An archetype-in-neighbourhood framework for modelling cooling energy demand of a city's housing stock

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Abstract

As hot days are getting hotter and more frequent, urban dwelling is expected to increase cooling energy use in current and future climate. The applicability of dynamic building simulation in estimating cooling loads of a city's housing stock can be limited due to lack of fine-grained on-site current and future weather inputs. For predicative modelling of residential cooling energy demand to aid a city's energy supply planning resilient to excessive heat conditions, it requires cooling energy demand projection based on a relational account of (1) the thermal-environmental interaction between housing stocks and urban microclimate conditions, (2) the city dwellers' cooling energy use behaviour, and (3) the city's climate projections. In this paper, we introduce an 'archetype-in-neighbourhood' framework to meet these requirements. Combining empirical urban data modelling and EngeryPlus model calibration, this framework was developed to obtain statistically a maximal cooling energy demand model of a city's housing stock during yearly hottest periods. We applied the framework to multiple datasets selected from Seoul's open urban data sources for the period of 2014-2017 (2014 being the earliest year of data availability, 2017 being the end of the study period), including metered electricity use data of 659 apartment buildings (51,351 households) sampled from 18 city districts. The results show that maximal month cooling energy demand (MMCD, kWh/m^2) of Seoul's housing stock can be expressed as a regression function of two determinants: (1) the city's average outdoor temperature during the hottest month period (T_{ex}, ˚C), and (2) estimated indoor cooling temperature set-point (T_{in}, ˚C) of the city' housing stock during the same period. Through a *k*-fold (*k*=4) validation, the current regression model (2014-17) was evaluated to have an overall coefficient of determination R^2=.969. Assuming no housing stock renovation, we applied the model to generate scenarios of maximal month cooling demand in future years according to some of the highest summer temperatures projected for Seoul (RCP8.5 2045, RCP4.5 2047, MM5 2071-2100). We conclude this paper with a brief discussion of the implication for cooling energy supply planning and further work to extend the applicability of this new framework to housing stock adaptation planning and design.

Keywords: housing stock energy modelling; housing archetype; cooling energy demand; urban microclimate; EnergyPlus; cooling temperature set-point; climate projections

1. Introduction

As global warming continues, there has been an increasing concern about unmet cooling energy demand in urban living, leading to indoor thermal discomfort, heat-related illness and mortality (De Wilde and Coley, 2012; McMichael et al., 2006; IPCC, 2018). This is particularly impactful in the residential sector, considering the likely compounding effects of ageing populations, intensified urban heat islands (Aniello et al., 1995; Knight et al., 2010; Tomlinson et al., 2012), and increased frequency of urban heatwave episodes (Meehl and Tebaldi, 2004; Jones et al., 2008; Perkins et al., 2012). It can be potentially devastating to an urban population if cooling demand could not be met during heatwaves (Kovats and Hajat, 2008). The heatwave in France in August 2003 caused 14,802 heat-related deaths in a 20-day episode (Fouillet et al., 2006). In the UK, heat-related mortality is projected to increase by 70% in the 2020s, 260% in the 2050s and 540% in the 2080s, compared with the 2000s baseline of around 2,000 premature deaths, assuming no adaptation (Hajat et al., 2014). As hot days are getting hotter and more frequent, there is a need for modelling the impact of heat conditions on residential cooling energy demand to inform sustainable energy supply planning.

Over the past decade, researches into building stock energy modelling at various scales (neighbourhood, city, regional, or national) have developed the field of urban building energy modelling (Reinhart and Davila, 2016). Parekh (2005) introduced three basic criteria in developing 'archetypes' of housing stock for building energy simulation: building thermal characteristics, geometric configuration and operation parameters. In a bottom-up approach, estimated energy consumption of archetypes as a statistically representative set of individual buildings can be extrapolated to regional and national levels (Swan and Ugursal, 2009). In studying the Hellenic building stock, Dascalaki *et al*. (2011) reported the link of residential building topologies to energy performance assessment. In modelling the Irish dwelling stock, Famuyibo *et al.* (2012) identified 13 Irish residential archetypes using clustering statistics. Similarly, a classification of residential building stocks using 12 sample building typologies was proposed by Filogamo *et al.* (2014), which was applied to the whole residential building sector of Sicily. More recently, Sandberg *et al.* (2017) developed a segmented dynamic stock modelling approach to scenario analysis of future energy demand of the Norwegian dwelling stock towards 2050. A comprehensive review and evaluation of 29 housing stock energy models developed in the UK has identified several areas for improvement including transparency, accuracy, sensitivity and updatability (Sousa et al., 2017). Given the modelling frameworks and large urban datasets available, there are software platforms developed specifically for building stock energy modelling. *TEASER* (Remmem et al., 2018) and *EnHub* (Sousa et al., 2018), for instance, are two open-source platforms implemented for scenario analysis of stock change towards reduced energy demand and decarbonisation.

Despite that interior temperature was identified as one of the most dominant parameters in residential energy use (Famuyibo et al., 2012), the aspect of indoor thermal conditions of building stock has been paid much less attention. Facing potential large-scale residential overheating in future climate, predicative modelling of cooling energy demand of housing stock can aid a city's energy supply planning. To be resilient to warm spells and heatwaves, it requires a robust relational account of (1) the thermal-environmental interaction between housing stock and local urban microclimate conditions, (2) the city dwellers' cooling energy use behaviour, and (3) the city's future climate projections. In this paper, we introduce an 'archetype-in-neighbourhood' framework for modelling cooling energy demand of a city's housing stock to meet these requirements.

The archetype-in-neighbourhood framework starts with identifying a city's residential areas each of which is a 1 km-radius circle bounded by an automatic weather station at the centre. This specifies the spatial location and dimension for housing stock sampling at an urban (neighbourhood) microclimate scale within which the local urban weather data are readily available. Then, a set of housing archetypes representative of the housing stock at the city scale is identified according to a classification scheme of built ages, constructional characteristics and floor sizes. EnergyPlus modelling of the archetypes is conducted with weather inputs from the local weather station data, hence 'archetype-in-neighbourhood.' Adopting a bottom-up hybrid approach to combining empirical urban data modelling and EnergyPlus model calibration, this framework was applied to modelling the maximal month cooling energy demand of the high-rise apartment stock in the city of Seoul.

Unlike other building sectors, residential energy use highly depends on household-related factors such as socio-economic circumstances (Schuler et al., 2000) and energy use behaviour (Bae and Chun, 2009; Yun and Steemers, 2011). Also, in our previous study (Yi and Peng, 2017), we observed that the correlation between cooling energy use and local weather data shows significant temporal and spatial variations at the micro (city-district) level during the summer months in Seoul. Here, we first introduce the scope and sources of the open urban data selected for the current study, followed by a preliminary similarity analysis of building, socio-economic and maximal month cooling energy use characteristics. We then describe the proposed 'archetype-in-neighbourhood' framework that incorporates housing stock interaction with urban microclimate and residential cooling energy use behaviour. Based on Seoul's open urban data (2014-2017), a maximal month cooling energy demand (MMCD) model of Seoul's high-rise apartment housing stock is developed. Applying the MMCD model, we show estimated increases of the maximal month cooling energy demand according to Seoul's climate change projections, assuming no housing stock renovation. We conclude the study with a brief discussion of the implications for cooling energy supply planning and further work on applying this new framework to extend the scope of modelling a city's housing stock.

2. Data selection

For housing stock energy use modelling, the data selected for this study include: (1) urban weather data collected at the neighbourhood level; (2) residential neighbourhood energy use data; and (3) building stock information such as building envelop, floor area, and property price. The city of Seoul was selected for the study, where such urban data are openly available under Article 23 in "Multi-Family Housing Management Act" (MoLiT, 2016). The city of Seoul consists of 25 "*Gu*" (city district) and each *Gu* has its own automatic weather station (AWS). According to the Korean Statistical Information Service (KOSIS, 2017), the total population of Seoul in 2016 was 9,805,506 and the total number of households was 2,830,857 of which about

58% (1,641,383) lived in apartments. Under the country's Article 23 (MoLiT, 2016), multi-family housing complex (also called *apartment complex*, "*Danji*" in South Korea) with more than 300 households are required to upload monthly utility energy use data to the Apartment Management Information System (AMIS), which has been openly accessible via the Internet since 2014 (available at http://www.k-apt.go.kr/).

2.1. Data for urban microclimate and residential neighbourhood energy use

Firstly, to account for building interaction with urban microclimate, we define an urban area within 1 km radius of a city-district automatic weather station (CD-AWS) as the spatial location and boundary in sampling a city's housing stock. This is considered an acceptable spatial scale reflecting climatic variation in an urban climate zone (Oke, 2004). Stewart and Oke reported observations of thermal differentiation about 2.0 K in compact high-rise local climate zone and about 1.5 K in open high-rise local climate zones on average (Stewart, 2011; Stewart and Oke 2012). Thus, we consider that there could be similar temperature conditions affecting residential neighbourhoods within a city-district spatial resolution. As most of the CD-AWS sites in Seoul are located above the street surface level, the temperature measurements reflect to some extent the vertical dimension of the microclimate conditions surrounding the apartment complex neighbourhoods (**Table 1**). Urban weather data (air temperature) were selected considering the meter reading day for monthly electricity use data. According to the Korea Electric Power Corporation (KEPCO, 2016), 95% of apartments have the same meter-reading day: the 18th of each month. Thus, the weather data used in this study matched the metering period.

Table 1. The location and height information of Seoul's 18 City District (CD) Automatic Weather Stations (AWS) and size information of the apartment stock within 1 km radius of each CD-AWS site (Sources: KMA; AMIS, 2018). *The street surface level was estimated from the sea level with 3 m down for each floor

CD-AWS Residential Neighbourhood Areas	CD AWS Locations					Seoul's Dwelling Stock			
	Lat.	Long.	Sea lv. (m)	Street lv. (m)	Floor lv. of AWS building	No. Apt. Complexes (ACs)	Avg. Top floor lv. (storey)	No. Apt. Building	No. Apt. Household
CD1	37.5134	127.0470	59.6	50.6	3	7	20	42	3054
CD2	37.5555	127.1450	56.9	47.9	3	6	17	53	4405
CD3	37.6397	127.0257	55.7	34.7	7	3	17	15	1517
CD4	37.5499	126.8425	79.1	64.1	5	2	18	43	2355
CD6	37.5336	127.0853	38.0	38.0	-	3	18	12	1071
CD8	37.4655	126.9001	41.5	29.5	4	4	21	30	2156
CD10	37.6661	127.0295	55.5	43.5	4	1	15	7	690
CD11	37.5846	127.0604	49.4	34.4	5	4	20	40	2587
CD12	37.4937	126.9181	33.8	33.8	0	4	21	15	1665
CD13	37.5655	126.9027	25.0	13.0	4	3	16	18	1192
CD15	37.4889	127.0156	35.5	26.5	3	7	18	58	5491
CD16	37.5472	127.0388	33.7	18.7	5	3	18	17	1429
CD18	37.5115	127.0967	53.6	29.6	8	3	19	75	7310
CD19	37.5296	126.8782	9.7	6.7	1	8	18	115	7176
CD20	37.5271	126.9070	24.4	12.4	4	7	21	49	3722
CD21	37.5204	126.9761	32.6	20.6	4	7	21	52	4681
CD22	37.6077	126.9338	65.0	56.0	3	1	15	15	662
CD25	37.5855	127.0868	40.2	28.2	4	1	15	3	178

Figure 1 shows the August (the hottest month of the year) month average temperatures of the selected 18 CD-AWS urban areas during 2014-17. August 2016 was the hottest (Max, 30.26ºC; Min, 27.08ºC), August 2014 the mildest (Max, 26.24ºC; Min, 24.53ºC). August 2015 and 2017 were close to the average of August 2014-17. According to KMA (2016), August 2016 was one of the warmest summer months on record since 1908, while August 2014 was one of the mildest in Seoul. Therefore, the urban weather data of this study period present some extreme cases.

