A HYBRID SIMULATION APPROACH TO EVALUATE COOLING ENERGY CONSUMPTION FOR PUBLIC HOUSINGS OF SUBTROPICS

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A hybrid simulation approach to evaluate cooling energy consumption for public housings of subtropics

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Certificate of Originality

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Abstract

Cooling energy use in building is marked especially in the sub–tropical climate region. Cooling demand in residential sector, different from office or commercial buildings, is significantly subject to occupant decisions where in–depth investigations are found limited. Electricity consumption assessment is conducted in apartments and communal areas for both public and private housing in Hong Kong. It is found to be associated with the occupant load per apartment (tenant) and the gross floor area per building (communal). Residential electricity demand forecast shows that energy consumptions could be associated with housing types. It can be efficiently lessened by increasing the public housing stock and reducing communal energy use.

The Hong Kong public housing sector is being targeted in this study. Surveys have been conducted in existing public housings to understand the housing characteristics, apartment electricity demands, occupant's thermal expectations and air–conditioning usage patterns for further cooling energy saving assessments.

Despite several simulation programs and mathematical expressions are available for cooling energy prediction, these tools are too sophisticated for layman use and limited to relative small scale simulation which are unsupportive or time consuming for city scale housings energy forecast. A hybrid model, integrated by EnergyPlus (EP) and artificial neural network (ANN), is proposed to simulate the cooling energy demands for public apartments. Advantage of this new hybrid model attributes to its quick response time in predicting cooling electricity use available from individual apartment to entire housing sector. Good

agreement on energy prediction of the proposed model is confirmed via peer literatures, government statistics and surveyed public housings.

The model provides a foundation on cooling energy prediction for apartments in public housings that helps prioritize energy conservation in terms of building material use, construction design, climate change and occupant behaviour in air–conditioning needs. Impacts on public residential cooling energy consumption are evaluated regarding to sensitivity of external wall and window material selection, window size reduction, shading extension, building orientation and apartment size control. Significant energy reduction is recorded with material thermal insulation enhancement and a larger stock of medium size flats (30–50m^2) in the public housing sector.

Occupants' thermal comfort conditions in their living environment are revealed and corresponding thermal comfort zones are established to identify the thermally neutral conditions perceived by occupants for potential cooling energy saving. The cooling energy consumption is specified by optimal comfort temperature set–point and outdoor temperature variation due to climate change. Besides, home air–conditioner operation criteria are studied with respect to occupants' thermal expectation, socio–economic group and occupancy schedule. More precise cooling demand, validated by energy use in surveyed households, is confirmed by implementing the updated occupant behavioural air–conditioning operation schedule instead of fixed occupancy patterns for simulation in residential buildings.

The above findings are integrated into strategies, considering both housing design arrangements and occupants' thermal comfort behaviours, of cooling energy reduction in public housings. Since cooling demand in public apartments is occupant behavioural

dependent, incentive with an example of energy pricing strategy is proposed to reduce cooling electricity use specifically in the summer months from May to October. The achievements are summarized into a cooling energy calculator for layman use to enhance cooling energy saving awareness in their own living. Findings present in this study can be a directory framework for future cooling energy evaluation in residential buildings, especially focus on the occupant behavioural air–conditioning operation and criteria of energy saving incentives.

Publications related to the thesis

Cheung, C.T., Mui, K.W., Wong, L.T., 2013. Energy efficiency of elevated water supply tanks for high-rise buildings. Applied Energy 103, 685–691.

Cheung, C.T., Mui, K.W., Wong, L.T., Yang, K.C., 2014. Electricity energy trends in Hong Kong residential housing environment. Indoor and Built Environment 23(7), 1021–1028.

Cheung, C.T., Mui, K.W., Wong, L.T., 2015. A hybrid simulation approach to predict cooling energy demand for public housings in Hong Kong. Building Simulation. Accepted on 28 May 2015, DOI: 10.1007/s12273-015-0233-8.

Wong, L.T., Mui, K.W., Cheung, C.T., 2014a. Bayesian thermal comfort model. Building and Environment 82, 171–179.

Wong, L.T., Mui, K.W., Cheung, C.T., Lee, E.W.M., Lee, M.C., 2014b. Performance impact of indoor environment policy implementation for airside system in Hong Kong Grade A offices. Building Services Engineering Research and Technology 38 (5), 525–534.

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List of abbreviations

AC	Air–conditioning
ANN	Artificial neural network
CDA	Conditional demand analysis
CO_2	Carbon dioxide
CDD	Cooling degree–days
CLP	China Light and Power
COP	Coefficient of performance
CVRMSE	Coefficient of variation of root mean square error
EMSD	Electrical and Mechanical Services Department
EP	EnergyPlus
GDP	Gross domestic product
GFA	Gross floor area
HK$	Hong Kong dollar
HDD	Heating degree–days
HOS	Government subsidies home ownership scheme
HVAC	Heating, ventilation and air–conditioning
MRE	mean relative error
OTTV	Overall thermal transfer value
PMV	Predicted mean vote
PPD	Predicted percentage of dissatisfaction
PRH	Public rental housings
PRI	Private housings
PRI_{CH}	Private housings with club house

RETV	Residential envelope transmittance value
RMSE	Root mean square error
PUB	Public housings
SHGC	Solar heat gain coefficient
SHR	Sensible heat ratio
SVM	Support vector machines
TDP	Temperature dependent pattern
TMY	Typical meteorological year
TRY	Test reference year
TSV	Thermal sensation vote
UEC	Unit energy consumption
WWR	Window to wall ratio

List of symbols

A	area (m^2)
a	neuron output
B_m	Cooling energy benchmark in summer month m
b	bias
b_f	building shape factor (m^{-1})
C_L	clothing value (clo)
C_{pa}	heat capacity of air (kJ kg^{-1} $^oC^{-1}$)
D	diameter of the globe
d	power density (Wm^{-2})
E	Annual electricity consumption (GWh yr^{-1}, TJ yr^{-1})
E_c	Annual cooling electricity consumption (TJ yr^{-1})
e_{BC}	electricity intensity of communal sector (kWh yr^{-1} hd^{-1})
e_T	electricity intensity of tenant sector (kWh yr^{-1} hd^{-1})
f_{tansig}	tan–sigmoid transfer function
$f_{purelin}$	linear transfer function
G	G–factor, fraction of window area exposed to direct sunlight
g_{sol}	global solar radiation (Wm^{-2})
H	heat gain (W)
h	height (m)
h_{fg}	latent heat of evaporation of air (kJ kg^{-1})
h_T	total building height (m)
IW	input weighting
J	weighting factor for air velocity in operative temperature calculation

K	thermal conductivity (W m^{-1}K^{-1})
L_{lat}	Latent load (W)
L_{sen}	Sensible load (W)
LW	layer weighting index
l	length (m)
M	Material alternatives
M_e	Metabolic rate (met)
m	measured data sample
N	number of occupant
N_{ap}	number of apartment
n	number of parameter or sample
O	occupant load (hd)
O_f	occupant load factor (m^2 hd^{-1})
O_a	occupant area ratio (hd m^{-2})
P	input parameter
p_w	vapour pressure (kPa)
p_{ws}	saturated vapour pressure (kPa)
Q	heat transfer (W)
R	correlation coefficient
R–$value$	thermal resistance (m^{2}K W^{-1})
R_h	relative humidity
S	Shading construction alternatives
S_c	shading coefficient
S_d	standard deviation
SF	solar factor

s	simulated data sample
T	temperature (°C)
TD_{EQr}	equivalent temperature difference of roof
TD_{EQw}	equivalent temperature difference of wall
t	time (hour)
U	U–value, thermal transmission (W $m^{-2}K^{-1}$)
V	Flow rate (m^3s^{-1}, Ls^{-1})
V_{BC}	space volume of building (m^3)
v	velocity (ms^{-1})
W	Window construction alternatives
w	moisture content (kg kg^{-1}, dry air)
X	thickness of material / insulation
x	randomly selected time frame (hour)
Z	meteorological index Z
Δ	difference
α	confident level
β	solar Altitude angle (°)
ε	emissivity
ζ	clearness index
θ	adjacent angle of overhangs (°)
q	random number taken from a pseudo random number set
λ	Cooling energy index (kWh m^{-2})
ϕ	occupancy schedule
ϕ_{AC}	air–conditioning (AC) operation schedule
ϕ_{in}	internal load schedule

ψ	occupant load variation factors
η	percentage of housing sample
ρ	air density (kg m^{-3})
μ	mean value
σ_h	horizontal shadow angle (°)
σ_v	vertical shadow angle (°)
τ	period (hour)
–	operator of sample average
~	distribute function

Subscripts

0, 1, 2…	of conditions 0, 1, 2…
a	of indoor air
BC	of building
C	of communal
dry	of dry bulb
e	of external wall
en	of envelope
es	of estate
eq	of equipment
fl	of floor
g	of globe
h	of household
i, j	of sample or parameter
in	of internal

inf	of infiltration
k	of time by hour, 0, 1, 2 … (hour)
L	of large size apartment
li	of lighting
M	of medium size apartment
m	of month
max	of maximum
neu	of neutral
o	of outdoor air
op	of operative
out	of output
p	of interval by hourly or monthly
r	of roof
rad	of radiant
rf	of roof fenestration
S	of small size apartment
T	of tenant
tar	of target
total	of total
vent	of ventilation
wd	of window
wet	of wet bulb
wl	of opaque wall
∞	of infinite

Chapter 1

Introduction

1.1 Background

Urbanization is a global issue of population shift from rural to urban areas (WUP 2014). The increased population in urban city can initiate a number of related issues including energy consumption, housings, ruining of environment and series of society and political problems. Severity of urbanization effects can be worsened by population expansion, where the world population would be raised up to 8 billion in next decade (WPP 2013).

Over consumption on energy and resources, lack of living places and abuse of environment are observed especially in several high population dense urban countries or areas such as Hong Kong (% of urban population: 100%), Singapore (100%), Belgium (98%), United States Virgin Islands (95%), Japan (93%), Argentina (92%), Netherlands (90%), Republic of Korea (82%), United Kingdom (82%) and others (WUP 2014). High-rise residential building can be a solution to accommodate the expanded population with limited landscape. But extra energy is consumed in these skyscrapers for water supply and internal transport (Cheung et al. 2013). Besides, increasing greenhouse gas emission may take further step in damaging the environment and aggravating the impacts on global warming. In return, extra air–conditioning (AC) demands are required in maintaining satisfactory indoor thermal comfort. A vicious cycle between standard of livings, energy uses and abuse of environment is thus being established.

Energy conservation is without doubt a way out of the vicious cycle. Researchers have been working for decades on minimizing thermal energy consumptions in buildings (Lam 2000, Cheung et al. 2005, Shimoda et al. 2007, Mirsadeghi et al. 2013, Vakiloroaya et al. 2014). Despite a number of epochal inventions on building materials, construction designs and system efficiency enhancements, cooling energy demands in buildings are breaking new high record per year (Perez-Lombard et al. 2008). Aren't we underestimating the impacts of global warming and cooling energy demand? Or a wrong focus had been highlighted in this research area? No matter what are the answers, a more comprehensive study on cooling energy consumption in buildings is necessary to understand the whole picture. This thesis aims to point out the major shortcomings in current building cooling energy studies and to provide alternative solutions in accordance with the recognized limitations. The key arguments of this thesis are further introduced below.

1.2 Limitation to existing cooling energy simulation tool

Building energy simulation tools are widely adopted for evaluating cooling energy demands. Existing simulation tools can be briefly classified as physical and statistical model using bottom–up approach (Swan and Ugursal 2009, Kavgic et al. 2010). Purely physical simulation approach, including computer simulation software (EnergyPlus, DOE–2, ESP–r and others), can perform detailed simulation output for advance energy analysis without using any historical data support. However, physical simulation requires complex model set–up and lengthy simulation time which may not be cost effective for large scale simulation

(Catalina et al. 2008). Besides, this simulation approach is not flexible to reflect the impact due to occupant behaviour variations (Coakley et al. 2014).

On the other hand, purely statistical models, such as regression, artificial neural networks (ANNs) and support vector machines (SVMs), can give quick and accurate response according to the parameter inputs. These models are good at estimating non–linear relationships between inputs and output data and the simulation speed is superior to the physical method (Li and Wen 2014). The statistical approach, however, requires a large database to identify the input–output relationships, where insufficient data would affect the model prediction performance (Paudel et al. 2014). In addition, physical meaning is not necessary for model architectural development, which the reliability of energy forecast is criticized by some scholars (Ahmad et al. 2014).

The limitation of both approaches can be minimized by hybridizing the physical and statistical technique to develop a new simulation tool. A number of scenarios are first simulated using physical approach, while the statistical model is trained by this tailor–made input–output database. The strength of both physical and statistical approach is maintained using the hybridizing method, while individual shortcomings can be diversified.

1.3 Accuracy in predicting AC operation in residential buildings

Conventional simulation program which requires standard schedule, by means of time and set–point condition, to operate air–conditioner in indoor space may not be adequate to reflect actual occupant AC usage patterns. Operation of AC in apartment is dominated by occupant behavioural, physical, demographical and socio–economical backgrounds (Yun and Steemers 2011, Schweiker and Shukuya 2009). Difference in AC usage pattern is expected among groups of resident. Decision of AC start time and duration of utilization for different target groups shall be identified.

Even though the AC usage pattern of specific occupant group is being identified, actual AC functioning hours will vary day by day. However, existing simulation tools are not designed for implementing probabilistic AC operation schedule, while accuracy of simulation performance with fixed schedule is questioned (Ren et al. 2014). A probabilistic approach to evaluate AC operation in apartment is therefore urged to represent the variations of daily AC demand. Parameters used in this probabilistic method should be consistently designed but flexible to identify AC usage pattern for individual target group.

1.4 Effectiveness of cooling energy saving strategies

Research on cooling energy saving in buildings has been discussed over two decades. However, an increasing trend of cooling energy consumption in building is continuously observed (Li and Wen 2014). A number of strategies regarding to cooling energy reduction have been published including alternatives of building materials and construction designs to minimize envelope heat gain, improvement of building cooling system efficiency and implementation of policies in altering energy price to depreciate energy use (Cheung et al. 2005, Bojic and Yik 2007, Sa'ad 2009, Wong et al. 2010). Notwithstanding strong correlation is confirmed between occupant's decision and cooling energy demand in apartment, limited study is focused on encouraging or enhancing occupant's AC energy saving awareness.

Enhancement of energy saving awareness may not be successful by reporting saving potential with strategies that are not related to personal benefits. In other words, improved electricity charging system with higher rebate rate in electricity tariff corresponds to larger energy saving in apartment can be a positive remote cause to encourage occupant's energy saving decision. Meanwhile, a cooling energy prediction tool designs for layman usage can enhance occupant's understanding on their current AC electricity usage pattern. This prediction tool should be simple to function but capable to quantify or even visualize the current level of cooling energy demand as compared with other households within the housing stock. Furthermore, recommendations of achievable energy saving strategies shall be listed, such as raising air–conditioner set–point and shortening AC operation hour, to compare the difference in money and energy saving.

1.5 Selection of target city, Hong Kong

Geographical location of Hong Kong is at (22^{o}N 114^{o}E), which is situated in the subtropical climate region. A greater building cooling than heating demand is required, due to its climate condition with average outdoor air temperature of 28.3^{o}C and 16.8^{o}C respectively in summer and winter months (HKO 2014). Besides, a trend of increasing yearly averaged outdoor air temperature of 22^{o}C to 23.5^{o}C from year 1893 to 2013 was reported by the Hong Kong Observatory. Energy consumption for space conditioning contributed 23.4% (13423TJ yr^{-1}) of total residential energy expenditure in year 2011, where an increase of 883TJ was recorded as compared with the value in year 2001 (EMSD 2013).

Hong Kong is one of the densest populated cities, which accommodating 7 million people in 1067km^2 land areas. High–rise residential building is commonly found in satisfying the population needs (Wong et al. 2008). According to the housing figures in Hong Kong, the number of flats for private and public housing in year 2003 to 2013 has been increased from 1,258,000 to 1,458,000 and 679,000 to 766,000 respectively (HF 2013). Housing needs would be one of the prime livelihood concerns due to increasing population trend (PPD 2009). Together with issue of global warming and increases in housing stock, higher space cooling energy is expected in future. Prior to minimize the heat gain from outdoor environment, effective envelope design is necessary for residential buildings, especially benefits for high–rise public housings with standardized block layout.

Residential energy consumption is reported to be significantly correlated with occupant behaviour and socio–economic factors (Tso and Yau 2003, Yun and Steemers 2011). A survey conducted by the Hong Kong government has confirmed 65.4% of the respondents were willing to reduce electricity consumption when receiving an increased electricity charge (THSH 2004). However, current electricity charging system in Hong Kong is not favourable in encouraging energy conservation. Potential of residential energy saving, in particular to the AC energy use in summer months, is observed by reviewing current energy charging system with higher incentive strategies.

Taking Hong Kong as an example, the aim of this study is to develop a hybrid cooling energy prediction model to estimate cooling energy consumption in public residential sector. Sensitivity tests are conducted to evaluate the energy impacts with changing building parameters. Assessments are employed to investigate the relationships between cooling demands and occupant behaviour on thermal environment criteria and AC operation patterns. Lastly, a new energy rebate scheme adopting the benchmarking system with higher incentive is proposed to enhance energy saving in the summer months.

1.6 Objectives

To evaluate cooling energy demand in residential buildings is a major step in achieving building energy conservation as well as reducing total CO_2 emission rate. Concerns arisen from improving residential cooling energy saving potential lead to the needs in comprehensive evaluation on building construction, climate change, and occupant behavioural aspects. Besides, research base energy saving strategies at occupant's end–use level should not be overlooked.

The objectives of this study are:

1. To understand the thermal energy consumption patterns and its contributors in public housing sector in Hong Kong;
2. To develop a new hybrid cooling energy simulation model to evaluate the impact of each energy contributor;
3. To recommend more effective and realistic methods for cooling energy prediction and energy conservation strategy implementation in public housings;
4. To demonstrate an example in strengthening the linkage between professional research analyses and layman energy saving actions.

1.7 Research scope

In regard to the objectives listed above, this study is divided into the following four tasks:

Task 1: Selection of target housing group

Surveys on electricity consumption are conducted for the three common housing types in Hong Kong residential sector, including public rental housings (PRH), home ownership scheme flats (HOS) and private housings (PRI). Besides, the luxury type of private housing together with club house (PRI_{CH}) is also considered. Electricity consumption is recorded in both apartments and communal areas (including club housing) to understand the total electricity expenditure in each housing type. The electricity use associated with the highest correlation factor in each housing types is studied. Total electricity consumption in residential sector with various housing type combinations is estimated. The results can be useful in identifying the recommended housing type for future residential development in terms of greater energy saving potential. The selected housing group is used as target housings in developing cooling energy simulation model in Task 2.

Task 2: Development of hybrid cooling energy simulation model

The development of cooling energy simulation model in this study includes 3 steps of procedures as shown below:

Step 2.1 Database for input parameters

To identify the potential building–related parameters for public housing development, existing housing details of various block types are reviewed to obtain the following: apartments per floor, apartment floor area A_{fl} (m^2), total external wall and window area A_e (m^2), window area A_{wd} (m^2), opaque wall U–value U_{wl} (W $K^{-1}m^{-2}$), window U–value U_{wd} (W $K^{-1}m^{-2}$), window shading coefficient S_c, vertical shadow angle σ_v (degree), orientation (degree) and the numbers of each block type. Possible ranges for these parameters are collected from current design practice, standards, open literature data and government housing statistics.

Step 2.2 Develop the hybrid EP–ANN model

Based on the parameter ranges and representative public housing blocks identified in Step 2.1, series of hourly envelope heat gains H_{en} (W) are simulated via a widely used non–commercial building energy simulation tool EnergyPlus (EP). From the simulation cases, the input parameters (including outdoor temperature T_o (^oC), day of a year, hour of a day, air temperature set–point T_a (^oC), and existing housing parameters (as stated in Step 2.1) and the corresponding energy output values are randomly extracted to construct input/output files. A total of about 60000 apartment configuration sets are simulated via EP with parameters randomly chosen for the corresponding parameter ranges. These input/output files are used for the database in training a multi–layer artificial neural network (ANN) with parameters randomly chosen for the corresponding parameter ranges. The trained ANN model is capable to provide a quick response on envelope heat gain value according to corresponding inputs.

Step 2.3 Evaluate the building cooling energy demand

Algorithm for cooling load prediction is expressed as the sum of building envelope heat gain, ventilation load and the internal load. The hourly envelope heat gain is calculated by the hybrid EP–ANN model in Step 2.2, while the hourly ventilation and internal heat gains are evaluated by physical expressions and supporting findings in literatures. Together with the consideration of air–conditioner coefficient of performance (COP) and operation schedule, cooling energy demand in an apartment, a building block or housings of regional scale can be estimated.

The proposed cooling energy prediction tool is used to predict the cooling energy consumption in an existing public residential sector and to test the impacts of cooling consumption with sensitivity change of input parameters. Suggestions for new public housing designs and strategy considerations in terms of cooling energy reduction are recommended.

Task 3 Study on occupant behaviour in apartment

Physical measurement and subjective survey will be conducted in some apartments to understand occupant's thermal comfort and air–conditioner operation criteria. A probabilistic approach is proposed to estimate the AC operation schedule of different occupant groups classified by housing types, age, income, education level, job nature and energy saving awareness. By integrating the model proposed in Task 2, the cooling energy saving potential for different occupant groups is identified. Example applications such as cooling energy saving potential with shortening AC operation hour and enhancing occupant energy saving awareness are demonstrated.

Task 4 Development of a layman usage cooling energy saving prediction program

With the simulated energy data of existing public housing sector, an energy consumption index in the summer months, i.e. May to October, is developed to quantify the level of cooling energy use per apartment. This index is used as a benchmarking parameter of cooling energy demand in an apartment to distinguish the level of energy saving and is presented in a star–rating system for easier understanding. An example of new electricity pricing system with higher incentive for summer months is demonstrated. The benchmarking index is integrated with the proposed model in Task 2 to provide information of cooling energy consumption profiles for layman understanding. Potential energy saving strategies and the improved cooling energy usage profiles are included.

1.8 Organization of thesis

This introductory chapter has presented the background and motivation in conducting this study. The ultimate goal is to develop a quick response and high flexibility cooling energy prediction tool, in understanding the strategies of cooling energy improvement for public housing sector in Hong Kong. The objectives and scope of research were identified. The major structures and findings of this study are presented in the following chapters in this thesis and a flowchart is summarized in Figure 1.1.

Chapter 2 reviews the influencing factors and available tools for building thermal energy simulation. The influencing factors for building thermal energy performance are categorized in groups and the energy impact of corresponding parameters is shown. The fundamental theories and examples of different building energy simulation models are reviewed and the strength and limitation in each approach are discussed. Besides, the strategies of cooling energy saving, especially for residential sector, are grouped for comparison.

Chapter 3 aims to select the target housing group in an existing residential sector for further cooling energy evaluation. The electricity consumption for both tenant (apartments) and communal area (public utilities) are surveyed in each housing types and analyzed for comparison. Electricity demands in residential sector with different housing mix combinations are predicted. The housing group which has greater energy saving potential for sustainable residential development is selected.

Development of a hybrid cooling energy prediction model is presented in Chapter 4. The information of existing public housing characteristics is collected via literatures and standards. A hybrid EP–ANN cooling energy simulation model is developed using the surveyed ranges of input parameters and other supporting information from open studies. Cooling energy predictions for an apartment, a housing block and a region scale flats are available. Prediction performance of the proposed model is validated by peer literature, government energy statistics and some surveyed apartments.

Chapter 5 evaluates the cooling energy consumption in a residential sector with sensitivity change of building material selections and construction designs. Simulation flexibility on a single apartment and an entire housing sector using the proposed model mentioned in Chapter 4 is demonstrated. Alternatives of material section on external wall and window glazing are proposed. Besides, cooling energy improvement of construction designs including window area, floor area, external wall area, shading and building orientation are discussed.

Cooling energy impact based on occupant behaviour including thermal comfort and air–conditioner (AC) operation are presented in Chapter 6. Physical measurement and interview survey are conducted in some public apartments to understand occupant's thermal comfort needs. Meanwhile, their tendency of operating air–conditioner is recorded. A probabilistic approach is proposed to estimate the occupant's AC operation pattern based on the surveyed findings. Applications of cooling energy assessment with shorter AC operation hour and enhanced occupant's energy saving awareness are demonstrated.

By integrating the findings in previous chapters, a forecast on cooling energy demand in future public housing sector is presented in Chapter 7. Alternative electricity charging scheme is suggested with higher incentive to reduce cooling demand in summer months. An electricity consumption index is applied as a benchmarking parameter to quantify the level energy saving per apartment. Application of the charging scheme and cooling electricity benchmark is demonstrated via an apartment cooling energy prediction sub–program for layman use.

Finally, Chapter 8 summarizes the key findings and draws a conclusion of this thesis. The significance and value in previous chapters are emphasized. Besides, some future research directions are highlighted.

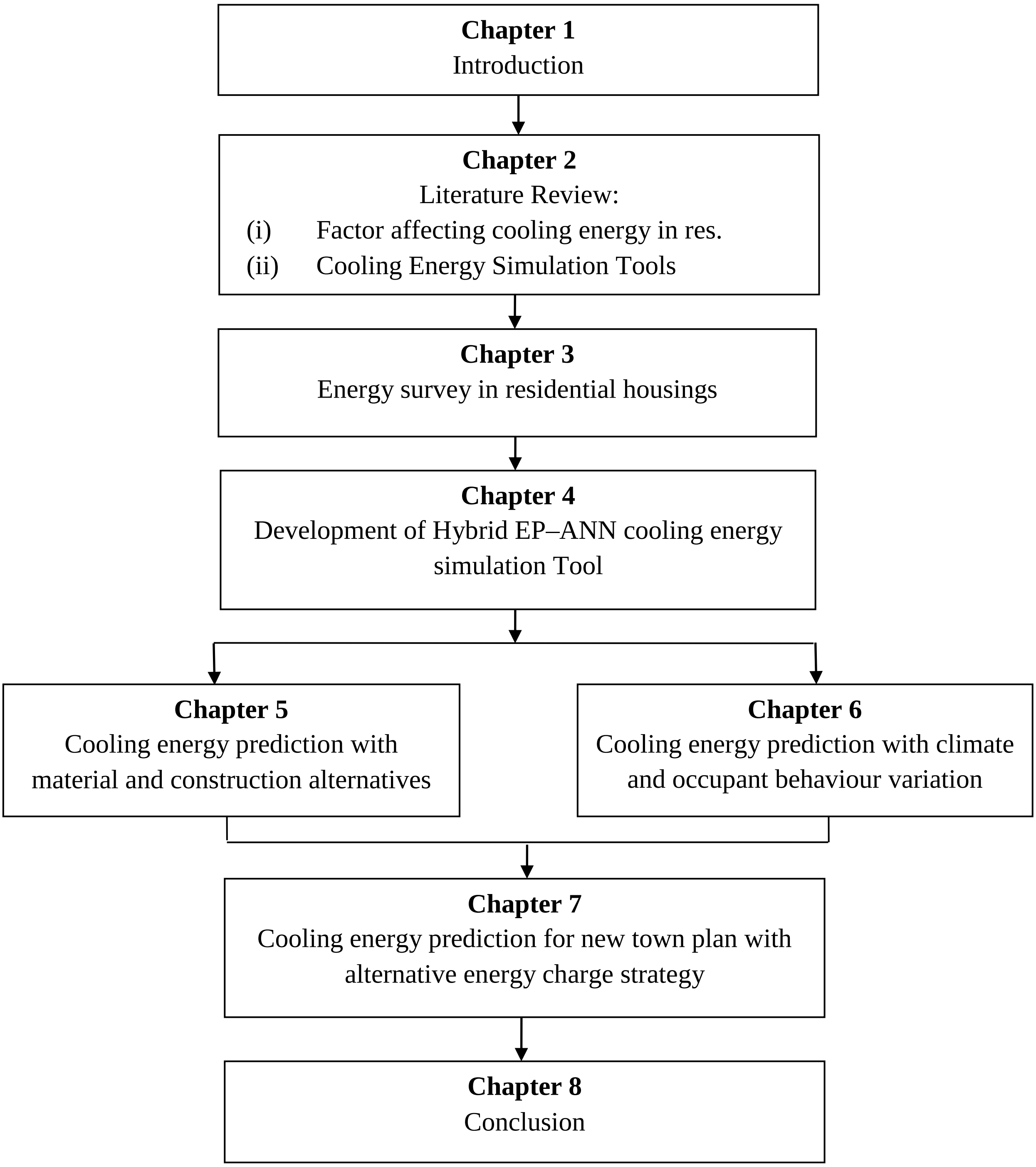


Figure 1.1 Organization of thesis

Chapter 2

Literature Review: Building cooling energy related parameters and simulation tools

2.1 Introduction

Regarding the same performance on indoor thermal environment demand and practice, an trend of increasing cooling energy consumption in buildings is confirmed in foreseeable future due to climate change with raising outdoor temperature. In view of implementing effective energy conservation measures, the influencing factors for building cooling energy consumption have to be identified. Besides, methods of building energy prediction are important in specifying the simulation performance for various strategies. This chapter is organized into two sections to review (i) the factors affecting cooling energy consumption (mainly focus on residential building) and (ii) the types of building energy simulation tools available in the existing field.

2.2 Factors affecting cooling energy use in residential buildings

The amount of heat gain in an indoor space can be attributed by three components: (i) envelope heat gain, (ii) ventilation heat gain and (iii) internal heat gain, where the internal heat gain can be sub–classified into lightings, equipment and occupants' load (Wong et al. 2008). The envelope heat gain through wall and fenestration to indoor space is a major topic in building energy prediction studies, since it contributes the highest portion of cooling demand in various types of buildings (Lin and Deng 2004; Aktacir et al. 2010). Cooling energy prediction in buildings is complex and it relates to a group of factors including the building material and construction characteristics, climatic variation, occupant's background and behaviour considerations (Tham 2013, Turhan et al. 2014). Besides, the use of cooling system and its efficiency may also significantly influence the energy performance (Shimoda et al. 2007, Neto and Fiorelli 2008). In addition, some other factors not belonging to, but indirectly affecting, the issues mentioned above also report with significant effect to the building energy consumption, such as socio–economic and demographic issues (Tso and Yau 2003, Goldblatt et al. 2005, Yang et al. 2010). This section reviews the impacts of these influencing factors for building cooling energy consumption, especially for residential buildings, and a detailed classification is illustrated in Figure 2.1.

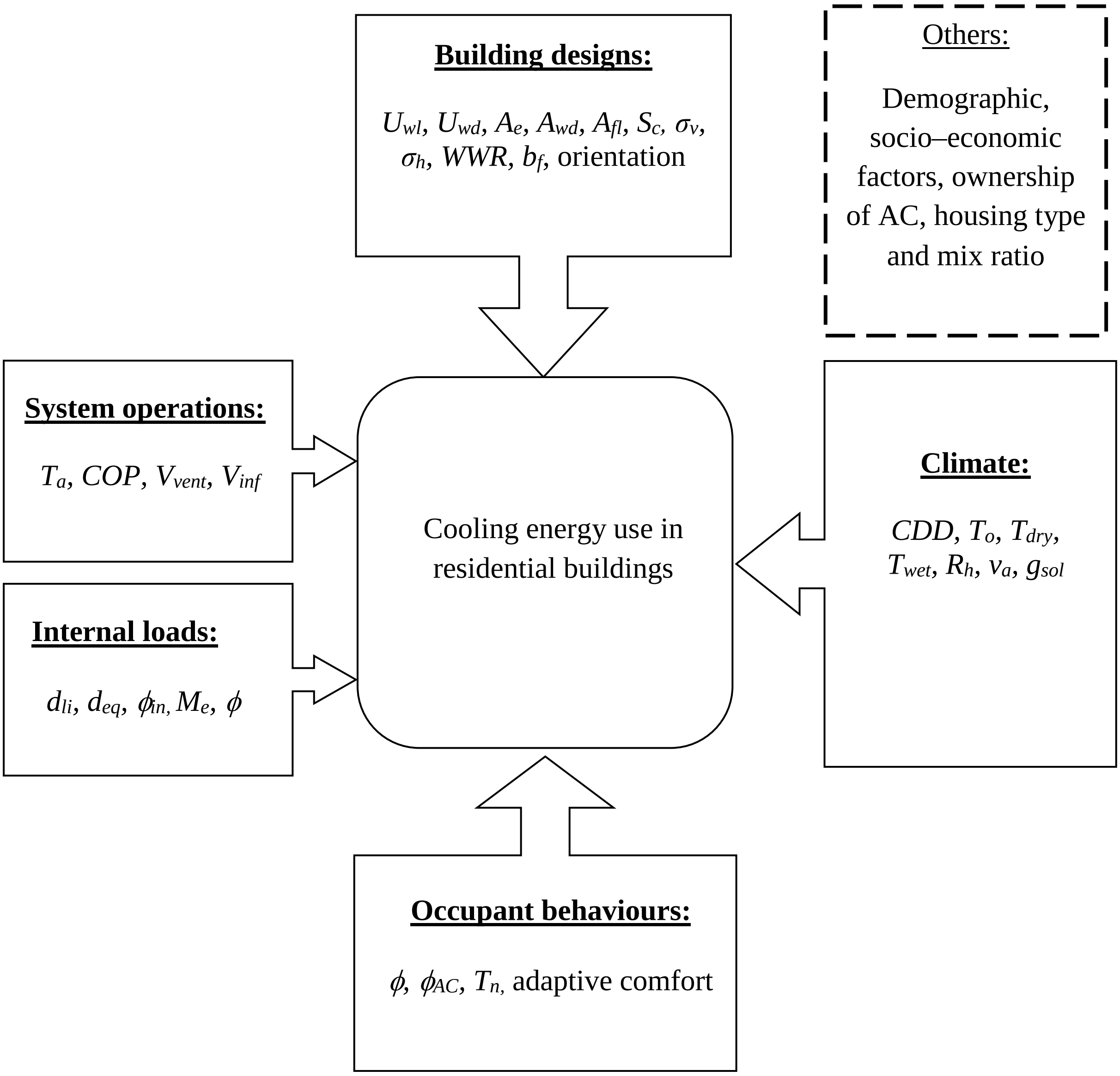


Figure 2.1 Influencing factors of building cooling energy consumption

2.2.1 Building designs

Building materials properties (U_{wl}, U_{wd} and S_c)

U–value is an index for thermal transmission. It is defined as the rate of heat transfer in a unit surface area of building element including wall, fenestration or roof with one unit (1K) temperature difference. It represents also the reciprocal of the R–value (total thermal resistance, $m^2K\ W^{-1}$) for the building material components. Mathematical expression of U–value ($W\ m^{-2}K^{-1}$) is illustrated in Equation 2.1, where Q (W) is the heat transferred through the material, A (m^2) is the area, ΔT (K) is the temperature difference between two surfaces, X (m) is the thickness of the material and K ($W\ m^{-1}K^{-1}$) is the material's thermal conductivity (Al–Homoud 2005).

$$U = \frac{Q}{A\Delta T} = \frac{1}{R-value} \quad ; \qquad R-value = \frac{X}{K} \tag{2.1}$$

U–values of opaque wall U_{wl} and window glazing U_{wd} are often being selected as parameters to identify the heat transfer through conduction from building fabric, even being implemented in building energy simulation programs (Mirsadeghi et al. 2013), where a higher value indicates greater heat transmission and thus reveals a smaller thermal insulation. The values of U_{wl} and U_{wd} are dependent to the building construction materials and are available in international standards and open literatures (ASHRAE–90.1 2013, ISO–10077–1 2009, Reilly et al. 1992). Regulations of U–value for various building enclosures in different counties were reviewed by Rodriguez–Soria et al. (2014).

Different from the opaque wall, solar radiation can transmit through window into the indoor space. Thermal insulation of fenestration is therefore accounted with one more insulation component for radiation. The shading coefficient S_c is an index to quantify thermal insulation of glazing, specifically it is identified as the ratio of solar radiation passed through the glazing to the solar energy passed through the reference glazing (i.e. 3mm clear float glass). The value of S_c can be approximated by the solar heat gain coefficient (*SHGC*) divided by 0.87. Equation 2.2 presents the expression of S_c for glazing G.

$$S_c = \frac{solar-heat \quad through \quad glazing \quad G}{solar-heat \quad through \quad reference \quad glazing} \;;\; S_C = \frac{SHGC}{0.87} \tag{2.2}$$

A higher value of S_c represents lower resistance of solar radiation into the indoor space. S_c of a standardized 6mm clear glass is about equal to 0.96, while glass type of high reflectivity such as tinted or low–emissivity glass may obtain a S_c value down to 0.7 (Chua and Chou 2010). More references of S_c for different glazing type are available via standards and open literatures (ASHRAE–90.1 2013, ISO–10077–1 2006, Reilly et al. 1992). Besides, the thermal performance databases for windows or fenestration products can be identified via computer software, such as Fenspec and Catalogue (Sadineni et al. 2011).

Since the heat gain through building envelope contribute the highest portion among other heat sources (Lam 2000, Lin and Deng 2004), the effects of insulation to building thermal energy use are commonly discussed via simulation, and analytical studies (Shariah et al. 1997, Cheung et al. 2005, Kolaitis et al. 2013, Aktacir et al. 2010, Alaidroos and Krarti 2015). In Feng (2004) study at Wuhan city, an exponential increase of building thermal energy consumption was evaluated by raising the external wall *U*–value from 1 to 2 $Wm^{-2}K^{-1}$ and an optimal value for U_{wl} = 1.5 W $m^{-2}K^{-1}$ was suggested in terms of energy saving and cost effectiveness. Simulation results conducted by Wang et al. (2007) in a Singapore residential sector showed larger difference between indoor ambient and outdoor mean radiant temperature, especially in hot afternoon, by reducing U_{wl} from 3.5 to 1.5$Wm^{-2}K^{-1}$, where U_{wl} less than 2$Wm^{-2}K^{-1}$ for north and south facing fabric was recommended to avoid thermal asymmetry near openings. Besides, improvement of *U*–value on building envelope could help in minimizing thermal discomfort in naturally ventilation buildings (Pereira and Ghisi 2011). Turhan et al. (2014) confirmed the wall *U*–value was one of the most sensitive factors for building thermal. Latest studies on new technology of phase change material (PCM) can enhance thermal storage capacity for building envelope, where up to 4^{o}C of maximum indoor temperature can be lowered by comparing cases with PCM and non–PCM walls (Athienitis et al. 1997, Kuznik and Virgone 2009).

Instead of using *U*–value, the impact of cooling load by fabric thickness X (m) and materials conductivity K (W $m^{-1}K^{-1}$) was broadly investigated by Bojic et al. (2001, 2002a). Their findings showed an increase of thermal insulation thickness would reduce the residential cooling load, but the saving was implicit when the thickness exceeded 5cm. Besides, inadequate position of insulation materials might, in contrast, raise the cooling energy consumption. Similar studies focusing on insulation thermo–physical properties are also commonly reported via open literatures (Kemal and Bedri 2003, Dombayci et al. 2006, Yu et al. 2009, Pan et al. 2012), where an energy conservation strategy of different thickness for external wall according to its orientation facing was suggested by Fang et al. (2014). Furthermore, the thermal absorptivity of external wall finishing can result in a significant impact to building thermal performance. Cheung et al. (2005) presented a linear relationship between the annual cooling energy in residential building with the absorption coefficient of external surface, where 12.6% of cooling energy saving can be achieved by reducing 30% solar absorptance.

A study conducted by Lam (2000) showed that solar heat gain through window comprised up to 45%, followed by 24% from external wall conduction heat gain, of the total cooling load for residential building in Hong Kong, where the conduction heat through window contributed only 6%. Significant energy saving was estimated by replacing clear glazing with tinted glass. Cheung et al. (2005) found that the cooling energy decreased with S_c, via an almost linear relationship, where 3.8% of cooling energy was conserved if S_c changed from 0.9 to 0.4 in the simulated apartment. Another study in Hong Kong residential building by Sang et al. (2014) also reported up to 20% energy saving by replacing clear glazing ($SHGC$=0.72) to double low–E tinted glass ($SHGC$=0.37). Chua and Chou (2010) studied the cost effectiveness in replacing single clear glazing by other types of energy efficient glass types, where the results reported the shortest payback period with remarkable cooling energy saving by implementing low–E single glazing (U_{wd}=4.2Wm^{-2}K^{-1}, S_c=0.7). Despite a larger amount of heat gain was avoided by double–layer glazing, its satisfactory level of day–lighting was however insufficient as compared with single low–E glazing (Huang et al. 2014). U_{wd} and S_c are actually varied together with glazing type, instead of individual change. Alaidroos and Krarti (2015) evaluated the potential cooling energy saving of window glazing with sensitivity variation of both U_{wd} and SHGC, where greater saving potential was reported with sensitivity change of $SHGC$ value. Similar study was also conducted by Ihm et al. (2012) in South Korea with both cooling and heating energy concern.

Window area and shading designs (A_{wd}, WWR, σ_v)

Energy use to compensate heat gain from fenestrations can contribute up to 22% of total energy consumption in residential building (Wong and Agustinus 2004). According to Equation 2.1, an increase of window area A_{wd} (m^2) may enhance heat gain through glazing, where evidences have been provided in a number of studies (Cheung et al. 2005, Persson et al. 2006, Hygh et al. 2012, Turhan et al. 2014, Alaidroos and Krarti 2015). In order to emphasize the effect of heat gain through window compared with the external wall, an index of window to wall ratio (*WWR*), defined as the portion of window area to the overall gross external wall areas (opaque wall + windows), is often applied for building energy simulation. A survey of Hong Kong housing sector conducted by Lam et al. (2005) showed the existing *WWR* was ranged from 20 to 40%, where bigger luxury flats were having larger *WWR* and vice verse to older and smaller apartments. If the *WWR* in a large flat was reduced from 40% to 25%, a cooling energy saving of 18% could be achieved (Sang et al. 2014). Similar findings by Inanici and Demirbilek (2000) also recommended an optimal south facing window size of 25% on the southern facade to reduce summer heat gain in the cooling dominant region at the north hemisphere.

