



(b) Estimated elctricity energy consumption

Figure 7 Estimated energy consumption with the probability of the standardised conditions

4. Conclusions

This study questioned the inflexible conventional modelling which disregards the various occupant random behaviour of controlling energy consumption in apartment buildings. The actual energy consumption shows 10 – 30% deviation from average values in apartments built in the 1970s – 1980s. Moreover, the range between minimum and maximum values is much greater, up to 128%. This variation reveals that deterministic values of defining typical conditions in apartment buildings could provide a limited interpretation of energy consumption in these buildings. This study attempted to identify the probability in energy consumption in apartment buildings, regarding the variation in actual energy consumption.

The probability of energy consumption with a 25% deviation was drawn through Gaussian Process Classification. The updated values of input parameters represent the probability of the standardised condition in apartment buildings, according to Bayesian inference. The 90% probability of heating consumption is formed by 17 – 20°C set temperatures and 3 – 8 operating hours.25% deviation in electricity is derived from 3 – 6 hours of ranges in operation. Compared to the values in conventional modelling, these results imply that conventional modelling may overestimate energy consumption. Overall, sets of parameter in 50 – 90% probability could achieve nearly the standard deviation, 10 – 30%, in real energy use, whereas sets of parameters in total probability showed a far greater distribution of estimating energy consumption, nearly about the minimum and maximum ranges. Hence, the standardised conditions in apartment buildings can be varied depending on the probability of energy consumption.

This paper applies the actual energy consumption and develops the probabilistic models of occupant random behaviour controlling heating and electricity in apartment buildings. How people consume energy is difficult to be determined by a certain value, which is often preferred for building simulations. However, stochastic data provide the probability of occupant energy behaviour for more specified occupants' groups, which reduces uncertainties and discrepancies in the estimation in building simulations. In the case of South Korea, the general characteristic of residents living in apartment buildings is comprised of parents with one or two offspring. By taking socio-economic factors the group of residents became more specific. The deviations in energy consumption of the resident group led to refine most of the possible range of energy behaviours. Moreover, the generalisation process drew the specific operating hours of heating and electric appliances. The result provides the adapted energy controls of the resident group, called "new middle class", living in old apartment buildings constructed before 1980 and 1981 – 1988, respectively. It is noted that the behaviour model developed in this study is specified for residents living in apartment buildings in particular districts in Seoul, so that residents in a different context could be difficult, due to the different life styles, such as types of domestic appliances and their usage, although the application for South Korean residents would be applicable, because the original surveyed data are based on South Korean residents. Moreover, the behaviour model only included several influencing factors into the stochastic model. Although these factors were selected by their generalities of usage in households and the high levels of correlation with energy consumption, the impacts of the disregarded appliances and operating hours could contain uncertainties in the model in certain situations.

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