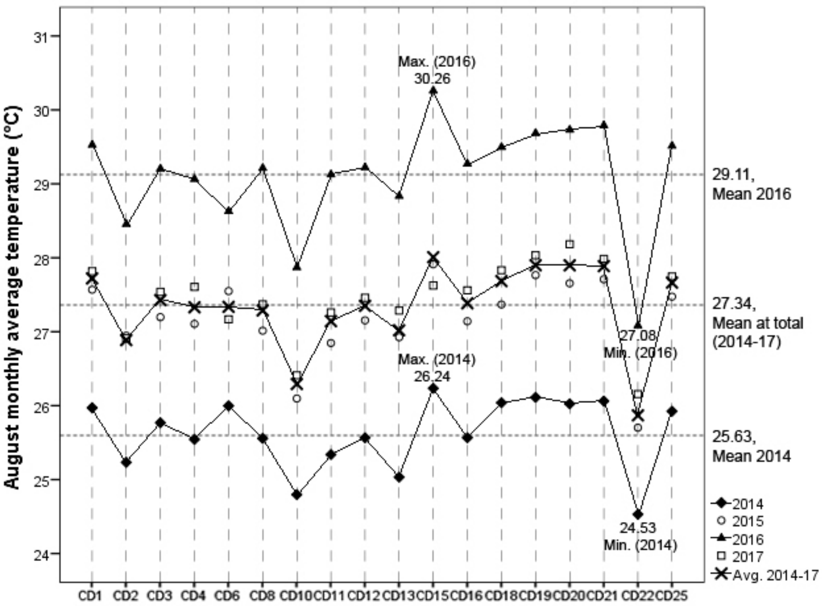


Figure 1. External August monthly average air temperatures of 18 CD-AWS areas in Seoul, August 2014-17. (Source: MDOP)

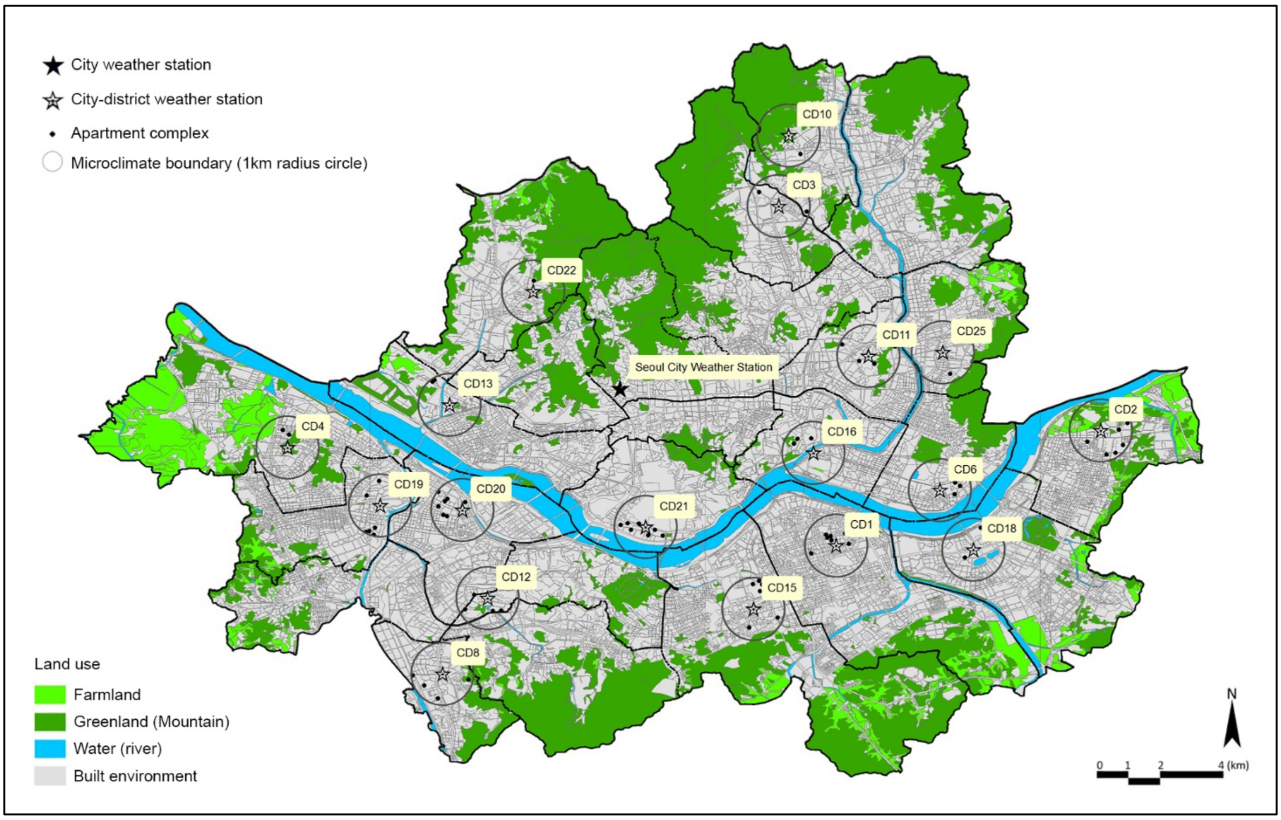


Figure 2. Locations of the 74 apartment complexes (*Danji*) within 1 km radius of the 18 city-district automatic weather stations (CD-AWS) in Seoul

Secondly, energy use data was collected from the apartment management information system (AMIS), open data portal providing aggregate monthly utility bill data and the amount of monthly electricity use. Only the electricity usage data calculated by 'lettable area' (kWh/m^2) are used in this study for estimating the energy used for cooling (e.g. air-conditioning, electric fans, fridges for cool drinks/food). The lettable area used in this study represents the main dwelling spaces where residential cooling energy uses occur. Thus, common areas (i.e. parking space, stair and lift) and balcony areas are not included (see also Figure 10 in Section 4.1). The spatial resolution of the AMIS energy use data is given at the multi-family housing complex (*Danji*) level, not at an individual household nor a building level. As the AMIS first reporting electricity use data in 2014, the period of 2014-17 was selected for this study (2017 being the end of the study period). Following the CD-AWS locations and residential neighbourhood boundaries, the electricity usage data on the AMIS was first assessed, and 74 apartment complexes (659 apartment buildings, 51,351 apartment households) from 18 (out of 25) city districts of consistent data availability were identified (**Figure 2**).

2.2. Data for other possible factors affecting residential energy use

The AMIS also provides other types of building-related information, such as built year, total floor area, site area, the number of apartment households by floor area and property price. The data of built year and the number of apartment household by floor area in each neighbourhood were selected to obtain building physical characteristics such as building envelopes and floor plans. These two datasets were used as the main sources for determining the building characteristics representative of Seoul's housing stock. The property price data (KRW/m^2) were collected from Korea Appraisal Board (KAB, 2015), which is linked to the AMIS. **Figure 3** shows an overview of the building information (building envelop, floor area, and property price) data selected across the 18 CD-AWS areas.

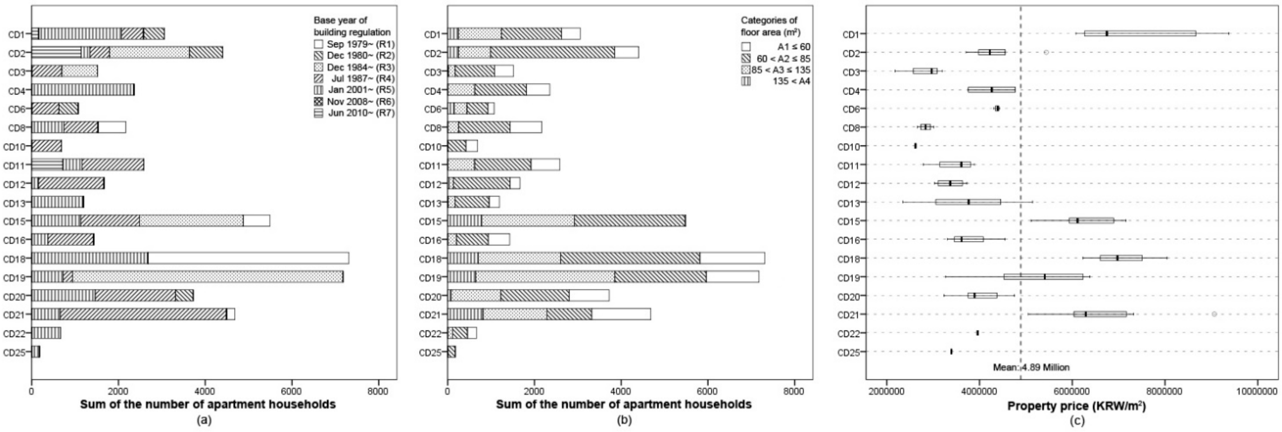


Figure 3. (a) The number of apartment households within each CD-AWS area according to the year of building insulation criteria applied (R1-R7); (b) and the floor area sizes (A1-A4); and (c) the distribution of apartment neighbourhood property prices in each city district

Most of Seoul's apartment buildings were built during seven epochs of building regulations (R1-R7, from September 1979 to June 2010**, Figure 3(a)**) and **Table 2**. Each building regulation epoch adopted a set of building component U-values (Kim et al., 2013b). In housing unit sizes in **Figure 3 (b)**, the range of apartment floor areas (m^2) are of four sizes based on the lettable areas classified by AMIS: A1 $\leq$ 60; 60 < A2 $\leq$ 85; 85 < A3 $\leq$ 135; 135 < A4. As seen in Figure 3 (a) and (b), there appears a similarity of building characteristics within the given ranges of classifications in each city-district neighbourhood. Furthermore, Figure 3 (c) shows that the ranges (diversities) of property price are much reduced at the neighbourhood scale compared to citywide (2.2 to 9.4 million Korean Won/m^2). This suggests a high probability of similarity in residential cooling energy use by apartment complexes within each city-district neighbourhood. The similarity may come from multiple factors affecting residential energy use including the homogeneity of the surrounding climate within the 1 km radius boundary defined in section 2.1.