Smaller window size may effectively reduce solar heat gain from fenestration, however at the same time minimized daylighting level which in return increase artificial lighting load (Huang and Chen 2014). A rule of thumb in Swedish standard suggested the area of glazing should be larger than 10% of the floor area in apartment to provide sufficient daylight for occupant needs. (Persson et al. 2006). Wang et al. (2007) suggested increasing *WWR* in naturally ventilated building would enhance indoor air velocity but at the same time introduce more solar heat gain through fenestration which may result in thermal discomfort. An extension of the study reported adequate natural ventilation for an acceptable comfort level could be achieved by sizing window area to about 20% of apartment floor area (Wang and Wong 2007). The study also showed that maintaining *WWR* at 24% could maximize the indoor thermal condition but horizontal shading devices should be installed for all four orientations.

Overhangs and side fins are two commonly observed shading devices for high–rise residential buildings (Bojic 2006). Evidence of cooling energy saving from shading devices was reported by Cheung et al. (2005) with continuous increasing length of overhang and wing wall (i.e. side fin) to reduce solar heat gain through windows. However, the situation may not be thoroughly described by considering only the length of shading extension, since the size and position of window remained unknown. Lam et al. (2005) identified the effectiveness of shading device via the ratio of overhang projection to window height. The incidence of solar energy was decreased with an increasing ratio, while the reduction rate was diminished when the overhang projection to window height ratio exceeded 0.5. In other words, the efficient of overhang shading decrease if its extension length exceeds half–length of window height.

Chua and Chou (2010) proposed using the '*G factor*', i.e. the fraction of window area exposed to direct sunlight, to evaluate the effectiveness of shading device, where the opposite angle, or the adjacent angle of overhangs θ_1 (^{o}), was a parameter to identify the shading efficiency. The expression of *G factor* is presented in Equation 2.3 with supporting legend description of h_{total} (m), l_3 (m), l_1 (m) and l_2 (m) in Figure 2.2. This approach can quantify both the overhangs extension length and the height of window below the shade.

$$G = \frac{\left[h_{total} - \left(l_3 \tan\theta_1\right)\right]}{h_{total}}\left(\frac{l_1}{l_2}\right) \tag{2.3}$$

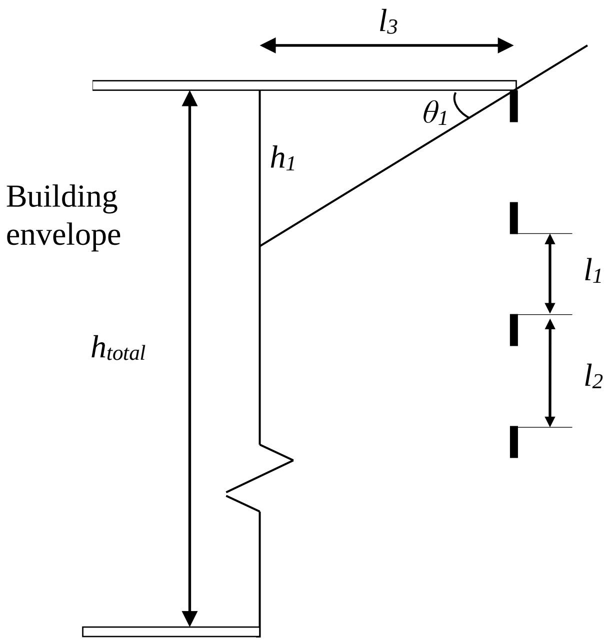


Figure 2.2 Diagram of overhang in G–factor evaluation

Another method in defining the efficiency of shading devices is the vertical and horizontal shadow/shading angles describing the relationship between the lengths of shaded area on the wall or window surfaces (Bansal et al. 1994). Equations 2.4 and 2.5 respectively show the expression of the horizontal σ_h (°) and vertical shadow angles σ_v (°) .

$$\sigma_h = \text{solar Azimuth angle–orientation (Azimuth of the surface normal)} \tag{2.4}$$

$$\tan\sigma_v = \frac{\tan\beta}{\cos\sigma_h} \qquad \text{where } \beta \text{ is the solar Altitude angle (°)} \tag{2.5}$$

Building construction characteristics (A_{fl}, A_e, orientation, b_f)

The building floor area, external wall area, orientation and building shape also contribute to the building thermal energy demands. The building floor area A_{fl} (m^2) and external wall area A_e (m^2) are two building geometry parameters, where its impact on building thermal energy performance can be explained by physical sense and simple heat transfer equation (Equation 2.1). Significance of floor area to apartment electricity consumption, especially in summer time, was confirmed by Tso and Yau (2003) using the factor analysis test. These area parameters are also discussed together with building shape and orientation for more in–depth discussions or used as input to statistical models for building thermal energy evaluation (Tsai et al. 2008, Wong et al. 2008, Chou and Bui 2014). Considering a city scale energy forecast, however, the impact of an apartment size to the energy use in residential sector is not being discussed. A solution to this aspect can be helpful in sustainable housing development plan.

Thermal energy consumption for unidirectional facing zone can be significantly influenced by the building orientation due to the sun–path at various climate zones. Cheung et al. (2005) simulated the cooling energy use in Hong Kong public apartment and tested against different orientations, where the highest cooling consumption was recorded when the apartment was facing west, followed by facing south–west and then north–west direction. Simulation results of 20 terraced houses in Sweden by Persson et al. (2006) showed apartments which orientated to south and west direction would require higher cooling demand, while the one facing north would require the least cooling but highest heating demand. A study in Singapore residential buildings by Wang et al. (2007) reported that north and south facing apartments would receive natural wind to enhance indoor air velocity, but higher solar heat gain was reported for those apartments facing south which triggered thermal discomfort (Wang and Wong 2007). Strategy of different insulation thickness according to different apartment direction was suggested by Feng et al. (2014) to minimize cooling load in summer period. Reported by Hemsath and Banhosseini (2015), the orientation effect to thermal heat gain for whole building simulation was diminished as compared with other related parameters, because the entire building envelope was exposed to all directions. This finding is, however, questioned where it is accepted only if the building envelope area is uniformly facing towards different orientations. Cooling energy impact on building orientation is still sensitive especially for non–uniformly shaped buildings.

Building shape can significantly influence energy consumption (Asadi et al. 2014). It can be an essential factor to optimize building construction cost and thermal energy performance due to seasonal effect. A simple tool was developed by Ourghi et al. (2007) to optimize the annual cooling energy consumption from building morphology change. Yang et al. (2008) adopted the building shape coefficient b_f (m^{-1}), i.e. the ratio of total building envelope area $A_{e,total}$ (m^2) to the enclosed space volume V_{BC} (m^3) as shows in Equation 2.6, as a parameter to evaluate the heating and cooling load of office building in five climate zones in China. The results showed that both heating and cooling demand would increase with shape coefficient, where the effect was more sensitive in hot and humid climate region.

$$b_f = \frac{A_{e,total}}{V_{BC}} \tag{2.6}$$

Granadeiro et al. (2013) developed a new shape grammar–based parametric system to identify the architectural composition of building envelope and confirmed a larger variation of annual heating and cooling energy value for a target building with similar geometry data but different shapes. Recently, a building energy prediction index, named EETPO index, was proposed by Yu et al. (2015) to evaluate the whole building energy and thermal performance of office building envelope. The highlight of this index was the availability to incorporate building shape coefficient b_f (m^{-1}) for energy prediction, which provided a more flexible alternative in estimating building thermal energy consumption with different geometries. The building shape coefficient b_f highlighted by Yu et al. (2015) is expressed in Equation 2.7, where n_{wl} and n_{wd} are the numbers of opaque wall and window and i represents the different orientations.

$$b_f = \frac{\sum_{i=1}^{n_{wl}} A_{wl_i} + A_r + \sum_{i=1}^{m_{wd}} A_{wd_i}}{V_{BC}} \tag{2.7}$$

2.2.2 Climate

Climate zone

According to ASHRAE–90.1 (2013), the world can be classified into 8 climate zones according to the thermal criteria using cooling or heating degree days. The degree–day is specified as the total difference between the average daily outdoor temperature $\overline{T}_{o,i}$ and the target temperature set–point T_{tar} to actuate air–conditioning (i.e. cooling or heating) within a year. The number of degree–days for heating and cooling is, respectively, quantified as the sum of heating degree–days (*HDD*) and cooling degree–days (*CDD*) as illustrates in Equations 2.8, where N is the number of days (Rodriguez–Soria, 2014).

$$HDD = \sum_{i}^{N} (T_{tar} - \overline{T}_{o,i}) \ ; \qquad\qquad CDD = \sum_{i}^{N} (\overline{T}_{o,i} - T_{tar}) \tag{2.8}$$

It can also express the input parameters to evaluate the annual thermal energy forecast through building fabric as indicates in Equation 2.9, where U is the thermal transmittance of the building fabric, A_e is the total external wall area.

$$\text{Annual thermal energy loss through building fabric} = \Sigma U \times A_e \times \text{(annual degree–days)} \tag{2.9}$$

However, the degree–days approach was criticized by Hekkenberg et al. (2009) from lacking possible dynamics with socio–economic concerns in long term demand forecast. Lam et al. (2008a) developed a long–term meteorological index Z, as a regression function of dry–bulb T_{dry} (°C), wet–bulb T_{wet} (°C) temperature, global solar radiation g_{sol} (Wm^{-2}), clearness index (ζ) and air speed v_a (ms^{-1}) being presented in Equation 2.10, to identify the climatic conditions in past and future years. This index was proved effective to represent seasonal variations and climate change in identifying the impact of building thermal energy performance (Lam et al. 2010).

$$Z = f\left(T_{dry}, T_{wet}, g_{sol}, \zeta, v_a\right) \tag{2.10}$$

Weather data

The weather conditions including outdoor temperature T_o (°C), relative humidity R_h (%), wind speed v_a (ms^{-1}), solar radiation g_{sol} (Wm^{-2}) and others are confirmed significant to building thermal energy variation (Li et al. 2012, Fumo 2014). Weather data files, with hourly climate variables, of different geographical locations are essential inputs for building energy simulation software (Crawley 1998, Pedersen 2007). The weather data is evaluated either from test reference year (TRY) or typical meteorological year (TMY), where the latter one is more recommended, according to Fumo (2014), because the reproduced year file is closer to long term average benefits to energy consumption prediction.

Outdoor temperature T_o (°C) variation is one major concern in building cooling energy consumption, while raising T_o due to global warming is an important topic for building energy forecast (Belzer et al. 1996, Christenson et al. 2006, Lam et al. 2008b, Wang et al. 2010). Predicted by Radhi (2009), T_o would be raised by 1.6–2.9°C and 2.3–5.9°C at the year of 2050 and 2100. Li et al. (2012a) reviewed the impact of climate change on building energy use in different climate zones. The results showed a significant increase of cooling demand while the heating demand would have been reduced. Identical results were also reported by Hekkenberg et al. (2009) via the temperature dependence pattern of thermal energy use in building. Generally agreed mitigate actions to reduce cooling energy consumption would be raising indoor temperature set–point and enhancing building insulation to reduce envelope heat gain (Bojic et al. 2002a, Fang et al. 2014, Karimpour et al. 2015).

2.2.3 System operations

Indoor temperature set–point (T_a)

Higher indoor set–point temperature T_a (°C) is widely discussed as an effective strategy against climate change (Al–Sanea and Zedan 2008; Sadineni and Boehm 2012; Sadeghifam et al. 2015). T_a in residential building can be varied in wide ranges, different from the pre–set temperature introduced in office premise, which depends on occupant's thermal comfort decision. T_a may influence occupant's working performance and mental alertness even within the acceptable thermal comfort range (Tham and Willem 2010). The criteria of thermal comfort are complexly correlated to occupant's physiological, psychological, behavioural and adaptive actions (Brager and de Dear 1998, Djongyang et al. 2010, van Hoof et al. 2010, Wong et al. 2014a). An indoor temperature set–point which is neither too cool nor too warm is generally defined as the neutral temperature T_{neu} (°C) perceived by the occupant (Mui and Wong 2007b). T_{neu} is believed strongly correlated with the outdoor temperature T_o (°C) and has been broadly investigated in literatures (de Dear 1998, Humphreys and Nicol 2000). The T_{neu} and T_o relationship for free running and air–conditioned building was studied by de Dear et al. (1998) respectively shown in Equation 2.11 and 2.12.

Free running buildings: $$T_{neu} = 13.5 + 0.546 \times T_o \qquad (R^2 = 0.94) \qquad (2.11)$$

Air–conditioned buildings: $$T_{neu} = 22.2 + 0.003 \times {T_o}^2 \qquad (R^2 = 0.49) \qquad (2.12)$$

Similar relationship but for the sub–tropical climate zone was reported by Mui and Chan (2003) in Equation 2.13.

Air–conditioned buildings: $$T_{neu} = 18.3 + 0.158 \times T_o \qquad (R^2 = 0.59) \qquad (2.13)$$

The operative temperature ranges for residential building suggested by various kinds of standards were compared by Rodriguez–Soria et al. (2014) and the results are summarized in Table 2.1. Indoor temperature range for air–conditioned households in Hong Kong was recorded as 21–23.5^{o}C by Lam and Li (2000). Set–point of relative humidity is generally not specified in residential buildings, since it is difficult to be controlled by room air conditioner. However, the dehumidification effect does affect the cooling system efficiency (Kosar 2006).

Table 2.1 Operative temperature in residential building required by studied standards (Rodriguez–Soria et al. 2014)

Countries / References	T_{op} ranges (^{o}C)	Conditions / Remarks
ISO 7730 (2010)	19–27	PPD* < 15%
Germany	20–24	Mean value for winter and summer
France	19–22	Daytimes
	15–18	Nighttimes
UK	20–26	
Spain	21–25	
USA	20–26.6	

* Noted that PPD is the predicted percentage of dissatisfied (Fanger 1970)

Coefficient of performance (COP)

Coefficient of performance (*COP*) is identified as the ratio of energy required for heating or cooling to the actual electrical energy input for an air–conditioning system and can be a system efficiency indicator for thermal energy consumption prediction (Neto and Fiorelli 2008). Chua and Chou (2010) predicted the required cooling energy consumption in high–rise residential buildings with *COP* choices varied from 2.5 to 4.5. Great impact on actual energy use by *COP* was reported as compared with other factors. The value of *COP* is dependent to the machine heat rejection efficiency and the external factors including outdoor temperature T_o, moisture content w and sensible heat ratio (*SHR*) (Kosar 2006; Shimoda et al. 2007). The Japan Refrigeration and Air–Conditioning Industry Association (JRAIA) modelled the room air conditioner *COP* as a function of outdoor temperature and evaluated a drop of *COP* from 6 to 2 when the outdoor temperature increased from 10 to 35^{o}C (Shimoda et al. 2007). The drop of air–conditioner *COP* was further explained by Kosar (2006) with extra dehumidification demand due to moist outdoor air intake especially in a sub–tropical climate region, where a relationship between *COP* and *SHR* was evaluated. The approach of fixed *COP* for air–conditioning system is commonly adopted in building energy simulation, however the sensible and latent load in an indoor space are varying by time. Relatively low system *COP* could have happened, at low *SHR* situation, for nighttimes cooling with hot and humid outdoor intake by ventilation or infiltration (Lstiburek 2002; Li et al. 2006). Dynamic system *COP* varied with hourly *SHR* at indoor space can be a solution to provide more accurate prediction results.

Ventilation rate, V_{vent}

Ventilation rate V_{vent} can be a key contributor of total cooling energy consumption in a residential building especially for nighttimes air–conditioner operation (Lin and Deng 2004). Fresh air ventilation rate introduces to an indoor space is dependent to building type and occupant's requirements, which aims to enhance indoor air quality by diluting indoor pollutants and minimizing possible sick building syndrome symptoms (Chao et al. 1997, Tham and Willem 2007, ASHRAE–62.1 2010). It can be generally expressed by people outdoor air rate ($Ls^{-1}ps^{-1}$), area outdoor air rate ($Ls^{-1}m^{-2}$) and air change per hour *ACH* (h^{-1}). A minimum ventilation rate of 2.5$Ls^{-1}ps^{-1}$ or 0.35*ACH* was recommended by ASHRAE–62.1 (2010) for residential dwelling unit. According to a review of residential building construction standards or regulations in 15 developed countries, Yoshino et al. (2004) reported a minimum ventilation rate of 0.5*ACH* evaluated by a standard apartment model. Different from the centralized air–conditioning system in office building, ventilation rate in residential apartment is difficult to be controlled by a window type or split type air conditioner. A field survey by Lin and Deng (2003) showed the outdoor ventilation rate in a bedroom environment ranged from $1.5Ls^{-1}ps^{-1}$ to $4.5Ls^{-1}ps^{-1}$ varied by room air–conditioner types and an optimal value of $3.0Ls^{-1}ps^{-1}$ was suggested.

Infiltration, V_{inf}

Apart from ventilation introduced via air–conditioner, outdoor air will infiltrate V_{inf} to indoor space through leaks, cracks or other building envelope openings. The building infiltration rate can be influenced by stack effect, climate, building construction characteristics, building age and operation of mechanical ventilation equipments (Sadineni et al. 2011). Air infiltration would influence the building cooling load and its losses were the most difficult to be controlled (Al–Homoud 2005). Thermal energy prediction for perfectly air tight building can be performed by computer software in ideal case simulation. However, this assumption can never be practical for a real building, where a small infiltration rate shall be included to represent possible air leakage (Liu and Nazaroff 2001; Crawley et al. 2008). A study conducted by Persily (1999) and co–workers (Persily et al. 2009) reported that air–tightness in taller building with more careful construction and design was superior to shorter buildings.

2.2.4 Internal loads

The internal load is defined by the heat generation through lightings, equipments and occupants inside the indoor space. These loads may consume up to 20% of the total cooling consumption in residential buildings (Lam 2000, Lin and Deng 2004). The lighting and equipment loads are actually varied by system types (Wan and Yik 2004). For simplicity in building energy simulation studies, it is expressed as an index normalized by floor area as the lighting and equipment power density, d_{li} and d_{eq} (Wm^{-2}). Values of power density would be varied by the internal load schedule ϕ_{in}, penetration of appliances in different locations and building types (Cheung et al. 2005, Bojic et al. 2002a, EFBS 2012). The heat gain from occupants is evaluated by the occupancy ϕ and corresponding metabolic rates M_e (met) , i.e. heat generation through per meter square skin surface (Wm^{-2}), for various activity levels. The metabolic values for different activities are available from ASHRAE–55 (2010) and ISO–7730 (2005) standards. Assuming the average surface area for a person is $1.8m^2$ (ASHRAE–55 2010), the heat production per person ($W\ ps^{-1}$) by activity levels can be estimated, whereas the number of person for instant can be identified by occupancy schedule varied among building types. Different from offices and commercial buildings, the cooling energy impact by internal loads in residential buildings is marked as a lower priority (Lam 2000).

2.2.5 Occupant behaviour

Occupancy (ϕ)

Impact on building thermal energy consumption by occupancy schedule ϕ is confirmed to be significant in AC office and commercial sectors (Mui and Wong 2007a, Yun et al. 2012, Azar and Menassa 2012, Leung et al. 2012, Asadi et al. 2014, Silva and Ghisi, 2014). Remarkable energy impact was confirmed in morning with the initial thermal requirement (Sun et al. 2013a). Besides, Azar and Menassa (2012) reported higher sensitivity of building thermal energy use by the occupancy profile in particular to small buildings. Operation of air–conditioner in buildings is dependent to corresponding occupancy schedule, changing with system on / off status or part load conditions with respect to time (Paudel et al. 2014). However, equivalence between profiles of occupancy and air–conditioning operation may not hold in the residential sector, since AC operation in apartment is occupant behavioural dependent instead of time dependent control. The occupancy and AC operation schedule in residential sector shall be investigated separately, where over–estimation on total cooling energy consumption could have happened if assumption of equivalence is made improperly.

Fixed occupancy profiles varied by hour are adopted in building energy simulation software including simulation in residential buildings in some studies (Bojic and Yik 2005, Cheung et al. 2005). However, the presence of residents in a real apartment should be probabilistic instead of following standard schedule (Kwok and Lee 2011). Some advance models, including Sub–Hourly Occupancy Control (SHOCC) and User Simulation of Space Utilization (USSU), are developed exclusively for dynamic occupancy prediction (Hose et al. 2009), however these prediction tools are limited to office and commercial premises. Wong and Mui (2006) conducted a survey to understand the occupant load variation in 720 households in Hong Kong. Index of hourly occupant load variation factors ψ, as the percentage of maximum occupant number in an apartment, were evaluated in different housing types to identify the possible number of occupant at specific time N_k. Corresponding expression is listed in Equation 2.14. This approach provides alternatives with probabilistic understanding to non–standard occupancy schedule in a residential building, in particular practical to estimate variation of hourly building energy consumptions (Mui and Wong 2007a).

$$N_k = N_{\max}\psi_k \qquad \text{where k = 0, 1 , 2 …23 hour} \qquad (2.14)$$

AC operation schedule (ϕ_{AC})

Similar to occupancy, the AC operation schedule ϕ_{AC} in an apartment should be varied and significantly dependent to individual's behavioural, physical and socio–economic factors (Hose et al. 2009, Yun and Steemers 2011, Habara et al. 2013). AC operation patterns in residential building due to occupant individual choices were investigated by Schweiker and Shukuya (2008, 2009). Their results showed the major influencing factors were preference of AC operation, subjective evaluation effectiveness, current thermal environment, thermal background, behavioural background, demographic factors of occupants and individual difference in rooms, where the 'preference' was identified as one who prefer or not to work and sleep in the air–conditioned space. Demographic may include household's income, age group, gender and other related issues. Extensive studies on the impact of occupant's thermal comfort due to demographic and other individual decisions, i.e. adaptive comfort or neutral temperature, are available via literatures (de Dear et al. 1998, Nicol and Humphreys 2002, Indraganti and Rao 2010). Besides, the impact on cooling energy by occupant's clothing value C_L variation had been affirmed by Wong et al. (2014b).

In view of the function of computer thermal energy simulation tool, however, the AC usage patterns have to be specified by time or other conditions (i.e. temperature set–point or presence of occupant) for calculation, where occupant behavioural dependent schedule is difficult to be implemented. Wan and Yik (2004) suggested two fixed AC operation schedules, according to the housing survey results, with different percentage of operation chance for cooling energy prediction in apartment. This approach may not effectively solve the problem, but intends to marginally specify the difference. A different approach based on regression method with one or several key factors to predict AC operation patterns is therefore being established. One example refers to Kempton et al. (1992) who used the outdoor temperature and the hour within a day to predict air–conditioner on/off status in residential building. Another example by Schweiker and Shukuya (2009) used the mean outdoor temperature in two consecutive days, individual subject's preference and background and some other relevant factors to estimate the daily AC usage duration. Although these examples are proved effective with validations, the functions are lack of explanatory power in triggering the model. A more promising approach based on conditional probability analysis was proposed by Ren et al. (2014) to estimate the AC usage pattern in a residential section. The conditional probability was expressed via the environmental and event trigger sub–model. Besides, this model was flexible in simulation with different time steps from one minute to one hour interval. The probabilistic approach is adequate in addressing random choice of AC operation, but the method described by Ren et al. (2014) is not easy to be implemented for large scale simulation. Another AC operation method driven by probabilistic approach with simpler dependent variable is recommended.

2.2.6 Other factors

Apart from those direct issues mentioned above, a number of other factors are also reported to be correlate, but less or insignificant causal relationship, with the energy consumption in a residential building (Hirst 1978, Tso and Yau 2003, Goldblatt et al. 2005, Sa'ad 2009, Yang et al. 2010).

Demographic, Socio–economic

Energy consumption patterns in residential buildings are dependent on demographics, economics and technologies factors (Hirst 1978). Occupied housing stock, fuel and equipment price, income elasticity and energy use for equipment were found correlated with the energy consumption patterns (O'Neal and Hirst 1980). The chain effect of raising residential energy use in relation to these factors was explained by Sathaye and Meyers (1985). Economic and gross domestic product (GDP) growth in a country was partly a result of increase in household income. Occupants were willing to improve standing of living with increasing ownership of appliance, including air–conditioner, and thus electricity use in residential sector boosted. Increasing saturation and penetration rate of air–conditioners in residential buildings was thus recorded (Wan and Yik 2004). It explains how economics affect occupant's decision in owning and operating appliances in their living. The importance of socio–economic effect to building cooling energy demand was further emphasized by Hekkenberg et al. (2009) via the temperature dependence pattern (TDP) of thermal energy demand, where the authors concluded this factor was one indispensable concern in future thermal energy model development.

Housing type and housing mix

Similar studies are extended to evaluate energy consumption difference among housing types. Private housings are reported generally consuming higher energy consumption than public housings (Ang et al. 1992, Tso and Yau 2003, Cheung et al. 2014). The reason can be attributed by financially more stable, i.e. higher income, occupants in private housings who are willing to use more electricity in maintaining higher living standard and comfort (Sa'ad 2009). A thematic household survey conducted by Hong Kong government also suggested that the private housing owners would rather choose appliances with high electricity consumption for comfort of living and they seldom care about the electricity charge and amount of energy consumption at home, while the public housing residents would pay more attention to increased electricity charge (THSR 2004). Kaza (2010) introduced a quantitative regression approach to identify the residential energy consumption (especially for space cooling) by various parameters including housing density, type and location. The study suggested the number of household member would significantly affect apartment cooling demand, and the residential cooling energy consumption could be improved by re–organizing housing type mix including more large size multi–family flats in which to limit overall housing size. The author also suggested that targeting the adequate housings type for retrofit conservation measures would effectively maximize the energy and power saving.

This section reviews the influencing factor of thermal energy consumption in buildings, especially for cooling energy in residential sector, and categorizes the contents in six groups according to the related parameters. A summary of these resulting factors and corresponding parameters are shortlisted in Table 2.2 for reference. The proposed framework can be useful in addressing the research value for future study in this area.

Table 2.2 Parameters of building cooling energy related factors

Factor	Reference	Descriptions	Related Parameters
Building material properties	Feng et al. (2004)	Thermal resistance reduce with U_{wl}	U_{wl}
	Wang et al. (2007b)	Larger indoor and outdoor temperature difference is recorded by reducing U_{wl}	T_a, T_o, U_{wl}
	Pereira and Ghisi (2011)	Thermal comfort is improved by adequate U_{wl}	U_{wl}
	Kuznik and Virgone (2009)	Phase change materials can maximize envelope thermal storage capacity	U_{wl}
	Bojic et al. (2001), Bojic and Yik (2005)	Building cooling load is influenced by thickness of wall insulation and insulation positions.	X, K
	Fang et al. (2014)	Thickness of external wall should be varied in different orientation.	X, orientation
	Cheung et al. (2005)	Higher absorption coefficient of external wall can enhance cooling energy saving.	Absorption coefficient
	Lam (2000), Sang et al. (2014), Chua and Chou (2010), Ihm et al. (2012)	Significant cooling energy saving potential is achieved by replacing clean glazing to low–E glazing with higher solar insulation.	U_{wd}, S_c or $SHGC$
Window area and shading designs	Persson et al. (2006), Hygh et al. (2012)	Thermal heat gain is increased by window area	A_{wd}
	Lam et al. (2005), Sang et al. (2014)	Cooling energy can be reduced by minimizing window to wall ratio	WWR
	Inanici and Demirbilek (2000)	Smaller WWR should be adjusted in south facing window	WWR, A_{wd}
	Wang and Wong (2007)	About 20% window to floor area size can effectively improve apartment natural ventilation rate.	A_{fl}, A_{wd}, V_{vent}
	Cheung et al. (2005)	Increasing extension of overhang and side fin can minimize incidence of solar radiation.	Length of overhang
	Chua and Chou (2010)	Effectiveness of shading device can be improved by '*G factor*'.	G (details refers to Equation 2.3)
	Bansal et al. (1994)	Considering the vertical and horizontal shadow angle to improve shading efficiency	σ_h , σ_v (details refers to Equation 2.4 and 2.5)
Building construction characteristics	Tso and Yau (2003), Wong et al. (2008), Chou and Bui (2014)	Electricity consumption is increased with floor and external wall area.	A_{fl}, A_e
	Persson et al. (2006)	Apartment orientation would bring significant difference in cooling energy consumption	Orientation
	Hemsath and Banhosseini (2015)	Orientation effect in whole building thermal energy simulation is diminished as compared with other parameters under same conditions.	Orientation
	Yang et al. (2008)	Building shape coefficient is adopted as a parameter in evaluating heating	b_f, A_e, V_{BC}

		and cooling energy consumption.	
	Yu et al. (2015)	A more comprehensive building shape coefficient is used for evaluating a new building energy prediction index.	b_f, A_{wl}, A_r, A_{wd}, V_{BC} (details refers to Equation 2.7)
Climate zone	ASHRAE–90.1 (2013)	Climate zones are classified by number of degree–days, including heating and cooling degree–day index.	*HDD*, *CDD*
	Rodriguez–Soria (2014)	Number of degree–day is specified via the sum of outdoor and target indoor temperature difference.	*HDD*, *CDD*, T_o, T_{tar}
	Lam et al. (2008a)	A long term meteorological index *Z* is developed to identify past and future climate conditions.	*Z*, T_{dry}, T_{wed}, g_{sol}, ζ, v_a (details refers to Equation 2.10)
Weather data	Crawley (1998), Pedersen (2007)	Hourly weather data files are essential input for energy simulation, where test reference year and typical meteorological year are recommended for yearly data selection.	TRY, TMY (T_o, R_h, v_a, g_{sol})
	Belzer et al. (2006), Lam et al. (2008), Radhi (2009)	Global warming due to increasing T_o is an important issue in building energy forecast.	T_o
	Bojic et al. (2002a), Fang et al. (2014), Sadeghifam et al. (2015)	Increasing indoor temperature set–point can be an effective cooling energy strategy against global warming.	T_a, T_o
Indoor temperature set–point	Brager and de Dear (1998), van Hoof et al. (2010)	Temperature set–point in residential building can be varied in wide ranges dependent to thermal comfort decisions.	T_a
	de Dear (1998), Humphrey and Nicol (2000), Mui and Chan (2003).	The comfort of neutral temperature T_{neu} is reported correlate with outdoor temperature.	T_{neu}, T_o (details refers to Equation 2.11 –2.13)
Coefficient of performance	Kosar (2006), Shimoda et al. (2007)	Coefficient of performance (*COP*) of AC system is affected by T_o, moisture constant *w* and sensible heat ratio (*SHR*).	*COP*, T_o, *w*, *SHR*
	Lstiburek (2002)	Value of *COP* for AC system is varied by time according to the SHR change.	*COP*, *SHR*
Ventilation rate	ASHRAE–62.1 (2010)	Different ventilation rate is required depends on building type and occupant’s needs.	V_{vent}
	Bojic et al. (2002b)	V_{vent} of window type AC can be varied by installation configurations.	V_{vent}
	Lin and Deng (2003)	Range of $1.5 Ls^{-1}$– $4.5 Ls^{-1}$ is found and an average of $3\ Ls^{-1}$ is suggested in residential apartment.	V_{vent}
Infiltration	Sadineni et al. (2011)	Infiltration is affected by stack effect, climate, building construction characteristics, building age and operation of mechanical ventilation equipments.	V_{inf} and the related parameters in descriptions
	Persily (1999), Persily et al. (2009)	Infiltration is related to air–tightness of building, where it is tighter in tall buildings than the short one.	V_{inf}, air–tightness
Internal heat gain	Wan and Yik (2004)	The lighting and equipment loads are depend on system type and are expressed as a density function normalized by floor area.	d_{li}, d_{eq}, A_{fl}
	Bojic et al. (2002a)	The lighting and equipment power densities are set vary with internal load	d_{li}, d_{eq}, ϕ_{in}

		schedule in different locations and buildings.	
Occupancy	Cheung et al. (2005)	Fixed occupancy ϕ is set varied by time in energy simulation software.	ϕ
	Wong and Mui (2006)	A probabilistic occupancy is predicted using the occupant load variation factors ψ_k at time k and the maximum number of occupant in apartment.	ψ_k, ϕ, N_{max}
AC operation schedule	Schweiker and Shukuya (2008, 2009)	AC operation schedule ϕ_{AC} is occupant behaviour dependent which relates to occupant decision on thermal comfort.	ϕ_{AC}, some environment related parameters
	Wan and Yik (2004)	Two fixed ϕ_{AC} are adopted for apartment cooling energy prediction.	Different percentage of operation chance
	Kempton et al. (1992)	An AC operation pattern is identified by regression method.	ϕ_{AC}, T_o, hour of a day
	Schweiker and Shukuya (2009)	Another regression method for AC operation pattern prediction is expressed using other parameters.	Mean T_o in two consecutive days, subject preference and background, demographic
	Ren et al. (2014)	AC operation schedule based on conditional probability is developed.	Environmental and event triggered sub–model, time steps
Demographic and socio–economic	Schweiker and Shukuya (2008, 2009)	Demographic may influence occupant's AC operation needs and cooling energy consumption.	Income, age group, gender, education level
	Hirst (1978) and O'Neal and Hirst (1980)	A residential energy prediction model, integrated by sub–model of demographics, economics and technologies, is developed.	Housing stock, fuel and equipment price, income elasticity and equipment energy consumption
	Wan and Yik (2004)	Saturation and penetration rate of air–conditioner can affect total cooling energy use.	AC saturation and penetration rate
	Hekkenberg et al. (2009)	It is proved, via the temperature dependence pattern (TDP), socio–economic factor is important in future thermal energy model development.	TDP
Housing type and housing mix	Kaza (2010)	A quantitative regression approach is developed for residential energy consumption prediction.	Housing density, type, location
	Tso and Yau (2003), Cheung et al. (2014)	Private housings consume higher energy consumption than public housings.	Housing types

2.3 An overview on building energy simulation tools

The impact of relationship between influencing parameters and building cooling energy consumption is presented in previous section, while the method in evaluating this relationship is discussed in this part, which is the key factor in confirming the prediction accuracy. Energy performance in buildings is complexly related to building characteristics, equipment and systems, weather, occupants and sociological influences (Asadi et al. 2014). In order to predict the energy use in building, simulation models and energy prediction tool of various approaches were developed in the past 30 years. Swan and Ugursal (2009) reviewed the existing available simulation models and classified these tools in groups according to the nature of construction. These simulation models are of numerical, statistical, computational and intelligence bases and can be summarized into two major approaches, Top–down approach and Bottom–up approach. The top–down approach considers the entire energy consumed sector as an energy sink and excluding consumption of individual end–uses, while the bottom–up approach refers to the models which use input data from an end–use level instead of the sector as a whole (Kavgic et al. 2010). Classification of the building energy simulation methods is summarized in Figure 2.3.

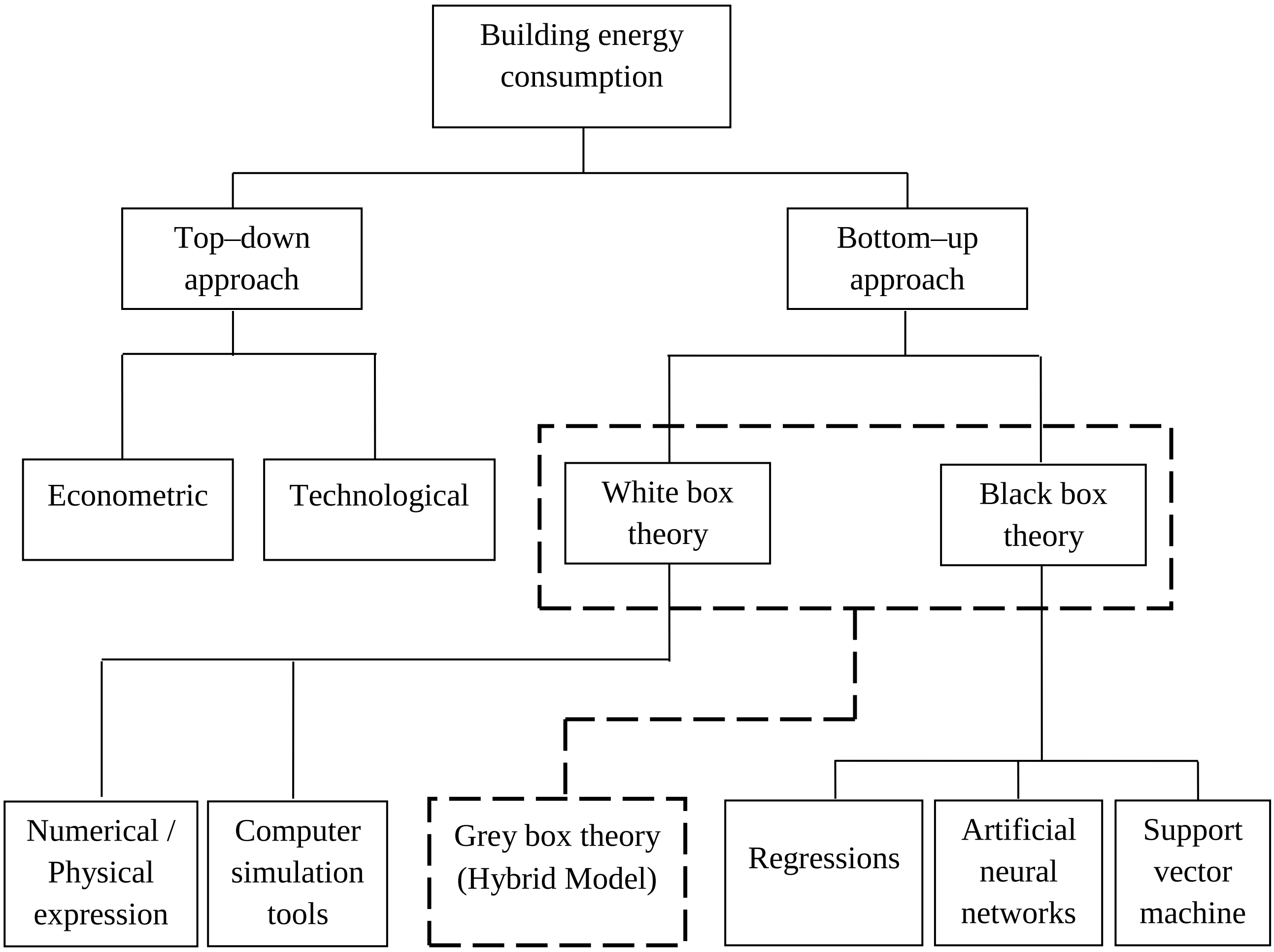


Figure 2.3 Classification of the building energy simulation methods

2.3.1 Top–down approach

The top–down modelling perspective functions at an integrated approach, aimed to predict the regional scale energy performance based on the relationship of historical time series energy usage patterns or transitions and corresponding influencing variables. Marco data of econometric and technological based variables are often being chosen as parameter inputs, including gross domestic product (GDP), fuel / electricity prices, income, social and economical conditions, climatic and environmental change, housing stock, saturation effects and appliance ownership trends (Swan and Ugursal 2009, Kavgic et al. 2010, Johnston 2003).

Regarding the energy crisis in the 1970s, development of top–down energy models for energy policies establishment was boosted and favoured by scholars with less consideration on the detailed end–user demand. A residential energy consumption model predicted by several econometric variables and the growth rate of housing stock in USA was introduced by Hirst et al. (1977). The model was further improved by adding technology components with energy intensiveness of appliances as a function of initial cost, and its effectiveness on energy conservation alternatives via technological and economic effects were successfully demonstrated with application examples (O'Neal and Hirst 1980). Ang et al. (1992) developed a multiple regression model to evaluate the residential electricity use in Singapore based on the historical data of housing electricity use, climate data and several socio–economic variables. One major finding reported substantial differences in electricity consumption between high and low income households.

Two more top–down examples adopting regional energy statistic were used to evaluate specific energy related issues. Using the national residential energy statistics, Zhang (2004) evaluated the relationship between unit energy consumption (UEC) and heating degree days (HDD) in China, and compared the results with Japan, Canada and USA. Energy use in Chinese residential sector was discussed using the past consumption characteristics in other countries. With respect to the Hellenic housing stock and energy consumption, Balaras et al. (2007) developed a model to estimate the energy impact in some houses that need renovation with different energy conservation alternatives. The results indicated insufficient insulation in existing houses where significant energy saving in space heating can be reserved by adding appropriate insulation to the building envelope.

The advantage of top–down approach is the easiness of data collection, which mainly relies on historical energy, economic and technological data and is always available from national published statistics. Besides, these models could provide good prediction capability for small deviations from the variables in real situation, such as the increment of population and housing stock (Swan and Ugursal 2009). However, the reliance of past aggregated data could also be the limitation of top–down model, since the relationship between energy use and parameter variations established in the past could be differed from current or future options (i.e. the presence of efficiency gaps), especially less suitable for technological based policies evaluation (MIT 1997). Also, individual end–use variations cannot be reflected via this model approach. In other words, top–down model is a good energy prediction tool for large scale simulation with light–variation inputs, but not flexible to sharp parameter change which the association might not be held permanently.

2.3.2 Bottom–up approach

The bottom–up model is constructed with aggregate end–use level data (individual energy usage pattern, household energy consumption or group of houses energy expenditure) and then speculated on the energy use for regional or city scale levels. One major advantages of this perspective refers to it availability to quantify impact of end–use variations to overall energy consumption. Both macroeconomic and socioeconomic effects on the total consumption can be clarified by grouping of the input parameters and are adapted to current and prospective change (River and Jaccard 2005, Shorrock and Dunster 1997). The bottom–up approach can be sub–divided into 3 simulation categories, as shown in Figure 2.3, including the (i) White box, (ii) Black box and (iii) a combination of both, i.e. the Grey box, theories according to the data inputs and structures.

2.3.2.1 White box theory

The white box theory is described as the purely engineering based prediction method (Li and Wen 2014). It is the only method that requires no historical energy consumption information in model development. The end–use consumption of each appliance can be predicted by the distributions of appliance ownership and corresponding usage patterns. Using the physical relationship such as the heat transfer or thermodynamic principles, the white box model can perform detailed dynamic building simulation results. However, development of these equations is often too complex and time consuming for manual calculation. Various types of engineering based computer simulation programs are therefore being developed to improve simulation time and accuracy (Crawley et al. 2008, Coakley et al. 2014). The drawbacks of such simulation approach are attributed to its incapability on behaviour prediction and relatively long model development and simulation time.

Numerical and Physical expressions

Capaso et al. (1994) proposed a model to predict the total apartment energy consumption based on distributions of appliance penetration, usage patterns, engineering data and demographic via a housing survey. The results were well compared with regional energy statistics. Kadian et al. (2007) predicted the residential energy use in Delhi by a simplified end–use model with penetration rate and use factors of appliances in households. Thereafter, the model was extended to integrate with several social–economical inputs including household income, population and numbers of housing stock to identify the impact of total energy consumption with a long range energy alternatives plan. The ideas of these prediction tools are easy to understand and self–explainable from the equations. However, it requires intensive surveys and precise input parameters where the results can be deviated by large variety inputs. Besides, relatively long calculation time is required for individual energy use calculation in large scale simulation.