Table 2. Insulation criteria for Seoul's housing stock according to the year of building regulation applied (U-value, W/m^2*K). (Source: Kim et al., 2013b) *Side wall represents the external wall without opening area, such as glazing

Building regulation	Base year	External wall (Side wall)	External/ Ground Floor	External Roof	Window
R1	Sep 1979	1.05 (-)	1.05	1.05	2.56
R2	Dec 1980	.58 (-)	1.16	.58	3.49
R3	Dec 1984	.58 (.47)	.58	.58	3.49
R4	Jul 1987	.58 (.47)	.58	.41	3.37
R5	Jan 2001	.47 (.35)	.35	.29	3.84
R6	Nov 2008	.47 (.35)	.35	.29	3.0
R7	Jun 2010	.36 (.27)	.30	.20	2.1

2.3. Characteristics of residential energy use during the hottest month (August) period

Given the similarity of multiple factors, the characteristics of dwellings' historical monthly energy use during the yearly hottest month (August) are investigated at neighbourhood level. **Table 3** shows the distribution of each apartment complex's ~~(AC)~~ August monthly electricity use data within each ~~CD~~ city-district neighbourhood in 2015 (close to average 2014-17 August) and 2016 (the hottest August summer year to date) as examples. At the macro scale (city level), the average of August electricity use in 2015 was 4.492 (kWh/m2) within the range from 3.129 to 6.026, while in 2016 was 5.232 within the range from 3.894 to 6.850. On the other hand, at the micro scale (neighbourhood level), the variance was much reduced across all ~~CDs~~ city-districts in both years. This suggests that there appears a similarity of apartment complexes' August electricity use within each city-district neighbourhood. Moreover, compared to 2015, the variance of 2016 was smaller than 2015 (10 out of 15 ~~CD~~s city-districts). This means that the distribution of neighbourhoods' August monthly electricity use under hot conditions is smaller than under milder conditions.

Statistically to confirm the ~~internal consistency~~ similarity in terms of the distribution of ~~neighbourhoods'~~ apartment complexes' monthly electricity use within each ~~CD~~ city-district neighbourhood boundary, a factor analysis was carried out. Due to the small sample size, the case (month) was extended to include whole summer months, where any cooling degree day (CDD) occurred (see section 3.2.2, Figure 7): May to October for 2014-17. The neighbourhoods where number of apartment complexes is less than three were excluded from the analysis, due to the fact that the factor analysis is run based on coefficients of inter-correlations among the variables (apartment complexes' monthly energy use).

Table 3. Descriptive variance analysis of apartment complexes' (AC) maximal (August) monthly electricity use (kWh/m^2) within each city-district (CD) neighbourhood in 2015 (close to average 2014-17 August) and 2016 (the hottest August) as examples. *. CD neighbourhoods with number of ACs less than two were excluded from the analysis

Neighbour-hood	Monthly electricity use										No. of ACs
	Min (kWh/m^2)		Max (kWh/m^2)		Mean (kWh/m^2)		Std. Dev., *S*		% of *S* to Mean		
	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	
CD1	3.994	4.500	5.368	6.324	4.634	5.352	.540	.656	11.6	12.3	7
CD2	3.978	4.733	5.779	6.237	4.840	5.347	.845	.648	17.5	12.1	6
CD3	4.076	4.643	4.608	5.304	4.369	5.081	.270	.379	6.2	7.5	3
CD4	4.336	5.181	4.554	5.387	4.445	5.284	.154	.146	3.5	2.8	2
CD6	3.129	3.894	4.313	5.139	3.886	4.716	.658	.712	16.9	15.1	3
CD8	3.703	4.272	5.294	4.950	4.364	4.572	.673	.312	15.4	6.8	4
CD11	4.574	4.144	6.026	6.257	5.039	5.371	.686	.886	13.6	16.5	4
CD12	3.995	4.826	5.748	6.668	5.037	5.887	.747	.783	14.8	13.3	4
CD13	4.190	4.738	5.260	5.898	4.584	5.216	.588	.607	12.8	11.6	3
CD15	3.464	4.125	5.389	6.296	4.189	4.970	.647	.752	15.4	15.1	7
CD16	4.015	5.176	4.474	5.880	4.287	5.578	.241	.363	5.6	6.5	3
CD18	4.197	5.154	5.723	5.761	4.906	5.527	.769	.327	15.7	5.9	3
CD19	3.868	4.922	4.415	5.411	4.159	5.202	.184	.180	4.4	3.5	8
CD20	3.434	4.387	4.441	5.464	3.906	4.837	.347	.445	8.9	9.2	7
CD21	3.757	4.569	5.627	6.850	4.732	5.548	.708	.764	15.0	13.8	7

Table 4 shows the factor analysis of monthly electricity use of apartment neighbourhoods in each CD-AWS area. Firstly, in order to determine if the datasets used for factor analysis are suitable or not, (which is the preliminary assumption for factor analysis), the factorability (suitability) of the data for factor analysis was assessed by inspecting Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1970; 1974) and significance of Bartlett's test of sphericity (Bartlett, 1954). The significance of Bartlett's tests of all city-district neighbourhoods were .000 ($p < .05$) and KMO values were above the recommended value (.600), except CD8 (.595) and CD18 (.590, but close to .600). Therefore, factor analysis is appropriate. Secondly, the number of factor extraction identified by the method of principal components analysis (PCA), that is principal component which explains most of the variance in the original variables, was only one in all city districts. This represents that the best interrelationships among the set of variables (apartment complexes' monthly energy use) could be explained within the city districts. The eigenvalue also supports this, which accounts for the total amount of the explanatory variance of the factor extracted. In all city districts, only one factor (component) had an eigenvalue of 1 or more, and each component (Avg. of apartment complexes' communalities within each city-district) explains about 85.2% (Avg.) of the variance within the range from 66.7% (Min., CD12 an outliner) to up to 95.4% (Max., CD19). Furthermore, the standard deviation of communality (ranging 0 to 1) showed a high similarity in terms of the distribution of apartment complexes' monthly electricity use within each city-district neighbourhood boundary. This suggests that there appear similar (homogenous) characteristics of residential cooling energy use at the urban neighbourhood microclimate scale. Therefore, housing archetypes can be reasonably developed at this particular spatial resolution for modelling cooling energy demands of a city's housing stock.

Table 4. Outputs of factor analysis of apartment complex (AC) monthly (May to Oct) electricity use 2014-17 within each neighbourhood of microclimate boundaries *. City-district neighbourhoods with number of ACs less than three were not included, taking into account the factorability of the data for factor analysis.

CD-AWS Areas	KMO value	Sig. of Bartlett's Test	No. of factor extraction (Eigenvalue)	Eigenvalues % of variance	Std. Dev. of ACs' communalities	No. of ACs
CD1	.747	.000	1 (5.983)	85.5	.209	7
CD2	.663	.000	1 (4.713)	78.5	.164	6
CD3	.623	.000	1 (2.570)	85.7	.100	3
CD6	.605	.000	1 (2.499)	83.3	.126	3
CD8	.595	.000	1 (2.970)	74.2	.167	4
CD11	.680	.000	1 (3.133)	78.3	.166	4
CD12	.731	.000	1 (2.666)	66.7	.431	4
CD13	.769	.000	1 (2.853)	95.1	.017	3
CD15	.858	.000	1 (6.191)	88.4	.061	7
CD16	.781	.000	1 (2.826)	94.2	.008	3
CD18	.590	.000	1 (2.552)	85.1	.091	3
CD19	.910	.000	1 (7.633)	95.4	.039	8
CD20	.877	.000	1 (6.545)	93.5	.055	7
CD21	.812	.000	1 (6.211)	88.7	.083	7

3. Methods

3.1. An 'archetype-in-neighbourhood' framework

To quantify a city's residential cooling energy demand according to climate projections, an 'archetype-in-neighbourhood' modelling framework is proposed (**Figure 4)**. Based on multiple regression analysis, we adopt a bottom-up approach to housing stock modelling by developing archetypes in neighbourhoods corresponding to the urban microclimate scale. This is to investigate how local climate conditions may affect residential cooling energy use. Previously, multiple regression modelling was used to identify major determinants on residential weather-dependent energy use. For instance, Jones and Harp (1982) identified climatic variables such as Heating Degree Day (HDD) a key determinant. Raffio et al. (2007) examined the relationship between utility bills and weather data within multiple residential areas and identified different coefficients in each of the residences as "energy signature", similar to "fingerprint" in an earlier study (Hirst et al., 1986). This suggests that unique metered energy use occurrences determined by weather can be residence specific (Swan and Ugursal, 2009). This method is appropriate if regional climate change projections are not readily applicable for dynamic building simulation. For instance, for city of Seoul, current data available for future climate is limited into daily temperature and precipitation (CIP, 2017).

Furthermore, to predict cooling loads under the projected changing climates, a required HVAC cooling temperature set-points in coming years must be given as a reference threshold for cooling. This requires present households' cooling temperature set-points. However, collecting such data from citywide survey would be cost-prohibitive if not possible. Thus, we develop an EnergyPlus model calibration process (**Figure 5**) to estimate archetypes' historical HVAC cooling temperature set-points (section 3.2). In turn, these estimates at the micro level (archetype in neighbourhood) are aggregated at a macro level as the input variables to a city's housing stock energy model. This was grounded that the history of residential cooling energy use reflects the interaction between buildings and local environmental conditions as well as the contingency of residents' energy use behaviour. Therefore, the archetypes in neighbourhoods are defined and specified for EnergyPlus model calibration with known data sources, such as housing thermal characteristics, geometric configurations, detailed energy use profile (cooling and non-weather-dependent energy use) and on-site weather station data.

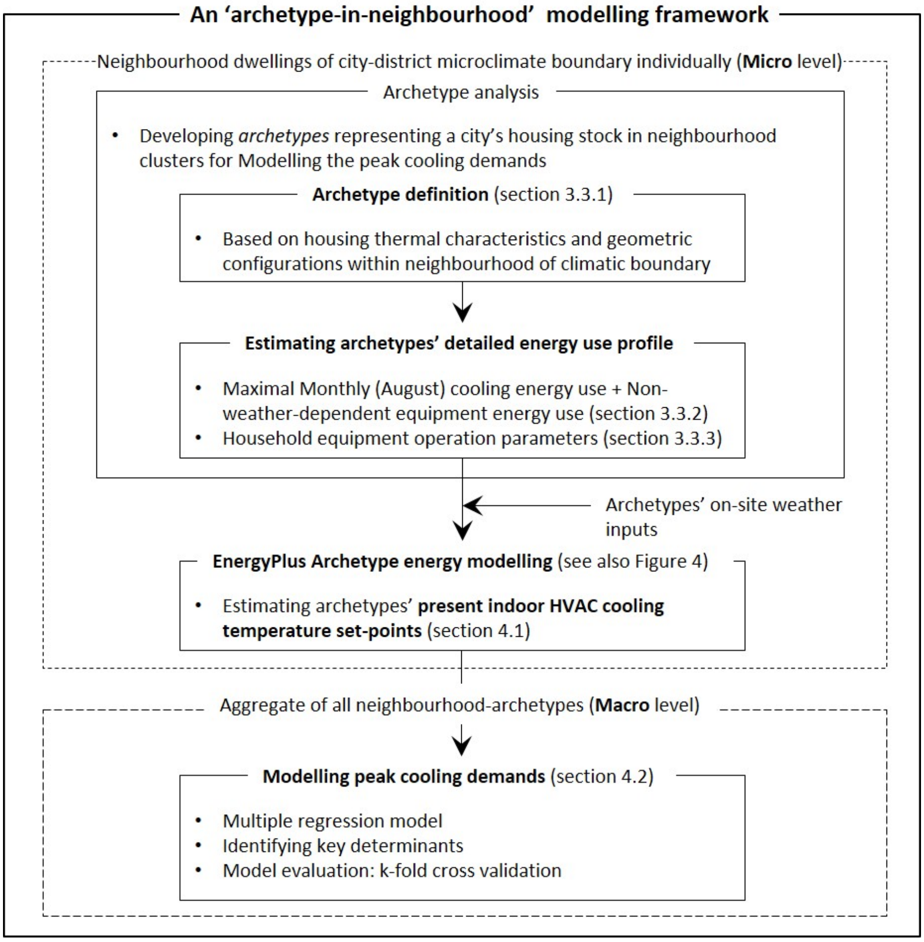


Figure 4. A bottom-up stock energy modelling framework for predicting maximal month cooling energy demands of a city's dwelling through combined building energy modelling and statistical modelling

3.2. Estimating archetypes' maximal month HVAC cooling temperature set-points

The archetype cooling energy model calibration follows an iterative process (Raftery et al., 2011a). As there are no field measurement data available for internal loads of household equipment, the calibration process consists of two phases: (1) initial archetype non-weather-dependent (NWD) energy model calibration to estimate internal heat gains of household NWD equipment, and (2) archetype cooling energy model calibration to estimate present-day monthly HVAC cooling temperature set-points expected during the hottest month of the year.