The overall thermal transfer value ($OTTV$) (Wm^{-2}) is one well known physical index to quantify the solar heat gain through building envelope of air–conditioned buildings. The index can be classified into two sections (wall and roof), each consists of three major components including (i) conduction through opaque walls, (ii) conduction through window glass and (iii) solar radiation through window glass. The two equations of $OTTV_{wl}$ through wall and $OTTV_r$ through roof are expressed in Equation (2.15) and (2.16), where A_{wl}, A_{wd}, A_e, A_r and A_{rf} are the area of opaque wall, window, external envelope, roof and fenestration at roof, U_{wl} and U_r are the thermal transmittance of wall and roof, TD_{EQw} and TD_{EQr} are the equivalent temperature difference of wall and roof, S_c is the shading coefficient, SF is the solar factor and ΔT is the difference between indoor and outdoor temperature.

$$OTTV_{wl} = \frac{\left(A_{wl} \times U_{wl} \times TD_{EQw}\right) + \left(A_{wd} \times S_c \times SF\right) + \left(A_{wd} \times U_{wd} \times \Delta T\right)}{A_e} \tag{2.15}$$

$$OTTV_r = \frac{\left(A_r \times U_r \times TD_{EQr}\right) + \left(A_{rf} \times S_c \times 434.7\right) + \left(A_{rf} \times U_{rf} \times \Delta T\right)}{A_r + A_{rf}} \tag{2.16}$$

By considering its impact of direct sunshine on the building envelope, *OTTV* was considered to be a more effective expression than the *U*–value for thermal transmission into air conditioned buildings in early 1980s (Stein et al. 1986). The *OTTV* standards of wall and roof values among the Asian countries were reviewed by Lam and Hui (1996). Although much works had been conducted to express the function of *OTTV* especially in the Asian countries (Lam et al. 2005, Yik and Wan 2005, Chua and Chou 2010), the use of *OTTV* was abandoned by ASHRAE in 1989, where the reliability of using TD_{EQ} to quantify thermal storage effects of envelope elements was criticized (Wilcox et al. 1985). Besides, *OTTV* was originally not designed for residential building due to the envelope thermal performance design and air–conditioning operation period different from commercial and office building (Chua and Chou 2010). Despite another similar index of residential envelope transmittance value (*RETV*), adoption of *OTTV* concept in residential building, was proposed by BCA (2008) in Singapore, the budding of computer–based building energy simulation software with detailed zonal load performance was superior to this physical index in term of flexibility and accuracy (Hui 1997).

Computer Simulation Programs

In order to enhance efficiency of comprehensive building energy simulation, a number of computer based building energy simulation tools are developed including BLAST, EnergyPlus, ESP–r, TRNSYS, DOE–2, HTB2, eQuest and more. A list of over a hundred updated building energy simulation tools information was summarized by the US Department of Energy (DOE 2014), while the history and simulation performance of 20 commonly used programs were reviewed and compared by Crawley et al. (2008). The strength and weakness of corresponding tools were discussed, while all programs were confirmed capable to provide a detailed energy analysis. Karlson et al. (2008) preformed building simulation tests using several dynamic simulation tools with the same design setup and criteria, where little deviation about 2% among models was found. The procedures of simulation and data flow from these programs were explained by Li and Wen (2014) and presented in Figure 2.4. The detailed input parameters of building characteristics (building geometry, material use and zonal division), system description (space conditioning selection, efficiency, operation schedule, ventilation rate and set–point) and component description (internal load) can be obtained from the targeted building (i.e. existing building or pre–constructed building), while the weather data can be evaluated by the hourly climate conditions from the weather observatory with respect to the best test reference year (TRY) or typical meteorological year (TMY) (Pedersen 2007, Fumo 2014). The simulation engine is constructed by various mathematical equations with respect to heat transfer and system operation principles for dynamic building energy consumption calculation. Finally, the output can be selected according to specific needs such as hourly heat gain, electricity use, peak load and annual consumption for either individual zone or the entire building.

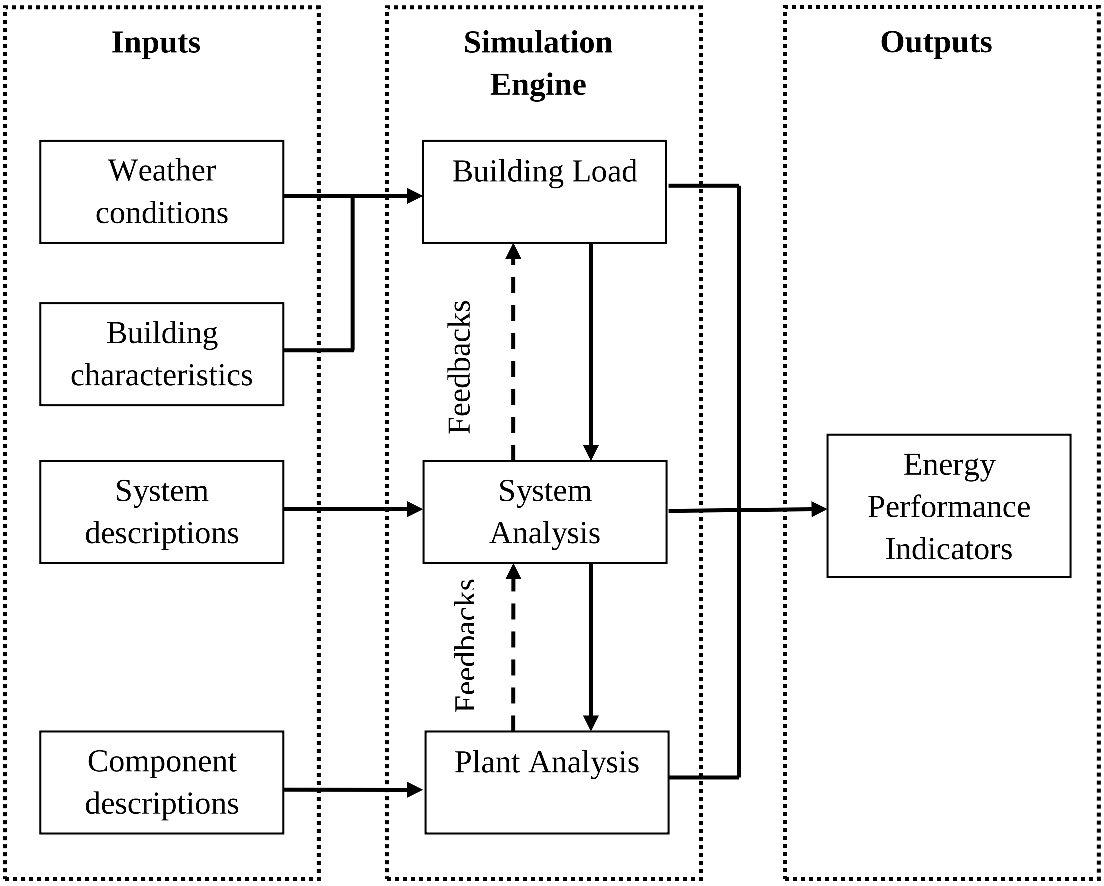


Figure 2.4 Procedures and data flow of computer based simulation (Li and Wen 2014)

Regarding to its detailed simulation performance supported with physical sense, dynamic building energy simulation programs are often being chosen for building energy optimization research. A critical review by Nguyen et al. (2014) suggested the most popular simulation program for building optimization study till year 2013 was EnergyPlus (37.2%), followed by TRNSYS (35.3%), DOE–2 (10%), ESP–r (5.6%) and the rest referred to other tools. EnergyPlus is one new generation building energy simulation program which is developed by creators of BLAST and DOE–2 in year 1996 (Fumo 2014). It is reported to be superior to the former simulation programs in terms of variable time steps simulation, user–configurable modular systems and availability for third party data input and output sources (Crawley et al. 2001). It is widely adopted for various kind of building energy simulation studies and good agreement is confirmed with calibration to actual measurement data (Pereira and Ghisi 2011). Apart from the whole building energy simulation programs, several computer simulation tools which specifically focus on the thermal performance characteristics of envelope components are reviewed by Sadineni et al. (2011), including Window, VISION4, FRAME4, FRAMEPlus, FENSIZE, Frame Simulator, RESFEN, SPACER etc.

Despite the details in thermal energy performance available from these dynamic prediction tools, a number of drawbacks are recognized by peer scholars when implementing for building simulations. Notwithstanding its advantage of free from historical energy data support for simulation process, these physical simulation tools function required detailed architectural layout for simulation process (Catalina et al. 2008). Besides, assumption has been made for occupant behaviours including occupancy and AC operation while using these engineering based models, where the model performance can be widely varied if the occupant’s energy usage patterns are uncertain (Swan and Ugursal 2009). Moreover, model construction and input process can be lengthy and complex, which may not be applicable for non–professional users and may be cost inefficient to large scale simulations (Coakley et al. 2014). Furthermore, archetype simulations with just one of the few trials are difficult to make any general deductions (Bojic et al. 2002a).

2.3.2.2 Black box theory

The black box theory is driven by purely data or statistical based prediction method. Common simulation models implementing black box theory were identified as regression models, artificial neural networks (ANNs) and support vector machines (SVMs). This modelling approach needs a relatively large database via measurements with sufficiently long time to ensure the data being obtained can cover and represent probable scenarios (Li and Wen 2014). The selected variables and the captured energy performance in building are represented as the cause and effect pairs to train the black box model, where the correlations are identified by mathematical or statistical analysis.

Regressions models

This approach expresses the aggregate energy end–use to one or a few parameters which correlate with the total energy expenditure. Establishment of these empirical models is based on historical data, where extensive measurement on energy record and related parameters are necessary. Existing works on regression analyses to building energy consumption were reviewed by Zhao and Magoules (2012) and classified in three aspects: (i) energy prediction with one of few simplified variable(s), (ii) estimation of important parameters and (iii) investigation of new energy index of energy performance. Superior to the physical simulation, this statistical approach is capable to bridge the non–linear relationship between the input and output variables with quick response time once the model is established. From the regression analysis, the model coefficients correspond to the input parameters are determined which may or may not have physical significance. Despite its accuracy on non–linear mapping, significant effort and time is required to construct and calibrate the model before use (Paudel et al. 2014). Besides, the robustness of these algorithms can be uncertain for very large data set and short term horizon with hourly energy prediction (Kumar et al. 2013, Wan et al. 2011).

Numerous studies attempted to evaluate the relationship between building space conditioning energy use and climatic variables or building characteristics by regression analysis. Ansari et al. (2005) applied a regression function to the temperature difference between the components of building envelope to evaluate the heat transfer and the building cooling load by adding all sub–loads in each component. Lam et al. (2005) evaluated the relationship between building peak cooling load and the overall thermal transfer value (*OTTV*) using a simple regression approach in sub–tropical region. Thereafter, *OTTV* was replaced by another significant but simpler and measureable value of total gross exterior wall area in the regression equation. Wong et al. (2008) predicted the building fabric load in Hong Kong office buildings via a multivariate regression model, with model correlation coefficient R=0.92, using relevant inputs included indoor temperature, maximum length of floor, floor area, floor volume, *U*–value of envelope, window to wall ratio and shading coefficient. Sa'ad (2009) developed a structural time series model (STSM) to estimate the residential electricity demand in South Korea with elasticity of electricity price and household activity. The annual growth of underlying energy demand trend in residential sector was also estimated. Similarly, a monthly dynamic time series regression was established by Tsai et al. (2008) to investigate relationship between electricity consumption and housing development trend in Taiwan.

Building energy usage pattern and important energy consumption determinants can be identified by extensive end–use survey. According to the domestic survey data over 1500 housings in Hong Kong, a multiple regression model was employed by Tso and Yau (2003) to forecast the weekly electricity consumption by groups of related parameters. The results showed that housing type, flat size, number of occupant, income and ownership of different appliances were significant for residential electricity consumption. Regression model with occupant behaviour and socio–economic factors as input parameters, such as income, number and age of household, housing type, floor area, number of cooled rooms, cooling type and cooling degree days (*CDD*), was proposed by Steemer and Yun (2009) to forecast the apartment cooling demand. Using the Residential Energy Consumption Survey Data from the Energy Information Administration (EIA), Kaza (2010) developed a quantile regression analysis to clarify the differential effect of variables in entire distribution range on energy consumption spectrum instead of using conditional average. The parameter inputs included climate (*CDD* and *HDD*), housing size, occupant number, housing age, neighbourhood density, household income, fuel price, ownership status and housing type. One major finding suggested that graduated increase of fuel prices would result more noticeable effect on residential energy saving than uniform increment.

Useful tool or index can be evaluated by regression analysis enhancing simulation performance. A regression–based method, called conditional demand analysis (CDA), was proposed by Aydinalp–Koksal and Ugursal (2008) to model the residential end–use consumption in Canada. This approach was recommended by its easiness to develop and operate, but required a large database and lack of details and flexibility as compared with ANN model. A climate index, named *Z*, listed in Equation 2.10, was developed by Lam et al. (2008b, 2010) using principle component analysis (PCA) to forecast the cooling energy use in building for different climate zone in China. Relationship between *Z* and building cooling load was obtained from linear regression analysis. Hygh et al. (2012) proposed an assessment tool developed by multivariate regression technique, testing sensitivity of 27 building parameters including building size, geometry, location and shading projection for cooling load prediction. The results were compared with EnergyPlus simulation with good agreement and it suggested linear regression model can be an effective method for building energy prediction.

Artificial Neural Networks (ANNs)

ANNs are generic denomination of simple mathematical model for human brain function, i.e. the biological neural networks. It is widely adopted in building energy simulation due to its preciseness for non–linear analysis, pattern recognition and classification between inputs and outputs relationship (Zhang et al. 1998, Kalogirou 2006). A basic ANNs consist of three layers, the input, hidden and output layers, respectively function in receiving input signal, classifying signal and supplying results estimated by the networks. Each layer is composed of and interconnected by series of parallel processors called “neuron”, which receives multiple signals from preceding neurons and then propagates to several others by integrating its own weighting factor. The weighting factor can be self–adjusted by a bias term and an array of coefficients during the network training stage. Regarding to its self–learning and fine tuning abilities, ANNs is particularly beneficial in forecasting the interaction between occupant behaviour, building energy consumption and system control (Chao and Hu 2004, Kalogirou 2006, Ahamd et al. 2014). Since the network is parallel in nature, one failed neuron is not fatal to entire network function. However, physical meaning is not explicitly derived via the network structure between input and output values (Ahmad 2014). Several neural network structures commonly applied for building energy simulation includes back propagation neural network BPNN (Kalogirou et al. 2001; Ekici and Aksoy 2009; Yokoyama et al. 2009, Kumar et al. 2013), general regression neural network GRNN (Zmeureanu 2002, Ben–Nakhi and

Mohmoud 2004, Sun et al. 2013b), recurrent neural network RNN (Kreider et al. 1995) and fuzzy neural network FNN (Kajl et al. 1997, Kubota et al. 2000).

The major advantage using ANNs for building energy simulation is the flexibility on selecting target input and output variables for network training. The output targets can be long term annual energy forecast as large in entire city scale or short term simulation with hourly energy use in individual space (Hippert et al. 2001, Olofsson and Andersson 2001, Kandil et al. 2006). A critical review on the ability of short–term load forecast by ANNs was confirmed by Hippert et al. (2001). Employing the ANN model, Yezioro et al. (2008) estimated the hourly heating/cooling demand in building with details hourly inputs of outdoor temperature, relative humidity, indoor set–point temperature and occupancy schedule. Neto and Fiorelli (2008) modelled the daily cooling energy consumption, including weekday and weekend schedule, by ANNs for a university building in Brazil. An error of ±13.8% was recorded when compared with the actual building loads, where this error range was also comparable to simulation using EnergyPlus. Based on the short–term measured energy data (2–5 weeks) as parameter inputs, Olofsson and Andersson (2001) proposed an ANN model to evaluate the annual heating demand in single family buildings in Sweden with high prediction accuracy. According to a comprehensive survey with electricity consumption billing and demographic data in 741 households, Aydinalp–Koksal et al. (2002) developed a neural network model to estimate the national residential cooling energy consumption in Canada.

Another advantage of ANNs approach refers to its non–linear patterns and behaviours recognition ability among training data, based on parallel neurons interaction and self–learning characteristics (Ahmad et al. 2014). Its flexibility can be extended to predict a target output which has indirect physical and causal relationship to the input variables. Gonzalez and Zamarreno (2005) applied the feedback ANNs technique to estimate the hourly energy consumption in building using the time series information including hour, day, current energy demand and temperature as parameter inputs. Adopting the same technique, Dombayci (2010) predicted the hourly heating energy consumption in building of Turkey, with extended time series inputs of pervious hour energy consumption and months to emphasize the seasonal impact. Different from a fixed occupancy schedule used in physical simulation tools, Kwok et al. (2011) introduced the hourly occupancy rate as one of the input parameters of an ANN–based multi–layer perceptron (MLP) model to simulation the cooling load patterns in a commercial building. The findings showed the time series occupancy input in ANN model contributed significant impact on mapping the actual building cooling load profile. Ben–Nakhi and Mahmoud (2004) used only the 24 hours outdoor dry–blub temperature to train ANNs in order to predict the forthcoming day cooling load. Ekici and Aksoy (2009) employed the transparency ratio, building orientation and thickness of external wall as data inputs for ANNs training to estimate building heating load with no weather data consideration.

Comparisons between neural networks and other statistical models were conducted. Farzana et al. (2014) compared the energy forecast precision for urban residential buildings in Chongqing city by six prediction models including ANNs, first order differential grey model, second order derivative grey model, regression model, polynomial model and polynomial regression model. The results showed that accuracy of ANNs is higher than the other five models with the lowest mean relative percent error. A similar study conducted in Taiwan by Pao (2006) also reported that ANNs was more suitable for building energy forecast as compared with several linear and non–linear models. Aydinalp–Koksal and Ugursal (2008) estimated the national level residential end–use energy consumption in Canada via ANNs, conditional demand analysis CDA and an engineering model. Despite its weakness on demonstrating energy impact to individual appliance, the ANN model was superior to both the CDA and the engineering model regarding to the prediction results, especially flexible in evaluating impact on socio–economic factors including household income, dwelling type and number of occupants in apartment. Kalogirou et al. (2001) predicted the daily cooling and heating demand in building by ANN model with several weather and building inputs. Insignificant difference was reported between the ANN results and the simulation outputs by TRNSYS. Neto and Fiorelli (2008) predicted the daily energy consumption of building using ANN and EnergyPlus with different climate variable including relative humidity, outdoor dry bulb temperature and solar radiation. High prediction accuracy was demonstrated in both methods, while neural network was slightly better in short–term prediction. Apart from the success in energy prediction, ANN model is superior over purely physical simulation by the forecasting ability, where it can provide information of primary thermal energy consumption of another project beyond the design stage, i.e. without the detailed building layouts, once the network is being established.

Support Vector Machines (SVMs)

SVMs are originally developed for data mining and classification purpose, using the method of support 'Hyper–plans' to distinguish the training data. In recent years, however, it transforms to be one famous self–learning tool in solving non–linear regression problems, risk minimization and decision making for building energy forecast (Dong et al., 2005; Liang and Du 2007; Zhao and Magoules 2012). The upper bound of the generalization error could be minimized by applying the foundation of Vapnik–Chenoverkis (VC) theory (Vapnik, 1995). The basic idea for SVM regression is to map the inputs into high–dimensional feature space, using kernel function via a non–linear mapping method, and to perform a linear regression in this feature space (Li et al. 2009a). Notwithstanding its superior robustness and accuracy in forecasting analysis, a major disadvantage of SVMs attributes to a high computational burden for the constrained optimization programming which takes longer time for model construction and simulation (Ahmad et al. 2014).

Dong et al. (2005) used three years monthly building electricity data to train a SVM in tropical regions. Good performance of prediction was showed and the model was fitted well with data in other year. Li and his co–workers applied SVMs to predict cooling load in some offices (Li et al. 2009a) and annual energy consumption in several residential buildings (Li et al. 2010) with high accuracy prediction in both building types. Some other studies are conducted to compare the simulation performance between SVMs and other prediction tools. Hou and Lian (2009) trained a SVM to estimate the cooling load for HVAC system and compared the results with autoregressive integrated moving average (ARIMA) model. SVM showed a better performance than ARIMA with smaller absolute error and relative error. Li et al. (2009b) compared the prediction of cooling load in building by SVM and three neural network approaches including traditional back propagation neural network (BPNN), radial basis function neural network (RBFNN) and general regression neural network (GRNN). The results showed all four models were good energy predictor, but a better performance was observed from SVM and GRNN methods analyzed by root mean square error (RMSE) and mean relative error (MRE).

Black box model summary

The strength of black box model attributes to its short development time and high accuracy on building energy forecast, especially beneficial in identifying non–linear relationship between input and output parameters such as occupant behaviour and appliances usage patterns. The characteristic of statistical data–driven approach enhances its ability for short–term load forecasting sensitive to parameter inputs (Hippert et al. 2001, Paudel et al. 2014). However, inappropriate prediction results could have happened if the database obtained via measurements is not comprehensive enough to reflect the possible output variation trend. Besides, implicit physical and causal significances between the selected variables and the energy output are required for model development. Re–training of model could be necessary if the building layout and system operation are significantly deviated (Coakley et al. 2014). The general performance of building energy prediction via three sub–groups of black box approach, regression, artificial neural networks ANNs and support vector machines SVMs, was established by Zhao and Magoules (2012) and summarized in Table 2.3. It revealed that the accuracy of prediction both ANNs and SVMs were high, but they were not easy to be used with high model complexity as compared with regression model. A longer simulation time was required for SMVs with higher computational burden as compared with ANNs simulation (Wang and Ying 2010).

Table 2.3 Comparative performance of regressions, ANNs and SVMs for building energy simulation (Zhao and Magoules 2012)

Methods	Complexity	Easy to use	Running Speed	Accuracy
Regressions	Fair	Yes	Fairly high	Fair
ANNs	High	No	High	High
SVMs	Fairly high	No	Low	Fairly high

2.3.2.3 Grey box theory

Since the white box and black box model are respectively having the pros and cons in specific concerns for energy prediction, a combined model with physical and statistical confidence to maximize simulation flexibility, accuracy and speed can be an effective solution for ongoing simulation development trend. The grey box approach, or the hybrid model, adopts a two–step development which a mathematical or physical based model is first developed with configurations relevant to the impact of building energy use, thereafter statistical analyses are established prior to the physical model estimating the target energy performance satisfactorily (Fumo 2014).

The major advantage of a hybrid model refers to the combination of physical calculation and statistical prediction components. The Canadian Hybrid Residential End–use energy and Emission Model (CHREM) is one typical example of hybrid model, where the physical half of the model was constructed by package ESP–r for building heating and cooling load simulation, while the statistical half was established by artificial neural networks tackling the use of appliances based on occupant behaviour (Aydinalp–Koksal et al. 2002; Mohmed and Ugursal 2008). Applying Laplace transform technique, Lu et al. (2014) exhibited a solution for building energy performance prediction including physical and generalized parameters. The model variables were further reduced to enhance simulation process by singular value decomposition techniques. Grey box model is also beneficial from its quick response time and with high prediction accuracy. Zhou et al. (2008) preformed a modified grey box model to predict the weather data (hourly temperature and humidity) for real time on–line building thermal load estimation. An improved energy performance was recorded by adopting the predicted weather data in further simulation process. Li and Wen (2014) reviewed the capability and effectiveness of white, black and grey box models for on–line building operation system. The results showed the grey box model was the most suitable choice in terms of energy and cost saving with less determinant parameters and shorter computation time.

Apart from the combination of physical–statistical model, scholars were also interested in the hybridization of statistical–statistical approach. Gonzalez and Zamarreno (2005) developed a hybrid ANNs model to predict the hourly energy consumption, with the first network estimating the climatic variables and the second network forecasting the energy consumption using the results in former network as parameter inputs. Fan and Chen (2006) forecasted the short–term load using SVMs and a hybrid model based on SVMs and self organized map (SOM). Better prediction performance was confirmed by using the hybrid SVMs–SOM network over the single SVMs approach. Similarly, a hybrid of ANNs and ARIMA model for building energy forecast was introduced by Wang and Meng (2012), where higher accuracy of the hybrid network was observed, by error tests, as compared with the predictions using single ANNs or single ARIMA approach.

The hybridizing technique of replacing building simulation software by regression approach, i.e. using simulation software to prepare a database of past history for network training, is studied. Asadi et al. (2014) predicted the energy consumption in commercial buildings using the grey box theory. Ten thousands simulation configurations were built and simulated by eQUEST and DOE–2, and the non–linear relationships between input parameters (building materials, thickness, building shape and occupant schedule) and the energy demand were expressed via a set of regression equations. Satisfactory accuracy, <5% error, was reported between the results by DOE–2 simulation and the regression model. This approach effectively redeems the limitation of lacking physical significance in regression model, since the training data was extracted from pure physical simulation and no historical data is required. Similar study was conducted by Ben–Nakhi and Mahmoud (2004) using ESP–r to establish energy database for ANNs training to predict cooling load in public residential and office buildings with high accuracy (R^2=0.95). The major advantage of this approach was emphasized as the reduction of necessity parameter inputs and thus significantly shortened simulation speed, while the quality of simulation performance is maintained. Although the hybrid approach is still not mature enough as compared with pure physical and statistical approach, increasing studies adopting this simulation method are observed. The hybrid simulation approach is of great potential to become a popular building energy simulation practice.

2.4 Model Validation and Sensitivity Analysis

Adequate validation in confirming accuracy of simulated data is required for the developed building energy model to assure reliability of simulation results before use. Summarized by Ryan and Sanquist (2012), model validation can be identified via three different methods of comparison including analytical solutions, empirical data and peer models. Analytical solution method is practical to quantify accuracy of different components in model development stage, but not functional to verify the overall prediction performance. Validation by the remaining two methods is broadly applied in literatures (Pedersen 2007, Neto and Fiorelli 2008, Yun and Steemers 2011, Pereira and Ghisi 2011, Maile et al. 2012, Fumo 2014, Coakley et al. 2014, Ren et al. 2014, Farzana et al. 2014). Comparison with empirical data, i.e. the actual metering and auditing data, is considered as a trustworthy method since it provides

n_p

'absolute truth standard' within the parameters uncertainty during simulation (Ostergaard Jensen 1995). One drawback of this method refers to its difficulty in obtaining the extensive 'True' data for validation and is time consuming (Loutzenhiser et al. 2007). Peer model approach is the most popular validation method when comparing the simulation results with another valid simulation tool under the same conditions and parameter inputs. However, this approach is strongly dependent to the simulation assumption of the peer model, since the 'absolute truth standard' is not allowed (Ostergaard Jensen 1995).

Several standardized statistical indices representing the performance of building energy model was reviewed by Coakley et al. (2014), including Mean Bias Error (MBE), Root Mean Square Error (RMSE) and Coefficient of Variation of Root Mean Square Error (CVRMSE). Corresponding equations are expressed in Equations 2.17 to 2.19, where m_i is the measured data point, s_i is the simulated data point, n_p is the number of data point at interval p (i.e., $n_{monthly} = 12$ and $n_{hourly} = 8760$) and $\overline{m}$ is the average of the measured data points.

$$MBE(\%) = \frac{\sum_{i=1}^{n_p}(m_i - s_i)}{\sum_{i=1}^{n_p}(m_i)} \tag{2.17}$$

$$RMSE(\%) = \sqrt{\frac{\sum_{i=1}^{n_p}(m_i - s_i)^2}{n_p}} \tag{2.18}$$

$$CVRMSE(\%) = \sqrt{\frac{\frac{\sum_{i=1}^{n_p}(m_i - s_i)^2}{n_p}}{\overline{m}}} \tag{2.19}$$

MBE is a good indicator of overall bias in model via the mean difference between the measured and simulated data points. However, cancellation effect between the positive and negative bias may occur. An improved test of CVRMSE is therefore recommended in capturing the offset errors between measured and simulated data which does not suffer from the cancellation effect (Coakley et al. 2014). The acceptance values of MEB and CVRMSE for building energy performance simulation by ASHRAE–14 (2002) are respectively for monthly (5%, 15%) and hourly (10%, 30%) intervals. The RMSE is focus on testing the variability of data set.

Sensitivity analysis is a valuable tool to quantify relative influence of different input parameters in an energy simulation model (Tian 2013). Three commonly used sensitivity analysis methods were reviewed by Lomas and Eppel (1992) for building energy simulation purpose, including Differential (or local) Sensitivity Analysis (DSA), Monte Carlo analysis and Stochastic sensitivity analysis. Operation of DSA considered the variation of one uncertain input for each simulation, while the Monte Carlo analysis and Stochastic sensitivity analysis both varying all uncertain inputs, respectively, for each simulation based on a defined probabilistic distribution and at each simulation time step.

DSA is easy to operate and thus a preferred method for many studies (Spitler et al. 1989; Simm et al. 2011; Molinari 2012) which provided both individual and total sensitivities. However, predictions outside the parametric range are not available. Besides, the interaction between parameters is not being identified from this analysis. The procedures of conducting DSA were outlined by Daly et al. (2014) and summarized as follows:

(1) Define a base case building configuration with most likely parameter values;

(2) Assign ranges for parameters that are of interest;

(3) Simulate the building with base case configuration;

(4) Simulate the building with varying parameter along the selected range, while at the same time keeping other parameters unchanged;

(5) Present the result of analysis.

2.5 Policies and strategies for cooling energy reductions

According to the review findings above, strategies for cooling energy reduction can be classified into four groups including material selection, building construction design, building system efficiency and socio–economic and behaviour. Table 2.4 summarizes the cooling energy related findings and corresponding strategies to enhance energy savings in each class. The recommended strategies are focused on minimizing heat gain or enhancing heat rejection efficiency, while the occupant behaviour related strategies are generally linked to government energy policies and advance simulation models. User behaviour is indispensably a critical issue in building energy evaluation, where new methods and determinant parameters in understanding occupant behaviour have been developed for more accurate simulation (Leung et al. 2012, Hoes et al. 2009, Schweiker and Shukuya 2009, Yun and Steemers 2011). Despite its confirmed impact on building energy use, research works focus on helping or encouraging users in energy conservation are rarely established. Effective energy conservation policies should be targeted on users, in terms of energy costs, incentives and ease of implementation (Kaza 2010).

A household survey combined with ECO_2 simulation program in calculating individual's energy consumption in residential place was conducted by Goldblatt et al. (2005) to understand the occupants' energy saving potential. The results showed that occupants were over–estimating their environmental friendliness of their lifestyles, while the adoption of energy calculator was helpful in stimulating and educating respondent's awareness on energy saving behaviours. The study demonstrates an idea that strategies on building designs and system efficiency enhancement might not be the only way to achieve energy saving, where adoption of computer simulation tools and models to stimulate end–users energy saving awareness can be a lot more productive. Another example refers to Yu et al. (2011), who proposed a computational and statistical integrated method to identify occupant behaviour and to provide recommendations for individual's energy usage decisions in residential buildings. The model was proved more efficient in encouraging occupant's energy saving habits than traditional education method. Wong et al. (2009) proposed a 5–star energy benchmarking system to evaluate the sustainability of energy use in residential buildings. These approaches can be useful for occupants to visualize or understand their own energy usage status at home. It suggests that more studies focusing on thermal energy conservation practices with respect to user's view–points are necessary.

Table 2.4 Examples of cooling energy saving strategies in buildings

Class	References	Findings	Strategies to enhance cooling energy savings
Material selection	Cheung et al. (2005)	Change of solar absorptance of external wall can achieve energy saving up to 13% as compares with the base case cooling demand.	External wall should be finished with low solar absorptance material.
	Li and Lam (2000), Karlsson and Roos (2001), Bojic and Yik (2007), Chua and Chou (2010)	Remarkable thermal heat gain comes from window to indoor space, where the shading coefficient (or solar heat gain coefficient) and window U–value are important determinant parameters.	Single low–E glazing is recommended as a cost effective choice in replacing clear glass window to minimize thermal heat gain.
	Bojic et al. (2002a), Radhi (2009), Sadeghifam et al. (2015)	Selection of insulation material has the greatest effect in altering apartment cooling load.	Improving thermal insulation of partition walls between AC and non–AC spaces. Material of reverse brick veneer R20 is recommended for external wall to reduce heat gain.
	Feng (2004), Turhan et al. (2014), Alaidroos and Krarti (2015)	The most quantitative parameters for building thermal energy consumption are envelope *U*–values and index of thermal inertia.	The envelope *U*–value should remain low to minimize thermal transmittance in building. The values of external wall and roof shall not exceed 1.0 and 1.5$Wm^{-2}K^{-1}$, while the thermal inertia is suggested higher than 3.0.
Building construction and design	Asadi et al. (2014)	Building orientation and shape have significant impact on cooling electricity consumption.	Optimizing building orientation and shape before construction.
	Kaza (2010)	Household size is significant to cooling energy use.	Changing housing type mix with larger multi–family houses and reducing overall housing size.
	Cheung et al. (2005)	High–rise residential cooling energy reduction is related to several integrated passive designs.	Passive strategies include replacement of thicker thermal insulation, reduction of window area, extension of shading length and orientation of apartment facing north direction.
	Bojic and Yik (2005), Pan et al. (2012), Fang et al. (2014), Aktacir et al. (2010)	External wall insulation thickness is an important factor affecting cooling energy demand.	Adding insulation to the building envelope, i.e. increase wall thickness, can effectively reduce apartment cooling load. Besides, different thickness is recommended according to the envelope orientation.
	Inanici and Demirbilek (2000), Persson et al. (2006), Ihm et al. (2012), Huang et al. (2014)	Large window is beneficial to incident of natural light, but also initiates excessive solar heat gain.	Optimal window to wall ratio should be considered in balancing both visual and thermal needs for indoor space. Besides, size of window should be adjusted in different orientations.
	Chua and Chou (2010), Bojic (2006)	Effective shading device can significantly minimize direct thermal heat gain, especially for higher floors and rooms far from building core.	Angle of shading devices should be adjusted to maximize its shading effectiveness with respect to different orientations.

Table 2.4 Examples of cooling energy saving strategies in buildings (continue)

Class	References	Findings	Strategies to enhance cooling energy savings
Building system and efficiency	Lam (1996), Kosar (2006), Shimoda et al. (2007), Chua and Chou (2010)	Air–conditioner *COP* varies in wide ranges which affect the cooling energy performance. Besides, system with low *COP* significantly increases the total cooling electricity use.	Suggestions for improvement include implementing energy efficiency labelling schemes for room air–conditioners, replacing existing system with higher *COP* choice especially for dehumidification consideration.
	Todorovic and Zivkovic (2005)	Cooling energy consumption is found proportional to system fresh air ventilation rate.	Night ventilation without outdoor air treatment for room cooling is recommended.
	Peterson et al. (1998)	Air–conditioning sizing is a significant concern to the diversified cooling demand in residential buildings.	Retrofit of AC with downsized high efficiency unit can effectively minimize local peak cooling load.
	Karimpour et al. (2015), Wong et al. (2010), Wangpattarapong (2008), Sadineni and Boehm (2012)	Increasing cooling demand is confirmed with climate change, where indoor temperature set–point significantly affects the residential cooling energy consumption.	A higher indoor temperature set–point is recommended for cooling energy saving.
	Bojic et al. (2002b)	The performance of window type air–conditioner is affected by its mounted location and the position associates with the neighbouring walls.	A critical distance is suggested between the sidewall and the window type air–conditioner to maintain satisfactory AC efficiency.
	Lam et al. (2008b)	Significant proportion of energy use in HVAC system is contributed by HVAC auxiliary especially for fans and pumps.	Using variable speed fans and pumps can enhance cooling energy saving potential in particular to part load conditions.
Socio–economic and behaviour	Sa’ad (2009)	Increasing electricity tariffs and taxes may not likely to reduce residential electricity consumption.	Suggest government to complement the pricing policies with non–market policies to limit electricity consumption and encourage energy conservation.
	Hoes et al. (2009)	Occupancy and user behaviour are important concerns for building energy performance assessment.	A decision method based on sensitivity analysis is developed to enhance user behaviour resolution level in building energy performance prediction.
	Sun et al. (2014)	Overtime working impacts building total energy use.	Stochastic overtime model and hybrid calibration approached are proposed to improve building energy simulation accuracy.
	Tsai et al. (2008)	Energy end–use in urban housings is found higher than in rural housings.	More rural housings are recommended in Taiwan to lower the total electricity demand.

2.6 Summary

Thermal energy demand in building contributes a significant part of total building energy expenditures. This chapter reviews the related parameters and methods of building thermal energy evaluation, especially focuses on cooling energy consumption in residential sector. Parameters which affect building thermal energy consumption can be classified into 6 groups, including materials and constructions, climatic factors, cooling systems, internal loads, occupant behaviours and the indirect factors. The energy impacts from building materials and construction designs are outstanding when compared with other factors, since the heat gain from building envelope is the major heat sources. Regarding the heat transfer effectiveness to the indoor space, outdoor climatic conditions also play an important role in affecting the building cooling energy use. Climate change with global warming is indispensably a hot topic in existing field, where raising indoor temperature set–point is agreed to be the most effective strategies in reducing future cooling energy consumption.

The building cooling system may influence the effectiveness in space heat rejection with respect to the required cooling demands. Important concerns may include indoor temperature set–points, system coefficient of performance (*COP*) and the infiltration and ventilation rate. Adjustment of temperature set–point can significantly influence the cooling energy consumption, but the desire neutral temperature by occupant is varied at living place. Besides, assumption of fixed *COP* for air–conditioner at home may not truly reflect the system performance, where dynamic approach with *COP* dependent to the sensible heat ratio can be a method of improvement. The internal heat load in building can be attributed by heat gain via equipments, lightings and occupants. The former two can be expressed as power density normalized by floor area, while the latter one is quantified by occupant's activities level dependent to the design internal load schedule.

A raising concern in occupant behaviours is emphasized in evaluating residential energy performance. Direct connection is referred to occupancy and air–conditioning operation in occupied space. Fixed schedule varying by time or desire condition (i.e. set–points) applied in building energy simulations is argued not truly representing the actual occupant's variation and AC consumption. Probabilistic occupancy and AC schedule are encouraged in matching the actual variation in accordance with building types and occupant's backgrounds. Besides, there are a number of other factors in relation to residential cooling energy consumption, including demographic, socio–economic factors, ownership of AC, housing type and mix ratio. The chain relationship can simply be explained by higher household income due to economic growth, and these occupants are willing to spend more money and energy in fulfilling a more comfortable lifestyle. Alternative energy pricing strategies with higher incentive could be helpful in encouraging occupant energy saving awareness.

Thermal energy prediction is important for system sizing and implementation of energy conservation measures. The available thermal energy simulation methods can be divided into two major types: top–down and bottom–up approaches. The bottom–up models, based on either physical or statistical approach, are more favourable to scholars nowadays. Pure physical expressions together with advance computational aid simulation tools can provide detailed dynamic energy simulation performance, but it is limited to occupant behavioural responses and requires lengthy development and simulation time for large scale prediction. The statistical based prediction method can be further classified into regression model, artificial neural networks (ANNs) and support vector machines (SVMs). Superiority in statistical method is ascribed to its fast response time and capability in non–linear pattern recognition especially beneficial in occupant behaviour and socio–economic relation modelling. The negative attributes of these models are that they require large survey sample data for training and validation. Besides, causal relationship between input and output variables is not explicitly required for model architecture.

Finally the grey box model is a combination between pure physical and statistical approach which hybridizes the strength between both. This method not only requires shorter simulation time as compared with physical simulation tool, but also redeems the lack of physical explanation between input and output data in pure statistical approach. Application of this hybrid model is still not well developed, but an increasing trend using this approach in building energy simulation is observed. It can be a new direction to enhance flexibility of thermal energy simulation performance.

Throughout the review findings, cooling energy saving strategies are highlighting the heat reduction from building envelope, enhancement of system efficiency and energy marketing policies. Despite the evident impact of occupant's decisions on cooling energy consumption, research work focusing on initiating energy conservation in user view–points is still limited. Extensive study includes supporting computer simulation tools and analysis for laymen understanding are encouraged.

Chapter 3

Selection of Housing Type for Cooling Energy Evaluation

3.1 Introduction

Energy consumption patterns are sensitive to housing types with different building design determinants and occupant usage behaviours. Correlations between energy consumption in residential buildings and parameters including occupant load, building floor area, household socio–economic class, appliance ownership, occupant behaviour and climatization were studied (Saidur et al. 2007, Cheng and Steemers 2011, Haas 1997, Shimoda et al. 2004, Tso and Yau 2003, Cheung et al. 2014). Socio–economic structure and occupant behaviour were found to be the important factors affecting energy consumption in South Korea (Oh et al. 2000). Cultural models could be significant parameters for estimating residential energy consumption (Loren 1992). However, models that have a bias on tenant–based consumption would underestimate the building electricity consumption. Reported by Lam (1996), electricity use in communal area or the public place comprised up to 20% of total building consumption. In view of an improved living standard, energy use in communal area can be significantly boosted, while a study on this sector is still limited.

About 25% of total building energy use is consumed in Hong Kong residential housing sector. In between, up to 70% of the energy is contributed by electricity consumption (EMSD 2010). The private housings dominate half of the entire residential housing stock in Hong Kong (1080 thousands) (HF 2009). Moreover, there is a trend of increasing leisure facilities (e.g. clubhouses), lighting decorations and air–conditioned communal areas in all high–rise developments. As energy required for interior circulation (e.g. lifts and escalators) and water supply increases with the average building height, energy expenditures in the communal sector must be studied for sustainable housing plans.

Adequate selection on target building can enhance effectiveness on energy conservation strategies implemented for sustainable housing development plan. This chapter investigated the residential electricity consumption of tenants and communal areas in terms of housing types. Impacts of energy outlook on future housing construction plan in Hong Kong are discussed. Suitable housing type is selected, regarding to justification on sustainability and availability on input and output data, for extensive cooling energy evaluation in this study.

3.2 Overview of electricity consumption among housing types

Housing types in Hong Kong are mainly classified as: public rental housing (PRH), subsidized apartments under the home ownership scheme (HOS) and private housing (PRI). PRH are housings built for rent to low income families and they are owned by Hong Kong Housing Authority. HOS and PRI are housings owned by private residents, respectively constructed by the government and other private property companies. Table 3.1 shows the stock units, gross floor areas and occupant loads of the three housing types in 2007 and 2008 (HKADS 2001–2009, HKPR 2008–2010, HF 2009). About 80% of PRH, 40% of HOS and 55% of PRI buildings are over 20 years of age in 2007. Current statistics on private housing estates with clubhouses (PRI_{CH}) remain unknown. For each housing type, the total gross floor area is the product of the stock number and mean gross floor area (GFA). 33% PRI apartment have a GFA of 30 m^2, 49% have 55 m^2, 11% have 85 m^2, 5% have 130 m^2 and 2% have 180

m^2. 62% and 38% of PRH apartments and 30% and 70% of HOS apartments have mean GFAs of 30 m^2 and 55 m^2 respectively. (HKADS 2001–2009, HKPR 2008–2010).

PRH, HOS and PRI residents respectively contribute 30%, 10% and over 50% of the total residential electricity consumption in Hong Kong (EMSD 2010). According to Table 1, PRH has the lowest occupant load factor (11.8 m^2 hd^{-1}), per–apartment gross floor area (34.1 m^2 $unit^{-1}$), per–apartment annual electricity consumption (4228 kWh yr^{-1} $unit^{-1}$), and per–occupant annual electricity consumption (1458 kWh yr^{-1} hd^{-1}). As HOS and PRH have similar annual electricity consumption values per occupant but not per–apartment, occupant load can be taken as an explanatory parameter for public housing annual electricity consumption. Although in 2007 both PRI and HOS contributed comparable per–apartment annual electricity consumption (4599 vs. 4800 kWh yr^{-1} $unit^{-1}$), but PRI residents have contributed a higher per–occupant consumption (about 10%) than the other residents.

Table 3.1 Residential electricity consumption and housing data in 2007 and 2008

Parameters (Units)	Public Housing				Private Housing	
	(1) PRH		(2) HOS		(3) PRI	
	2007	2008	2007	2008	2007	2008
Stock (units)	673825	694099	207088	211678	1079243	1085922
Percentage vacancy (%)	0	0	0	0	4.9	4.9
Gross floor area (m^2)	22963023	23662802	9824788	10047407	61282075	61782790
Occupant density (hd $unit^{-1}$)	2.9	2.9	3.3	3.3	2.9	2.9
Total population (hd)	1954093	2012887	683390	698537	2976444	2994864
Per–occupant gross floor area (m^2 hd^{-1})	11.8	11.8	14.4	14.4	20.6	20.6
Per–apartment gross floor area (m^2 $unit^{-1}$)	34.1	34.1	47.4	47.5	56.8	56.9
Annual electricity consumption (GWh yr^{-1})	2849	2946	994	1047	4963	4974
Percentage shares in total electricity consumption (%)	28.1	286	17.5	18.2	49.1	48.3
Per–occupant annual electricity consumption (kWh yr^{-1} hd^{-1})	1458	1464	1455	1499	1667	1661
Per–apartment annual electricity consumption (kWh yr^{-1} $unit^{-1}$)	4228	4244	4800	4946	4599	4580
Per–area annual electricity consumption (kWh yr^{-1} m^{-2})	124	125	101	104	81	81

3.3 Surveys in apartments (tenant) and communal areas (communal)

Electricity charges for apartments (tenant) and communal areas (communal) are billed separately in Hong Kong. However, energy consumption related to communal services has not been reported individually. In this chapter the communal sector of 112 housing estates in Hong Kong (28 PRH, 25 HOS, 22 PRI and 37 PRI_{CH}) and tenant sector of 109 apartments (39 PRH, 32 HOS and 38 PRI) are surveyed. Both the tenant and communal electricity consumption records obtained are analyzed and the details are listed in Tables 3.2–3.8. The sampled apartments, among which 56% aged below 20 years, varied in size from 30 to 100 m^2 with an occupant load range of 2 to 6 people.

For each apartment, floor area, occupant load and annual electricity bills were collected. Among all surveyed apartments which use electricity for cooking were being eliminated to minimize difference in electricity usage pattern. Since Hong Kong is located at sub-tropical climate region, heating degree days (HDD) data with base temperature of 18^{o}C is found lower to 302 (ASHRAE–90.1 2013). The daily mean temperature recorded by the Hong Kong Observatory from November to February was 21.5^{o}C, 17.2^{o}C, 15.9^{o}C and 16.4^{o}C (HKO 2014). Although the temperatures occasionally drop below 10^{o}C in urban area and even lower on high ground, installation of heater for space heating purpose is generally not necessary in residential buildings. Evidences were also supported by an urban residential buildings survey from Yoshino et al. (2006), where over 80% of the surveyed Hong Kong apartments were not equipped with heating system and the operation rate of heating system in winter was found less than 20%. Therefore, an assumption of no heater for space heating was applied to all surveyed households.

Figure 3.1 graphs the per–apartment average monthly electricity profile among the surveyed housings. Disregarding a higher energy consumption recorded for PRI followed by HOS, a consistent trend with outstanding electricity use in the summer months (May to Oct) is observed. Electricity use by air–conditioning (AC) is predicted by the difference of energy use between summer and winter (Nov to Apr) seasons as shown in Tables 3.2–3.4. The average annual electricity demand for PRH, HOS and PRI are 4350, 4722 and 5280kWh respectively. The ranges of AC electricity use of 85–3367kWh yr^{-1}, 241–3079kWh yr^{-1} and 300–5750kWh yr^{-1} and the average percentage for AC demand of 27%, 29% and 31% are reported correspondingly in PUB, HOS and PRI apartments. AC energy usage in private housings is apparently higher than the other two apartments.

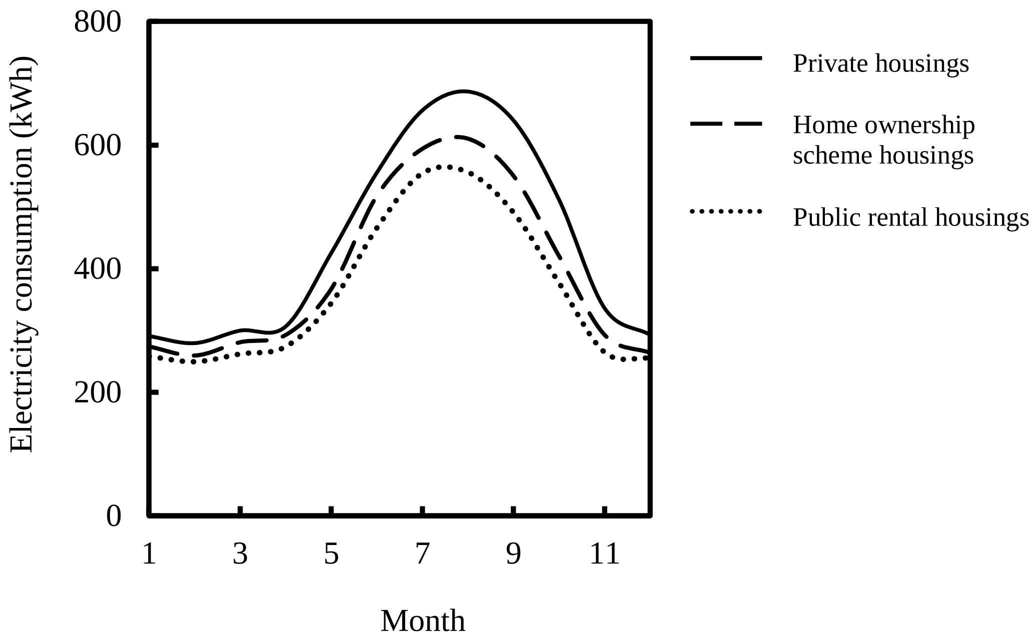


Figure 3.1 Average per–apartment electricity consumption distributions for tenant sector

Table 3.2 Apartment details for 39 surveyed public rental housings (PRH)

Ref no.	Flat Area (m^2)	Occupant (hd)	Building Age (Years)	Annual electricity consumption ($kWh\ yr^{-1}$)	Summer period consumption ($kWh\ yr^{-1}$)	Winter period consumption ($kWh\ yr^{-1}$)	Assumed electricity use for AC ($kWh\ yr^{-1}$)	Percentage of AC demand (%)
1	40.0	2	23	1920	1273	647	626	32.6
2	40.0	2	15	1722	1018	704	313	18.2
3	40.0	5	26	6102	3999	2103	1896	31.1
4	40.0	3	22	3498	2060	1438	622	17.8
5	40.0	3	13	2574	1429	1145	285	11.1
6	75.0	5	19	4374	3150	1224	1926	44.0
7	75.0	4	24	4578	3099	1479	1620	35.4
8	40.0	4	26	4734	3003	1731	1272	26.9
9	75.0	4	35	5610	3268	2342	926	16.5
10	75.0	5	32	4458	3032	1426	1606	36.0
11	41.0	4	7	7500	4800	2700	2100	28.0
12	30.0	2	7	1879	1039	840	199	10.6
13	35.0	3	7	5070	3448	1623	1825	36.0
14	37.0	3	11	4320	2970	1350	1620	37.5
15	36.0	3	33	3885	2568	1318	1250	32.2
16	60.0	4	25	4330	3170	1160	2010	46.4
17	31.0	4	28	4990	2853	2138	715	14.3
18	40.0	5	20	4638	3178	1460	1718	37.0
19	45.0	4	16	3570	2090	1480	610	17.1
20	37.0	4	19	3615	2450	1165	1285	35.5
21	45.9	2	18	2633	1359	1274	85	3.2
22	35.8	3	18	4582	2985	1597	1388	30.3
23	27.6	4	27	5218	3132	2086	1046	20.0
24	27.6	2	5	2239	1561	678	884	39.5
25	37.7	3	26	1710	948	762	185	10.8
26	41.3	4	22	4209	3137	1073	2064	49.0
27	38.6	2	31	3299	2518	781	1737	52.6
28	37.7	4	19	5768	3530	2238	1293	22.4
29	41.3	4	13	6920	4597	2324	2273	32.8
30	36.7	4	9	7358	4582	2776	1806	24.5
31	52.3	4	21	4155	2352	1803	550	13.2
32	64.3	5	17	4812	2815	1997	818	17.0
33	48.6	4	27	3378	2194	1184	1010	29.9
34	42.3	4	13	5254	3067	2188	879	16.7
35	38.5	4	26	4409	3001	1407	1594	36.2
36	40.1	5	21	4289	2336	1953	383	8.9
37	59.0	5	21	6060	4714	1346	3367	55.6
38	64.3	6	21	5226	3016	2210	806	15.4
39	62.5	5	27	4751	2961	1790	1171	24.6

Table 3.3 Apartment details for 32 surveyed subsidized housings (HOS)

Ref no.	Flat Area (m^2)	Occupant (hd)	Building Age (Years)	Annual electricity consumption (kWh yr^{-1})	Summer period consumption (kWh yr^{-1})	Winter period consumption (kWh yr^{-1})	Assumed electricity use for AC (kWh yr^{-1})	Percentage of AC demand (%)
1	75.0	5	16	1878	1094	784	310	16.5
2	75.0	4	8	3378	2297	1081	1217	36.0
3	75.0	3	12	3858	2469	1389	1080	28.0
4	75.0	4	18	5130	3408	1722	1685	32.8
5	75.0	7	18	8484	5283	3201	2082	24.5
6	40.0	4	24	2694	1467	1227	241	8.9
7	75.0	5	22	5340	4154	1186	2967	55.6
8	40.0	4	10	3498	1942	1556	387	11.1
9	75.0	4	12	4416	3180	1236	1945	44.0
10	75.0	5	24	4962	3374	1588	1786	36.0
11	40.0	2	21	2898	1962	936	1025	35.4
12	75.0	5	13	5664	3593	2071	1522	26.9
13	50.0	3	20	4490	2573	1918	655	14.6
14	68.0	4	10	5260	3305	1955	1350	25.7
15	78.4	2	9	2272	1522	750	772	34.0
16	36.7	4	26	4751	3300	1451	1848	38.9
17	68.0	4	14	4023	2437	1586	852	21.2
18	41.8	5	13	6127	3593	2534	1060	17.3
19	56.9	3	21	6381	4172	2209	1964	30.8
20	36.7	3	4	3836	2400	1436	963	25.1
21	73.5	4	11	6017	4089	1928	2160	35.9
22	50.5	4	24	5898	4036	1863	2173	36.8
23	61.5	4	15	4037	2665	1372	1293	32.0
24	64.3	4	12	5134	3243	1891	1352	26.3
25	61.3	6	23	8944	6012	2933	3079	34.4
26	61.1	3	9	4771	2898	1873	1025	21.5
27	52.0	4	28	4023	2958	1065	1893	47.1
28	48.0	4	13	5405	3460	1945	1515	28.0
29	48.5	4	25	4686	3223	1463	1760	37.6
30	60.0	3	10	4311	2626	1685	941	21.8
31	59.0	4	20	4992	3023	1969	1054	21.1
32	56.9	5	7	3530	2145	1385	760	21.5

Table 3.4 Apartment details for 38 surveyed private housings (PRI)

Ref no.	Flat Area (m^2)	Occupant (hd)	Building Age (Years)	Annual electricity consumption (kWh yr^{-1})	Summer period consumption (kWh yr^{-1})	Winter period consumption (kWh yr^{-1})	Assumed electricity use for AC (kWh yr^{-1})	Percentage of AC demand (%)
1	40.0	5	26	5610	4125	1485	2640	47.1
2	40.0	6	28	4680	2996	1684	1311	28.0
3	75.0	3	14	3534	2431	1103	1327	37.6
4	75.0	4	31	4296	2954	1343	1611	37.5
5	40.0	2	9	2430	1606	824	782	32.2
6	100.0	4	14	4188	3066	1122	1944	46.4
7	40.0	4	10	5472	3438	2034	1404	25.7
8	100.0	5	21	7428	4977	2451	2526	34.0
9	96.0	6	37	14350	10050	4300	5750	40.1
10	70.0	2	26	3930	2235	1695	540	13.7
11	82.5	3	17	2690	1495	1195	300	11.2
12	80.0	6	5	12500	7600	4900	2700	21.6
13	50.0	2	35	2898	1578	1319	259	8.9
14	65.0	4	8	4100	2478	1623	855	20.9
15	49.4	5	31	5116	3540	1575	1965	38.4
16	62.8	5	35	7114	5127	1986	3141	44.2
17	50.7	2	37	5680	3850	1830	2020	35.6
18	48.7	4	37	4638	2985	1653	1333	28.7
19	45.9	5	8	9243	6011	3233	2778	30.1
20	49.6	5	14	5142	3368	1774	1594	31.0
21	51.2	2	16	2376	1627	749	878	37.0
22	55.1	4	34	5492	3764	1728	2035	37.1
23	48.7	2	7	3676	2509	1167	1342	36.5
24	75.9	5	8	5807	3480	2327	1153	19.9
25	48.4	5	28	7056	4669	2388	2281	32.3
26	55.6	2	14	2894	1897	997	900	31.1
27	32.1	2	27	2285	1479	806	672	29.4
28	51.4	4	34	4705	3134	1571	1563	33.2
29	75.3	3	21	4558	3002	1557	1445	31.7
30	60.4	4	44	5784	3480	2304	1176	20.3
31	74.3	4	19	5311	3790	1521	2269	42.7
32	73.4	6	7	4155	2352	1803	550	13.2
33	50.2	4	10	3468	2255	1213	1042	30.0
34	46.5	3	6	4498	3207	1291	1916	42.6
35	65.2	3	9	6259	3899	2359	1540	24.6
36	65.0	3	27	5522	3627	1895	1732	31.4
37	65.0	4	46	6248	4338	1910	2428	38.9
38	88.5	4	19	5522	3627	1895	1732	31.4
39	40.0	5	26	5610	4125	1485	2640	47.1

For communal area, building age, floor area and the number of apartments served were recorded. Besides, electric bills of each housing block from year 2007–2009 were requested from the management office to evaluate the estate electricity demand. Communal electricity is used mainly for air–conditioning, lift services, water pumps and lighting for PRI and PRI_{CH}, while air–conditioning is found absent in all HOS and PRH estates. The building characteristics and electricity data for each block are summarized in Tables 3.5–3.8. Figure 3.2 plots the average per–area electricity intensity (kWh m^{-2}) profile in communal space for different housing types. The highest per–area electricity use is found in PRI_{CH} buildings, follows by PRI, HOS and PRH. Besides, remarkable energy use is observed in the summer months, of air–conditioning purpose, for private housings with and without a clubhouse, while no seasonal variation on electricity demand was found in HOS and PRH housing estates.

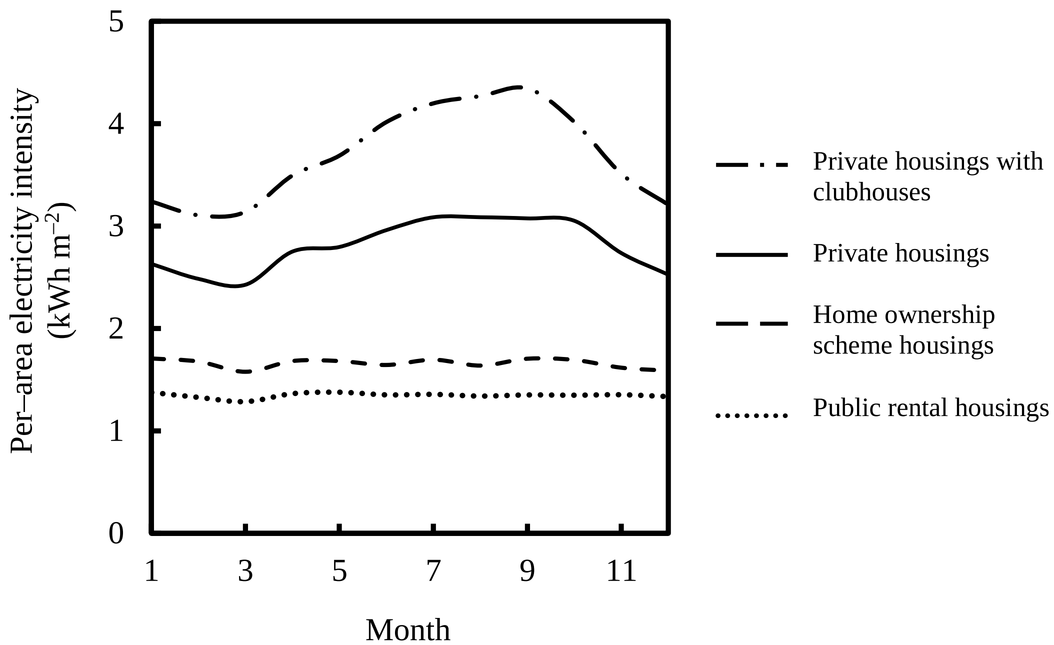


Figure 3.2 Average per–area electricity intensity distributions for communal sector

Table 3.5 Block details for 28 surveyed public rental housings (PRH)

Ref no.	Block no.	Building Age (year)	Stories	Flats per floor	Total GFA (m^2)	Estimated number of occupant (ps)	Annual electricity consumption (kWh yr^{-1})	Per area electricity intensity (kWh yr^{-1} m^{-2})
1	1	22	38	18	41049	1929	664045	16.26
2	1	17	43	16	44171	1981	725428	16.62
3	1	14	41	19	42950	2317	831422	19.40
4	1	14	41	21	43751	2491	747966	17.21
5	1	11	40	20	34629	2317	720124	20.90
6	1	18	37	20	35061	2137	801720	23.01
7	1	20	27	16	26627	1282	375501	14.19
8	1	18	27	14	25621	1131	528800	20.71
9	1	16	12	15	13177	534	150633	11.58
10	1	12	41	19	32816	2317	665732	20.47
11	1	7	41	29	51439	3434	693819	13.49
12	1	33	13	13	7800	499	44282	5.65
13	1	57	13	14	10164	545	99065	9.75
14	1	41	18	31	28742	1627	274981	9.66
15	1	37	23	29	36669	1908	364344	10.22
16	1	35	19	38	24563	2105	261362	10.56
17	1	29	19	66	33753	3631	659438	19.58
18	1	32	28	28	40334	2242	597326	14.80
19	1	32	26	14	19414	1085	259990	13.27
20	1	34	28	40	58682	3265	908336	15.41
21	1	45	28	31	38684	2485	545328	14.05
22	1	31	24	30	36608	2120	956406	28.58
23	1	14	41	10	24461	1160	581682	23.96
24	1	10	46	10	30137	1305	478586	15.86
25	1	24	20	15	18457	882	221721	12.08
26	1	25	23	23	27762	1517	418764	15.45
27	1	17	19	10	8973	534	180234	20.27
28	1	30	35	36	46215	3660	884759	19.30

Table 3.6 Block details for 25 surveyed subsidized housings (HOS)

Ref no.	Block no.	Building Age (year)	Stories	Flats per floor	Total GFA (m^2)	Estimated number of occupant (ps)	Annual electricity consumption ($kWh\ yr^{-1}$)	Per area electricity intensity ($kWh\ yr^{-1}\ m^{-2}$)
1	2	16	35	10	49238	2310	578669	11.75
2	1	19	34	18	40147	2020	492345	12.26
3	4	6	16	8	32948	1749	429182	13.03
4	2	16	36	10	52899	2313	693155	13.10
5	5	14	21	15	112311	5333	1487646	13.25
6	3	19	34	18	101383	6059	1402850	13.84
7	6	13	35	9	121432	6402	1861294	15.33
8	2	19	34	21	82421	4712	1273320	15.45
9	6	20	35	10	127900	6930	2032640	15.89
10	6	18	39	10	140000	7590	2297479	16.41
11	2	16	23	10	28800	1518	491396	17.06
12	5	12	38	14	165000	8712	2908948	17.63
13	7	16	35	10	149156	8085	2636287	17.67
14	2	15	38	16	62133	4013	1109488	17.86
15	7	17	34	22	236075	17609	4264608	18.06
16	5	16	35	10	99405	5775	1803788	18.15
17	7	21	35	8	100242	6468	2002744	19.98
18	16	8	40	7	287063	13781	5980977	20.84
19	3	14	35	10	61252	3432	1329567	21.71
20	1	8	37	10	21435	1221	465321	21.71
21	5	8	40	8	103902	5280	2317921	22.31
22	6	12	35	10	116128	6930	2626461	22.62
23	7	18	34	22	104976	17025	3533611	33.66
24	4	18	27	14	30139	5042	1325714	43.99
25	7	20	15	18	33924	6263	1511940	44.57

Table 3.7 Block details for 22 surveyed private housings (PRI)

Ref no.	Block no.	Building Age (year)	Stories	Flats per floor	Total GFA (m^2)	Estimated number of occupant (ps)	Annual electricity consumption ($kWh\ yr^{-1}$)	Per area electricity intensity ($kWh\ yr^{-1}\ m^{-2}$)
1	1	19	28	8	18887	663	340580	18.03
2	1	18	27	4	5714	324	116906	20.46
3	1	18	16	6	8772	288	209240	23.85
4	1	10	25	5	6996	360	173810	24.84
5	2	19	27	7	22267	1200	593121	26.64
6	1	19	16	3	4274	144	115145	26.94
7	1	9	31	2	4936	156	138220	28.00
8	1	15	28	4	6726	300	202230	30.07
9	1	20	27	7	10496	600	317784	30.28
10	6	18	26	8	70363	3600	2228858	31.68
11	2	17	29	7	23467	1284	770434	32.83
12	1	20	19	8	4491	456	147930	32.94
13	1	8	18	1	3010	48	104660	34.77
14	1	19	29	4	7600	312	272620	35.87
15	2	18	40	3	22192	705	812867	36.63
16	1	7	30	2	3916	189	152800	39.02
17	1	17	40	3	11911	351	465450	39.08
18	1	8	28	1	2749	120	114070	41.50
19	1	7	21	3	2322	171	96480	41.55
20	2	16	18	2	4831	264	224390	46.45
21	2	20	27	7	17244	1104	1163684	67.49
22	2	18	24	7	17151	978	332380	19.38

Table 3.8 Block details for 37 surveyed private housings with clubhouses (PRI_{CH})

Ref no.	Block no.	Building Age (year)	Stories	Flats per floor	Total GFA (m^2)	Estimated number of occupant (ps)	Annual electricity consumption (kWh yr^{-1})	Per area electricity intensity (kWh yr^{-1} m^{-2})
1	11	13	25	2	133866	1920	2892908	21.61
2	4	6	13	6	33810	990	786040	23.25
3	1	8	38	2	11799	258	298550	25.30
4	7	15	34	2	57599	1548	1525043	26.48
5	8	13	9	8	57452	1644	1678476	29.22
6	2	5	36	8	33557	1728	1032062	30.76
7	2	10	13	7	14864	528	464462	31.25
8	1	2	35	3	14320	336	450380	31.45
9	3	8	41	6	57710	2346	2007246	34.78
10	2	7	30	7	23159	1287	818330	35.33
11	14	7	14	8	92514	4854	3324750	35.94
12	4	10	39	7	70773	3102	2545303	35.96
13	2	9	50	4	39561	1182	1485445	37.55
14	3	5	52	7	66010	3120	2533099	38.37
15	7	8	59	5	145094	5877	5573982	38.42
16	4	5	16	11	39248	2052	1538506	39.20
17	13	11	13	7	80398	3300	3171545	39.45
18	12	7	49	8	263842	13626	10653222	40.38
19	14	14	8	4	54685	1494	2241931	41.00
20	9	11	12	7	45351	2178	1874573	41.33
21	2	10	37	3	17172	705	731086	42.57
22	6	9	32	3	55184	1854	2353079	42.64
23	1	8	22	2	3397	147	150143	44.21
24	4	7	35	7	49454	3072	2188798	44.26
25	7	16	28	8	96045	4512	4422463	46.05
26	5	12	13	5	32140	1050	1534158	47.73
27	2	5	31	10	36907	1800	1797274	48.70
28	1	1	31	3	5603	282	281957	50.32
29	4	9	14	6	20205	960	1048610	51.90
30	5	8	40	8	138606	5007	7284178	52.55
31	3	15	26	2	23524	414	1301478	55.33
32	1	5	39	3	12726	342	735935	57.83
33	7	1	22	16	160582	7410	9435656	58.76
34	7	4	18	6	56178	2292	3301070	58.76
35	1	5	48	7	23690	960	1689747	71.33
36	1	1	35	5	11787	498	895077	75.94
37	5	2	40	6	111483	3345	8608246	77.22

Table 3.9 shows the annual electricity consumption survey data in two sectors, namely tenant (apartments) *T* and communal *C*. The per–apartment, per–occupant and per–area annual consumption values for an entire building are determined by adding the corresponding mean values μ and standard deviations S_d from sectors T and C as represented in Equations 3.1 and 3.2:

$$\mu_{total} = \mu_T + \mu_C \tag{3.1}$$

$$S_{d,total}^2 = S_{d,T}^2 + S_{d,C}^2 \tag{3.2}$$

As compared with Table 3.1, insignificant difference is reported for both the per–occupant and per–area annual electricity consumption values for public housing ($p > 0.4$, t–test), however, a higher per–apartment annual electricity consumption ($p < 0.005$, t–test) is found because of higher surveyed occupant density (hd $unit^{-1}$). The variations of household financial backgrounds and physical building characteristics in public housing are small. For private housing, the per–apartment, per–occupant and per–area annual electricity consumption values surveyed are at least 60% higher than the values listed in Table 3.1 ($p \leq 0.001$, t–test). Electricity demands due to communal services and utilities, especially for those with clubhouse, are found higher in newer buildings (of age below 20 years) of taller building height.

Table 3.9 Residential electricity consumption survey data

Parameters (Units)	Public Housing		Private Housing
	Tenant sector (apartment)		
	(1) PRH	(2) HOS	(3) PRI
Counts	39	32	38
Area (m^2 $unit^{-1}$)	45.5 [13.6]	60.1 [13.8]	62.2 [18.9]
Occupant density (hd $unit^{-1}$)	3.8 [1.0]	4.0 [1.0]	3.8 [1.3]
Occupant load factor (m^2 hd^{-1})	12.6 [3.8]	15.8 [5.8]	17.8 [6.8]
Per–apartment annual consumption (kWh yr^{-1} $unit^{-1}$)	4349.6 [1449.2]	4721.5 [1522.1]	5280.4 [2469.1]
Per–occupant annual consumption (kWh yr^{-1} hd^{-1})	1168.2 [308.9]	1198.1 [319.3]	1404.3 [449.7]
Per–area annual consumption (kWh yr^{-1} m^{-2})	101.2 [42.0]	82.0 [29.2]	88.4 [37.2]

	Communal sector			
	(1) PRH	(2) HOS	(3) PRI	(4) PRI_{CH}
Counts	28	25	22	37
Per–apartment annual consumption (kWh yr^{-1} $unit^{-1}$)	832.3 [298.1]	998.4 [204.6]	2333.4 [1229.7]	3593.2 [1613.0]
Per–occupant annual consumption (kWh yr^{-1} hd^{-1})	287.0 [102.8]	302.5 [62.0]	805.6 [427.2]	1239.0 [556.2]
Per–area annual consumption (kWh yr^{-1} m^{-2})	16.2 [5.1]	19.9 [8.7]	33.1 [10.8]	43.3 [13.5]

	Entire building			
	(1) PRH	(2) HOS	(3) PRI	(4) PRI_{CH}
Per–apartment annual consumption (kWh yr^{-1} $unit^{-1}$)	5181.9 [1479.5]	5720.0 [1535.8]	7613.8 [2758.4]	8873.6 [2949.3]
Per–occupant annual consumption (kWh yr^{-1} hd^{-1})	1455.2 [325.6]	1500.6 [325.3]	2209.9 [620.3]	2643.3 [1674.5]
Per–area annual consumption (kWh yr^{-1} m^{-2})	117.4 [42.3]	101.9 [30.5]	121.5 [38.7]	131.7 [39.6]

Geometric standard deviation shown in [ ]

3.4 Prediction of electricity use in entire housing sector

Correlations between the annual electricity consumption and the gross floor area A (m^2), the occupant load O (hd), the occupant load factor O_f ($m^2\ hd^{-1}$) and the occupant area ratio O_a ($hd\ m^{-2}$) are tested and the correlation coefficients are shown in Table 3.10. It is noted that the occupant load is sub-classified as O_T and O_{es}, respectively representing occupant load for individual apartment and entire housing estate. The top ranked factors affecting electricity consumption (i.e. those with the highest absolute correlation coefficients) are occupant load for the tenant sector O_T ($p \leq 0.001$, t–test) and building gross floor area A_{BC} for the communal sector ($p < 0.0001$, t–test). Tso and Yau (2003) also highlighted O_T as a representative parameter for determining apartment electricity consumption. Although O_a and O_f are design parameters for some building systems, they have no significant correlation with electricity consumption (Wong and Mui 2006).

Table 3.10 Correlations for housing annual electricity consumptions

	Apartments (Tenant)			Housing Estates (Communal)			
Types	PRH	HOS	PRI	PRH	HOS	PRI	PRI_{CH}
Count	39	32	38	28	25	22	37
Gross floor area, A	0.19	0.11	0.34	0.85^{**}	0.92^{**}	0.94^{**}	0.92^{**}
Household occupant load , O_T	0.63^{**}	0.58^{*}	0.65^{**}	–	–	–	–
Estate occupant load, O_{es}	–	–	–	0.77^{**}	0.90^{**}	0.94^{**}	0.89^{**}
Occupant area ratio, O_a	-0.52^{*}	–0.36	–0.35	–0.20	–0.14	–0.16	–0.14
Occupant load factor, O_f	0.51^{*}	0.32	0.26	0.17	0.10	0.06	0.14

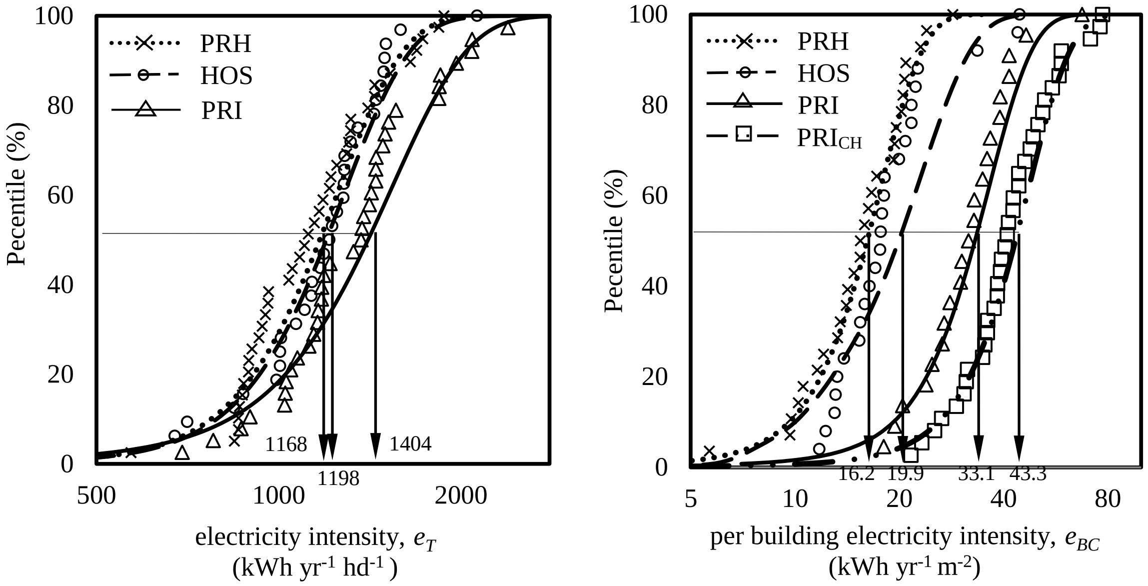
Note: ** for $p \leq 0.0001$; * for $p \leq 0.001$

The electricity intensity of the tenant sector e_T (kWh yr^{-1} hd^{-1}) and the electricity intensity per building of the communal sector e_{BC} (kWh yr^{-1} m^{-2}) are given by Equations 3.3 and 3.4 respectively, where E_T is the annual electricity consumption in the tenant sector and E_C is the annual electricity consumption in the communal sector.

$$e_T = \frac{E_T}{O_T} \tag{3.3}$$

$$e_{BC} = \frac{E_C}{A_{BC}} \tag{3.4}$$

Figure 3.3 illustrates the percentiles of the annual electricity consumption divided by the top ranked factors. Except for HOS ($p \geq 0.3$, Chi–square test), all values are assumed log–normally distributed ($p \geq 0.84$, Chi–square test). As shown in Figure 3.3(a), the mean electricity intensities in the tenant sector are 1168, 1198 and 1404 kWh yr^{-1} hd^{-1} for PRH, HOS and PRI respectively. An average PRI occupant consumes up to 20% more electricity than a PRH resident ($p<0.05$, t–test), yet no significant difference is reported between HOS and PRH occupants ($p>0.69$, t–test). As PRI residents are with higher incomes and larger homes, they can afford to use high energy consumption appliances to live more comfortably (Steemer and Yun 2009, THSR 2004, Chao and Kwong 2007, Zachariadis and Pashourtidou 2007). Comparatively, PRH and HOS residents will pay more attention to reduce electricity consumption. Similar results also reported in Singapore by Ang et al. (1992).



(a) Tenant (b) Communal

Figure 3.3 Electricity intensities for different sectors

The expected 'per–building' electricity intensities for PRH, HOS, PRI and PRI$_{CH}$ in the communal sector are 16.2, 19.9, 33.1 and 43.3 kWh yr^{-1} m^{-2} respectively as shown in Figure 3.3(b). Significantly higher consumption values are reported for PRI and PRI$_{CH}$ ($p<0.05$, t–test), this is probably due to the additional spaces and facilities that requires additional energy for air–conditioning and decorative lighting. Higher electricity consumption is observed in PRI$_{CH}$ buildings ($p<0.05$, t–test), which is 30% more than PRI housings and doubles of the consumption by PRH and HOS buildings.

The annual electricity consumption in residential housing $\widetilde{E}_{total}$ (GWh yr^{-1}) is determined by the electricity intensity used by the tenant $\widetilde{e}_T$ (kWh yr^{-1} hd^{-1}), communal electricity intensity $\widetilde{e}_{BC}$ (kWh yr^{-1} m^{-2}), tenant occupant load O_T (hd) and building gross floor area A_{BC} (m^2), where A_{BC} is estimated by the multiple of building occupant load O (hd) and occupant load factor $O_{f,BC}$ (m^2 hd^{-1}), as shown in Equation 3.5. It also represents the sum of the tenant electricity consumption $\tilde{E}_{T,i}$ (GWh yr^{-1}) and the communal electricity consumption $\tilde{E}_{C,i}$ (GWh yr^{-1}), where i = 1, 2, 3 and 4 for the housing types PRH, HOS, PRI and PRI$_{\mathrm{CH}}$ respectively.

$$\tilde{E}_{total} = \sum_{i=1}^{4} \left(\tilde{E}_{T,i} + \tilde{E}_{C,i} \right) = \sum_{i=1}^{4} \left(\tilde{e}_{T,i}\ O_{T,i} + \tilde{e}_{BC,i}\ \tilde{A}_{BC,i} \right) ; \quad \tilde{A}_{BC,i} = O_i\ \tilde{O}_{f,BC,i} \tag{3.5}$$

Table 3.11 shows the Hong Kong Energy End–use Data of 2007 and 2008 published by the Electrical and Mechanical Services Department (EMSD 2010) and the predictions of annual electricity consumption using the distribution functions given in Equation 3.5. For PRH and HOS, the deviation between predicted and recorded values is within 10% and recorded consumptions from EMSD are found within the 95% confident intervals. For PRI, an overestimation of the predicted $\tilde{E}_{total}$ up to 32% is reported and the recorded consumptions from EMSD are exceeding the 95% confident interval, where the electricity consumption deviation between the two consecutive years is insignificant. The overestimation can be accounted for the samples of the newer and taller buildings (i.e. building age ≤20 years, building height ≥40 stories), since more energy is required for lift and water pump and more fancy lightings are observed for decoration propose.

Regarding to the findings shown in Table 3.11, the communal–tenant electricity consumption ratios (i.e. E_C/E_T) for PRH, HOS and PRI are 1:4, 1:3.5 and 1:1.7 respectively. The results report about 20% of the total loads is consumed in the communal area for PRH and HOS, which is comparable to the value reported in previous study (Lam 1996). However, a significant portion of electricity used in the communal sector is found in PRI (up to 37%). To sum up, PRI buildings consume much energy in both communal and tenant sector as compared with PRH and HOS apartments. The phenomenon can be caused by (i) extra or luxury services installation by service providers to earn greater profit; and (ii) the end–users are more care–free with the electricity bill, i.e. energy expenditure, to enjoy a more comfortable living environment.

Table 3.11 Predicted and recorded annual electricity consumptions

Parameters	Unit	Public Housings PRH	Public Housings HOS	Private Housings PRI
		(a) Year 2007		
Tenant electricity consumption, $\tilde{E}_T$	(GWh yr^{-1})	2298 [612]	826 [270]	4128 [1273]
Communal electricity consumption, $\tilde{E}_C$	(GWh yr^{-1})	573 [243]	236 [131]	2401 [1222]
Predicted consumption, $\tilde{E}_{total}$	(GWh yr^{-1})	2871 [658]	1061 [297]	6529 [1724]
95% confident interval	(GWh yr^{-1})	2582 – 3111	935 – 1178	5808 – 7387
Recorded consumption (EMSD 2009)	(GWh yr^{-1})	2849	968	4962
Deviation	(%)	0.8	9.6	31.6
		(b) Year 2008		
Tenant electricity consumption, $\tilde{E}_T$	(GWh yr^{-1})	2367 [631]	844 [276]	4153 [1281]
Communal electricity consumption, $\tilde{E}_C$	(GWh yr^{-1})	590 [251]	241 [134]	2416 [1230]
Predicted consumption, $\tilde{E}_{total}$	(GWh yr^{-1})	2958 [678]	1085 [304]	6564 [1735]
95% confident interval	(GWh yr^{-1})	2659 – 3204	956 – 1204	5844 – 7433
Recorded consumption (EMSD 2009)	(GWh yr^{-1})	2946	1047	4974
Deviation	(%)	0.4	3.6	32.1

Standard deviation in [ ]

3.5 Housing mixes and energy demands

Housing mixes have significant impacts on electricity consumption. Year 2007 is taken as the base case scenario in which the total number of apartments is 1960156 at a mix ratio of PUB (= PRH + HOS)/PRI/PRI$_{CH}$ = 0.47/0.265/0.265. The electricity demand estimates have been given for three more scenarios "PUB only", "PRI only" and "PRI$_{CH}$ only" and these estimates were respectively deviated by −23.8%, 10.6% and 33.5% from the base case consumption 11138 GWh yr^{-1} (S_d=1551 GWh yr^{-1}) as summarizes in Table 3.12.

Table 3.12 Estimated electricity demands in residential sector

Scenario	Percentage of total building stock (%)			Annual electricity consumption (GWh yr^{-1})
	PUB*	PRI	PRI_{CH}	Average [SD]
Base case 2007	47	26.5	26.5	11138 [1551]
(1) PUB only	100	0	0	8484 [1512]
(2) PRI only	0	100	0	12315 [3252]
(3) PRI_{CH} only	0	0	100	14865 [4050]

* combining both PRH & HOS

The influences of various housing mixes on the percentage change of electricity consumption are further exhibited in Figure 3.4. Predictions are illustrated for hypothetically assumed cases of all PRI and all PRI_{CH} against the percentage of PUB in the total residential stock, with higher and lower predictions indicating one standard deviation different from the mean value in each housing mix condition. Compared with the base case, the results show that electricity consumption due to various housing mixes vary from −25% to +50%. In the case without PUB, the maximum variation between PRI and PRI_{CH} mix is 26%. If shifting the demand to PUB from PRI/PRI_{CH}, then the total consumption decreases. For instance, a 20% increases in PUB units will lead to energy reductions of 7% and 11.5% for extractions from PRI and PRI_{CH} respectively. According to the results, continuous increments of 20% in PUB from 0 to 100% gives PRI/PRI_{CH} differences of 23%, 18%, 14%, 9%, 5% and 0%. The results are explained by higher electricity consumption in private housings especially for air-conditioning use in communal areas and clubhouses. Greater electricity demand for lift and water pumping in taller building is also expected.