As shown in the upper block of **Figure 5**, an initial step is required to obtain estimates of internal heat gains from household equipment usage (i.e., lighting, cooking, machinery and others), which are then taken as inputs to peak cooling energy model calibration for each neighbourhood archetype (see the lower block of Figure 5). For the initial non-weather dependent (NWD) energy model calibration, three types of inputs (by measurement or by inference) are required: (a) physical properties in terms of 3D geometry and thermal property of building material assembly profile; (b) urban microclimate boundary specific TMY weather data; and (c) NWD energy usage data including NWD household equipment use profiles. We should note that the weather input used in this study is not a typical meteorological year (TMY) but temporally (August 2014-17) and spatially (city-district neighbourhoods) modified on-site weather input for archetype EnergyPlus modelling: hence, actual meteorological year (AMY) climate data converted to EnergyPlus wheather (EPW) file format.

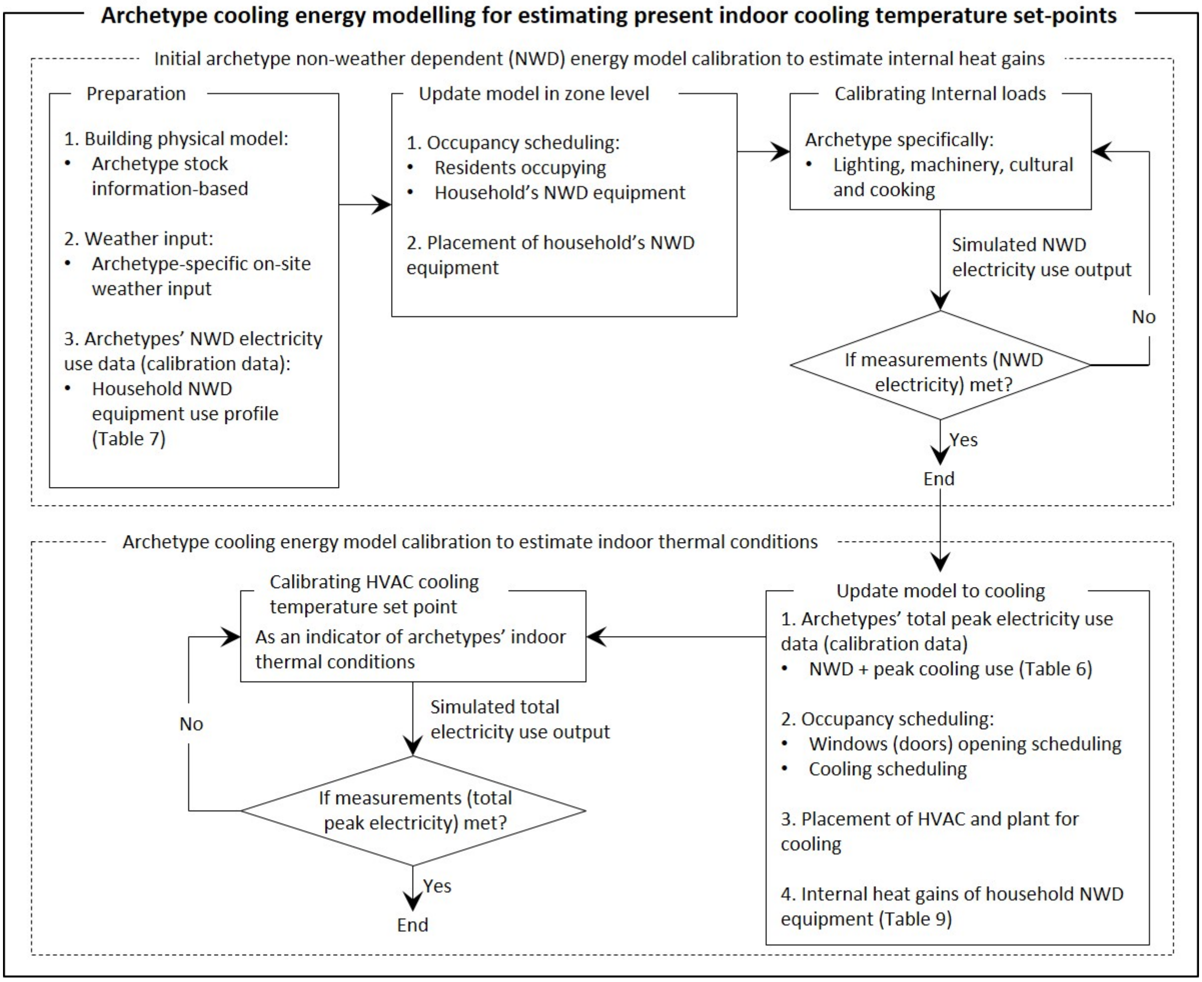


Figure 5. Model calibration process of peak cooling energy use for estimating an archetype's cooling temperature set-points (˚C)

Based on the initial preparation, the archetype model is updated at the zone level with inputs of occupancy scheduling and placement of household NWD equipment. Through iteration until the simulated NWD energy use outputs meet the measured NWD energy usage data, the internal loads for each archetypes' NWD energy use is obtained. The calibrated internal loads are then used to estimate internal heat gains of NWD equipment use, such as lighting, machinery, cooking and cultural. Next, as shown in the lower block of Figure 5, cooling energy model calibration can be further performed by: (1) replacing the calibration data from NWD to total monthly August energy use data, including cooling; (2) updating operating parameters of occupancy scheduling and HVAC placement for cooling; and (3) inputting the internal heat gains of NWD household equipment use estimated previously. Finally, archetypes' monthly cooling temperature set-points are derived from the iterative calibration process against the measured total amount of August energy use.

3.3. Estimating input requirements for EnergyPlus model calibration

The purpose of EnergyPlus model calibration (Figure 5) is to determine archetypes' August monthly (overall) HVAC cooling temperature set-points given the history of neighbourhoods' monthly energy use data. This requires detailed archetype-specific energy use profiles such as home appliance energy use for non-weather-dependent (NWD) and for cooling, and the related operation scheduling profiles. However, such data requirements are partly available in neighbourhood level of citywide. Hence, it is inevitable to estimate the details under the assumptions. For input requirements, archetype is first defined at neighbourhood scale in section 3.3.1. This includes archetypes' thermal characteristics and geometric configurations. Then, archetypes' August monthly energy use is subdivided into estimated NWD and cooling energy use in section 3.3.2. The occupancy scheduling profiles are configured in section 3.3.3.

3.3.1 Archetype definition for the housing stock in Seoul

For the purpose of EnergyPlus model calibration, three factors are involved in developing the archetypes of Seoul's apartment stock: thermal characteristics (R*i*), geometric configurations (A*j*) and city-district (CD*k*) microclimate neighbourhood boundaries. An archetype is denoted as CD*k*[R*i*/A*j*](actual area, m^2). For instance, CD12[R4/A2](82) denotes an archetype located in CD-AWS area no.12 built during building regulation epoch R4 (July 1987 in Table 2) with floor area type A2 (84m^2 in **Figure 6**); actually applied floor area is 82m^2 based on A2 floor plan. In order to calculate the actual area for each archetype in neighbourhood, the total area of each CD-AWS neighbourhood was divided by the number of households.

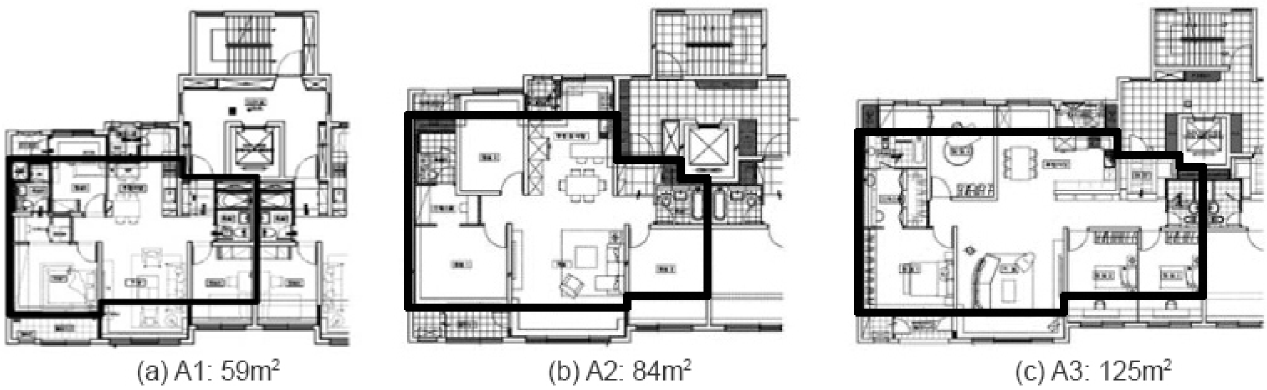


Figure 6. Floor plans of typical apartment flats based on lettable area (solid line): A1 (59m^2), A2 (84m^2) and A3 (125m^2) (Source: MoLiT, 2009; Tae et al., 2011) Note: all balcony areas are outside the floor plan boundary (in solid line)

Firstly, for the building thermal characteristics of an archetype, the dominant building regulation epoch was chosen (Figure 3(a)) as there appears one dominant insulation regulation in each city-district neighbourhood**,** of which the adjacent do not have large differences in terms of U-values (Table 2). Thus, the archetypes' thermal envelope components were fit to the insulation criteria as shown in Table 2. Secondly, to generate the archetypes' geometric configurations such as floor plan, the calculated actual floor areas were used owing to m^2-based energy use data. Then, it was referred to standard typical apartment floor plans proposed by local authority's green building design guideline based on floor areas (MoLiT, 2009): 36m^2 (1-bed), 46m^2 (2-bed), 59m^2 (3-bed), 84m^2 (3-bed), 125m^2 (4-bed) (Figure 6). Then, the archetypes' floor plans were resized to the calculated actual area (m^2).