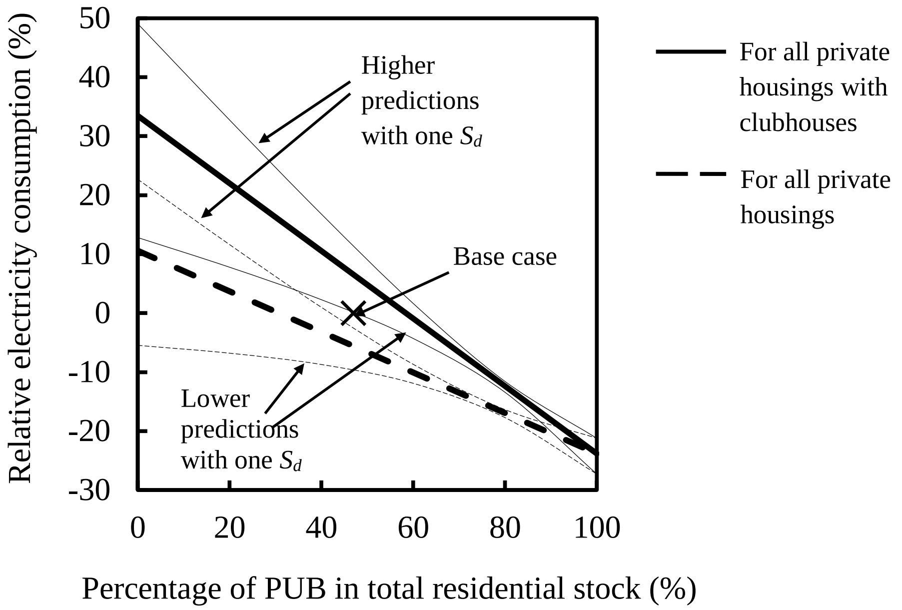


Figure 3.4 Estimated annual electricity consumption for various housing typologies in 2007

Energy planning implications for future housing development can be drawn from the results. By the end of 2017, an increase of 600 thousand residents (or an increase of 8.7% over the 2007 population) has been predicted in Hong Kong (PPD 2009). Figure 3.5 shows the electricity consumption forecasts for the new housing demands based on the 2007 housing mix data. An additional electricity demand of 1175 GWh yr^{-1} (symbol "×") is projected, corresponding to a 10% increment of the 2007 demand. As the additional demands projected for PRI_{CH}, PRI and PUB are 1568, 1299 and 895 GWh yr^{-1} respectively, the energy reduction due to housing mix is apparent. Every 20% increases in the number of PUB apartments will result in a reduction of 54 GWh yr^{-1} in the PRI/PRI_{CH} energy variation, i.e. corresponding energy reductions of 81 and 135 GWh yr^{-1} for the surplus units in all PRI and all PRI_{CH} respectively. Figure 3.5 also illustrates higher and lower predictions for the increased electricity demands for various housing mixes. The base case consumption estimates of these higher and lower predictions are 1339 GWh yr^{-1} (symbol "O") and 1011 GWh yr^{-1} (symbol "Δ"), corresponding to energy variations of 941 and 406 GWh yr^{-1}, respectively. Variation of electricity use in residential sector by housing typology is identified, where increasing PUB units can be an energy efficient strategy for future housing development.

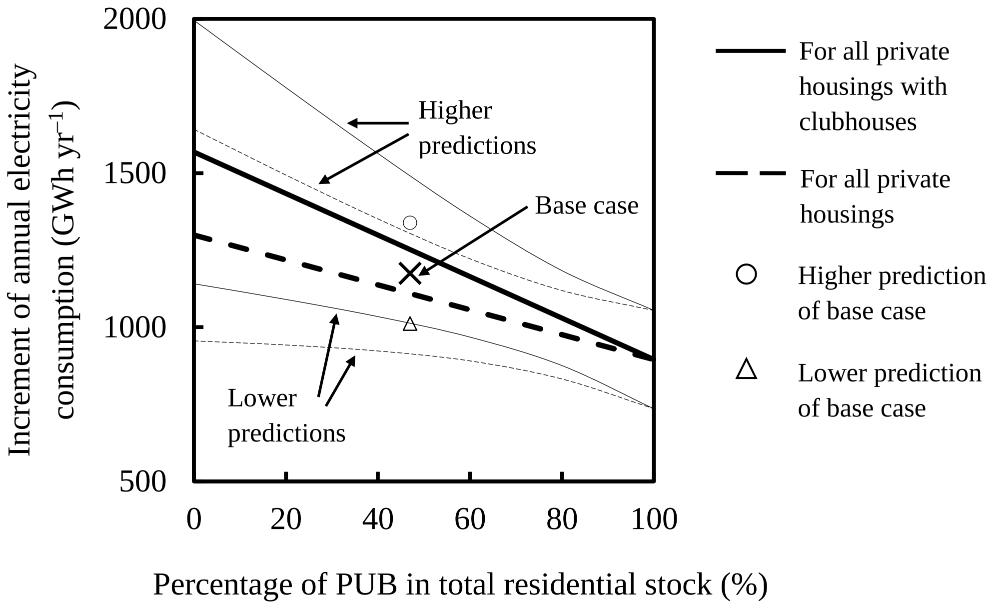


Figure 3.5 Annual electricity consumption forecasts for various housing typologies

3.6 Planning for cooling energy prediction in public housings

From the above findings, significant cooling energy demand is observed in Hong Kong residential sector. In fact, energy for space cooling is one of the highest energy contributors, over 20% of total energy expenditure, in residential buildings (EMSD 2012). It is worth studying in details the rationale of this residential energy contributor. An optimal selection on target buildings can enhance effectiveness of energy conservation strategies for sustainable housing development. According to the results presented in this chapter, public housing (PUB) is selected for in–depth investigation on cooling energy consumption in Chapter 4. Since PUB is of standardized construction designs with respect to the similar typical layouts, the references of housing characteristics including floor area, window size and external wall area can be easily identified from the Housing Authority which benefits the development of cooling simulation model. Besides, the electricity use in public housing estates is dominated by tenant usage and most importantly no cooling energy is required for the communal area, therefore the errors of cooling energy validation using government energy statistics can be minimized. Finally, it has been suggested in previous section that increasing PUB number for future housings development can effectively lessen the total electricity demand in residential sector. Therefore, public housing is being selected for further investigation on cooling energy consumption in later chapters.

Types of public housings in existing stock

By year 2012, a total of 761000 public rental apartments (PRH) are recorded in Hong Kong, which contributes 29% of the entire residential stock number (HF 2012). According to the housings descriptions in Housing Authority website, over 10 different types of PRH blocks are found in existing public housing sector. Figure 3.6 summarizes the available block types and number of blocks at corresponding construction time frames between years 1950 to 2012. Among the PRH sector, four typical housing layouts, namely Slab, Trident, Harmony and New Cruciform comprise over 70% of the total stock number in year 2011 (HKHA 2014), where the former two constructions are built generally over 20 years ago, while the latter two are common construction practices in past two decades. These older and newer typical layouts are selected as the representative public housing designs for cooling energy evaluation in Chapter 4.

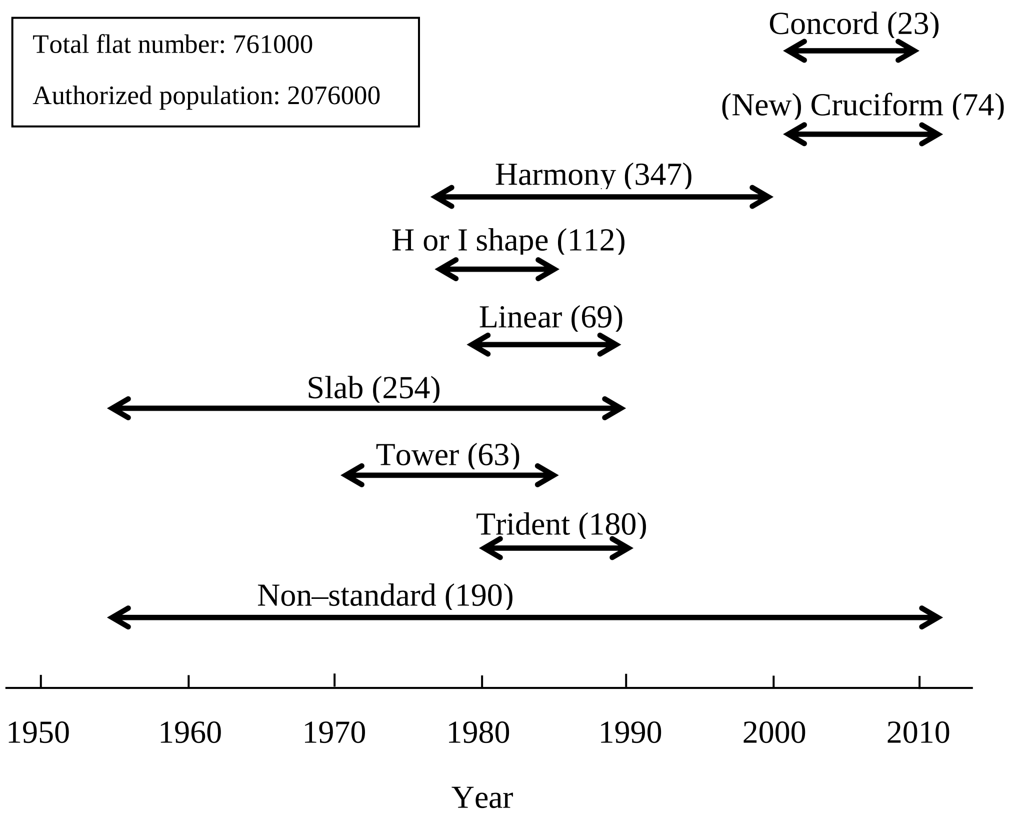


Figure 3.6 Public housing block types (number of block) along the construction time frame (HKHA 2014)

3.7 Summary

Energy efficiency in residential buildings is a key factor for sustainable housing development. This chapter investigates the electricity consumption in apartments and communal areas for both public and private housings in Hong Kong. Taking the examples of year 2007 and 2008, the housing's data and electricity consumption among housing types including public rental housing (PUB), housing of home ownership scheme (HOS), private housings (PRI) and private housings with club houses (PRI_{CH}) are reviewed as references.

The results show that electricity consumption increases with housing type followed by the sequence of PRH < HOS < PRI < PRI_{CH}. Cooling energy use in summer months is found to be obvious for all housing types, contributing an average of 27–31% to the total housing electricity expenditure. Seasonal impact on communal electricity consumption is found in PRI_{CH} and PRI with air–conditioning served, but not in HOS and PRH estates. Electricity intensity for tenant e_T (kWh yr^{-1} hd^{-1}) and e_{BC} (kWh yr^{-1} m^{-2}) for each housing types are evaluated and confirmed with log–normal distribution. It is reported that PRI apartments spend 20% more electricity than PRH housings. Besides, PRI_{CH} buildings consume 30% and 100% more electricity as compared with PRI and PRH estates.

A tool based on random sampling is proposed to predict total residential electricity consumption in terms of housing type, occupant load and building gross floor area. The accuracy of this tool is validated via government energy statistics in year 2007 and 2008 within one standard deviation error range. A greater communal–tenant electricity consumption ratio is reported in PRI buildings (1:1.7) than in PRH buildings (1:4). It suggests that communal electricity use is an important component for residential energy evaluation especially for private housings. The residential electricity consumption for different housing mixes is tested using the proposed tool. The results show that every 20% increase of public housings (PUB = PRH + HOS) number leads to energy reduction of 7% and 11.5% for extraction from PRI and PRI_{CH}. While considering an increase of population in year 2017, the residential electricity demand forecasts for Hong Kong show that substantial energy savings (> 670 GWh yr^{-1}) can be achieved through adjusting the mix of housing types. It is suggested that residential energy demand can be efficiently lessened by increasing the public housing stock and reducing communal energy use especially in summer period.

Construction of PUB is recommended considering a more sustainable housings development plan for future residential sector. Building characteristics for typical PUB layouts can be easily achieved. Besides, electricity consumption for PUB is tenant dominant which can minimize error when comparing the results with government energy statistics. It is therefore being selected as the target housing type, together with four typical housing block layouts namely Slab, Trident, Harmony and New Cruciform, in Chapter 4 for in–depth cooling energy evaluation.

Chapter 4

Development of Hybrid Cooling Energy Simulation Tool

4.1 Introduction

Regarding to the housings energy analysis in Chapter 3, electricity use for space cooling was confirmed significant in apartments. The public housing sector, with four typical public housing block layouts namely Slab, Trident, Harmony and New Cruciform, was selected as the target group for extensive cooling energy consumption study in this section.

A review on exiting cooling energy simulation tools in Chapter 2 summarizes the strengths and limitations for both pure physical and statistical simulation approaches. Detailed dynamic thermal energy performance can be evaluated by computer aid physical simulation. The physical approach is, however, not cost effective for city scale energy forecast with lengthy model input and simulation time. In contrast, the statistical approach is superior in its simulation speed and non–linear relationship prediction. Nevertheless, this method requires larger database for model training and physical explanation is not required for model development.

A closer look on the residential thermal energy simulation studies in Hong Kong are focused on cooling energy prediction at individual apartment via computer simulation programs. Impacts on apartment cooling energy by sensitivity variation of wall thickness, fabric insulation, glazing type, shading coefficient, window size, building orientation and shading extension were broadly investigated (Lam 2000, Bojic et al. 2001, Lin and Deng 2004, Cheung et al. 2005, Bojic and Yik 2007). These simulations are, however, limited only to large apartment size where its representativeness is doubted regarding cooling energy prediction in entire residential sector (Bojic et al. 2002a). In addition, the outputs from above studies are focusing on building materials and constructions for energy improvement, where energy conservation strategies at layman understanding level are rarely discussed.

Prior to maximizing the flexibility in building thermal energy performance, in terms of individual zone and city scale prediction, professional and layman application, and variation in occupant behavioural cooling demand, a hybrid EnergyPlus (EP)–Artificial Neural Network (ANN) model is developed in this chapter to predict cooling energy consumption for public housing sector in the sub–tropics. The proposed model is capable to give a quick response on cooling energy consumption to a series of input parameters. Variety of applications may include cooling energy impact on sensitivity change of building material and construction alternatives (Chapter 5), energy prediction with respect to dynamic occupant's cooling demand patterns (Chapter 6) and transformation to simple cooling energy calculator for layman usage in an individual apartment (Chapter 7).

Based on the design parameters for various public housing block types obtained from current design practices, standards, open literature data and government housing statistics, this study proposes a hybrid EP–ANN model for simulating the cooling energy consumption in the public housing sector and evaluates the cooling energy impacts related to building materials, window sizes, indoor–outdoor temperature variations and different apartment sizes. The proposed hybrid model can be a useful tool for policymakers to establish sustainable public housing development plans.

4.2 Development of simulation model

4.2.1 Background of the simulation model

In order to maximize the model validity, 4 typical public housing block layouts (Slab, Trident, Harmony and New Cruciform) with 14 different apartment settings are introduced for model development. In 2011, public housing apartments of these four block types comprised over 70% of the entire public housing stock in Hong Kong (HKHA 2014). The layouts on typical floor and apartment configuration details are respectively exhibited in Figure 4.1 and Table 4.1. The simulation model aims to evaluate the envelope heat gain H_{en} (W) using these representative public housing layouts. Schematic diagram for the proposed model is graphed in Figure 4.2. A number of simulations on envelope heat gain for the selected public housings are first simulated by EnergyPlus (EP) to create the input and output database. An artificial neural network (ANN) is thereafter trained by the input–output parameter pairs. Details of model development are summarized as follows.

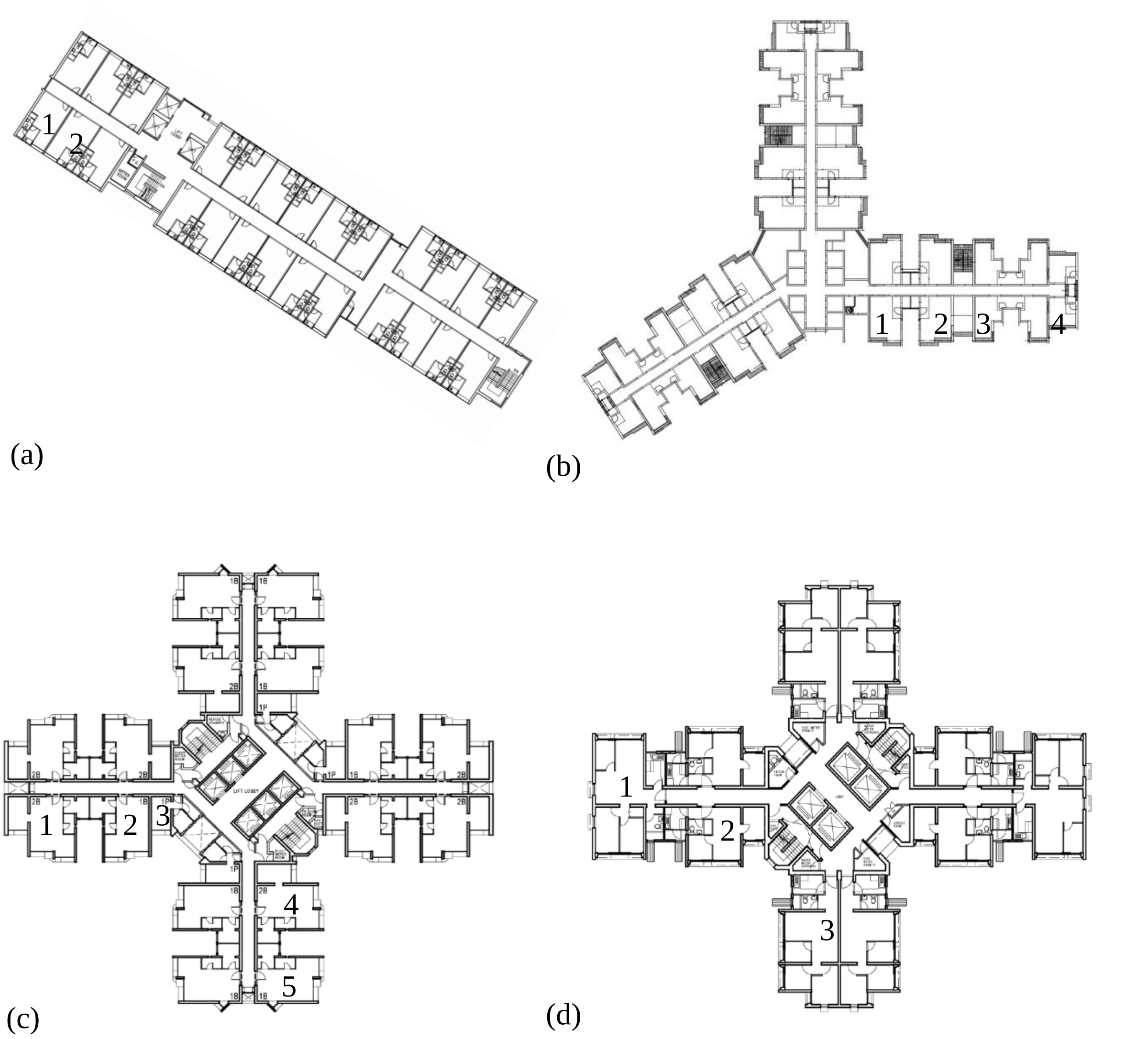


Figure 4.1 Typical public housing block layouts in Hong Kong: (a) Slab, (b) Trident, (c) Harmony, and (d) New Cruciform

4.2.2 Hourly envelope heat gain by EnergyPlus (EP)

The hourly envelope heat gain of a series of apartment configurations for the 4 public housing types in Figure 4.1 with 14 different apartments details in Table 4.1 are evaluated by EnergyPlus (EP), for a range of 9 input parameters for envelope heat gain estimation as shown in Figure 4.2 including the indoor temperature set–point T_a, apartment floor area A_{fl}, total external wall and window area A_e, windows area A_{wd}, opaque wall U–value U_{wl}, window U–value U_{wd}, window shading coefficient S_c and vertical shadow angle σ_v. These parameters are significantly related to building envelope heat gain from peer literatures and the ranges are selected from design standards and survey data in open studies (Lam 2000, Hogan et al. 2001, Bojic et al. 2002, Wan and Yik 2004, Cheung et al. 2005, Chua and Chou, 2012, ASHRAE–90.1 2013). A total of 68040 sets of apartment configurations are simulated by EP with parameters randomly chosen from corresponding parameter ranges presented in Figure 4.2. The output of EP simulation is the hourly envelope heat gain H_{en} (W) at various apartment configurations using the 1989 weather data file from Hong Kong meteorological observatory (Mui and Wong 2007).

Table 4.1 Apartment details for the four typical public housing blocks

Housing type	Block numbers	Average floors	Apartment type	Apartments per floor	Floor area, A_{fl} (m^2)	Envelope area, A_{en} (m^2)	Window area, A_{wd} (m^2)
Slab	254	10	1	4	30.4	30.4	4.2
			2	22	30.4	12.2	4.2
Trident	180	38	1	9	28.4	28.1	6.9
			2	3	35.9	40.0	9.2
			3	12	23.9	32.8	5.1
			4	6	15.1	21.1	4.6
Harmony	347	38	1	4	39.3	47.3	7.1
			2	4	49.6	42.1	8.3
			3	4	19.7	17.6	3.7
			4	4	39.3	35.6	6.0
			5	4	49.6	53.7	9.3
New Cruciform	74	35	1	2	54.9	35.9	8.3
			2	4	35.8	31.9	7.6
			3	4	52.1	46.4	11.5

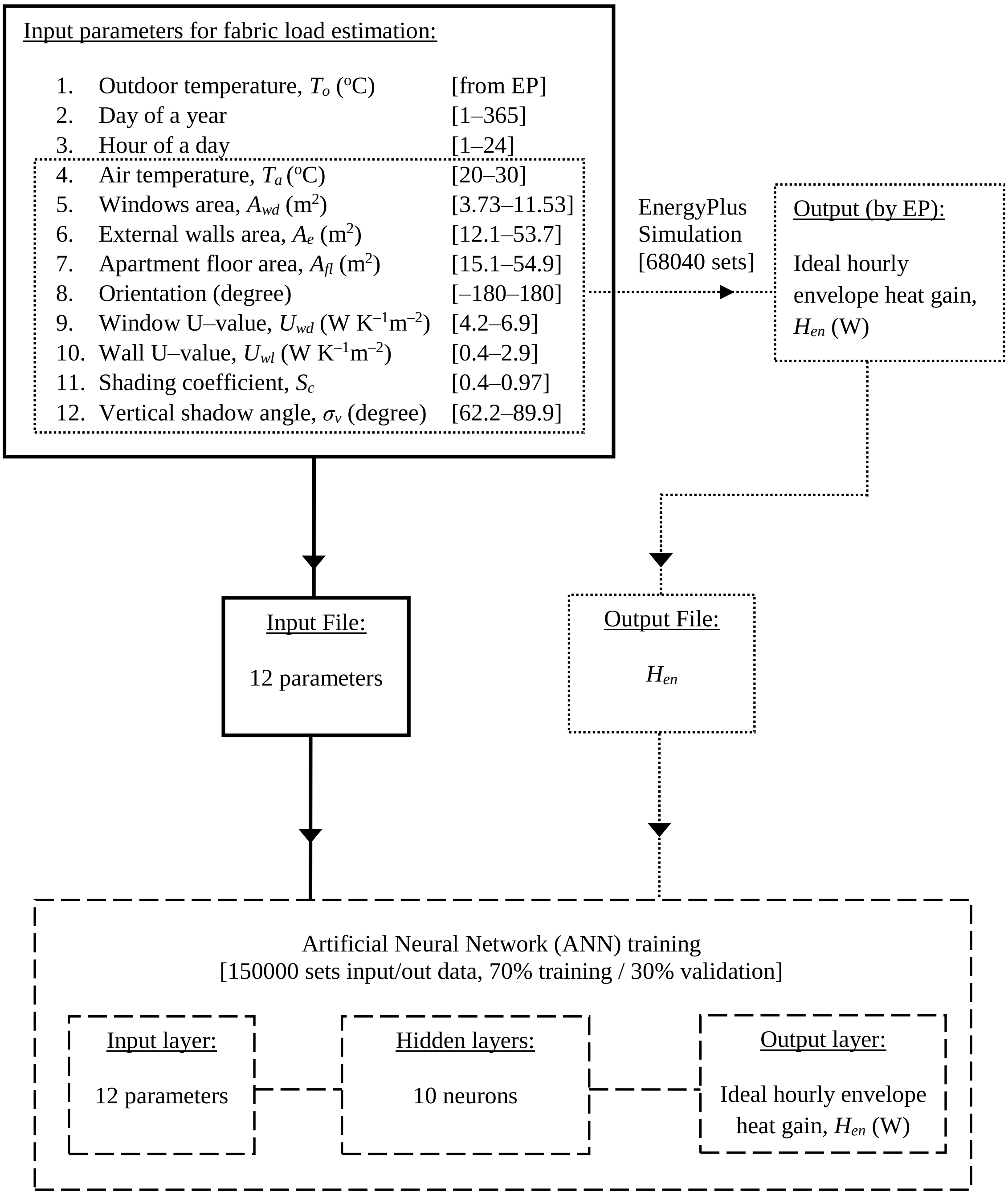


Figure 4.2 Schematic for cooling load simulation database and hybrid model setup

4.2.3 Artificial neural network (ANN) training

Prior to enhance simulation speed while maintaining simulation flexibility in different zones, an artificial neural network (ANN) is established to examine the hourly envelope heat gain in public housings. Figure 4.3 shows the schematic diagram for multiple–layer neural network constructed in this study. Corresponding network is presented as a general function approximator, beneficial to predict any function with arbitrary discontinuous finite numbers.

The *ANN* model has three layers, with 12 neurons, 10 neurons and 1 neuron for the input, hidden and output layers respectively. The input element specified in the input layer is P_i, for i = 1 to 12. Each input element P_i in the hidden layer is connected to a corresponding neuron through the input weight matrix *IW* and is expressed as a weighted input value $P_iIW_{j,i}$. An expression of *IW* is presented in Equation 4.1, where i is the number of elements in input vector and j is the number of neurons in hidden layer. The neuron output a_j in each hidden neuron can be evaluated by the net input vector n_j via the tan–sigmoid transfer function f_{tansig}, where n_j is presented as the sum of weighted input value $P_i\ IW_{i,j}$ and the bias b_j as summarizes in Equation 4.2.

$$IW = \begin{bmatrix} IW_{1,1} & IW_{1,2} & \cdots & IW_{1,i} \\ IW_{2,1} & IW_{2,2} & \cdots & IW_{2,i} \\ \vdots & \vdots & \vdots & \vdots \\ IW_{j,1} & IW_{j,2} & \cdots & IW_{j,i} \end{bmatrix} \tag{4.1}$$

$$a_j = f_{\tan sig}(n_j) = \frac{2}{(1+\exp(-2n_j))} - 1 \quad ; \quad n_j = \sum_{j=1}^{10}\sum_{i=1}^{12} P_i IW_{j,i} + b_j \tag{4.2}$$

Using the Levenberg–Marquardt algorithm to define the input–output relationship between the hourly envelope heat gain H_{en} and the input parameters, the *ANN* model is trained with 150000 sets of *EP* input–output data pairs (70% is used for training and 30% for validation). The number of data sets is maximized according to computer resource limitation. Further increases in the number of hidden neurons, i.e. from 10 to 11 and 12, are tested with insignificant change in the simulation results (p>0.9, *t*–test).

In the output layer, a_j is connected to the layer weight index LW_j to refine the layer–weighted value a_jLW_j. The hourly envelope heat gain H_{en} (W), defined as the output of the proposed *ANN* model, can be evaluated by the net output value n_{out} via the linear transfer function $f_{purelin}$ as expressed in Equation 4.3.

$$H_{en} = f_{purelin}(n_{out}) = n_{out} \quad ; \quad n_{out} = \sum_{j=1}^{10} a_j LW_j + b_{out} \tag{4.3}$$

The reason for applying the linear output neurons is to extend the network output range to any values for building designs. The simulation result of the ANN, i.e. the H_{en}, is indicated as an intermediate output presented in Figure 4.4.

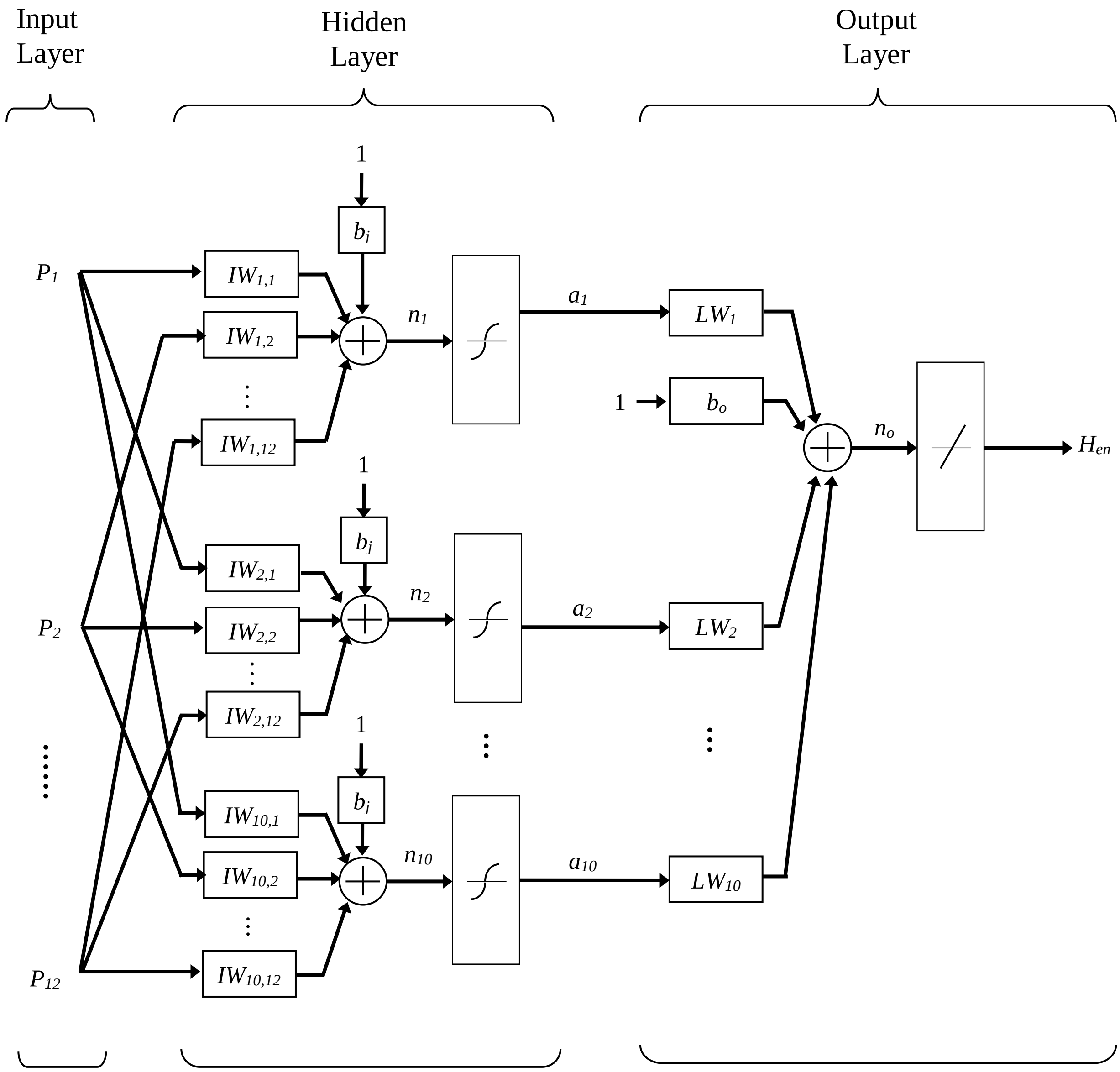


Figure 4.3 Schematic for a feed–forward neural network model

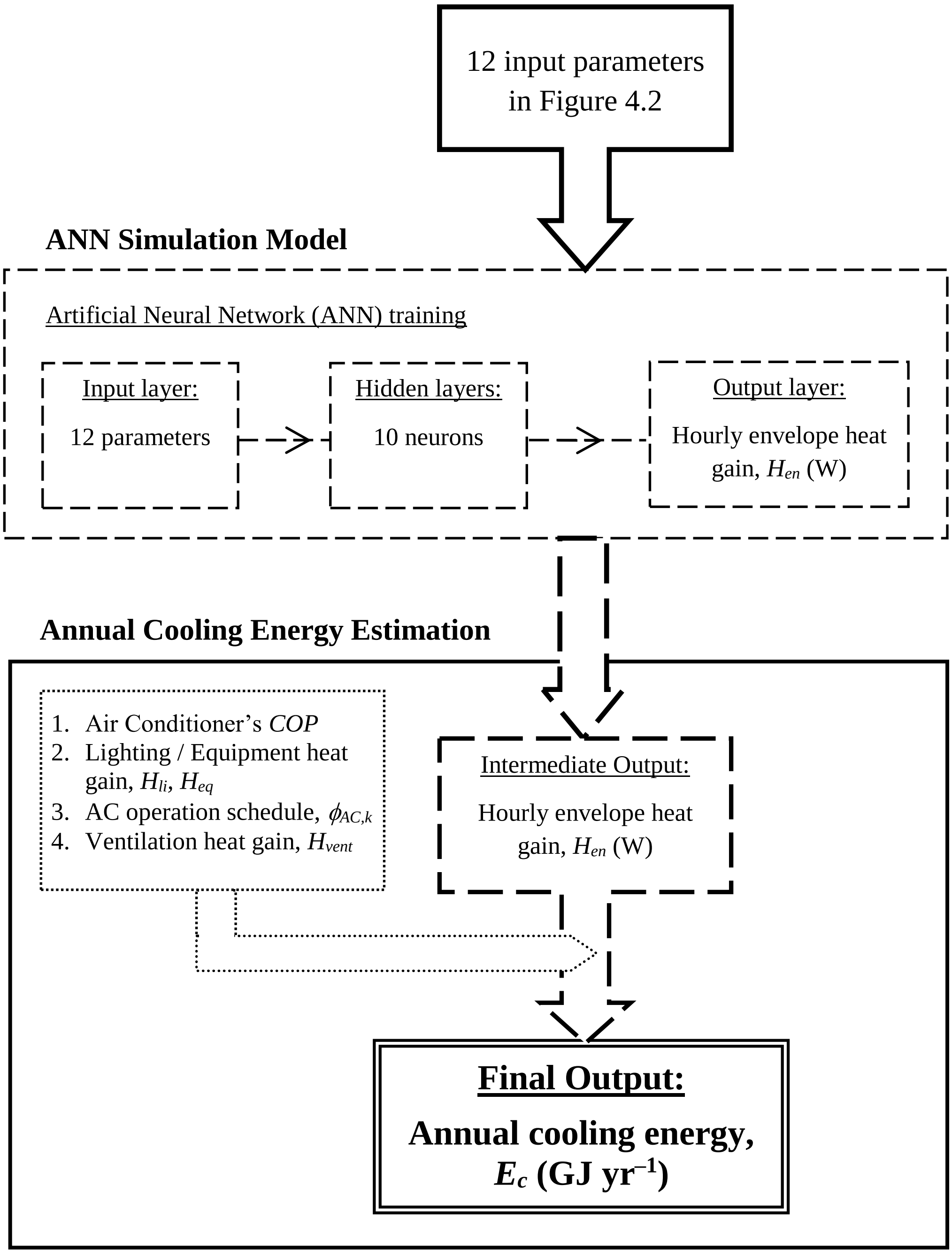


Figure 4.4 Schematic for hybrid cooling energy simulation model setup

4.2.4 Annual cooling energy prediction

Figure 4.4 graphs a schematic diagram to evaluate the annual cooling energy consumption E_c (GJ yr^{-1}) for Hong Kong public rental housings. As indicating in Equation 4.4, the annual cooling energy consumed in an apartment E_c can be evaluated by the division of total heat gain from the coefficient of performance (*COP*) of the air–conditioning device with respect to the hourly AC operation schedule $\phi_{AC,\,k}$ in a year for k = 1–8760 hour, where H_{en} is the hourly envelope heat gain, H_{in} is the internal heat gain and H_{vent} is the ventilation heat gain (Wong et al. 2008).

$$E_c = \sum_k \frac{\phi_{AC,k}\left(H_{en} + H_{in} + H_{vent}\right)_k}{COP_k} \tag{4.4}$$

The internal heat gain H_{in} can be expressed by the floor area A_{fl} times the sum of equipment power density d_{eq} and lighting power density d_{li} in Equation 4.5 (Cheung et al. 2005).

$$H_{in} = \left(d_{eq} + d_{li}\right) \times A_{fl} \tag{4.5}$$

The ventilation heat gain H_{vent} is determined by the sum of sensible L_{sen} and latent L_{lat} load listed in Equation 4.6, where N_k is the number of occupant at hour k, ρ = 1.2 kg m^{-3} is the air density, C_{pa} = 1.01 kJ kg$^{-1\,o}$C^{-1} is the heat capacity of air, h_{fg} = 2436 kJ kg^{-1} latent heat of evaporation of air, T_a and T_o (^{o}C) are respectively the indoor and outdoor temperature, w_a and w_o (kg kg^{-1}, dry air) are respectively the indoor and outdoor air moisture content, and V_{vent} = 3 Ls^{-1}ps^{-1} is the average ventilation rate between window type and split type room air conditioner (Lin and Deng 2003).

$$H_{vent} = L_{sen} + L_{lat} \quad ; \quad \begin{cases} L_{sen} = N_k \rho V_{vent} C_{pa} \left(T_a - T_o \right) \\ L_{lat} = N_k \rho V_{vent} h_{fg} \left(w_a - w_o \right) \end{cases} \tag{4.6}$$

A maximum *COP* of 2.9 has been reported for existing residential air conditioner (EMSD–AC 2010). However, its cooling efficiency would depreciate with the hourly sensible heat ratio SHR_k, determined by Kosar (2006), in Equation 4.7.

$$COP_k = \frac{\left(SHR_k + 0.45 \right)^{4.9}}{1.1} + 0.75 \tag{4.7}$$

Using data of the occupant load survey conducted by Wong and Mui (2006), the hourly occupant load N_k for public rental housings can be examined by the multiple of hourly occupant load variation ψ_k and the maximum number of occupant in apartment N_{max} in Equation 4.8, where N_{max} is estimated by the product of occupant area ratio O_a (hd m^{-2}) and the apartment floor area A_{fl} (m^2) (Wong and Mui 2006).

$$N_k = N_{\max} \psi_k \quad ; \quad N_{\max} = O_a A_{fl} \tag{4.8}$$

The indoor moisture content w_a can be identified by the pre–set indoor temperature and relative humidity using psychometric chart, where the indoor relative humidity is assumed 60% in the simulation (Li et al. 2006). The outdoor moisture content w_o can be expressed by corresponding vapour pressure p_w (kPa), saturated vapour pressure p_{ws} (kPa) and the outdoor relative humidity $R_{h,o}$ (%) in Equation 4.9.

$$w_o = \frac{p_w}{101.325 - p_w} \times 0.622 \quad ; \quad p_w = \frac{R_{h,o}}{100} \times p_{ws} \tag{4.9}$$

This proposed hybrid cooling energy prediction model can provide quick response on cooling energy output regarding to the parameter input listed in Figure 4.2. Series of input parameters can be modified by a simple computer program to predict multiple outputs for regional or city scale simulation. Most importantly, flexibility of the proposed model can be enhanced by dynamic out sources inputs including equipment and lighting power density d_{eq}, d_{li}, occupant load variation ψ_k and AC operation schedule $\phi_{AC,\,k}$.

4.3 Model validations

Four steps of comparison are applied to validate the resulting hybrid cooling energy consumption model, including (i) goodness–of–fit test by EnergyPlus simulation; (ii) validation of simulation performance with existing literatures; (iii) validation of the cooling electricity demands for public residential building as reported by Electrical and Mechanical Services Department (EMSD) and (iv) validation of cooling electricity demand in surveyed public housings.

4.3.1 Goodness–of–fit test by EnergyPlus

The peak hourly load (W) and annual cooling load (kW) for the 14 apartments listed in Table 4.1 with specific conditions [T_a = 24°C, Orientation facing South–west, U_{wd} = 6.9W $K^{-1}m^{-2}$; U_{wl} = 2.9W $K^{-1}m^{-2}$, S_c = 0.97 and σ_v = 75.3°] are simulated by both EnergyPlus and Neural Network model. Figures 4.5 (a) and (b) show a good linear relationship between EP and ANN simulation for the peak hourly load and annual cooling load (R>0.95, p<0.01). The hourly variation of Mean Bias Error (MBE) and Root Mean Square Error (RMSE) are respectively 0.073 and 0.046, which suggested the proposed ANN model is capable to substitute EP for public housing cooling demand prediction. Higher envelope heat gain in bigger apartments with larger external wall area (Flats 1 and 3 in New Cruciform block) is observed in Figure 4.5 (a) and (b). Excluding the time spend on model construction and data input, the simulation speed for individual apartment records an average of 20s and 1s respectively using EP and ANN method. The proposed ANN approach is superior in city scale energy forecast in terms of cost and time effectiveness.

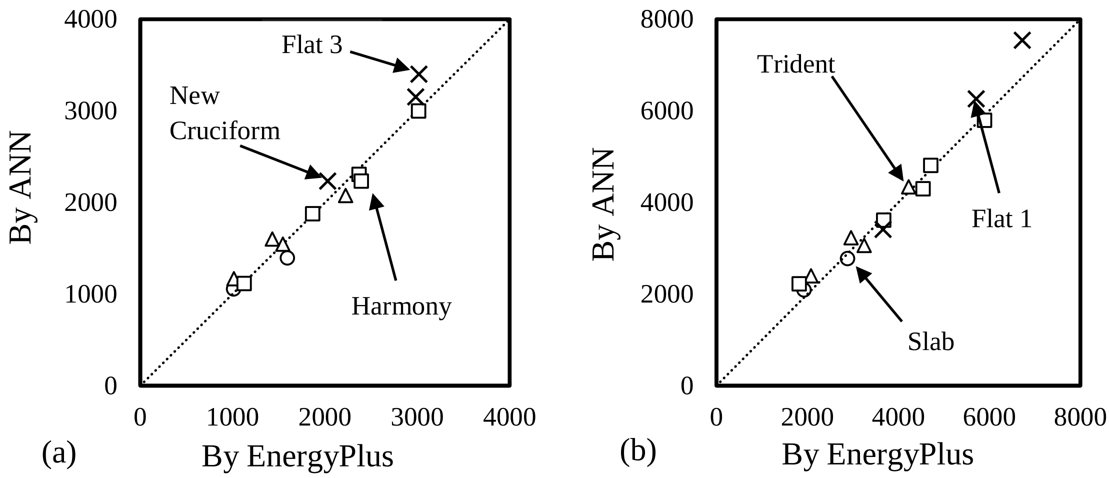


Figure 4.5 Envelope heat gain H_{en} comparison between EP and ANN simulation (a) Peak hourly load (W) and (b) Annual load (kW)

4.3.2 Validation with existing literature

Cheung et al. (2005) used computer program TRNSYS to simulate the annual cooling energy in some apartments for another public housing typical floor plan, i.e. Concord, with changing parameters including apartment orientation, shading coefficient, window area and length of overhang shading respectively. This section repeats the apartment configuration settings in Cheung's simulation by the proposed hybrid model and adjusts the hourly cooling energy using the same air conditioner operation schedule ϕ_{AC} from 19:00–07:00 with an averaged lighting and equipment power density of d_{li} =18 W m^{-2} and d_{eq} =26 W m^{-2} listed in Table 4.2. One difference is assigned to a fixed COP = 2.5 in Cheung's prediction, while a varied hourly COP_k is used in the proposed hybrid model.

Table 4.2 Power densities and occupancy in public rental housings (Cheung et al. 2005)

Power densities	Value
d_{li} for living room	20 Wm^{-2}
d_{li} for bedroom	17 Wm^{-2}
d_{eq} for living room	28 Wm^{-2}
d_{eq} for bedroom	24 Wm^{-2}
Occupancy	**Time**
In living room	19:00–23:00
In bedroom	21:00–07:00

The annual cooling energy predicted by the proposed model is compared with Cheung's study with four changing variables including shading coefficient S_c, window to floor area ratio *WFR*, length of overhang and apartment orientation correspondingly present in Figure 4.6. The hybrid model predicts a similar trend with higher (≤ 7%) cooling demands as compared with Cheung's findings for all changing parameters except the reduction of shading coefficient. The variation can be attributed by a fixed *COP* used in Cheung's simulation, while the dynamic COP_k value is occasionally observed down to 1.5 especially for a humid summer night with low SHR_k.

Annual cooling energy is reported decrease with S_c, where steeper slope is found in Figure 4.6a as compared with Cheung's findings. Higher cooling demand is found at apartment with larger window to floor area ratio (WFR), while increasing length of overhang can reduce the required cooling energy. Similar to Cheung's study, the highest per floor area cooling demand (GJ m^{-2}) is reported with apartment facing South–West followed by facing West, where the orientation facing North yields the least cooling consumption for the same apartment. The hybrid model is considered applicable for cooling energy prediction with various kinds of typical floor plans and applicable to estimate space cooling energy for overall public housing sector.

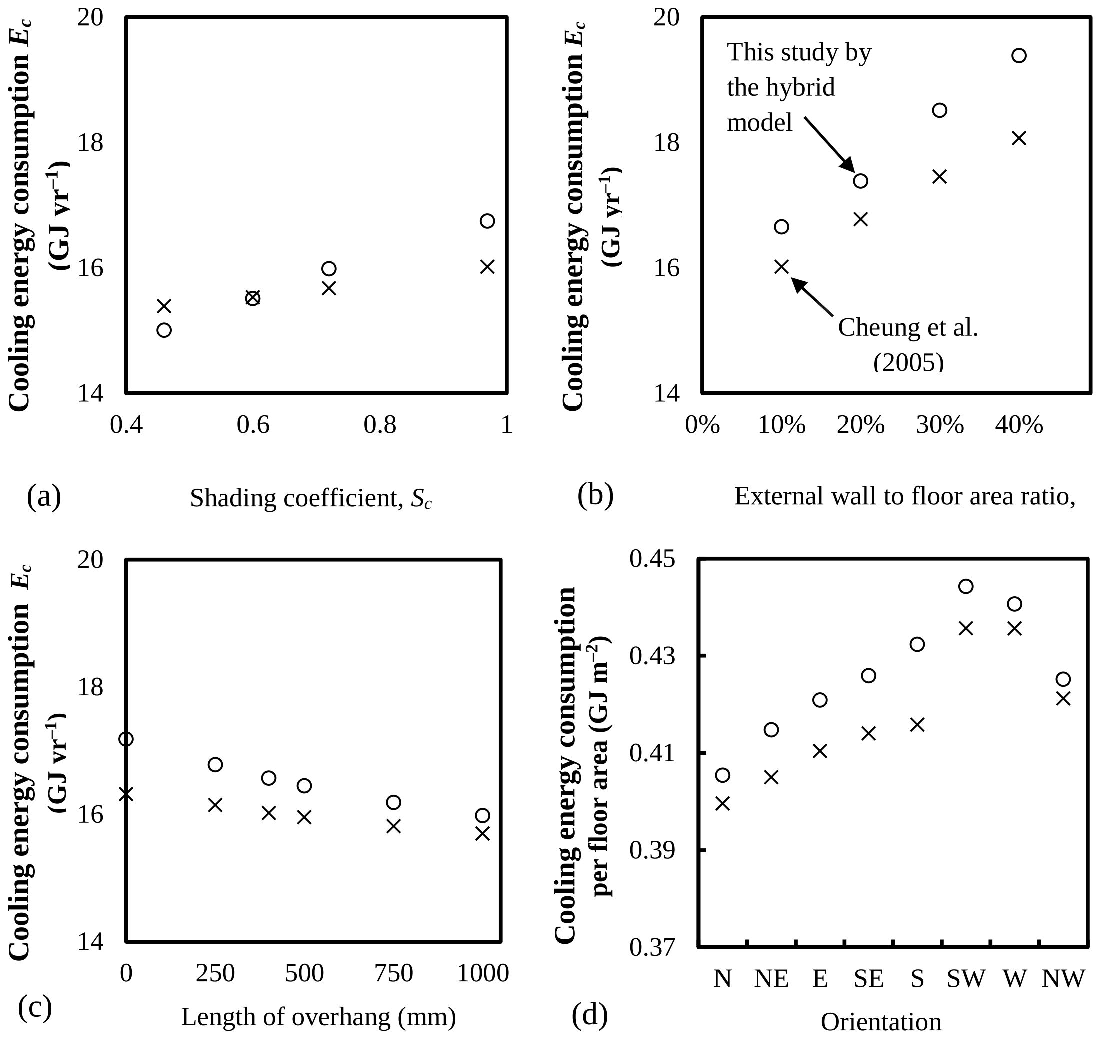


Figure 4.6 Comparison of cooling energy consumption between Cheung's et al. (2005) findings and the proposed hybrid cooling simulation model

4.3.3 Validation with government energy statistics

According to the housing statistics listed in Table 4.1, 533000 apartments (up to 70% of 761000 public apartments in year 2011 (HKHA 2014)) are brought into simulation to estimate the overall cooling energy demand in the existing public housing sector. The selected apartments are constructed with typical A_{fl}, A_e and A_{wd} settings which correspond to specific flat types listed in Table 4.1. Vertical shadow angel σ_v is assumed to be 75.3°, equivalent to 500mm length of overhang. Current rental blocks material configurations are selected randomly within ranges of U_{wd} = 5.6–6.9W $K^{-1}m^{-2}$, U_{wl} = 2.2–2.9W $K^{-1}m^{-2}$ and S_c = 0.9–0.97 as proposed in literatures (Cheung et al. 2005; Lam 2000). Apartments are orientated randomly in 8 directions (N, NE, E, SE, S, SW, W, NW), with cooling set–point temperature T_a fixed at 22, 24 and 26°C. Air conditioner operation schedule ϕ_{AC} from 19:00–07:00 and averaged lighting and equipment power density of d_{li} =18 W m^{-2} and d_{eq} =26 W m^{-2} is referenced by Cheung's et al. (2005). It is noted that Hong Kong residents tend to operate the room air–conditioners in the summer from May to October (Lam 2000).

Figure 4.7 shows the annual cooling energy use in apartment determined by the hybrid simulation model with different indoor temperature set-points. An average consumption of 4.71GJ yr^{-1}, 4.13GJ yr^{-1} and 2.67GJ yr^{-1} per apartment and an annual consumption of 3003TJ yr^{-1}, 2319TJ yr^{-1}, and 1700TJ $yr^{-1}$for entire residential sector with T_a fixed at 22, 24 and 26°C are predicted. Comparing the government energy statistics in year 2011(2052TJ yr^{-1}), the predicted cooling energy consumption is found 13% higher and 17% lower when T_a is arranged at 24°C and 26°C. Possible explanation can be assigned by the variation of AC usage pattern in real household, in particular to occupants who adapt to stronger energy saving practice. The results of occupant's AC usage pattern with updated cooling energy prediction in existing public housing sector will be discussed in Chapter 6.

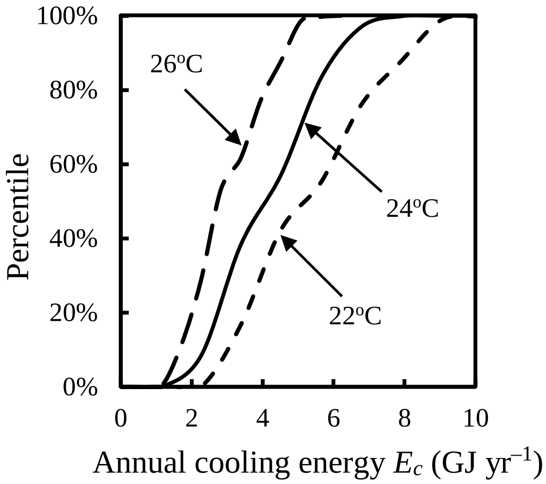


Figure 4.7 Distribution of per apartment annual cooling energy prediction with/without occupancy modification

4.3.4 Validation with surveyed public rental housings

Table 3.2 summarizes the annual cooling demands in 39 public rental housings and corresponding housing construction details (σ_v, A_{fl}, A_e, A_{wd} and orientation) are recorded for cooling energy simulations. Since the building construction materials remain unknown during the housing surveys, the simulated rental blocks material configurations for existing public housings are selected randomly within ranges of U_{wd} = 5.6–6.9W K^{-1}m^{-2}, U_{wl} = 2.0–2.9W K^{-1}m^{-2} and S_c = 0.9–0.97 as proposed in literatures (Cheung et al. 2005; Lam 2000) and T_a = 22–26ºC. Figure 4.8 graphs the comparison of annual cooling energy E_c between the surveyed AC consumptions and the average value of ANN simulations with errors varying among the parameter inputs. A linear association of the simulated average and surveyed E_c is reported with a sample correlation coefficient of 0.87 ($p<0.01$, t–test). The results from hybrid model are generally overestimating the cooling demands from the surveyed samples especially for those small apartments with lower energy consumption. The deviation can be explained by occupant behaviour in operating the air–conditioners at home (Steemers and Yun 2009), since a standardized AC operating schedule is applied to all simulations in current assessment (Cheung et al. 2005). Occupants tend to operate a fan instead of an air–conditioner when there are only one or two people present in small flats (Tso and Yau 2003). An updated simulation results will be discussed in Chapter 6 with dynamic public housing resident's AC operation behaviour consideration. Besides, the coefficient of performance *COP* of air–conditioners among the surveyed apartments, especially between newer and older apartments, can be varied at wide range. According to the results of energy performance monitoring test conducted by the Electrical and Mechanical Services Department, the range of *COP* for available window mounted air–conditioners was 2.1–3.1 (EMSD–AC 2010, 2013).

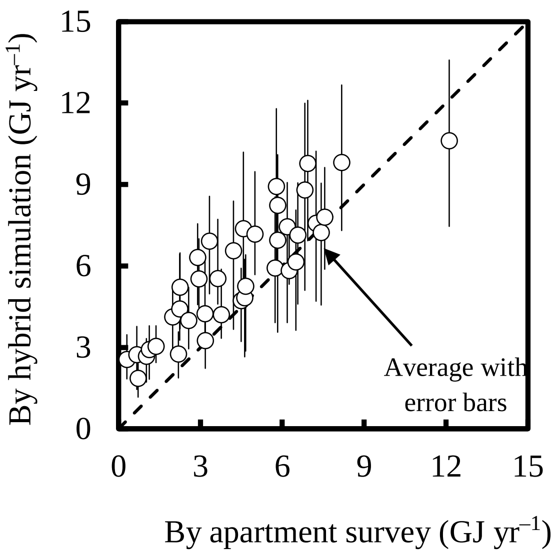


Figure 4.8 Comparison of apartment annual cooling energy consumption E_c (GJ yr^{-1}) between simulation and apartment survey

4.4 Summary

In this chapter, a hybrid EnergyPlus (EP)–artificial neural network (ANN) model is established to improve the conventional thermal energy simulation methods taken an example from Hong Kong public housing sector. The model is trained by ANN using the prior–simulated input–output data files from EP via the four typical public housing block layouts. The hourly envelope heat gain H_{en} is defined as the output of ANN, while this output is further modified to evaluate the cooling electricity demand in apartment.

The hybrid EP–ANN model presented in this chapter is validated via four sections including (i) goodness–of–fit test via EnergyPlus prediction, (ii) peer validation from literatures on sensitivity of cooling energy impact to the housing parameters, (iii) validation by government statistics on annual cooling electricity consumption in public housing sector and (iv) validation by field surveyed cooling demand in 39 public rental housings. Satisfactory energy prediction performances by the ANN are identified via these validation assessments. It reveals that the proposed model is capable to estimate the cooling energy consumption in different housing layouts and available for cooling simulation in entire public housing sector.

The hybrid model is confirmed beneficial for an easier parameters input process as well as a faster response (20 times faster) to simulation output, while at the same time simulations are available for both individual and multiple zones within a building. The tool is proved to be feasible in identifying the impact on cooling energy consumption with different input alternatives. Extensive cooling energy evaluation on sensitivity change of building material and construction alternatives is presented in Chapter 5. The flexibility of integration with out sourced input is demonstrated in Chapter 6 for cooling energy impact on dynamic AC operation schedule. Finally, its application on cooling energy prediction for layman usage in individual apartment is discussed in Chapter 7.

Chapter 5

Building Constructions, Materials and Cooling Electricity Use

5.1 Introduction

Cooling energy expenditure in indoor space is sensitive to building design and material selection. A hybrid cooling energy simulation tool with enhanced input flexibility and quick response on both individual and multiple zone bases is introduced in Chapter 4. The proposed simulation tool is applied in this chapter to evaluate the impacts on cooling energy consumption for individual households and entire public housing sector prior to sensitivity of parameter change in building material uses and construction designs.

Regarding to the input parameters for the artificial neural network (ANN) listed in Figure 4.2, it summarizes three material related (external wall U–value U_{wl}, window U–value U_{wd} and shading coefficient S_c) and five construction related (window area A_{wd}, external wall area A_e, apartment floor area A_{fl}, building orientation and vertical shadow angle σ_v) inputs. Cooling energy consumption in public housing arising from single parameter change and a combination of parameters variations are described. Besides, the most cooling energy efficient estate design, among the four typical public housing layouts shown in Figure 4.1, is discussed by assuming the same occupant load in each housing block.

5.2 Building materials

Heat gain to indoor space is mainly contributed from external wall and window, thus material use in these areas might have significant impact on the total cooling electricity use in apartment as well as the entire public housing sector. Prediction on cooling energy use prior to the sensitivity change in external wall U–value U_{wl}, window U–value U_{wd} and shading coefficient S_c are presented in this section. Besides, the cost–effective and cooling energy efficient material use for external wall and window are recommended.

External wall U–value, U_{wl}

Conduction heat gain through external wall is remarkable in total cooling electricity use (Lam 2000). The external wall thermal transmittance, i.e. wall U–value, U_{wl}, was selected as an index to specify the heat transfer rate of different wall construction materials (Feng 2004, Wang et al. 2007, Turhan et al. 2014). A majority of existing public rental housing buildings in Hong Kong are of reinforced concrete structure with ceramic tile finish and no addition thermal insulation. The external wall is about 125–250mm thick and the resulting U_{wl} is ranged typically from 2.2 to 2.9W $K^{-1}m^{-2}$ (Lam 2000).

Regarding to previous simulation results in section 4.3.3, the summer period electricity consumption in entire public housing sector is 2319TJ yr^{-1} (with per–apartment average of 4.13GJ yr^{-1}). By maintaining all other parameters unchanged, the impact on per–apartment and whole sector cooling electricity use with U_{wl} improvement between 0.7–2.9W $K^{-1}m^{-2}$ are presented respectively in Figure 5.1 and 5.2. The distributions of per–apartment cooling electricity use for standardized U_{wl} = 0.7, 1, 1.5, 2, 2.5 and 2.9W $K^{-1}m^{-2}$ is presented in

Figure 5.1. An increasing trend of the dominant cooling electricity consumption in apartment, i.e. the peak, is observed for U_{wl} from 0.7 to 2.9W $K^{-1}m^{-2}$. For U_{wl} = 0.7W $K^{-1}m^{-2}$, the average per apartment cooling consumption is 3.86GJ yr^{-1} with maximum value at about 7.96GJ yr^{-1}, while for U_{wl} = 2.9W $K^{-1}m^{-2}$, the average and maximum consumption are increased to 4.52GJ yr^{-1} and 10.12GJ yr^{-1}. Figure 5.2 shows the annual cooling electricity consumption for whole public housing sector with respect to sensitivity change of U_{wl}. The dotted line with arrow represents the predicted existing cooling electricity use (2319TJ yr^{-1}) at surveyed range of U_{wl} = 2.2–2.9W $K^{-1}m^{-2}$. The cooling demand in entire housing sector increases by 1.7% (2357TJ yr^{-1}) when the external wall U–value is standardized as 2.9W $K^{-1}m^{-2}$, while a reduction of 6.5% (2167TJ yr^{-1}) in total cooling electricity is recorded with U_{wl} equivalent to 0.7W $K^{-1}m^{-2}$.

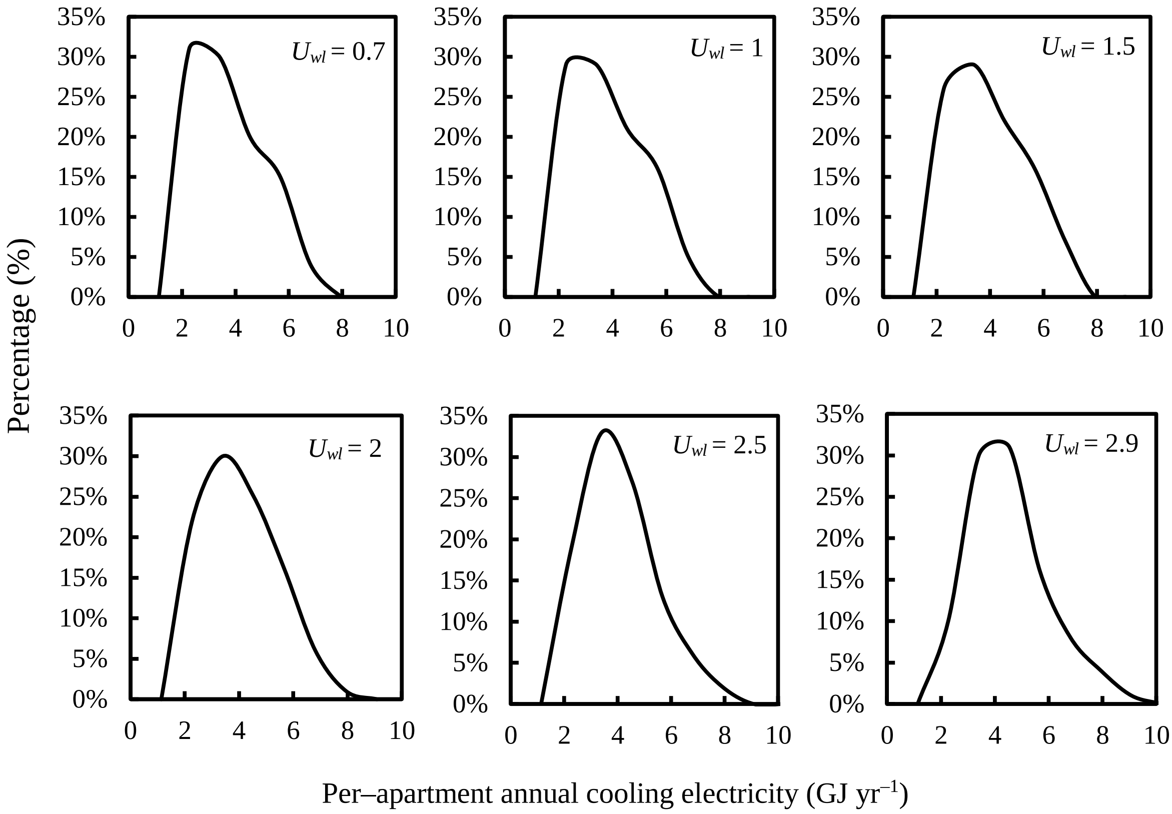


Figure 5.1 Per–apartment cooling electricity consumption varied by wall U–value

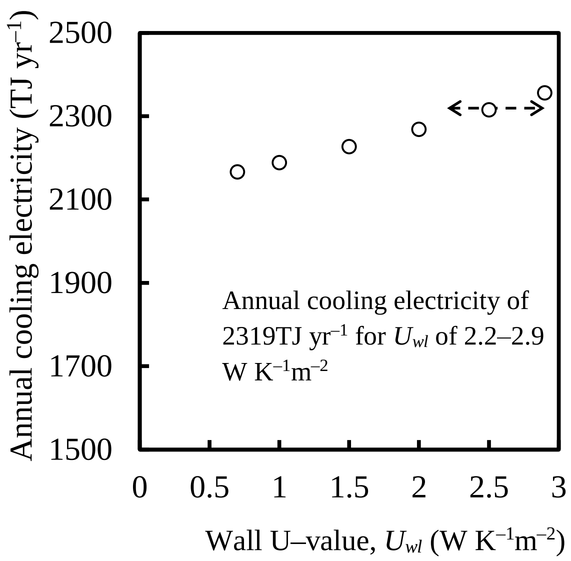


Figure 5.2 Whole sector cooling electricity consumption varied by wall U–value

Window U–value, U_{wd} and shading coefficient S_c

Heat gain through window can be marked by both conduction and radiation heat transfer. Thermal transmittance of window U_{wd} and shading coefficient S_c are selected as index of conduction and radiation heat transfer via the window. The public rental housings are all installed with single glazing, where double glazing is rarely used and usually installed for noise control especially near road side (Lam 2000). U_{wd} of 5–6mm thick glass with single glazing is ranged between 5.6–6.9W $K^{-1}m^{-2}$ (Cheung et al. 2005, Chua and Chou 2010), while U_{wd} of low emissivity or low–E single glazing can be reduced to 4.2W $K^{-1}m^{-2}$ (ASHRAE–90.1 2013). A majority of the surveyed windows are of clear glass while a few of them were installed with tinted glass with colour coating to reduce solar radiation, correspondingly complies a S_c range of 0.9–0.97 and 0.53–0.8 (Chua and Chou 2010, ASHRAE–90.1 2013).

Keeping the same simulation parameters range as marked in section 4.3.3, the whole public housing sector and per apartment cooling electricity consumption with sensitivity test on standardized U_{wd} at 4, 5, 6 and 7W $K^{-1}m^{-2}$ and S_c of 0.4, 0.6, 0.8 and 0.99 are respectively graphed in Figure 5.3 and 5.4. The rectangular shaped area, in Figure 5.3, is representing the covered ranges of U_{wd} (5.6–6.9 W $K^{-1}m^{-2}$) and S_c (0.9–0.97), and the '*' symbol is indicating the predicted annual cooling electricity use (2319TJ yr^{-1}) for existing public housing sector. The results show that reduction of U_{wd} decreases total cooling energy consumption, yet the impact is insignificant. Only 2.04% and 0.93% of energy savings are reported when U_{wd} reduces from 7 to 4W $K^{-1}m^{-2}$ respectively for S_c at 0.4 and 0.99.

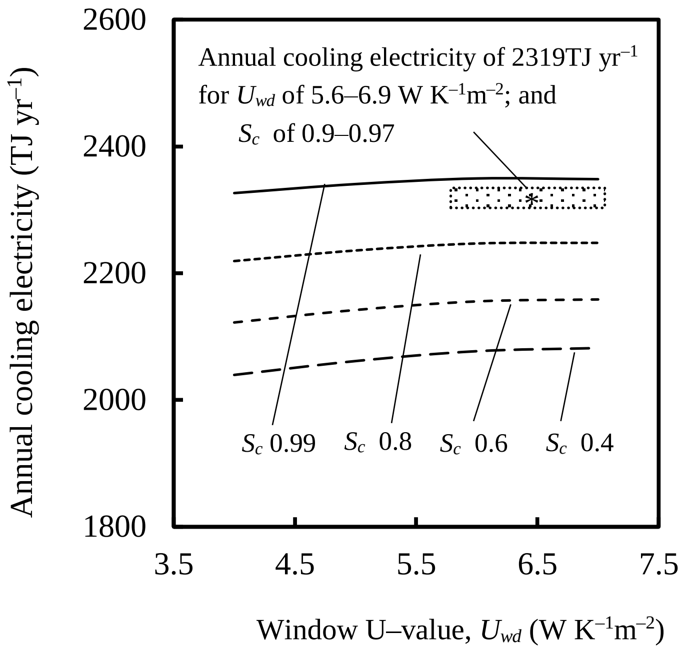


Figure 5.3 Whole sector cooling electricity consumption varied by window U–value and shading coefficient

In contrast, a remarkable cooling electricity saving potential is revealed for S_c reduction, where about 11.3%–12.3% of energy is reduced when the S_c value drops from 0.99 to 0.4 for U_{wd} between 4–7W K^{-1}m^{-2}. Figure 5.4 graphs the distribution of per apartment cooling electricity use for S_c equals to 0.4 and 0.99 and U_{wd} at 4 and 7 W K^{-1}m^{-2}. The average per apartment cooling demand is recorded as 3.69 and 4.25GJ yr^{-1} for S_c at 0.4 and 0.99 when U_{wd} fixed at 4W K^{-1}m^{-2}, while these values increase slightly to 3.77 and 4.29GJ yr^{-1} when U_{wd} fixed at 7W K^{-1}m^{-2}.

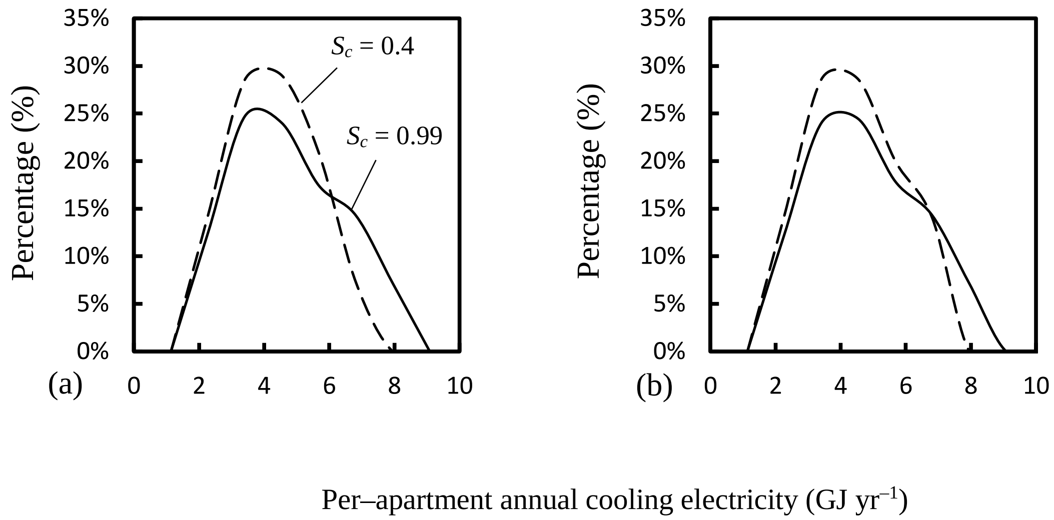


Figure 5.4 Per–apartment cooling electricity consumption varied by shading coefficient and window U–value fixed at (a) U_{wd} = 4W K^{-1}m^{-2}, (b) U_{wd} = 7W K^{-1}m^{-2}

Heat gain through window is dominated by radiation heat transfer over conduction heat transfer. Insignificant saving by U_{wd} can be explained by limited conduction heat gain from window prior to relatively thin glazing (5–6mm) used. Besides, low emissivity or tinted glass with smaller S_c value may physically enhance reflection of incident solar radiation and reduce transmission and absorption for solar heat on window area, thus an outstanding cooling reduction is revealed. Regarding to the above prediction, cooling energy saving strategies on window shall be implementing low emissivity or tinted glazing to existing or future public housings, while consideration of double glazing installation with lower U_{wd} may not be cost effective (Chua and Chou 2010).

Integration of wall and window materials alternatives

Table 5.1 predicts the annual cooling electricity consumption by replacing the external wall and window material use in existing public housing sector with alternatives. Considering the replacement of M(i) existing reinforced concrete external wall (U_{wl} = 2.2–2.9 W $K^{-1}m^{-2}$) to light–weight concrete (U_{wl} = 0.7–1.5 W $K^{-1}m^{-2}$) and M(ii) 5–6mm clear single glazing (U_{wd} = 5.6–6.9 W $K^{-1}m^{-2}$, S_c= 0.9–0.97) to 6mm tinted single glazing window (U_{wd} = 4.2–5.7 W $K^{-1}m^{-2}$, S_c= 0.53–0.8), the corresponding annual cooling electricity demand are reported 2182 and 2173TJ yr^{-1} respectively (Lam 2000, Feng 2004, Cheung et al. 2005, ASHRAE–90.1 2013). Meanwhile, implementation together with both strategies can further lower the cooling demand to 2016TJ yr^{-1}. Figure 5.5 graphs the cumulative percentile of per apartment cooling demand for strategies M(i), M(ii) and M(i+ii). The corresponding average cooling demand is reported 3.90, 3.87 and 3.59GJ yr^{-1}. These results suggest the cooling energy consumption in the public housing sector can be significantly reduced by replacing materials use for external wall and glazing type. Both strategies are recommended for newly constructed housing, while only replacement of glazing is suggested in existing housings regarding to the effectiveness on implementation.

Table 5.1 Existing / alternatives materials and construction settings for Hong Kong public housings

		Existing	Alternatives	Annual cooling electricity (TJ yr^{-1})
Materials	External Wall	Reinforced concrete U_{wl} = 2.2–2.9 W $K^{-1}m^{-2}$ [13]	*M(i): Light–weight concrete* U_{wl} = 0.7–1.5 W $K^{-1}m^{-2}$ [20, 21]	2182 (–5.92%)
	Glazing	5–6mm clear single glazing U_{wd} = 5.6–6.9 W $K^{-1}m^{-2}$ S_c= 0.9–0.97 [12, 13]	*M(ii): 6mm tinted single glazing* U_{wd} = 4.2–5.7 W $K^{-1}m^{-2}$ S_c= 0.53–0.8 [20, 21]	2173 (–6.31%)
	Mixed		*M(i) + M(ii)*	2016 (–13.07%)
Constructions	Window area, A_{wd}	As listed in Table 4.1	*W(i): 10% area reduction* *W(ii): 20% area reduction* *W(iii): 30% area reduction*	2286 (–1.42%) 2254 (–2.79%) 2224 (–4.11%)
	Shadow angle, σ_v (length)	75.3° (0.5m)	*S(i): 89.9° (0m)* *S(ii): 82.5° (0.25m)* *S(iii): 68.5° (0.75m)* *S(iv): 62.2° (1m)* *S(v): 51.7° (1.5m)*	2408 (3.82%) 2360 (1.77%) 2287 (–1.37%) 2262 (–2.44%) 2245 (–3.18%)
	Mixed		*W(i) + S(iii)* *W(i) + S(iv)* } Figure 5.9 (a) *W(i) + S(iii)* *W(i) + S(iv)* } Figure 5.9 (b) *W(ii) + S(iii)* *W(ii) + S(iv)* } Figure 5.9 (c)	2254 (–2.79%) 2232 (–3.77%) 2246 (–3.13%) 2209 (–4.75%) 2224 (–4.11%) 2190 (–5.58%)

Note: Negative value indicates energy saving

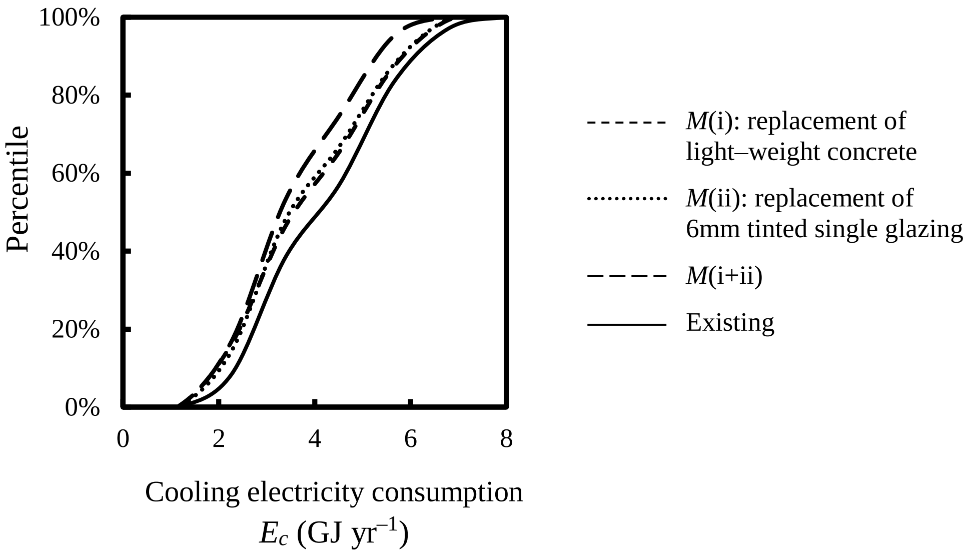


Figure 5.5 Per–apartment cooling electricity consumption varied by materials alternatives

5.3 Building construction alternatives

In this section, the cooling energy impact for public housings with various construction design alternatives is discussed. Energy efficient choices for window area reduction and overhang extension are co-ordinately analyzed. Cooling electricity demand with different apartment floor area mix ratio is studied. Besides, energy saving potentials with external wall area reduction and the optimal orientation for various housing estates are investigated.

Window Area, A_{wd}

Remarkable heat gain from window to the indoor space is confirmed by literatures and the analysis above (Lam 2000, Wong and Agustinus 2004). Window construction with smaller area to minimize total space cooling energy is discussed as an energy saving measures in Hong Kong public housing sector. Using the flat details of existing public housings (Table 4.1), the annual cooling energy consumption with window construction alternatives of *W*(i) 10% area reduction, *W*(ii) 20% area reduction and *W*(iii) 30% area reduction are predicted in Table 5.1. Figure 5.6 shows the cumulative percentage of per apartment cooling electricity use for the window construction alternatives as compared with existing housings arrangement. The predicted annual cooling electricity (per–apartment average) is 2286 TJ yr^{-1} (4.08 GJ yr^{-1}), 2254 TJ yr^{-1} (4.02 GJ yr^{-1}) and 2224TJ yr^{-1} (3.96 GJ yr^{-1}) for window size adjustment *W(i), W(ii)* and *W(iii)* respectively. Reportedly, the saving of window area reduction is less sensitive as compared with building materials change.

Despite up to 4.11% of cooling energy is rewarded, too small window size of 30% area reduction could be worse for glare as the eye struggles for large lighting contrast between wall and window area. Besides, increased energy use in apartments would have happened as occupants pull the curtains against glare and frequently turn on artificial lights (Sanders 2010). Cooling energy saving by window area reduction can be recognized by statistics, yet this strategy is doubted for implementation due to consideration of occupants' visual needs and optimization of overall energy usage.

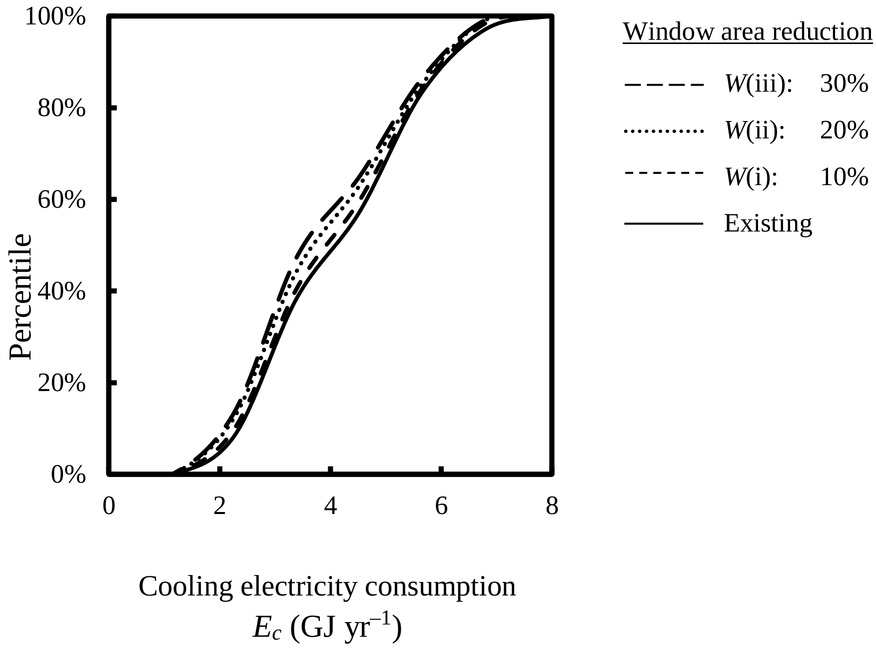


Figure 5.6 Per–apartment cooling electricity consumption varied by window area

Shadow angle, σ_v

Overhangs instead of vertical fins are generally adopted for shading devises in Hong Kong public housings. Some studies used the extension length from external wall as an indicator to identify the effectiveness of overhang (Cheung et al. 2005). However, the actual function of overhang shading is to block direct sun–light onto the window glazing. It suggests that the extension length and window location are both important measures to identify the overhang efficiency. This section uses vertical shadow angle $\boldsymbol{\sigma_v}$ as the indicator to quantify the effectiveness of overhang by considering the contribution of both measures.

Figure 5.7 identifies the $\boldsymbol{\sigma_v}$ (75.3°) in existing public housing for a 1.8m height window located 0.1m below ceiling and together with a 0.5m long overhang extension. Keeping the window size and location unchanged, Table 5.1 shows the annual cooling electricity use in public housing sector regarding to various shadow angles (overhang extensions) alternatives of *S*(i) to *S*(v). Extra cooling energy of 3.82% (2408TJ yr^{-1}) is required for no shading devices installed, while an energy saving potential of 3.18% (2245TJ yr^{-1}) is recorded for shadow angle reduced from 75.3° (0.5m) to 51.7° (1.5m). Figure 5.8 graphs the cumulative percentage of per–apartment cooling electricity use for strategies *S*(i) and *S*(v), respectively reveals an average value of 4.29GJ yr^{-1} and 4.00GJ yr^{-1}. Despite a greater energy saving potential is reported for *S*(v), an extension of 1.5m overhang is rarely constructed. Besides, less than 1% saving improvement on cooling electricity use is reported for overhang extension beyond 1m. Thus, the overhang extension length for public housing shading purpose longer than 1 meter is not recommended.

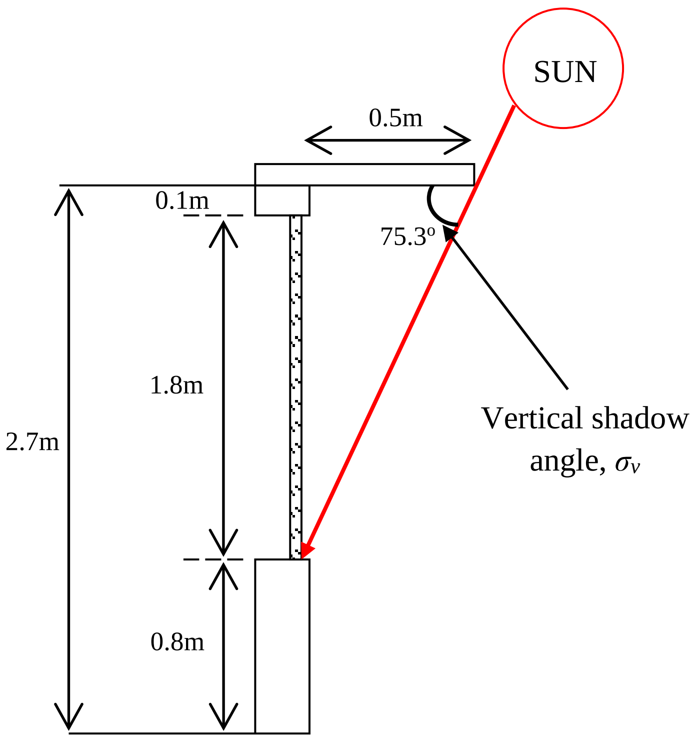


Figure 5.7 **Identification of vertical shadow angle σ_v in existing public housing blocks**

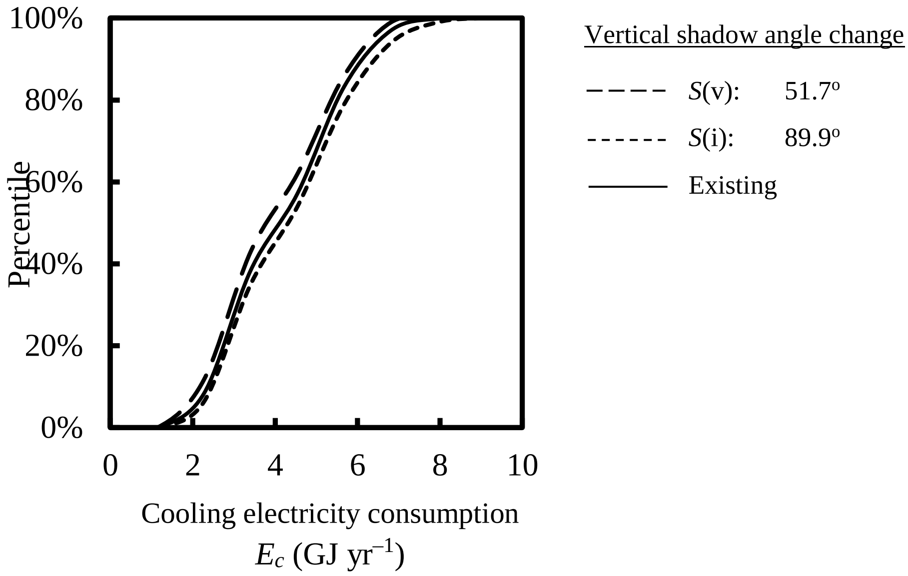


Figure 5.8 **Per–apartment cooling electricity consumption varied by vertical shadow angle**

Since the function of overhang shading is to block direct sun–light through window into the indoor space, evaluation on cooling energy impact between window and shading should be discussed together. Cooling energy saving strategies with combination of 10% and 20% window area reduction and 0.75m and 1m overhang shading extensions are suggested in Figure 5.9. The corresponding annual cooling electricity use is summarized in Table 5.1.