3.2.2. Estimation of detailed energy use profile

As the energy use data selected are metered monthly electricity usage, containing not only heating/cooling energy use but also energy use for other home appliances, it is necessary to deduce the monthly electricity use data into two types: non-weather-dependent (NWD) use for operating home appliances and weather-dependent (WD) use for cooling or heating. This study assumes that NWD energy use is the minimum monthly electricity use for the study period 2014-17, and peak (August) cooling energy use can be estimated as the net of August total energy use minus the NWD use identified. Here, the estimated NWD energy use drawn from the 2014-17 dataset was adopted as a constant value applied to the subsequent energy modelling of the archetypes.

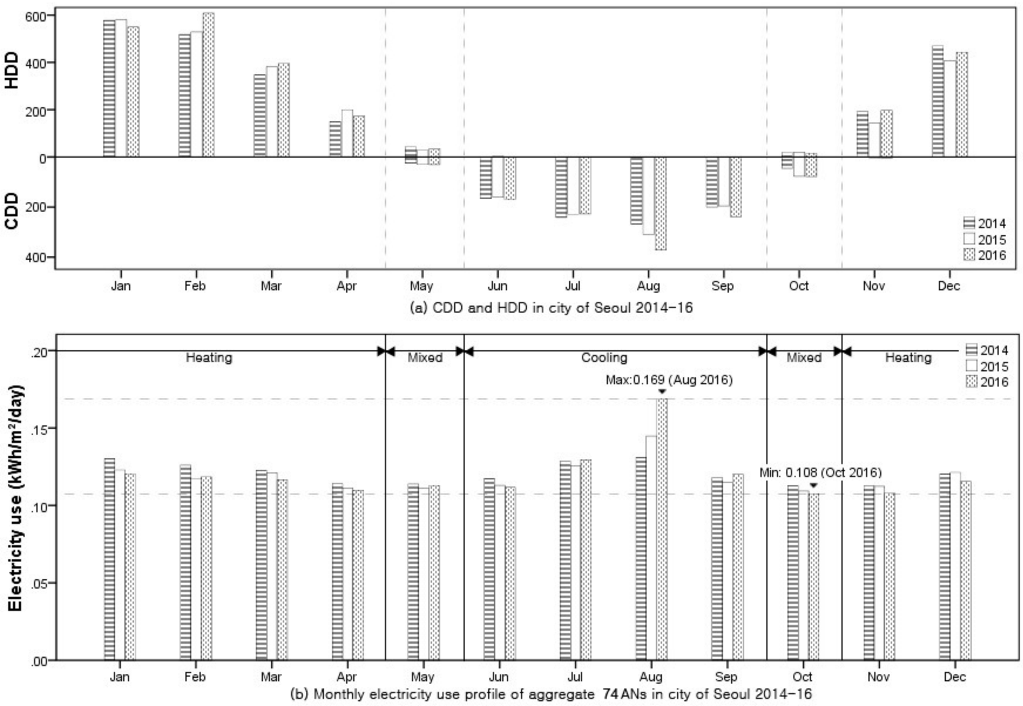


Figure 7. **(a)** HDD and CDD based on daily temperature dataset from the Seoul city weather station; **(b)** monthly electricity use profile from aggregated 74 apartment neighbourhoods in Seoul, 2014-16

To confirm the assumption above, we analysed the relationship between cooling degree days (CDD), heating degree days (HDD), and monthly electricity use 2014-16. CDD and HDD were calculated by 17.1^{o}C as the base temperature for Seoul (Lee et al., 2014). As shown in **Figure 7 (a)**, the heating, cooling and mixed period can be clearly identified by CDD and HDD: Nov-Apr (heating); Jun-Sept (cooling); May and Oct (mixed), suggesting there can be no NWD months theoretically. The mixed period had a relatively small amount of CDD/HDD days, implying a high probability of NWD energy use occurring in both months (May and October). The actual energy use profile in **Figure 7(b)** supports this assumption: the minimum electricity use occurred in both May and October of each year, which is further tested with a Pearson correlation analysis.

If the minimum electricity use can be attributed to NWD use, it would be weak or negative for the correlation coefficients between CDD and monthly electricity use for May and October in explaining the relationship. **Table 5** shows the relationship between CDD and electricity use in the cooling period (Jun-Sep) was very strong and positive, meaning that the monthly electricity use during the cooling period contains cooling energy use certainly. However, in the mixed period (May and October), there was a very strong but negative correlation coefficient between CDD and electricity use, suggesting that the electricity use in this period was determined by aspects other than CDDs. Despite the correlation analysis, this assumption can still lead to over or under estimate of NWD energy use due to the current limited data availability. Nonetheless, inclusion of weather-dependent energy use in the minimum electricity use period will be minimal.

Table 5. Correlation between monthly electricity use and CDD for cooling and mixed periods. **. p<0.01 and *. p<0.05

	Cooling period (Jun-Sep)	Mixed period (May and Oct)
	CDD (sqrt) and Electricity (log)	CDD and Electricity
Pearson-C	.951**	-.887*
Sig.	.000	.018
R squared	.905	.787
N	12 (4mon*3yr)	6 (2mon*3yr)

Table 6 shows the NWD and peak cooling energy use estimated for each neighbourhood archetype. Notably, the archetype energy use data is not an average value of apartment complexes' monthly (August) electricity use in each neighbourhood but the weighted value by each apartment complex's total floor area. Taking CD4 as an example, where there are two apartment complexes, each of their 2016's August electricity uses (kWh/m^2) are 5.387 (a) and 5.181 (a') and of their total floor areas (m^2) are 13,063 (b) and 190,886 (b') respectively. Thus, the CD4's floor-area-weighted value (kWh/m^2) is 5.194, calculated by (a*b + a'*b') / (b + b'), which is different from the average, 5.284. These estimates were later used in the EnergyPlus model calibration process to output archetypes' HVAC cooling temperature set-points in present years (2014-17).

Table 6. Archetypes' NWD and August (hottest month period) cooling energy use data for cooling energy model calibration

Archetype in Neighbourhood		NWD electricity use (kWh/m^2)	August cooling energy use (kWh/m^2)			
City District	Type (actual area m^2)		2014	2015	2016	2017
CD1	R5/A2 (94)	2.936	1.338	1.612	2.322	1.739
CD2	R3/A2 (98)	3.083	1.478	1.704	1.998	1.280
CD3	R3/A2 (75)	3.165	0.865	1.279	2.044	1.317
CD4	R5/A2 (87)	3.216	0.779	1.134	1.979	1.452
CD6	R4/A2 (100)	2.531	0.923	1.118	1.931	1.116
CD8	R4/A2 (77)	2.985	0.794	1.140	1.606	1.373
CD10	R4/A1 (64)	3.365	0.605	1.098	2.060	1.243
CD11	R4/A2 (86)	3.432	1.168	1.451	1.694	1.457
CD12	R4/A2 (82)	3.086	0.775	1.518	2.363	1.499
CD13	R5/A2 (83)	3.186	0.920	1.127	1.859	1.550
CD15	R3/A3 (108)	2.542	0.880	1.422	2.317	1.464
CD16	R4/A2 (80)	3.074	0.886	1.249	2.567	1.435
CD18	R1/A2 (89)	3.355	0.821	1.306	2.118	1.235
CD19	R3/A2 (88)	2.733	0.866	1.325	2.425	1.304
CD20	R4/A2 (91)	2.760	0.677	1.048	1.941	1.056

CD21	R4/A2 (102)	2.782	1.018	2.316	3.009	1.866
CD22	R5/A2 (82)	3.301	0.667	1.994	2.661	1.721
CD25	R5/A2 (84)	3.085	0.740	1.409	1.968	1.792

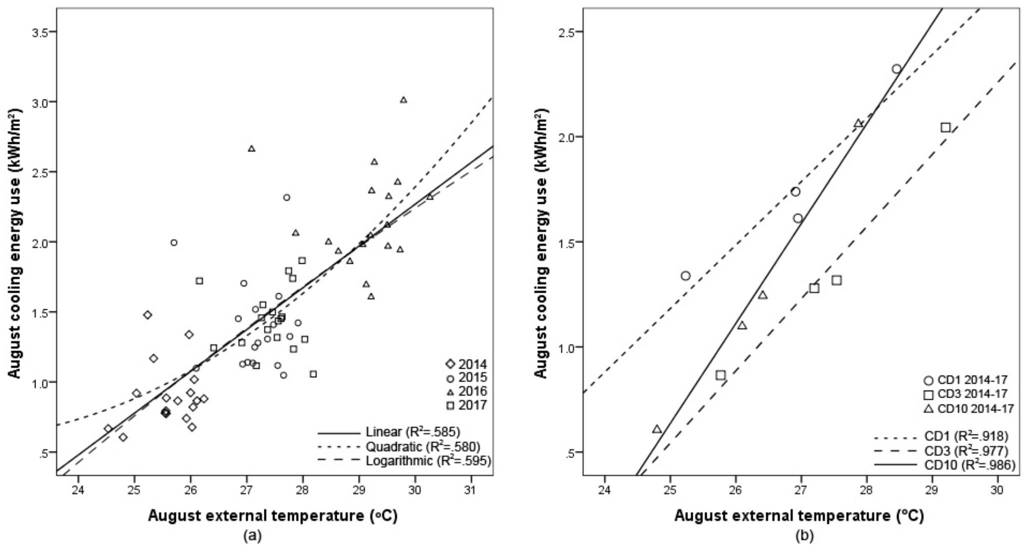


Figure 8. **(a)** The relationship between neighbourhood-archetypes' peak month (August) cooling energy use and external August average temperature 2014-17 in Macro (aggregated 18 neighbourhood-archetypes; **(b)** Micro (neighbourhood-archetype independently; CD1, 3, 10 as examples

Following the NWD and August cooling energy use estimated for each archetype in neighbourhood, as shown in Table 6, **Figure 8** shows the relationship between neighbourhood-archetypes' August cooling energy use and the external August temperature in Macro (aggregated 18 neighbourhood-archetypes) and Micro (archetype-in-neighbourhood) plots. Figure **8(a)** shows that all models (linear, quadratic, logarithmic) are not well fitted in the Macro plot with R^2=.585, .580, .595 respectively; while using CD1, CD3, CD10 as examples, the Micro plot shows well-fit linear models (**Figure 8(b)**). This suggests, relatively speaking, the peak month cooling energy use behaviour can be better explained at the archetype-in-neighbourhood scale. Special attention should be paid to the different gradients (model coefficients) of each city district. As the relationship between the two variables indicates how the dwellings responds to external climate for peak month cooling energy use (hence, behaviour), there were substantial differences of peak month cooling energy use predicted according to the external climate. For instance, if external temperature reaches at 30ºC, the estimated peak month cooling energy use can be dynamic: 2.693 (kWh/m^2) in CD1, 2.260 in CD3, 3.014 in CD10.

Given the estimated archetypes' non-weather dependent (NWD) electricity use, the detailed archetypes' household NWD equipment electricity use profiles were further investigated. In this study, they were required to extract internal loads for calibrating internal heat gains in EnergyPlus modelling. This is due to the fact that a detailed household equipment energy use profile is unavailable for Seoul's housing stock, a certain proportion (%) of total NWD electricity use was estimated by referring to the household equipment energy use profile surveyed from both the UK (Palmer and Cooper, 2014) and Korea (Seo and Hong, 2014). This crossnation referencing was to combine the limited Korean survey covering only a small sample size (30 apartment households) in a different city (Daegu) for a short time period (2 weeks) with the UK survey, which is of a national and annual scale. The actually applied percentage of total NWD electricity use for Seoul was adjusted by considering Seoul's social cultural circumstances with reference to the UK and the Korean household equipment energy use profile. For instance, the fermentation process for long-term food preservation and warming of cooked rice in Korean cooking spends relatively more electricity (Kim et al., 2016). Therefore, the percentage for cold appliances and cooking had more weight than others. **Table 7** lists the archetypes' NWD household equipment energy use profiles.

Table 7. Detailed amount of NWD household equipment in each neighbourhood archetype as calibration data in NWD energy model. * Machinery: cold and wet appliances, Cultural: consumer electronics and IT

Archetype in Neighbourhood		NWD elec. use	Actual Floor area	Total NWD elec. use	Lighting (18%, kWh)	Machinery (36%, kWh)	Cultural (26%, kWh)	Cooking (20%, kWh)
City District	Type (actual area m^2)	(kWh/m^2)	(m^2)	(kWh)				
CD1	R5/A2 (94)	2.936	93.88	275.59	49.61	99.21	71.65	55.12
CD2	R3/A2 (98)	3.083	97.91	301.90	54.34	108.68	78.49	60.38
CD3	R3/A2 (75)	3.165	74.62	236.17	42.51	85.02	61.40	47.23
CD4	R5/A2 (87)	3.216	86.60	278.49	50.13	100.26	72.41	55.70
CD6	R4/A2 (100)	2.531	100.37	254.09	45.74	91.47	66.06	50.82
CD8	R4/A2 (77)	2.985	77.11	230.17	41.43	82.86	59.84	46.03
CD10	R4/A1 (64)	3.365	64.11	215.75	38.84	77.67	56.10	43.15
CD11	R4/A2 (86)	3.432	85.74	294.27	52.97	105.94	76.51	58.85
CD12	R4/A2 (82)	3.086	82.03	253.13	45.56	91.13	65.81	50.63
CD13	R5/A2 (83)	3.186	82.91	264.19	47.55	95.11	68.69	52.84
CD15	R3/A3 (108)	2.542	107.85	274.19	49.35	98.71	71.29	54.84
CD16	R4/A2 (80)	3.074	79.72	245.09	44.12	88.23	63.72	49.02
CD18	R1/A2 (89)	3.355	88.97	298.52	53.73	107.47	77.62	59.70
CD19	R3/A2 (88)	2.733	88.24	241.13	43.40	86.81	62.69	48.23
CD20	R4/A2 (91)	2.760	91.28	251.91	45.34	90.69	65.50	50.38
CD21	R4/A2 (102)	2.782	102.22	284.33	51.18	102.36	73.93	56.87
CD22	R5/A2 (82)	3.301	82.33	271.75	48.92	97.83	70.66	54.35
CD25	R5/A2 (84)	3.085	83.98	259.04	46.63	93.25	67.35	51.81

3.3.3 Household operation parameters and occupancy schedules

The operation parameters in building energy modelling include detailed occupancy scheduling profiles of household equipment and the placement in zones. As user behaviour has been shown to be one of the key determinants in residential energy use (Yu et al., 2011; Yun & Steemers, 2011), accurate values of the operation parameters are required for model accuracy and reliability. To establish an estimated occupancy scheduling profile in the energy modelling for each archetype, this study first analysed hourly residential electricity use profile (KOSIS, 2016) and then identified relevant energy standard and guidelines for partially inferred scheduling profiles. **Figure 9** shows the index of relative coefficient of hourly residential electricity use profile for July and August 2015 (the hottest months in Korea). The index was calculated by $Dn/A*1000$ (n=1,2,…,24), where A is the average of all hourly electricity uses for the month, and Dn is average of specific hourly electricity use for the month. In this case, 1000 is used as the base reference line to differentiate high or low energy use by hour (KOSIS, 2016), and there are four temporal segments identified by the transition points of electricity use. Firstly, during the midnight segment, there may be no energy use activities other than operational use of essential home appliances. Secondly, the morning segment from 7 am, certain activity started and increased until 9 am. Thirdly, between 9 am and 17 pm (day time), there was consistent electricity use near to the average, implying mixed activities occurred but there may be no or minimal cooling. Finally, the dramatic change and diversity occurred in the evening/night segment, implying mixed activities including cooling activity.

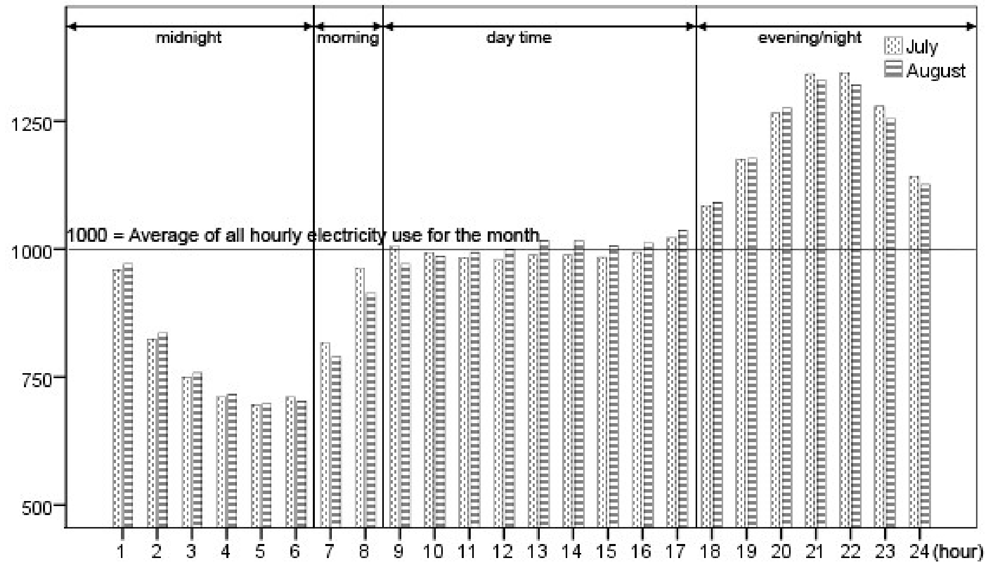
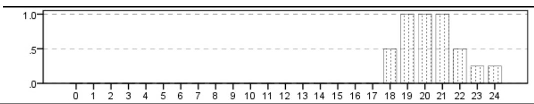
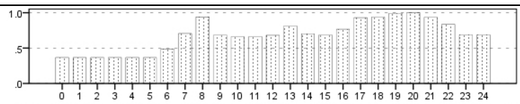
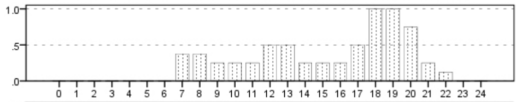
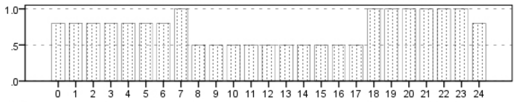
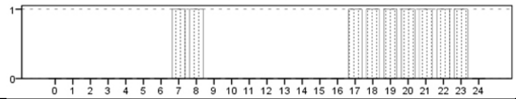


Figure 9. Index of relative coefficient of hourly residential electricity use profile for July & August 2015 (Source: KOSIS, 2016)

Based on the analysis of hourly residential electricity use profile, this study selected a standard and guideline of an occupancy profile database provided by the IES VE package (IES, 2017), which is closest to the profile analysis shown in **Table 8**. Here we assume the reference occupancy profile of household equipment equally applicable to all archetypes. Ideally, the occupancy profile should be calibrated for the model specifically through the iterative model calibration process (Raftery et al., 2011b), as the occupancy profile plays a certain role in energy use, especially weather dependent heating and cooling energy use (Yang and Becerik-Gerber, 2014). Finally, the air-conditioning system capacity profile was based on the IES VE system database for residential HVAC system: nominal coefficient of performance (COP, kW/kW) is 3.125, seasonal COP (2.500), and system seasonal COP (2.000).

Table 8. Assumptions of placement of household equipment and occupancy scheduling profile in zoning inputs. * (*a*: master bedroom, *b*: bedrooms, *c*: bathroom, *d*: kitchen, *e*: living room, *f:* balcony)

	Placement						Occupancy scheduling profile
	a	*b*	*c*	*d*	*e*	*f*	
Lighting	o	o	o	o	o	-	

Machinery	-	-	-	o	-	-	
Cultural	o	o	o	-	o	-	
Cooking	-	-	-	o	-	-	
People (residents)	o	o	o	o	o	-	
Cooling	o	-	-	-	o	-	

Opening profile	Type	Openable area (%)	Opening threshold (°C)	Degree of opening
External window	Sliding	50	26	On continuously
Internal window	Sliding	50	-	Off continuously
Door	Side hung	100	-	Off continuously

4. Results

4.1. Estimated indoor cooling temperature set-points of archetypes in neighbourhoods

The EnergyPlus modelling process was conducted using one apartment household unit located in the middle of an archetype building (i.e. 8th floor in 15-story tall, CD25). Also, the West located apartment was selected, considering the influential solar gain on indoor thermal environment than the East. Taking CD25[R5/A2](84) archetype apartment building as an example, **Figure 10** illustrates the model details, which is R_5 building envelop thermal property in Table 2 and A_2 floor plan in Figure 6 with 84m^2 of actually applied floor area. Firstly, archetypes' internal loads (maximum power consumption) of household non-weather dependent (NWD) equipment (lighting, machinery, cooking and cultural) were estimated through the iterative calibration process of the initial archetype NWD energy model. As shown in **Table 9**, there are spatial (neighbourhood archetypes) variations in the estimations of each NWD equipment component energy use due to the differentiated NWD calibration inputs.

Secondly, the internal heat gains of household NWD equipment were estimated by the determining heat gain ratio to the calibrated internal loads, and 25% was used as the determinant ratio in this estimation except lighting (Hosni et al., 1999). For the lighting, 80% was used, which is the combined radiant (37%) and convective heat (42%) to the total lighting load (100% including 21% of visual light) in case of fluorescent light (Ahn et al., 2014). In addition, for the people, low-density office (20m^2 per person) with light work was benchmarked from CIBSE (2015, pp. 6-2): 4W/m^2.