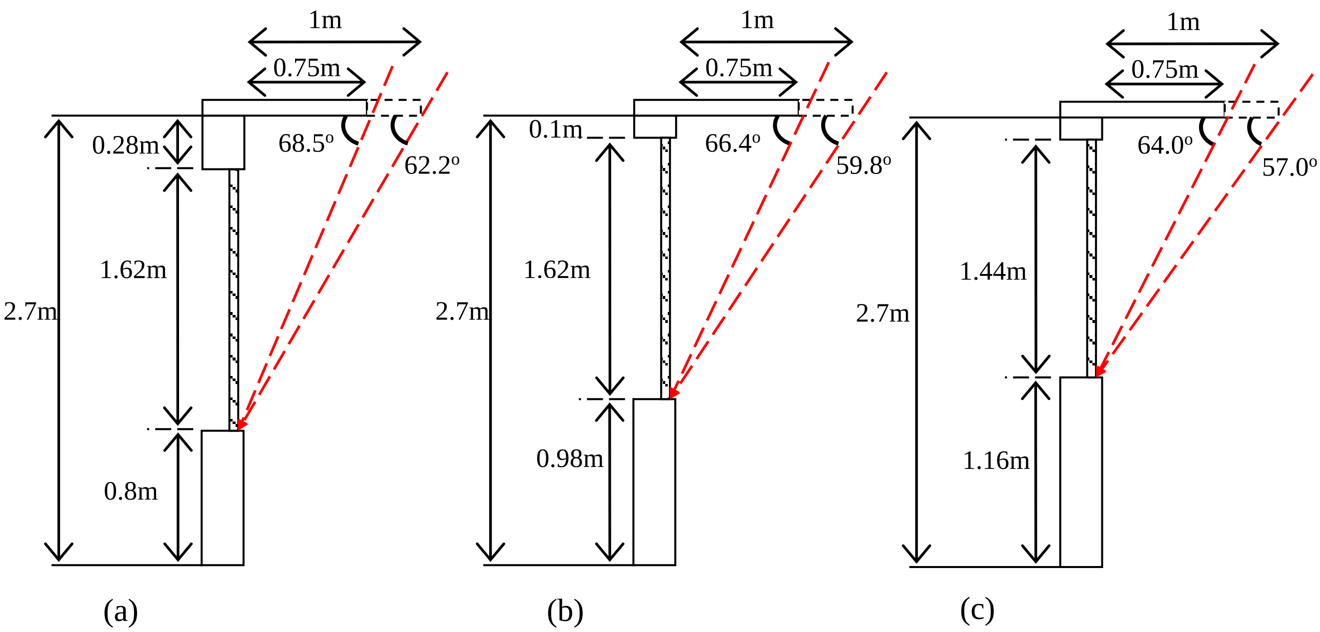


Figure 5.9 Diagrams for window reductions ((a, b) 10%, (c) 20%) and shadow angles alternatives

Extra energy savings of 1–1.6% are observed with longer shading, i.e. 1m extension, in all scenarios. Window area reduction of 10% and overhang extension of 0.75m and 1m are both presented in Figure 5.9 (a) and (b), where the main difference refers to the reduction starts from top or from bottom of the window frame which provides different shadow angles in corresponding case. Lower cooling energy consumptions (2246TJ yr^{-1} / 2209TJ yr^{-1}) are reported by window area reduction at the bottom frame for both 0.75m and 1m shading extensions which contributes smaller shadow angles as compared with cases of upper frame area reduction (2254TJ yr^{-1} / 2232TJ yr^{-1}) in Figure 5.9(a). These examples suggest that window area reduction should be started from the bottom frame to enhance energy saving efficiency by limiting the shadow angle.

Figure 5.9(c) shows a 20% window area reduction from the bottom as compared with the original apartment settings. Annual cooling electricity consumptions of 2224TJ yr^{-1} and 2190TJ yr^{-1} are predicted for 0.75m and 1m overhang extension respectively. These assessments provide evidences for cooling energy saving potential of 2.79–5.58% with various window and overhang shading alternatives. The results can be beneficial to initiate future public housing block window and shading designs by reducing solar heat gain.

Apartment floor area, A_{fl}

Cooling energy demand is generally increased by floor area A_{fl}, where bigger room requires more energy to cool air at desired set–point temperature as compared with small room. Besides, more lightings and equipments, together with greater heat generation, were expected with larger floor area (Bojic et al. 2002a, EFBS 2012). Quantity of public housing with various sizes is, therefore, an important concern for future residential sector development regarding to optimization for cooling electricity consumption.

Hong Kong had 761000 public housings in year 2011 accommodating 2076000 residents (HF 2012). Accordingly, a population up to 1530000 was living in the four typical public housing blocks specified in Table 4.2, since these blocks comprised 73.7% of the total stock (HKHA 2014). Using the average occupant load factor O_f, of 12.6m^{2}hd^{-1}, reported in Chapter 3 in this study, an assumption of public apartment size is classified into three levels, including small (<30m^2), medium (30–50m^2) and large (>50m^2) flats respectively available for 1–2, 3–4 and 5–6 number of occupants.

Figure 5.10 shows the cooling electricity consumption of Hong Kong public housings for the existing population of 1530000 with various quantity combinations of three apartment areas. The cooling electricity consumption for the existing combinations (indicated as '×') of small η_S (42.3%), medium η_M (54.9%) and large η_L (2.8%) apartments is 2319TJ yr^{-1}. Total apartment number $N_{ap,total}$ for public housings is determined by fixed desired percentages η_S, η_M and η_L indicates in Equation 5.1, where coefficients 1.5, 3.5 and 5.5 are the average occupant loads of small, medium and large apartments respectively.

$$N_{ap,total} \times (1.5 \times \eta_S + 3.5 \times \eta_M + 5.5 \times \eta_L) = 1530000 \qquad (5.1)$$

From Figure 5.10, in case of accommodating the same population only with small, medium and large flats, the corresponding annual cooling electricity consumptions (per meter square values) are 2974 TJ yr^{-1} (133.9 MJ yr^{-1}m^{-2}), 2132 TJ yr^{-1} (125.7 MJ yr^{-1}m^{-2}) and 2035 TJ yr^{-1} (136.7 MJ yr^{-1}m^{-2}), respectively. The results exhibit higher total cooling electricity consumption with cases of small flats dominating the public housing sector, while significant electricity reduction is predicted if more medium or large flats are being constructed. The occupant area ratios are found to be 0.069, 0.090 and 0.103hd m^{-2} respectively for small, medium and large flats. Apparently, large apartment is designated for higher occupancy (i.e. to accommodate more occupants in a unit area) and therefore a more effective use of cooling energy is expected for the same occupancy schedule. Electricity impact of future public housing development is affected by apartment size, which the construction of medium size flat is resulted from the least cooling electricity use per unit floor area.

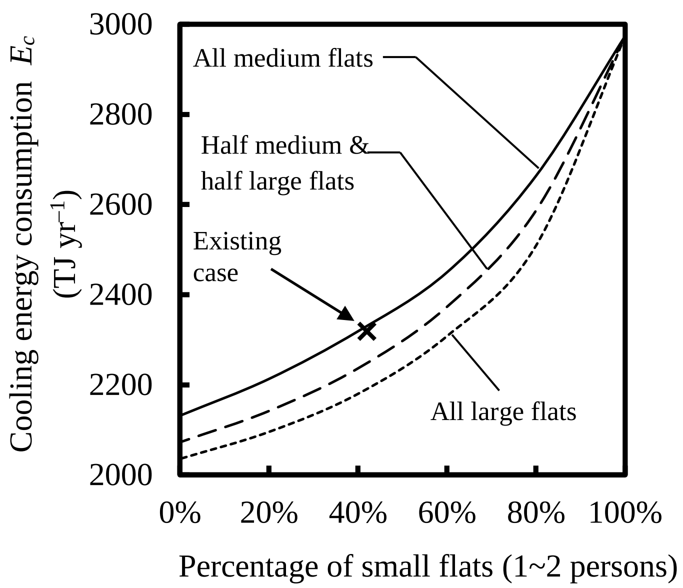


Figure 5.10 Cooling electricity consumption varied by apartment floor area

External wall area, A_e

According to the heat transfer expression in Equation 2.1, envelope heat gain from outdoor is significantly influenced by the external wall area A_e. Presumably, smaller external wall area would minimize conduction heat gain and thus to reduce cooling energy consumption in apartments. Figure 5.11 illustrates the cumulative percentage of per apartment cooling electricity use of 10%, 20% and 30% area reduction of A_e with apartment floor area remains unchanged. The total cooling energy consumption (and per–apartment average value) corresponding to 10%, 20% and 30% A_e reductions are 2177TJ yr^{-1} (3.88GJ yr^{-1}), 2020TJ yr^{-1} (3.60GJ yr^{-1}) and 1889TJ yr^{-1}(3.34GJ yr^{-1}) respectively.

Despite significant energy saving potential is numerically presented by smaller A_e, the assumption of A_e reduction with unchanged apartment size is not practical. The findings in this section concluded that reduction of A_e is identified as a cooling energy saving strategy for public housings. However modification of existing apartment layouts should be together considered in terms of safety and relevant construction regulations, where these are out of the scope in this study.

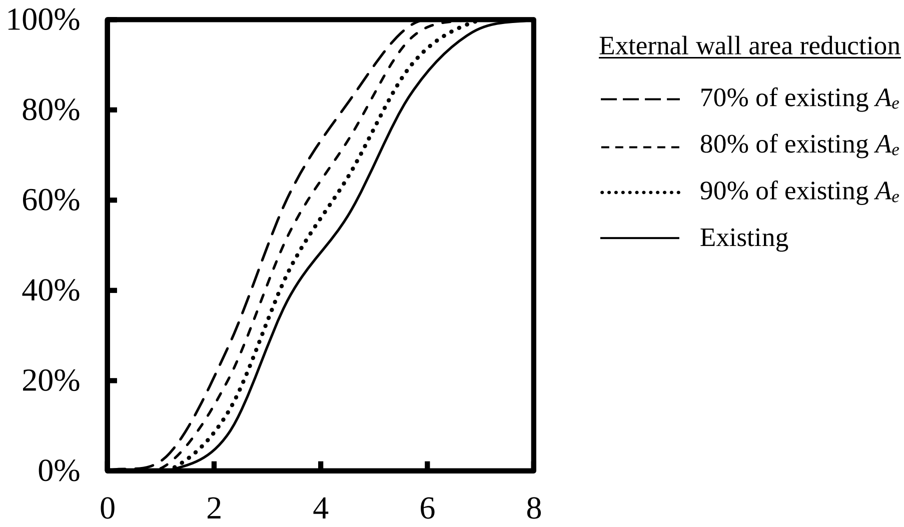


Figure 5.11 Per–apartment cooling electricity consumption varied by external wall area reduction

Orientations of housing estates

Prior to the daily sun movement, heat gain into building via external wall is varied. Orientation arrangement in housing estate can be a concern to minimize direct solar gain into the apartments. Assuming up to 2000 occupants are respectively occupied in the four public housing types, including slab, trident, harmony and new cruciform as shown in Figure 4.1, with average occupant number of 1.5, 3.5 and 5.5 respectively in small, medium and large flats. With respect to a fixed value of U_{wl} (2.5W $K^{-1}m^{-2}$), U_{wd} (6W $K^{-1}m^{-2}$), S_c (0.9), and σ_v (75.3^o), Table 5.2 presents the estate information and the average, highest and least cooling electricity use among all tested orientations in each housing types.

Table 5.2 Cooling electricity demand in public housings with orientation variations

	Slab	Trident	Harmony	New Cruciform
No. of story	22	40	33	43
Total floor area (m^2)	17389	29628	26070	19840
Total external wall area (m^2)	8500	35724	25912	16555
Wall to floor area ratio	0.49	1.21	0.99	0.83
Average electricity for all direction (GJ yr^{-1})	1773	3956	3186	2510
Highest cooling electricity (GJ yr^{-1})	1791	3995	3199	2524
Least cooling electricity GJ yr^{-1})	1747	3930	3171	2502
Percentage difference (%)	2.52	1.65	0.88	0.88

The highest and lowest average cooling electricity predictions are respectively found in trident (3956 GJ yr^{-1}) and slab (1773 GJ yr^{-1}) type estate to accommodate similar population (~2000 occupants). Higher cooling electricity demand in trident estate can be explained by more lighting and equipment loads for larger total floor area (29628m^2) and extra solar heat gain for larger external wall area (35724m^2), whereas lower cooling electricity demand in slab type with the smallest floor (17389m^2) and external wall (8500m^2) area is reported among all housing types. Estate design with a smaller wall to floor area ratio, i.e. slab and new cruciform, can reveal greater energy saving potential by limiting external wall area so as to minimize the solar heat gain.

Hong Kong is located at the north hemisphere where an apartment facing south shall perceive larger amount of sun–light and solar heat gain. According to different housing estate layouts, total heat gain in entire building prior to different orientation arrangements can be varied. Orientations of the four housing types for (a) the highest and (b) the least cooling energy consumption are graphed in Figure 5.12. Table 5.2 reports the largest percentage variation of cooling energy use in slab type estate (2.52%) for different building orientations, followed by trident (1.62%), while difference for harmony and new cruciform (both 0.88%) is found relatively lower. It indicates different building layouts may contribute to the overall cooling energy consumption with respect to various building orientations. A majority of flats in slab and trident estates are found unidirectional facing which create maximum and minimum solar heat gain during a day according to the sun–path, while flats orientation for harmony and new cruciform estate are evenly distributed in all directions which reduce changes of maximum heat gain from the sun during a day.

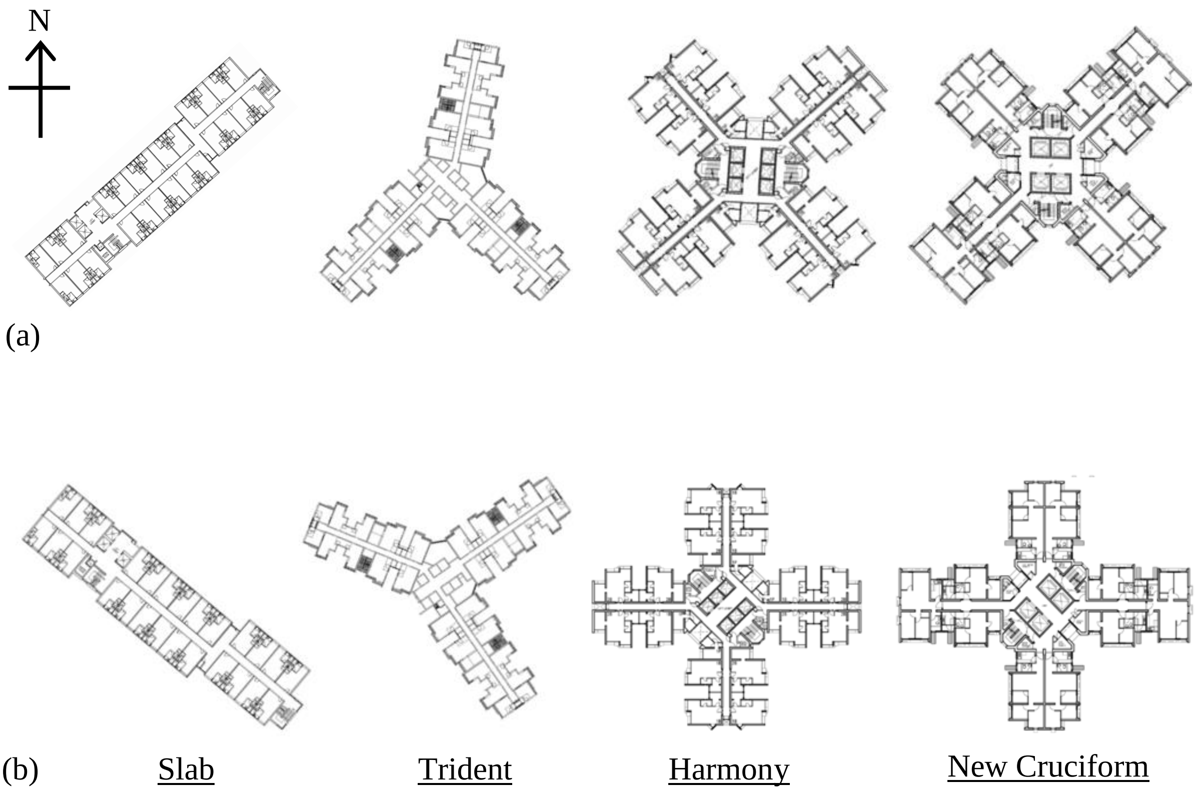


Figure 5.12 Orientation arrangements of the four housing types for (a) the highest and (b) the least cooling electricity consumption

Prior to Hong Kong's geographical status, direct sun–light in the morning, afternoon and evening is respectively from the east (E), south (S) and west (W) direction. Since occupants are tended to turn on air–conditioner in the evening after they have returned home from school or work, greater cooling energy demand for apartments facing SW and W are expected. The highest cooling energy consumption for a single apartment facing SW has been confirmed previously in Figure 4.6(d) and in Cheung et al. (2005) study. The least total cooling energy consumption is, however, reported in Figure 5.12b when a majority of flats facing SW for slab and trident estates. Despite one side of the estate has perceived the greatest solar heat gain, the other side is completely shaded by the building itself and thus the least total cooling demand is recorded. In contrast, building orientations illustrated in Figure 5.12a, especially for slab and trident estates, are having minimum self–shading effect where most of the apartments are exposed to direct sun–light during the evening and thus a higher total cooling demand is observed. The results indicate a significant impact on cooling electricity demand of various estate types with different orientation arrangements and it is favourable for policymakers in considering residential estate arrangements in new town development.

5.4 Summary

Flexibility of the proposed hybrid cooling energy consumption model is demonstrated via the application examples in this chapter, where cooling energy consumption with sensitivity change on building materials and construction designs for individual apartment and entire public housing sector is evaluated. These application examples aim to numerically investigate the residential cooling energy saving potential, while new housing layout designs, with building regulations and safety issues, are excluded from current scope of discussion.

Public housing material alternatives for cooling energy improvement is confirmed by lower U_{wl} and S_c values, while insignificant change was reported by U_{wd} variations. Remarkable cooling energy saving potential (–13.07%) is recorded by replacing existing external wall and window respectively with light–weight concrete and tinted single glazing, while double glazing is not recommended for cost–effectiveness.

Window area and extension of overhang should be discussed accordingly for the effectiveness on reducing direct solar heat gain through fenestration. Example strategies integrating both window area and vertical shadow angle reduction are discussed and proved with evident savings of –5.58%. Decreasing window area can effectively avoid solar heat gain, yet visual discomfort will be triggered by glare with too small window to wall ratio.

The cooling energy use for entire residential sector by changing number of flats in different size groups (i.e. small (<30m^2), medium (30–50m^2) and large (>50m^2) flats) is evaluated. More medium or large size flats are recommended for future housing consumption plan, since cooling energy use is more efficient in larger apartment with the same occupancy schedule.

This application may not be practical for existing housing sector, but the findings can be useful in directing the future housings development strategy.

Cooling energy consumption for public housings is predicted by 10%, 20% and 30% external wall area reduction with the same floor area in current apartment layouts. In spite of a reduction of cooling energy consumption is numerically presented, more details on construction criteria and regulations have to be discussed for new housing designs which are not being considered in this study.

Cooling energy consumption influences by orientation effect is investigated via four typical public housing blocks, each accommodating approximately 2000 occupants. The highest cooling energy consumption is recorded in trident block with largest total floor and external wall area, while the slab block consumes the least cooling energy consumption. Besides, larger variations of building cooling energy is reported in slab and trident blocks, where the difference is insignificant in harmony and new cruciform blocks with evenly distributed apartment number in all directions. In addition, the orientations for each housing block with maximum and minimum cooling energy consumption are identified.

The findings reported in this chapter can be practical in cooling energy reduction in existing public housing sector and useful for reference in new town for sustainable housings development plans.

Chapter 6

Investigation on residential thermal comfort and air–conditioning operation

6.1 Introduction

Despite significant thermal heat gain can be reduced by building materials and construction alternatives, actual cooling energy demands in apartments are attributed by occupants' behaviour in terms of thermal comfort and air–conditioner (AC) operation status (Schweiker and Shukuya 2008, Indraganti and Rao 2010, Wong et al. 2014a). Existing literatures on cooling energy simulations often overlooked occupant's thermal comfort needs. Besides, AC operating schedule in simulation was assumed equivalent to standardized occupancy profile among households in some studies (Bojic and Yik 2005, Cheung et al. 2005). The accuracy of this assumption is doubted regarding to variation in occupancy, as well as AC operating criteria, yet detailed studies in these areas were found limited in open literatures.

In this chapter, physical measurements and interview surveys are conducted in some apartments to understand occupants thermal comfort behaviour in their livings, including the neutral temperature set–point and corresponding thermal comfort zones. Cooling energy savings potential in residential buildings are determined regarding to indoor and outdoor temperature variation with thermal comfort considerations. Besides, interview surveys are extended to evaluate occupant's AC operation schedule and its relationships among housing types, resident's social–economic groups and other potential aspects. A probabilistic model is developed to simulate the hourly AC on/off profile with respect to household characteristics. The results presented in this chapter can contribute in more precise cooling energy prediction in apartments, which assists implementation of energy saving strategies prior to occupant behavioural concerns.

6.2 Physical measurements and interview surveys

Physical measurements to the thermal environment were conducted in 54 apartments, including 34 public housings (PUB) and 20 private housings (PRI). Laboratory grade instruments, with specifications listed in Table 6.1, were used to measure the indoor thermal environment parameters, including air temperature T_a (°C), relative humidity R_h (%), air velocity v_a (ms^{-1}), and globe temperature T_g (°C). The radiant temperature T_{rad} (°C) is determined from Equation 6.1, where D and ε are respectively the diameter of the globe and the emissivity.

$$T_{rad} = \left[\left(T_g + 273\right)^4 + \frac{0.25 \times 10^8}{\varepsilon} \left(\frac{\left|T_g - T_a\right|}{D} \right)^{0.25} \times \left(\left|T_g - T_a\right| \right) \right]^{0.25} - 273 \tag{6.1}$$

Table 6.1 Specification of instruments used for physical measurement

Logger Type	Q–TRAK Plus IAQ Monitor, TSI 8554		StowAway data logger	VELOCICAL Plus Anemometer, TSI 8384
Parameters	Air temperature, T_a	Relative humidity, R_h	Globe temperature, T_g	Air Velocity, v_a
Measurement Ranges	0–50°C	5–95%	–40–70°C	0–50 ms^{-1}
Accuracy	± 0.6% of m.v.*	± 3% of m.v.*	± 5% of m.v.*	± 3% of m.v.*

* measured value

Measurement was conducted during the interview surveys (details in next paragraph), and it took at least fifteen minutes in each measurement to ensure validity. Equipments were set at a location near to the occupant to ensure the collected data were reflecting the real–time indoor thermal conditions but the measurement results were made unknown to the interviewees during the interview. The data is used to determine the occupant exposed thermal environment.

A total of 217 occupants, with 130 females, were participated for the interview survey on thermal comfort evaluation. Direct feedback on thermal acceptability was studied with a two–point dichotomous scale from the subjects, where thermal satisfaction represented an occupant who voted 'Acceptable' for thermal comfort. Since the adaptive behaviour on thermal comfort is presumably accepted by the occupant themselves, only those thermal acceptance data would be intensively evaluated in this study. Meanwhile, a 7–point ASHRAE scale of thermal sensation vote (TSV) was used to examine occupants' thermal perception, where hot = +3; warm = +2; slightly warm = +1; neutral = 0; slightly cool = −1; cool = −2 and cold = −3. The interview was conducted in the mother tongue of the interviewees to avoid misunderstandings. In addition, all data received concerning thermal comfort were also noted for reference, for example, age group, gender, clothing value (C_L) and activity level (M_e) of interviewee.

Aiming to understand occupant's air–conditioning usage pattern in residential building, an extension of questionnaire survey to 109 resident's (with 57 females) in 30 apartments was conducted to examine the household backgrounds including income range, number of air–conditioner at home, occupant's load and other housing characteristics (construction materials use, area of window and external wall, flat size and apartment orientation). Individual's information such as age group, education level, occupation, experienced AC functioning months and their self–rated hourly occupancy and AC operation schedule for both weekday and weekend routines were surveyed. Besides, several questions were asked, as summarizes in Table 6.2, to identify occupant's cooling energy saving awareness in their livings.

Table 6.2 Questionnaire of self–awareness on AC cooling energy saving

–1 (Disagree) 0 (Neutral) 1 (Agree)	(*–1* *0* *1*)
1. You are energy–saver.	______
2. You turn on the fan first when you feel hot	______
3. You turn on air–conditioner when no one at home in summer day.	______
4. You turn on the air–conditioner when you are alone at home.	______
5. You turn on air–conditioner immediately when you back home in summer day.	______
6. You turn off air–conditioner before sleeping.	______
7a You set timer of the air–conditioner during sleeping. (sample with timer)	______
7b You set timer if your air–conditioner has timer function. (sample without timer)	______
8. Electric bill is a considerable factor when you turn on air–conditioner.	______

6.3 Thermal environment and energy assessment in residential buildings

Thermal comfort studies in apartments

Table 6.3 summarizes the results for 204 "Acceptable" and 13 "Unacceptable" thermal votes in 54 residential apartments and the corresponding thermal comfort related parameters, including indoor air temperature T_a (°C), radiant temperature T_{rad} (°C), relative humidity R_h (%), air velocity v_a (ms^{-1}), metabolic rate M_e (met), clothing value C_L (clo), operative temperature T_{op} (°C), predicted mean vote (PMV), predicted percentage of dissatisfy (PPD)

(Fanger 1970) and thermal sensation vote (TSV). T_{op} is a function of T_a, T_{rad} and v_a, and is determined by Equation 6.2 below, where J is the weighting factor accounting for the convective and radiant heat transfer coefficients and it is a function of v_a (ASHRAE–55 2010).

$$T_{op} = JT_a + (1-J)T_{rad} \quad ; \quad J = \begin{cases} 0.5; & v_a < 0.2 \\ 0.6; & 0.2 \le v_a < 0.6 \\ 0.7; & 0.6 \le v_a < 1 \end{cases} \tag{6.2}$$

Table 6.3 Thermal comfort parameters in surveyed apartments

	T_a (ºC)	T_{rad} (ºC)	v_a (ms^{-1})	R_h (%)	C_L (clo)	M_e (met)	T_{op} (ºC)	*PMV*	*PPD*	*TSV*
					Overall [n=217]					
Unacc	28.3*	28.4*	0.40*	84.8*	0.51	1.10	28.4*	0.82*	33.78	1.54*
[n=13]	(2.54)	(2.46)	(0.22)	(9.8)	(0.11)	(0.11)	(2.48)	(0.94)	(25.68)	(1.20)
Acc	24.9*	25.1*	0.24*	73.1*	0.45	1.11	25.1*	–0.44*	31.78	–0.04*
[n=204]	(3.46)	(3.43)	(0.20)	(14.6)	(0.11)	(0.07)	(3.42)	(1.31)	(29.91)	(0.96)
					Acceptable [n=204]					
PUB	25.3*	25.6*	0.25	76.1*	0.46	1.13	25.5*	–0.26*	30.93	0.10*
[n=134]	(3.28)	(3.20)	(0.22)	(14.9)	(0.12)	(0.12)	(3.22)	(1.18)	(26.28)	(0.89)
PRI	24.3*	24.2*	0.23	67.4*	0.45	1.11	24.3*	–0.78*	33.4	–0.31*
[n=70]	(3.70)	(3.66)	(0.17)	(12.0)	(0.11)	(0.06)	(3.68)	(1.48)	(36.00)	(1.04)
					Acceptable [n=185], for TSV between –1 and 1 only					
PUB	25.2	25.54	0.25	76.0*	0.45	1.10	25.4	–0.30	31.3	0.04
[n=124]	(3.31)	(3.23)	(0.22)	(14.9)	(0.12)	(0.08)	(3.25)	(1.17)	(26.7)	(0.74)
PRI	24.9	24.76	0.22	68.8*	0.46	1.11	24.8	–0.47	26.44	–0.16
[n=61]	(3.15)	(3.04)	(0.17)	(10.6)	(0.12)	(0.06)	(3.09)	(1.08)	(30.37)	(0.76)

* Significance between groups (p<0.05, t–test)

The finding shows that occupants feel warm (TSV=1.54 (1.2)) in the predicted slightly warm conditions (PMV =0.82 (0.94)) and dissatisfied with higher T_a, T_{rad}, T_{op} and R_h as compared with the predicted acceptable environments ($p<0.05$, t–test). However, a wide range of acceptable T_a (17.5°C~31.5°C) and R_h (47%~100%) is revealed under sedentary activity level 1.11 (0.07) met and casual clothing value 0.45 (0.11) clo, which also suggests that some occupants are adapted to their living environment with high toleration to extreme thermal conditions. An interesting observation reports that some occupants desired to wear more clothes (up to 0.83clo) in an air–conditioned space instead of raising the indoor temperature set–point of air–conditioner, which explains the thermal acceptance responses in relatively cold temperature. Figure 6.1 graphs the relationship between TSV against mean PMV (with a standard deviation range) in residential apartments, with significant linear correlation reports in Equation 6.3 ($R=0.98$, $p\leq0.05$). A steeper slope indicates an over–estimation of occupant's actual thermal sensation by Fanger's PMV model, where a slightly warm environment (TSV = 0.68) is perceived by the occupants for a predicted neutral condition (PMV = 0).

$$TSV = 1.28 \times PMV + 0.68 \tag{6.3}$$

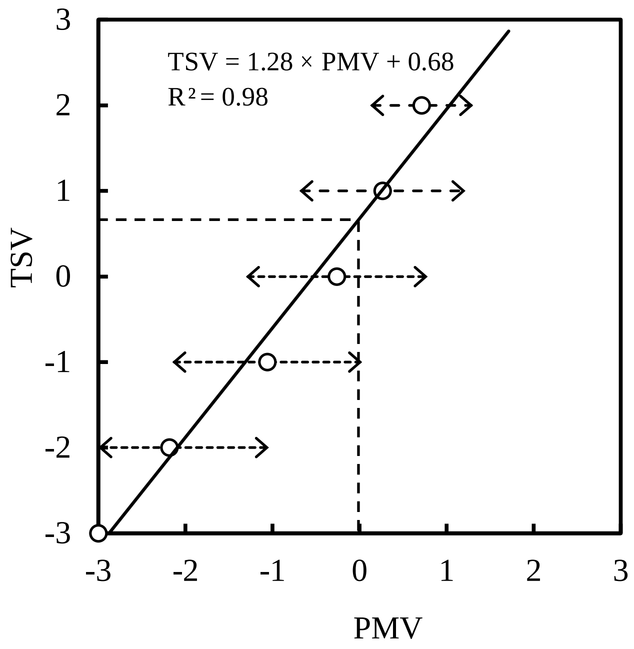


Figure 6.1 Relationship between TSV against PMV in residential apatrments

Figure 6.2 shows the TSV count for both public (PUB, 134 votes) and private (PRI, 70 votes) housing's residents. It reveals over 90% of the responses are within the slightly cool (TSV = –1) to slightly warm (TSV = 1) region, while the counts of extreme vote for ±3 are below 5. A predicted and perceived cooler environment (PMV = –0.78, TSV = –0.31) for PRI, as compared with PUB, is observed in Table 6.3 with lower mean value of T_a, T_{rad}, T_{op} and R_h ($p<0.05$, t–test). It can be explained by more air–conditioned households surveyed in private housings during the assessment. Insignificant difference among PRI and PUB for all measured parameters and thermal sensation choice are reported ($p>0.1$, t–test), except the relative humidity, if these date are confined within the occupant's self–rated slightly cool (TSV = –1) to slightly warm (TSV = 1) environments. It suggests that occupants who live in PUB and PRI housings perceive the same thermally neutral environment in terms of the six thermal comfort parameters. Figure 6.3 shows the relationship of TSV against mean operative temperature T_{op} for both PUB and PRI housings. Sampling counts, in each TSV value, less 5 is ignored to ensure statistical confidence. Neutral operative temperature (TSV = 0) of 25.2°C and 25.1°C were, respectively, reported in PUB and PRI housing via Equations 6.4 and 6.5.

$$TSV = 0.61 \times T_{op,PUB} - 15.38 \quad (6.4)$$

$$TSV = 0.54 \times T_{op,PRI} - 13.55 \quad (6.5)$$

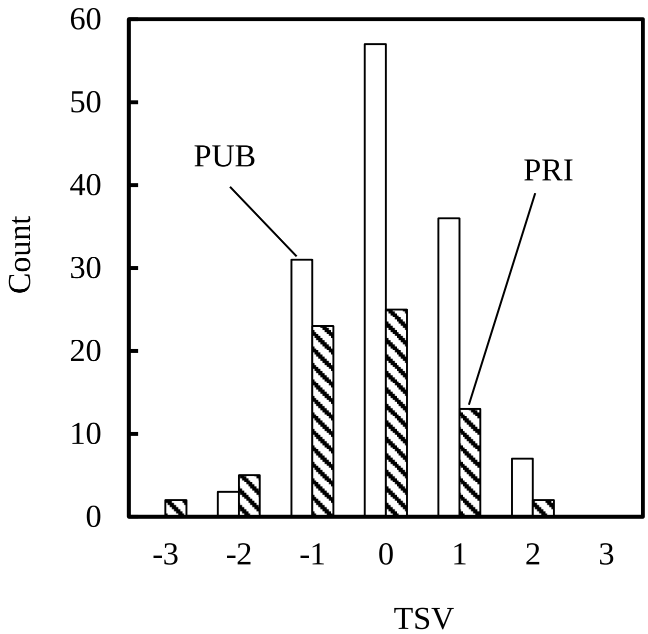


Figure 6.2 Frequency of thermal sensation vote for public (PUB) and private (PRI) housings

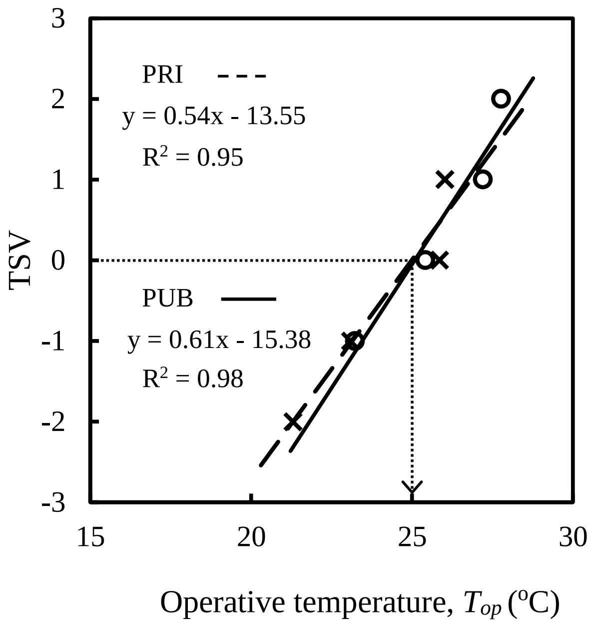


Figure 6.3 Neutral operative temperature for public (PUB) and private (PRI) housings

Presumably, the most comfortable environment from occupant lies between −0.5≤TSV≤0.5 where 90% of thermal satisfaction, i.e. PPD=10%, is assumed (ASHRAE–55 2010). Figure 6.4 estimates the thermal comfort zones for residential buildings in the sub–tropics using the relationship summarized in Equation 6.3 using the mean thermal environment parameters (T_{rad}=1.01T_a, v_a=0.24ms^{-1}, C_L=0.45clo and M_e=1.1met) of the surveyed households. The five zones are classified as "Cool", "Slightly cool", "Neutral", "Slightly warm" and "Warm" conditions, corresponding to thermal sensation vote of –2, –1, 0, 1 and 2, with a boundary range of ±0.5 vote scale. Regarding to the mean R_h of 76% in surveyed public housings, the corresponding T_a boundaries for the neutral thermal comfort zone are observed between 24–26^{o}C. Potential cooling energy saving is observed by raising the indoor temperature set–point from 24 to 26^{o}C, while maintaining a neutral environment (i.e. PPD≤10%) to satisfy occupant's thermal comfort needs in apartment environment. Besides, the lower and upper T_a boundaries for slightly cool and slightly warm conditions are 22^{o}C and 28^{o}C respectively.

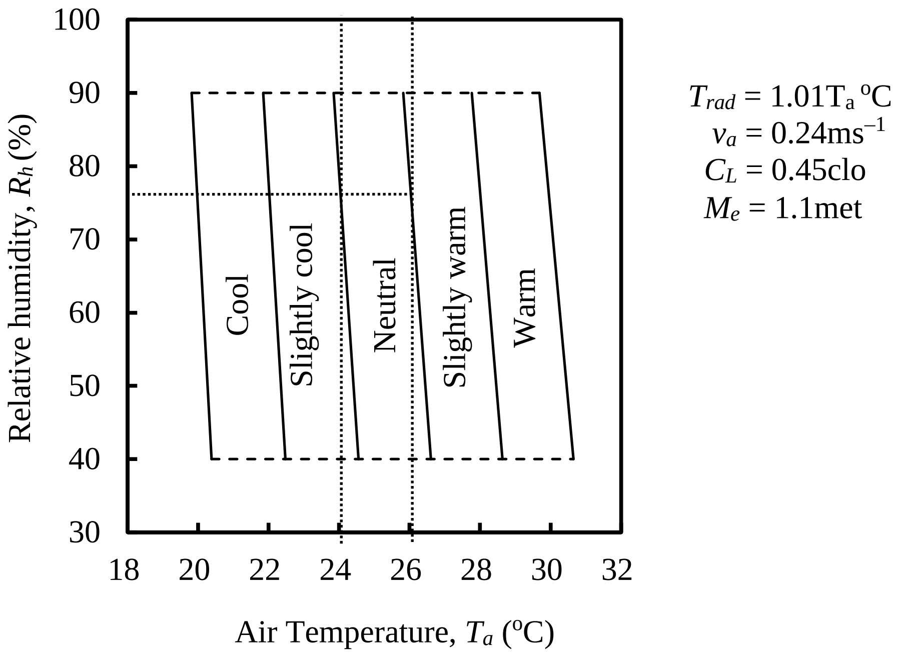


Figure 6.4 Thermal comfort zones for residential buildings in sub–tropics

Cooling energy forecasts by indoor and outdoor temperature variations

Climate change with increasing outdoor air temperature T_o (°C) is a global issue and has significant impact on building energy use (Li et al. 2012, Tung et al. 2013). Raising indoor temperature set–point was confirmed as an effective measure to reduce cooling demand in apartments (Wong et al. 2010, Sadineni and Boehm 2012). Using the existing public housing characteristics described previously in section 4.3.3 (random orientation, σ_v of 75.3°, U_{wd} = 5.6–6.9W K^{-1}m^{-2}, U_{wl} = 2.0–2.9W K^{-1}m^{-2} and S_c = 0.9–0.97), Figure 6.5 illustrates the annual cooling energy forecasts for public housing sector with different outdoor temperature profiles and indoor temperature set–points. The hourly T_o profile of year 1989 is selected as the base case weather data (Mui and Wong 2007), while two more cases with hourly T_o increment of 0.5°C and 1°C are introduced to represent levels of climate change. Meanwhile, indoor air temperature set–points ranged from 22°C to 28°C are implemented for energy saving measures.

From Figure 6.5, annual electricity saving potential of 619TJ yr^{-1} is achieved by increasing T_a from 24°C to 26°C within the neutral thermal comfort zone, which about 7% reduction in total cooling energy use is recorded for each 0.5°C increment of T_a. Further increase of T_a to 28°C (the slightly warm boundary) reduces the cooling energy to half of the original consumption. In contrast, an increase of cooling demand to 3003TJ yr^{-1} is observed when T_a is lowered to 22°C reaching the slightly cool boundary. On the other hand, for 0.5°C and 1°C increments of hourly T_o, the cooling demands would go up 9.7–17.2% and 20.0–37.9% respectively (i.e. the cooling energy is very sensitive to global warming). The results also show that for an increase of 1°C in T_o, the T_a shall be adjusted from 24°C to 25.5°C in balancing the excessive cooling energy consumption at the existing level.

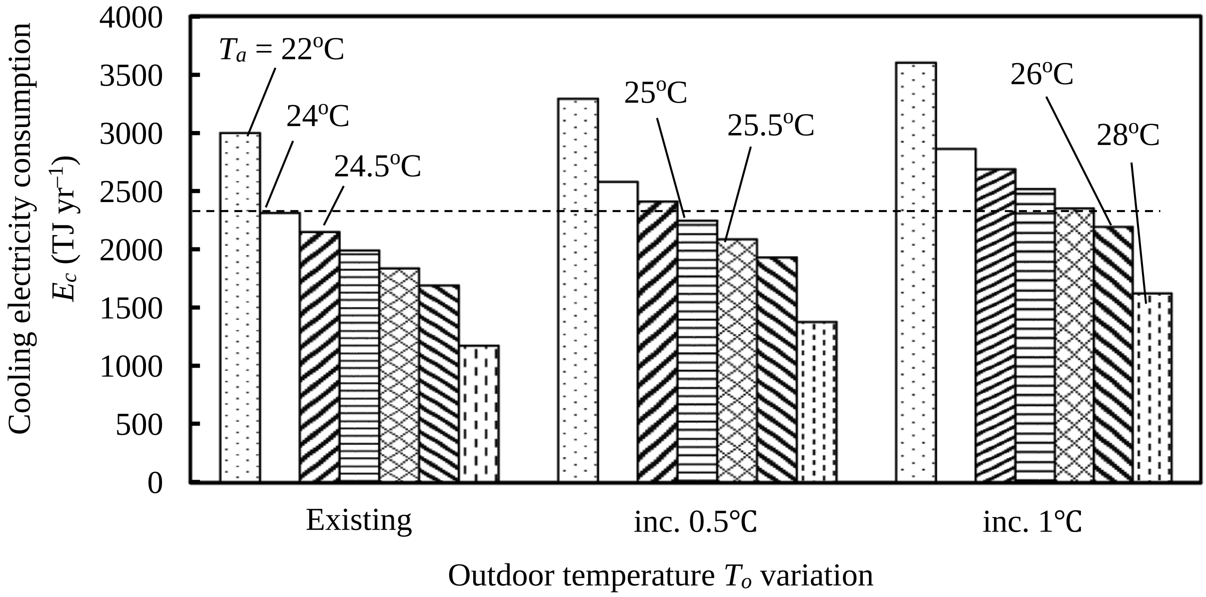


Figure 6.5 Cooling electricity consumption forecast for public housings varied with indoor temperature set–point and outdoor temperature changes.