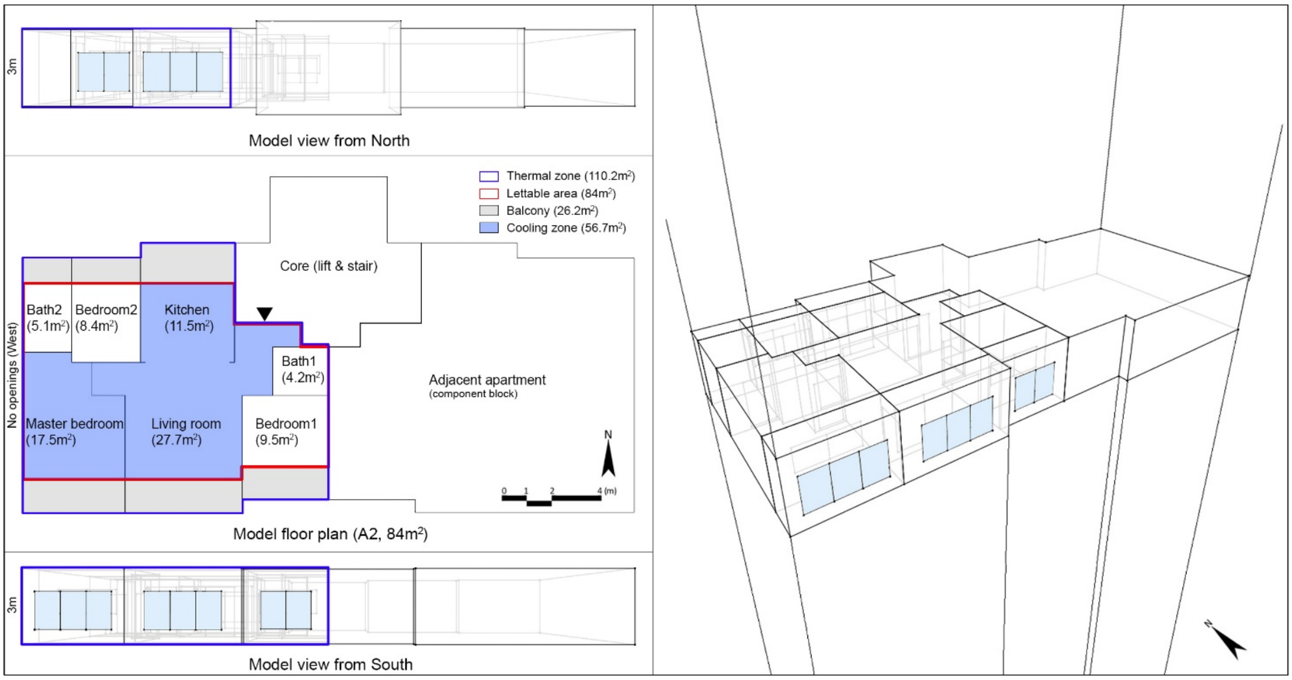


Figure 10. EnergyPlus modelling details of an archetype apartment building in CD25 as an example: A_2 floor plan in Figure 6 and 84m^2 of actual floor area)

Finally, the initial archetype NWD energy model was updated to a cooling energy model through updating the zoning inputs, including calibration data of total August electricity use (NWD + cooling use in Table (6), operating parameters of occupancy cooling scheduling (Table 8), and HVAC and estimated internal heat gains (Table 9). **Figure 11(a)** shows the modelling outputs of the archetypes' August cooling temperature set-points estimated for Seoul, August 2014-2017. There appears a trend that most of the highest set-points occurred in 2016, the year of the largest cooling degree day (CDD) count, while the lowest set-points occurred in 2014 with the lowest CDD count (see Figure 7 - August). Based on the data collected for the August months of 2014-17, **Figure 11(b)** shows the relationship between indoor and external temperatures in Seoul's 18 city-district neighbourhoods, which we propose as a history of residential cooling set-point (RCS) 2014-17. This RCS history would be used later in assessing the maximal month cooling demand of Seoul's housing stock in future years (section 4.2).

Table 9. Profiles of calibrated internal loads (maximum power consumption) and estimated internal heat gains of household NWD equipment based on the determining heat gain ratio (80% for lighting and 25% for others) to the calibrated internal loads. * People (4W/m^2) is equally applied to all neighbourhood archetypes

Archetype in Neighbourhood	Calibrated internal loads (W/m^2)				Internal sensible heat gain (W/m^2)			
	Lighting	Machinery	Cultural	Cooking	Lighting	Machinery	Cultural	Cooking
CD1[R5/A2](94)	4.936	15.111	1.730	20.080	3.949	3.778	.433	5.020
CD2[R3/A2](98)	5.185	15.872	1.817	21.091	4.148	3.968	.454	5.273
CD3[R3/A2](75)	5.322	16.292	1.866	21.649	4.257	4.073	.466	5.412
CD4[R5/A2](87)	5.407	16.553	1.895	21.995	4.325	4.138	.474	5.499
CD6[R4/A2](100)	4.256	13.065	1.492	17.360	3.405	3.266	.373	4.340
CD8[R4/A2](77)	5.019	15.365	1.759	20.417	4.015	3.841	.440	5.104
CD10[R4/A1](64)	5.659	17.323	1.984	23.019	4.527	4.331	.496	5.755
CD11[R4/A2](86)	5.771	17.668	2.023	23.477	4.617	4.417	.506	5.869
CD12[R4/A2](82)	5.189	15.884	1.819	21.107	4.151	3.971	.455	5.277
CD13[R5/A2](83)	5.358	16.402	1.878	21.795	4.286	4.101	.470	5.449

CD15[R3/A3](108)	4.275	12.457	1.510	16.562	3.420	3.114	.378	4.141
CD16[R4/A2](80)	5.169	15.825	1.812	21.028	4.135	3.956	.453	5.257
CD18[R1/A2](89)	5.642	17.271	1.978	22.950	4.513	4.318	.494	5.738
CD19[R3/A2](88)	4.595	14.067	1.611	18.692	3.676	3.517	.403	4.673
CD20[R4/A2](91)	4.640	14.206	1.627	18.877	3.712	3.551	.407	4.719
CD21[R4/A2](102)	4.677	14.318	1.640	19.026	3.742	3.580	.410	4.756
CD22[R5/A2](82)	5.550	16.991	1.946	22.577	4.440	4.248	.486	5.644
CD25[R5/A2](84)	5.186	15.878	1.818	21.099	4.149	3.970	.455	5.275

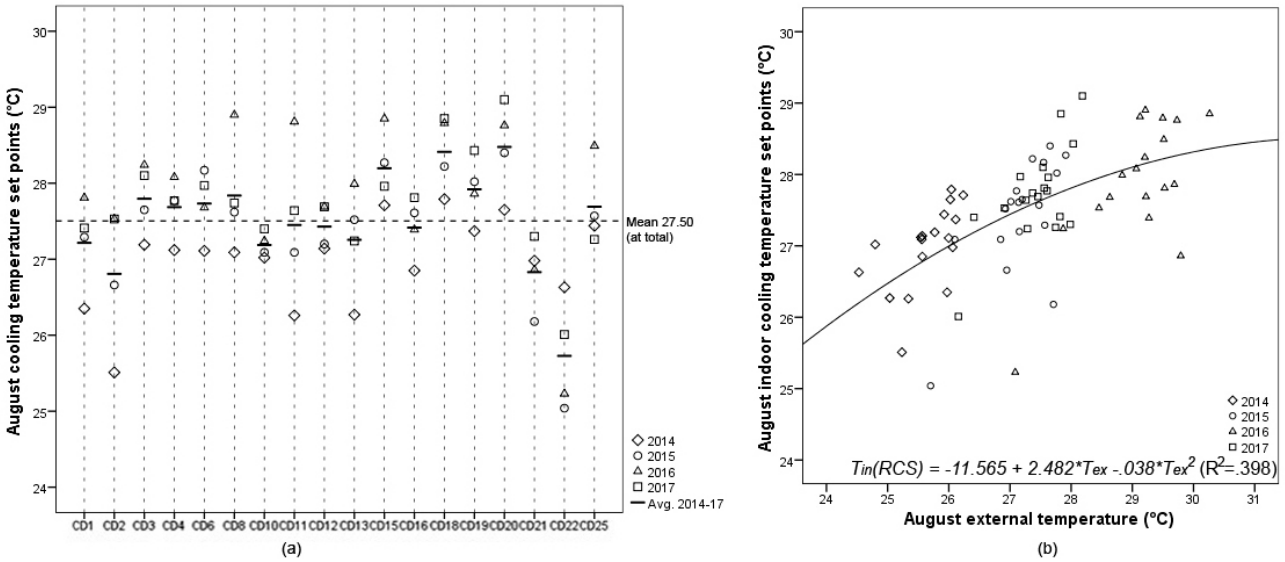


Figure 11. **(a)** Estimated August cooling temperature set-points as an indicator and **(b)** the relationship between indoor and external temperatures as Seoul's residential cooling set-point (RCS) history based on the data collected for the August periods of 2014-17

4.2. Seoul's maximal month residential cooling energy demand model

To identify key determinants affecting maximal month cooling energy use, five independent variables were used in further multiple regression analysis: (1) August average temperature (ºC) in each city-district neighbourhood (Figure 1); (2) NWD household equipment energy use (kWh/m^2, Table 6); (3) estimated present August cooling temperature set-points (ºC, Figure 11(a)); (4) the collected property price (KRW/ m^2) in Figure 3 (c); and (5) U-value (W/m^2*K) of the external wall (Table 2) according to the determined archetypes' thermal characteristics, R_i (section 3.3.1). Considering the current data sample scope and size, a decision was made to perform the multiple regression analysis at a macro-level (a bottom-up approach), that is, an aggregate of all city-district archetypes. Thus, total number of sample was 72, i.e. 4 years (2014-17) * 18 archetypes-in-neighbourhoods. **Table 10** shows the outputs of multiple regression analysis.

Here two parameters were identified as the highest standardised coefficients (Beta) occurred in both: August external average temperature (T_{ex}, ºC) and August indoor cooling temperature set-points (T_{in}, ºC). Arguably, the property price (employed as a socio-economic characteristic) plays a key role in residential energy use, which can be linked to energy affordability. However, as our previous study (Yi and Peng, 2017) showed that the property price is more dominant in cooling energy use under the mild summer condition (July), while it is opposite in August (peak summer month).

Table 10. Coefficients of multiple regression analysis to identify key determinants of August cooling energy use in Seoul

	Dependent	Independent	*B*	Std. error	Beta	Sig.
R^2 = .988, R^2 (adj.)=.987 *p* = .000 N=72 (18 * 4 yrs)	August cooling energy use (kWh/m^2)	(Constant)	1.944	.316		.000
		August external average temperature (^{o}C)	.502	.007	1.288	.000
		NWD energy use (kWh/m^2)	.099	.034	.050	.005
		August indoor cooling temperature set-points (^{o}C)	-.536	.013	-.826	.000
		Property Price (KRW/m^2)	-.001	.000	-.002	.908
		Building envelope (W/m^2*K)	.427	.076	.098	.000

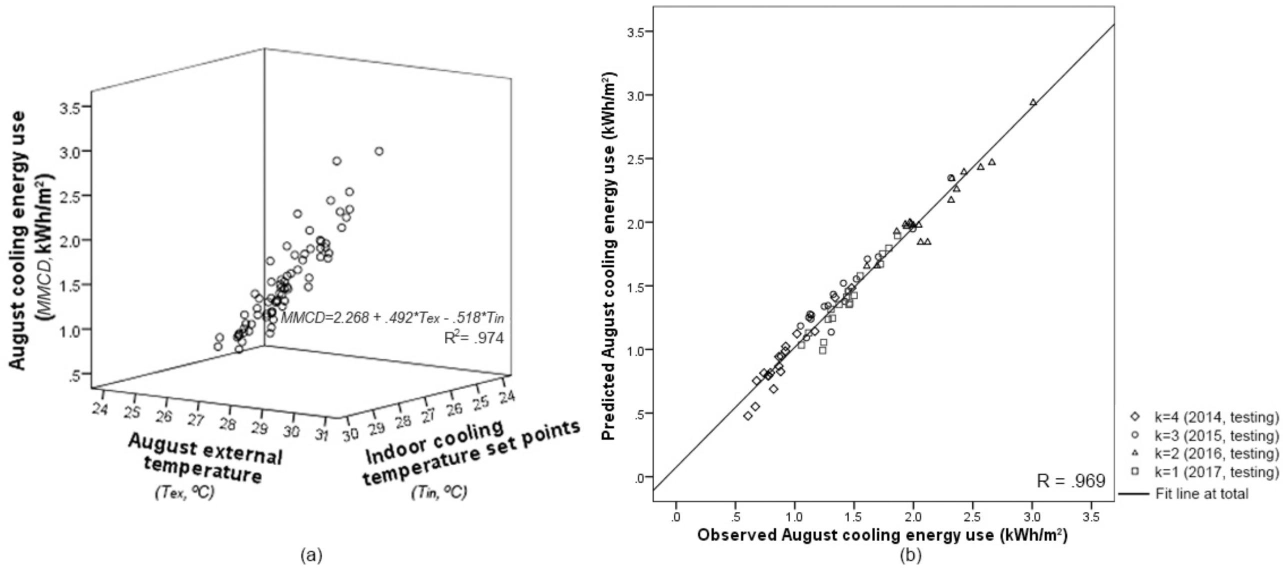


Figure 12. (a) Coefficients of modelling maximal month cooling demands (*MMCD*) based on the August average external temperature (T_{ex}) and August indoor cooling temperature set-points (T_{in}); and **(b)** Coefficient of determination (R^2) between the predicted and observed maximal month cooling energy use at total (aggregate of all four *k*-folds)

Given the two determinants, the Seoul's maximal month cooling energy demand (MMCD) model (kWh/m^2) was generated (**Figure 12(a)**). A *k*-fold cross validation was applied to evaluate the model accuracy from individual neighbourhood to aggregate city scale. Four folds were generated as there were datasets of four years (2014-17). Five criteria were used in the error statistics: mean absolute error (MAE); mean square error (MSE); root mean square error (RMSE); mean absolute percentage error (MAPE); coefficient of determination (R^2). The predicted data represents the output resulted from each *k*-fold multiple regression model while the observed represents the outcome estimated by NWD energy use assumption (Table 7).

Table 11 shows the outputs of the error statistics of each *k*-fold. Overall, the coefficient of determination from the scatter plot between the observed and the predicted was .969 (**Figure 12(b)**), representing about 97% of variance in the observed peak cooling energy use could be explained by the corresponding fourfold multiple regression models. Moreover, all four *k*-fold's errors were near to zero, indicating no over fitting training datasets to the testing sets in all four cases.

Table 11. Coefficients of modelling peak month cooling demands of each *k*-fold to evaluate model accuracy and the error statistics between the predicted and the observed of each *k*-fold. * *y*: maximal month cooling energy use (kWh/m^2), x_1: August average temperature (˚C), x_2: cooling temperature set-points (˚C).

k-fold model $y(x_1, x_2)=a+bx_1+cx_2$	*a*	*b*	*c*	R^2	Sig.
k=1 (2014, 15, 16)	2.488	.498	-.533	.979	.000
k=2 (2014, 15, 17)	2.198	.472	-.496	.951	.000
k=3 (2014, 16, 17)	2.163	.490	-.512	.980	.000
k=4 (2015, 16, 17)	2.381	.493	-.523	.963	.000

Error statistics	MAE (kWh/m^2)	MSE (kWh/m^2)	RMSE (kWh/m^2)	MAPE (%)	R^2
k=1 (testing 2017)	.058	.007	.086	4.31	.930
k=2 (testing 2016)	.087	.013	.114	3.93	.921
k=3 (testing 2015)	.083	.009	.097	6.56	.939
k=4 (testing 2014)	.064	.006	.076	7.88	.918
At total	.073	.009	.093	5.67	.969

To summarise, the main results of the cooling energy demand modelling are as follows:

1. Based on Seoul's open urban data 2014-17, the maximal month cooling energy demand (MMCD) model of Seoul's apartment complex stock is expressed as:

   $$MMCD_{Seoul} = 2.268 + .492 * T_{ex} - .518 * T_{in} \ (R^2 = .974) \tag{1}$$

   where *MMCD* is maximal month cooling energy demand (kWh/m^2), T_{ex} is August outdoor temperature (˚C), T_{in} is August indoor cooling set-point temperature (˚C).

2. A regression analysis of the August cooling temperature set-points (˚C, T_{in}) and the August outdoor temperature (˚C, T_{ex}) gives a residential cooling set-point (RCS) history 2014-17 as:

   $$T_{in} = -11.565 + 2.482 * T_{ex} - .038 * T_{ex}^2 \ (R^2 = .398) \tag{2}$$

3. Given the RCS history 2014-17, Seoul's MMCD model can be further deduced as:

   $$MMCD(RCS)_{Seoul} = 8.260 - .794 * T_{ex} + .020 * T_{ex}^2 \ (R^2 = 1.000) \tag{3}$$

4.3 Scenarios of cooling energy demand of Seoul's housing stock in future climate

Concerning potential summer heat events in Seoul, the MMCD model was applied to generate some scenarios of future cooling energy demand according to the climate projections published by the Korean Meteorological Administration (KMA). Based on MK-PRISM (Kim et al., 2012; Kim et al., 2013a), Seoul's climate change datasets are available on the Climate Information Portal (CIP, 2017). Based on different Representative

Concentration Pathways (RCP), in 2050s, Seoul's highest August temperature is set to reach 29.71ºC (RCP4.5 in 2047) and 30.60ºC (RCP8.5 in 2045). The MM5 mesoscale model (2071-2100) (Grell et al., 1994) downscaled to South Korea (Boo et al., 2006) is set to reach 32.85ºC (+5.5ºC from present Mean of 2014-17, 27.35ºC).

Figure 13 shows that assuming no housing stock renovation, Seoul's residential maximal month cooling energy demand is estimated to increase about 56% (29.71ºC, RCP4.5 2047), 81% (30.60ºC, RCP8.5 2045) and 155% (32.85ºC, MM5 2071-2100) according to the $MMCD(RCS)_{Seoul}$ model (RCS history 2014-17, 27.35˚C, Mean of Augusts 2014-17). Our bottom-up 'archetype-in-neighbourhood' approach to housing stock cooling energy demand modelling seems broadly in line with a previous projection (Lee and Levermore, 2010) where the cooling degree days (CDDs) by the year of 2099 from 1980 were predicted to increase up to 160% while heating degree days (HDDs) would be reduced up to 63% in South Korea. Further modelling of the housing stocks in other major cities in South Korea can be carried out to test if such alignment still holds.

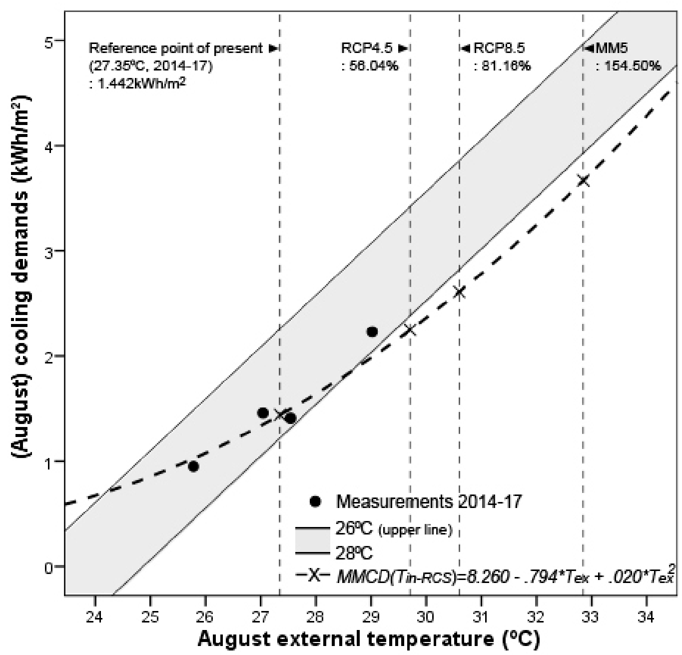


Figure 13. Scenarios of future cooling energy demand of Seoul's housing stock according to three climate projections (RCP8.5 2045, RCP4.5 2047, MM5 2071-2100) with reference to the residential cooling set-point (RCS) history 2014-17 *.26-28ºC: the local (Korea) authority recommendations (MoLiT, 2017)

5. Conclusion and further work

An 'archetype-in-neighbourhood' framework is proposed to address the requirements of cooling energy demand modelling of a city's housing stock. This new framework takes into account building stock interaction with local urban microclimate and residents' cooling energy use history. As shown in the Seoul housing stock study, a peak month cooling energy demand model can be expressed in terms of the city's external air temperatures and indoor cooling temperature set-points during the hottest month period. An urban weather station centric approach to housing archetype development and subsequent EnergyPlus calibration of the archetypes with real energy use data addresses the modelling requirements successfully. The resultant maximal month cooling energy demand model can be plugged in to a city's climate projections to generate future peak month cooling demand scenarios. At present, the future cooling demand scenarios generated do not reflect realistically how the existing housing stock and household composition may evolve in future decades. However, the “business as usual” scenarios could help with identifying targets of cooling demand reduction to be achieved by initiating sustainable renovation of the existing housing stock and neighbourhood environments.

The empirical urban data based approach means that both the maximal month cooling demand model and the residential cooling set-point history need to be updated whenever new data are made available. Further work on developing the data processing algorithms will ensure automation of model update. Given that the frequency, duration and intensity of warm spells and heatwaves are likely to increase in future climate, the archetype-in-neighbourhood modelling framework can aid planning of residential energy supply by tracking closely a city's climate projections and indoor thermal conditions of the housing stock. Residential energy supply planning should also develop more a more responsive and equitable electricity-pricing policy, alleviating plight of summer fuel poverty. There could be an important relationship yet to be uncovered between the energy price for peak summer months and energy use profiles. Residents may sacrifice their thermal comfort during those peak pricing periods. Our ongoing work aims to extend the scope of applicability of this new framework to identify effective pathways of housing stock adaptation that will reduce cooling energy demand while maintain the indoor thermal comfort required of the city dwellers.

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