6.4 Occupant behaviour of AC operation schedule in apartments

Classification of surveyed data

Table 6.4 summarizes the statistics of extensive interview survey from 109 respondents in 30 households. The data is summarized into 6 categories including two household characteristics (housing types and income groups) and four personal factors (age groups, education levels, job natures and AC energy saving levels). Both public and private housings are surveyed and further classified into four income groups with 20000HK$ difference among types. The respondents are sorted into 4 groups by age. Childs with age younger than 10 years old are not being selected in this survey since they are not at liberty to turn on air–conditioner where this action is decided by the adults. Besides, age group of "31–40" is combined with "21–30" due to small sample size and similar performance in both occupancy and AC operation schedule. Occupant's education background is clustered into 5 levels, where an associate degree referred to any academic program which is above secondary education but below a bachelor's degree in university. Resident's job status is summarized into 3 categories. Classification of "No job" is attributed to either housewife or retired person, while "Routine job" is assigned to person who is neither "No job" nor "Student". The respondent's environmental awareness level on AC operation is determined via the eight questions listed in Table 6.2. One mark is awarded in questions 1, 2, 6, 7 and 8 for "Agree" vote and questions 3, 4 and 5 for "Disagree" vote, while –1 mark is given in these questions with the opposite choices. Zero mark is given if a "Neutral" vote is selected in each question. Occupant's energy saving awareness on AC operation is represented by the total marks awarded among the questions and the levels are classified via the distribution as shown in Figure 6.6. Regarding to a one–third portion over the distribution, the survey data is divided into "Low" (marks ≤ 0), “Medium” (marks ≤ 4) and “High” (marks ≥ 5) levels where higher marks imply a more energy efficient behaviour in operating air–conditioners at home.

Table 6.4 Classification of surveyed occupant samples

Classifications	Types				
Housing types	PUB	PRI			
Count (%)	16 (53%)	14 (47%)			
Income groups (HK$)	< 20000	2–39999	4 –59999	≥ 60000	
Count (%)	6 (20%)	14 (48%)	4 (13%)	6 (20%)	
Age groups	10–20	21–40	41–50	≥ 51	
Count (%)	19 (17%)	35 (32%)	21 (19%)	35 (32%)	
Education levels	Primary	Secondary	Associate	University	Master or above
Count (%)	16 (15%)	41 (38%)	10 (9%)	33 (30%)	9 (8%)
Job natures	No job	Routine job	Student		
Count (%)	25 (23%)	49 (45%)	35 (32%)		
Environmental awareness levels	Low	Medium	High		
Count (%)	36 (33%)	38 (35%)	35 (32%)		

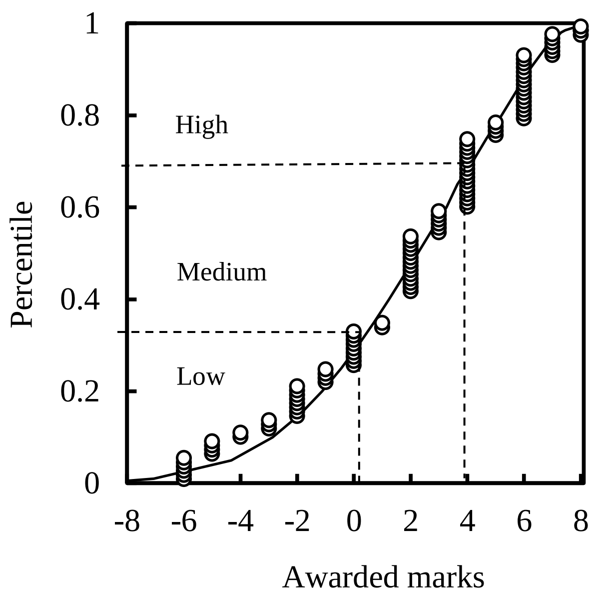


Figure 6.6 Results of the self–rated energy saving awareness on air–conditioner operation in apartments

Figure 6.7(a) & (b) respectively graph the surveyed occupancy and air–conditioning operation schedules, including both weekday and weekend samples, in all apartments. The probability of occupant presence and AC operation in each hour is evaluated in Equation 6.6, where N is the number of respondents. $Vote_{i,k}$ is the self-voted occupancy and AC operation status at hour k, where $Vote_{i,k}$ =1 represents a condition of presence or AC turned on, while in contrast for the value equal to 0.

$$probability(\%)_k = \frac{\sum_{i=1}^{N} Vote_{i,k}}{N} \quad \text{for } Vote_{i,k} = 1 \text{ and } k = 0, 1, 2 \ldots 23 \text{ hour} \qquad (6.6)$$

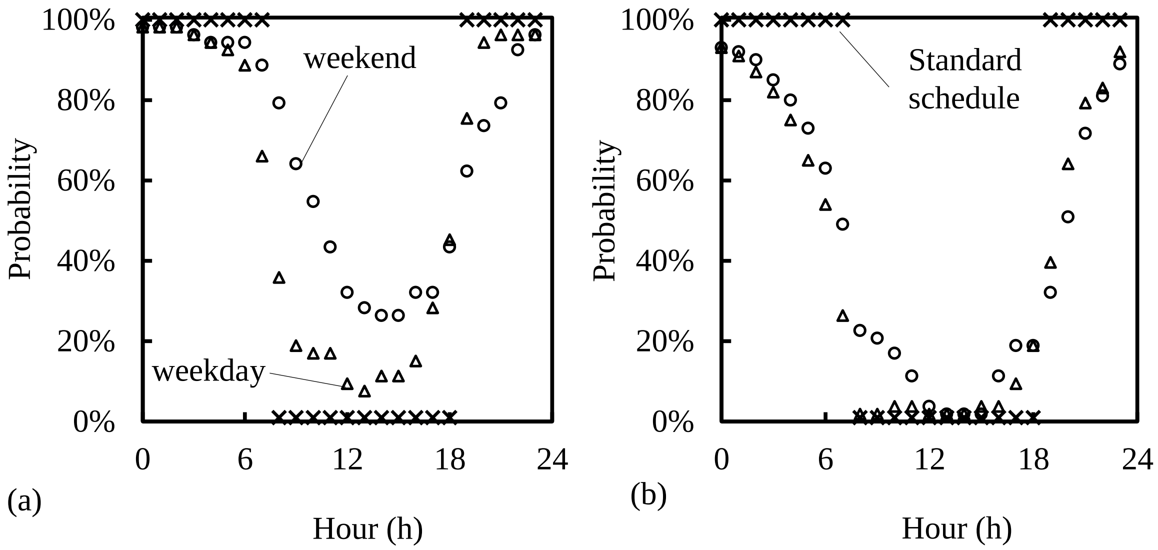


Figure 6.7 Surveyed weekday and weekend schedules for (a) occupancy and (b) air–conditioning operation

Significant different profiles are reported between the occupancy and AC operation schedule, which suggests that an assumption of equivalence among these two schedules may not be truly held in residential cooling energy simulation. Also, the weekday and weekend schedules have to be separately considered regarding to the observed difference.

Besides, the standard occupancy or AC schedule, suggested by Cheung et al. (2005), used in our previous simulations is also plotted as reference. The standard schedule is found different from either the surveyed occupancy or the AC operation pattern. The main reason can be explained by the assumption of discrete hourly profile for the standard reference under all circumstances, whereas the surveyed profiles are continuous with probabilistic durations of staying or leaving home and AC operation hours within a day based on different occupant behaviour. The observed difference can explain the over–prediction of cooling electricity use in Hong Kong public housing sector as compared with government energy statistics in Chapter 4. This is a major phenomenon in all existing energy simulation programs which it is yet to be discussed in performing a more realistic simulation results.

Probabilistic model for occupancy and AC operation schedule in apartments

In responses to the argument established above, a statistical model with probabilistic function is developed to identify the profile variation due to occupant behaviour. Taken an example for AC operation status in apartments, the operation hours of an air–conditioner within a day can be expressed by the time period of non–zero demands $\tau_{i,1}$, $\tau_{i,3}$ (hour) and zero demands $\tau_{i,2}$ (hour) for i = 1, 2 , …, 365 which represents the day of a year as shown in Figure 6.8. The time periods are defined by the air–conditioner start times and end times as summarized in Equation 6.7.

$$AC \quad on \quad \begin{cases} \tau_{i,1} = t_{i,1} - t_{i-1,3} \\ \tau_{i,3} = t_{i,3} - t_{i,2} \end{cases}$$

$$AC \quad off \quad \{\tau_{i,2} = t_{i,2} - t_{i,1} \tag{6.7}$$

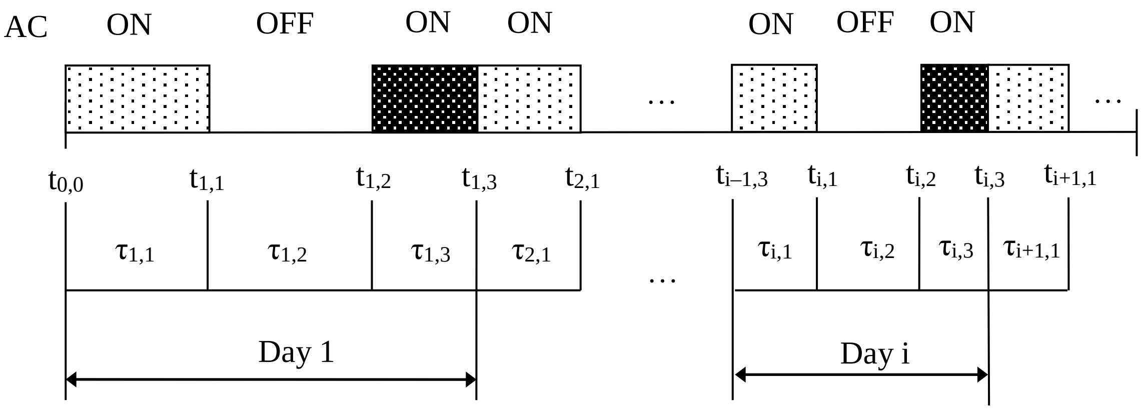


Figure 6.8 Time series of air–conditioning operation profile

Duration of each time period ($\tau_{i,1}$, $\tau_{i,2}$, $\tau_{i,3}$) is collected from the occupants during the interview survey. A normal distribution is assumed for these time periods with corresponding surveyed mean μ_j and standard deviation $S_{d,j}$ for j = 1, 2 or 3 time period. A time frame $x_{i,j}$ (hour) of parameters $\tau_{i,j}$ is randomly selected from the distribution functions $\tilde{\tau}_{i,j}$ at percentile $\vartheta \in [0, 1]$ as expresses in Equation 6.8, where ϑ is a random number taken from a pseudo random number set generated by the prime modulus multiplicative linear congruential generator (Park and Miller 1988).

$$x_{i,j} = \tau_{i,j,\vartheta}; \qquad \int_{-\infty}^{\tau_{i,j,\vartheta}} \tilde{\tau}_{i,j}\, d\tau_{i,j} = \vartheta; \qquad \tau_{i,j} \in \tilde{\tau}_{i,j}(\mu_j, S_{d,j}) \tag{6.8}$$

Since one day is taken to be the primary repeating unit for simulation as shown in Figure 6.8, the integrated time spend in each period (i.e. $\tau_{i,1}$ + $\tau_{i,2}$ + $\tau_{i,3}$) has to be confined exactly to 24 hours. The randomly selected time frames ($x_{i,1}$, $x_{i,2}$, $x_{i,3}$) are modified into a fraction in each period as expresses in Equation 6.9 to satisfy the requirement.

$$\tau_{i,j} = \frac{x_{i,j}}{x_{i,1} + x_{i,2} + x_{i,3}} \times 24 \qquad ; \qquad j = 1,2,3 \tag{6.9}$$

The first day (i = 1) AC on–off schedule is completed by assigning '1' for the period of $\tau_{1,1}$, $\tau_{1,3}$ and '0' for the period of $\tau_{1,2}$. The process is repeated with different random number sets for the next 364 days (i = 2, 3, 4, …, 365), with weekday and weekend consideration, to identify the variation of air–conditioning operation status regarding to occupant's AC usage behaviour.

Figure 6.9(a) & (b) show the simulated weekday and weekend schedules respectively for occupancy and air–conditioning operation in apartments. Insignificant difference is found between the simulated and surveyed patterns (α=0.05, K–S test). Regarding to the six classifications listed in Table 6.4, corresponding AC operation patterns are illustrated in Figure 6.10 using the proposed probabilistic approach. Significant variation is not observed between the predicted and surveyed schedule for all groups (α=0.05, K–S test), except for "< 20000HK$" of income group and "Associate" of education level. The difference may be attributed by larger variation in relatively small sample size.

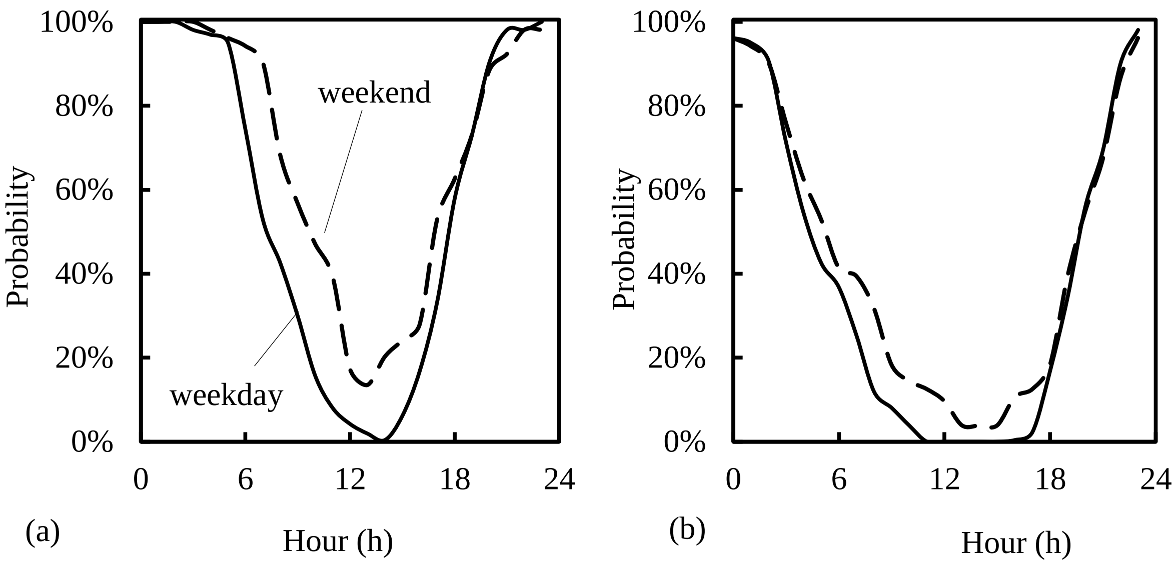


Figure 6.9 Simulated weekday and weekend schedules for (a) occupancy and (b) air–conditioning operation

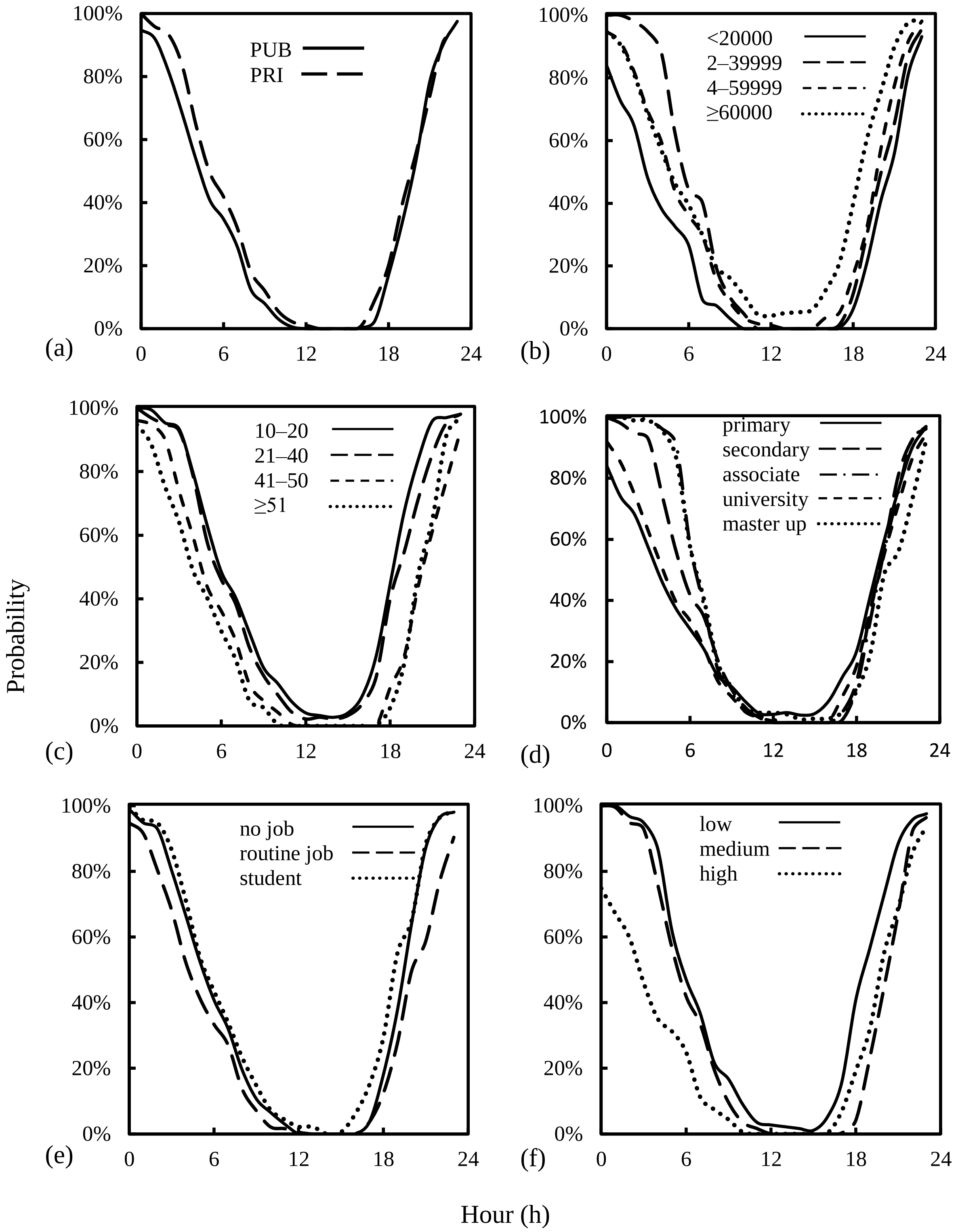


Figure 6.10 Air–conditioning operation schedules for (a) housing types, (b) households income, (c) age groups, (d) education levels, (e) occupations and (f) energy saving awareness

Similar AC usage pattern is reported in Figure 6.10(a) between public and private housings, with slightly lower probability of PUB AC operation at midnight or morning. It suggests that PUB occupants are intended to practice timer in turning off AC at night, but they are having similar AC usage pattern with PRI residents in the evening.

The AC schedule classified by household income is found different among groups. The least income group "< 20000HK$" is found having the lowest AC usage probability, with delay AC operation in the evening and early switch off during midnight. According to the AC energy saving assessment listed in Table 6.2, occupants of lower income group are more likely in practicing AC timer before sleeping and they are more alert to their electricity tariff during summer day. In contrast to high income group "≥ 60000 HK$", occupants are likely to turn on AC immediately once they are back home after work and pay less attention to electricity use in summer.

For personal factor, a lower AC usage probability is observed in older age groups "41–50" and "≥ 51" in Figure 6.10(c). Probably, window opening, clothing adjustment and ventilation by electric fan are of higher priority favour by the elderly, while younger people are satisfied more in an air–conditioned space (Hwang and Chen 2010).

Despite significant variation of AC usage pattern is illustrated in Figure 6.10(d), the trend is not well explained with occupant's education level. Larger variation is observed only in the mid–night (or morning) period with the least AC operation probability of "primary" group, followed by "university", "secondary", "master up" and "associate". Since the sampled primary educated group is mainly elderly or from low income household, less frequent AC usage at mid–night is explained.

Regarding to occupant's job nature in Figure 6.10(e), insignificant AC usage pattern is reported between "no job" and "student" groups, while person with "routine job" are practiced with lower AC operation probability for they have to leave home earlier in the morning and back home late at night.

In Figure 6.10(f), a smaller probability in AC operation is observed for the "high" energy saving group. A similar trend for the "medium" group is found during the evening, while the pattern in morning is the same as compared with "low" saving awareness group. All of the above comparisons are confirmed by K–S test (α=0.05).

6.5 Cooling energy consumption prediction with dynamic AC operation schedule

Accuracy of the hybrid cooling energy prediction model described in Chapter 4 can be enhanced by implementing the probabilistic AC schedule for dynamic AC operation performance. Using the housing characteristics in existing public housing sector as shown in section 4.3.3, Figure 6.11 graphs the distribution of per–apartment cooling energy consumption using the standard and updated public housing AC operation schedule. Remarkable cooling energy saving, from 2319TJ $yr^{-1}$to 1815TJ yr^{-1}, in entire public housing sector is reported if the standard AC operation schedule is updated by the probabilistic PUB AC schedule. The ranges of cooling energy per apartment are between 1.57–6.29GJ yr^{-1} with an average value of 3.24GJ yr^{-1}.

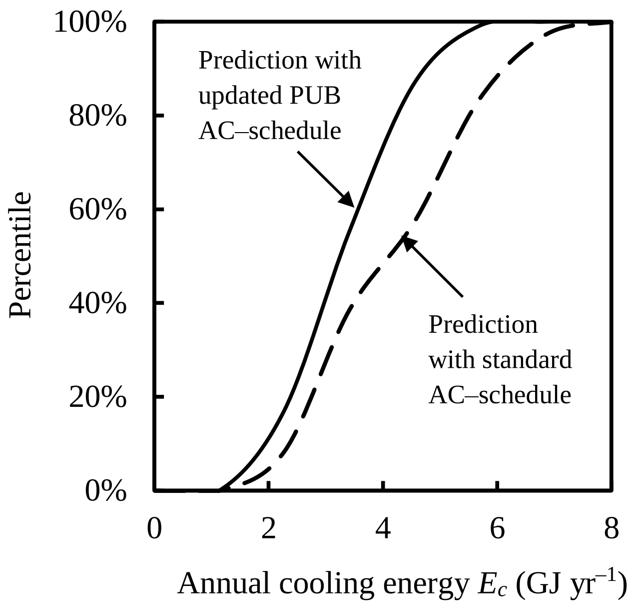


Figure 6.11 Distribution of per–apartment annual cooling energy prediction using standard and dynamic AC–operating schedule

In spite of this huge energy saving potential, the result is not comparable to the government statistics (2052 TJ yr^{-1}) (EMSD 2010). The difference can be attributed to inappropriate temperature set–point used in the simulations (T_a=24^{o}C) as compared with the real households, where a lower temperature set–point is introduced to evaluate a more comparable simulation results. The above simulation is repeated with different T_a lowered to 22^{o}C. Figure 6.12 shows the cooling energy demand in public housing sector with T_a varies from 22^{o}C to 24^{o}C. The resulting cooling energy consumption is matched with government cooling energy statistic (2052TJ yr^{-1}) if T_a is lowered to 23.1^{o}C. This set–point temperature is closed to the value (T_a = 23^{o}C) suggested by Lin and Deng (2004) for Hong Kong residential building and it is within the ranges of 21–23.5^{o}C in another air–conditioned household survey conducted by Lam and Li (2000). Further decreases of T_a to 22^{o}C and 23^{o}C would increase the cooling demand to 2350TJ yr^{-1} and 2078TJ yr^{-1} respectively, which represents a slightly cool region in previous predicted thermal comfort zone for residential building in sub–tropics in section 6.3.

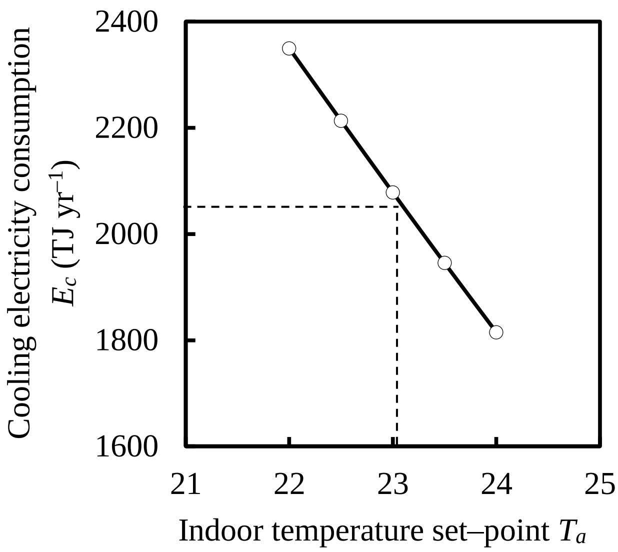


Figure 6.12 Cooling energy prediction with various indoor temperature set–points using the dynamic public housing AC schedule

Figure 6.13 repeats the validation of cooling energy demands in 39 public rental housings in section 4.3.4, with updated probabilistic public housing AC operation schedule and indoor temperature set–point at 23°C. More promising results are reported as compared with Figure 4.8 and it fits well with the cooling energy consumption in surveyed apartments. A few outliers suggested that the hybrid simulation model is underestimating the actual cooling demands. It can be explained by an even lower temperature set–point for air–conditioner in the surveyed apartments, where relatively low T_a at 17.5°C was recorded in some households during measurements.

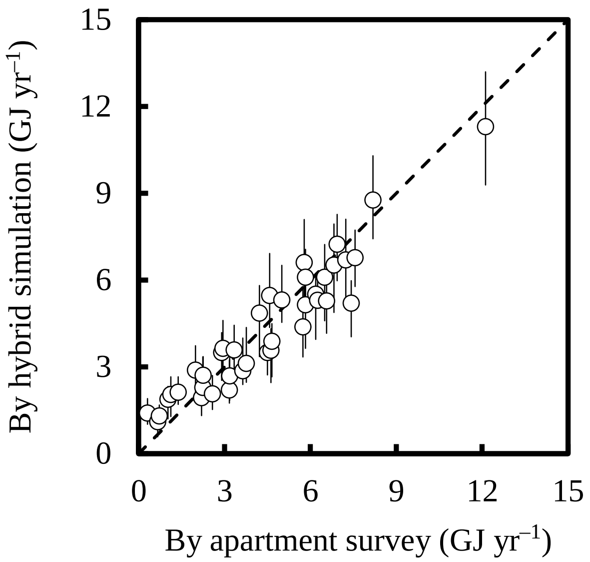


Figure 6.13 Comparison of apartment annual cooling energy consumption E_c (GJ yr^{-1}) between simulation (using dynamic AC–schedule) and apartment survey

6.6 Cooling energy saving strategies with AC operation alternatives

According to the probability to AC schedule for different groups in Figure 6.10, significant energy saving potential is reported at mid–night (or early morning) instead of the evening period. The energy saving measure is recognized by early switch off air–conditioner before sleeping or set timer to stop function during sleeping. According to the interview survey, air conditioners in 40% of the surveyed households were not equipped with timer function. However, 62% of occupants in these households expressed that they would try to set timer at night if their air–conditioners has such function. It suggests that air–conditioner equipped with timer function is one important motivation to reduce cooling energy consumption in apartments.

Assumes the proposed AC operation schedule for public housings do not consist any early switch off strategies. A modified daily AC schedule with cooling hour reduction *h* (hour) by timer is shown in Equation 6.10, where $\tau_{i,1}^*$ and $\tau_{i,2}^*$ represent the updated first (AC = ON) and second (AC = OFF) period as shown in Figure 6.8 while the third period (AC = ON) of $\tau_{i,3}$ remains unchanged.

$$\left.\begin{aligned} \tau_{i,1}^{*} &= \tau_{i,1} - h \\ \tau_{i,2}^{*} &= \tau_{i,2} + h \\ &\tau_{i,3} \end{aligned}\right\} \quad ; \quad h = 1,2,3\,(\text{hour}) \tag{6.10}$$

The assessment aims to test the effectiveness of cooling energy saving potential in the public housing sector with various portions of households utilizing AC timer at mid–night during sleeping for 1, 2 and 3 hour(s) reduction based on their normal AC switch off time. Figure 6.14 presents the cooling energy consumption predictions for the three early AC switch off strategies as described above. Apparently, a greater saving potential is awarded to strategy of shorter AC functioning period (i.e. 3 hours reduction). As demonstrated in the figure, every 20% increases in the number of PUB apartments, respectively using the 1, 2 and 3 hour(s) time reduction strategy, would result in annual cooling energy reduction of 21TJ yr^{-1}, 40TJ yr^{-1} and 58TJ yr^{-1}, where the maximum reduction level reached 1976TJ yr^{-1}, 1880TJ yr^{-1} and 1787TJ yr^{-1} for 100% PUB households practicing corresponding strategy.

Similarly, AC operation schedule for occupant's energy saving awareness level, i.e. Low, Medium and High, is selected as an important energy saving measure in apartments and is brought into simulation of energy sensitivity test in the public housing sector. Figure 6.15 predicts the cooling energy use for public housings with the "Low", "Medium" and "High" energy saving AC operation schedules. It is observed that the annual cooling energy consumption will go up by implementing "Low" saving awareness AC schedule, while a reduction of cooling demand is found by "Medium" and "High" level conscious of saving energy. Every 20% increases the stock of PUB household results in cooling energy variation of –24TJ yr^{-1}, 89TJ yr^{-1} and 144TJ yr^{-1}. Figure 6.15 also exhibits the overall cooling demand changes to 2198TJ yr^{-1}, 1641TJ yr^{-1} and 1370TJ yr^{-1} if the existing AC schedule for public housing is respectively replaced by "Low", "Medium" and "High" energy saving schedule in all PUB apartments.

It is worth noting that the increasing indoor temperature set–point and implementing "High" AC energy saving schedule record significant cooling energy retrench rate (26.7% and 34.1%) among all other proposed strategies in Chapter 5. It suggests that occupant behaviours on air–conditioning usage in residential buildings are dominant to cooling energy demands, where strategies on promotion and education for effective AC usage are indispensably important which shall not be overwhelmed.

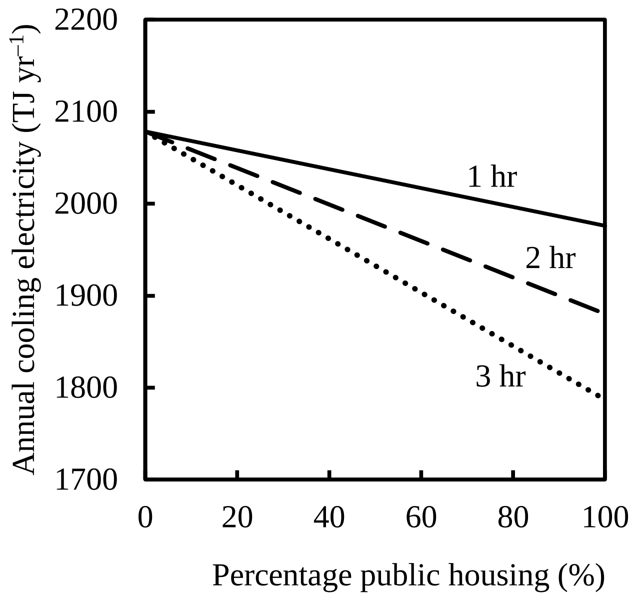


Figure 6.14 Cooling energy prediction in public housing sector for hour reduction AC schedules

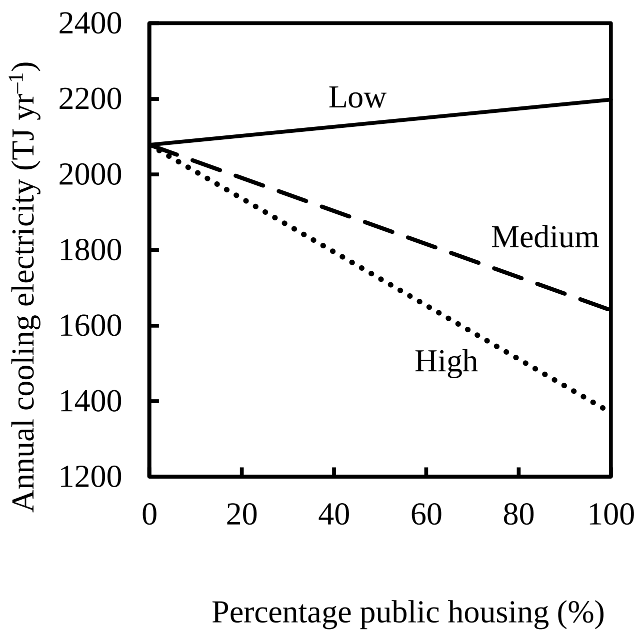


Figure 6.15 Cooling energy prediction in public housing sector for energy saving awareness AC schedules

6.7 Summary

In order to enhance accuracy of the proposed hybrid model, this chapter investigated the cooling energy demands in residential buildings via occupant's thermal comfort needs and their behaviour on air–conditioner operation.

Physical measurements and interview surveys are conducted to evaluate occupant's thermal comfort in residential buildings, where Fanger's PMV model is found slightly over–estimating occupant's actual thermal sensation. Similar neutral operative temperature T_{op} (TSV = 0) of 25.2^{o}C and 25.1^{o}C are, respectively, reported in PUB and PRI housings. Besides, residential thermal comfort zones, plotted with T_a against R_h, are proposed using the surveyed mean thermal environment parameters. The 'Neutral' thermal comfort zone is observed with boundary of T_a between 24–26^{o}C at mean R_h of 76%. An extensive survey is also conducted to understand the occupancy and AC operation schedule from occupants via six socio–economic groups. The results suggest that resident's occupancy and AC operation pattern are distained with each other, while thermal energy simulation using the discrete standard schedule might not be able to reflect the actual cooling demands in apartments.

The annual cooling energy consumption in public housing sector is predicted by increasing the hourly T_o of 0.5^{o}C and 1^{o}C at various T_a between 22–28^{o}C. The result is found sensitive to outdoor temperature change (up to 37.9% increment of T_o raised by 1^{o}C). Besides, about 7% reduction in total cooling energy use is recorded for each 0.5^{o}C increment of T_a.

A probabilistic approach, using the means and standard deviations of surveyed AC operation time periods, is proposed to model the actual AC functioning schedule in each classified occupant's group. Less probable AC usage hour is observed for the lower income group. Besides, older people "Age ≥ 51" is less favour in operating AC as compared with younger people "Age ≤ 40". Occupants who have "routine job" are practiced with lower AC operation probability as compared with the "no job" and "student" groups. Furthermore, shorter AC usage hours are observed for "high" energy saving group.

Remarkable annual cooling energy reduction is presented by implementing the updated dynamic AC operation schedule in public housing sector. The corresponding indoor temperature set–point is adjusted from 24°C to 23°C in simulation to match comparable cooling energy consumption with government statistics (2078TJ yr^{-1}). Besides, two application examples for cooling energy reduction strategy are preformed including (i) reduce AC operation hour(s) by setting timer at night and (ii) enhance occupant's AC energy saving awareness. Significant cooling energy saving potential is determined for reducing AC operation by 3 hours (1787TJ yr^{-1}) and practicing the 'high' energy saving AC schedule (1370TJ yr^{-1}) in public housing sector.

The findings in this chapter examine the availability of out sources data to enhance energy forecast performance of the hybrid cooling energy prediction model. The simulation input can be justified via prior understanding of occupant's thermal comfort needs and the AC operation patterns regarding to more promising cooling energy prediction. It would be useful for policymakers in promoting energy efficient AC usage and for individual user practicing AC energy conservation at home.

Chapter 7

Application of hybrid cooling energy simulation tool

7.1 Introduction

In view of existing available tools for cooling energy simulation in buildings, apart from the sophisticated modelling procedures such as construction drawing, parameters input, debugging of compatibility and time required for large scale simulation, the interpretation of simulation results posed a barrier of understanding to the public for establishing cooling energy saving care in their own apartments.

This Chapter 7 discusses the feasibility and flexibility by using the proposed hybrid simulation tool in cooling energy prediction for both multi–zones and individual zone basis. Taking an example of new town housing development plan in year 2021, the cooling energy saving potentials with respect to alternatives of materials use, building constructions and occupant behaviours consideration are determined. Besides, the per–area cooling energy consumption for public housing sector during summer period (May to October) is benchmarked via a 5–star–rating system to identify the level of incentive on electricity tariff for individual household. In addition, a sub–program is developed for public use to estimate the monthly energy charge and to provide recommendation on energy saving strategies in their own apartments by simple building characteristics and electricity consumption inputs.

Table 7.1 Cooling energy predictions for extra public housings in year 2021

Cases	Conditions	Annual Cooling Energy *Ec* (TJ yr^{-1})
Base case	➢ 600000 occupants ➢ T_a = 23ºC; T_o as per 1989 weather data ➢ U_{wl} =2.2–2.9 W $K^{-1}m^{-2}$ (heavy concrete) ➢ U_{wd} =5.6–6.9 W $K^{-1}m^{-2}$; S_c = 0.9–0.97 (clear glazing) ➢ Window sizes as listed in Table 1 ➢ Flat sizes same as 'the existing case' in Chapter 4 (Total area = 7379745m^2) ➢ Using existing public housing AC operation schedule	1044
	Materials	
External wall and window materials alternatives	(a) U_{wl} = 0.7–1.5 W $K^{-1}m^{-2}$ (light–weight concrete)	984 (–5.7%)
	(b) U_{wd} = 4.2–5.7 W $K^{-1}m^{-2}$, S_c = 0.53–0.8 (tinted glazing)	981 (–6.0%)
	(c) Both of the above	910 (–12.8%)
	Constructions	
Window area and vertical shading angle reductions	(a) 10% window reduction	1030 (–1.3%)
	(b) 20% window reduction	1017 (–2.6%)
	(c) σ_v of 68.5º (i.e. 0.75m overhang extension)	1031 (–1.2%)
	(d) σ_v of 62.2º (i.e. 1m overhang extension)	1021 (–2.2%)
	(e) 20% window reduction + σ_v of 57.0º (1m extension)	988 (–5.4%)
Flat sizes variations	(a) All small flats (< 30m^2) (9045045m^2)	1330 (27.4%)
	(b) All medium flats (30m^2–50m^2) (6955829m^2)	953 (–8.7%)
	(c) All large flats (>50m^2) (5785459m^2)	909 (–12.9%)
	Occupant behaviours	
Outdoor and indoor temperature variations	(a) T_a = 22ºC; T_o increased by 1ºC	1263 (20.1%)
	(b) T_a = 24ºC; T_o unchanged	806 (–22.8%)
	(c) T_a = 24ºC; T_o increased by 1ºC	997 (–4.5%)
	(d) T_a = 26ºC; T_o unchanged	591 (–43.4%)
	(e) T_a = 26ºC; T_o increased by 1ºC	765 (–26.7%)
Cooling energy saving awareness	(a) Low energy saving AC schedule	1104 (5.8%)
	(b) Medium energy saving AC schedule	825 (–21.0%)
	(c) High energy saving AC schedule	697 (–33.1%)
Hour(s) reduction with AC timer	(a) 1 hour reduction	992 (–4.9%)
	(b) 2 hours reduction	944 (–9.5%)
	(c) 3 hours reduction	932 (–10.7%)

7.2 Cooling energy outlook for new town public housing plans

Predicted by the statistics of planning department, a population of ~600000 residents will be increased by year 2021 (HKPP 2012). If these surplus populations are all accommodated by public housings in new town, strategies on cooling energy reduction in newly constructed public residential buildings can be a prime issue for discussion. Table 7.1 summaries the annual cooling energy use for those extra public housings with a base case prediction and the potential energy reduction by saving strategies on building materials, construction and occupant behaviours concerns as described in Chapters 5 and 6. The base case is referenced by existing public housing characteristics and occupant AC usage behaviour with annual cooling demand of 1044TJ yr^{-1}.

By replacing the external wall with light–weight concrete and the window with tinted glazing, corresponding cooling saving potential is –5.7% and –6.0%, while an integration of both practices further lower the cooling energy demand to 910TJ yr^{-1} (–12.8%). The building construction strategy with 20% window area reduction and vertical shading angle of 57.0^{o} can lower the cooling energy consumption to 988TJ yr^{-1} (–5.4%), while rearrangement of flat size dominates by medium and large flats respectively decreases the total load to 953TJ yr^{-1} (–8.7%) and 909TJ yr^{-1} (–12.9%).

Increasing outdoor temperature by 1^{o}C significantly raises the cooling energy consumption by 20.1%. Occupants are suggested to adjust the indoor temperature set–point T_a at 24^{o}C to compensate the excessive cooling load (997TJ yr^{-1}), where further increasing T_a to 26^{o}C records a remarkable saving potential of 279TJ yr^{-1} (–26.7%). Besides, huge cooling energy saving is reported by encouraging occupants to practice the medium (825TJ yr^{-1}) or even high (697TJ yr^{-1}) cooling energy saving AC schedules. Also the promotion of energy saving strategy with early switch off AC by 1, 2 and 3 hour(s) respectively determines an annual cooling energy use of 992TJ yr^{-1} (–4.9%), 944TJ yr^{-1} (–9.5%) and 932TJ yr^{-1} (–10.7%).

The summary of different energy saving alternatives suggested that occupants' behaviour on indoor temperature set–point and air–conditioner operation habit are of exclusively important impact, as compared with building material and construction alternatives, to the total cooling energy use in residential sector. The government and the power supply company are advised to focus on residential cooling energy reduction by introducing more energy saving rebate programs.

7.3 Incentive to encourage cooling energy saving in summer period

It has been mentioned that incentive to encourage residents saving energy from air–conditioning usage is an effective strategy to reduce total residential cooling energy consumption. Taken an example of China Light and Power (CLP), one of the two power supply companies in Hong Kong, Table 7.2 shows the current electricity tariff for energy charge and energy saving rebate in residential sector (CLP 2015). The tariff is based on bimonthly meter–readings where higher consumption usage households will be charged at higher rates. The energy saving rebate is only applicable to a bill with total bimonthly consumption of 400 units or less. Besides, a minimum charge of HK$36 is required for each bill.

Table 7.2 Existing (CLP) and newly proposed electricity tariff and rebate scheme

Electricity Charge (existing)		Energy Saving Rebate (existing)	
Bimonthly consumption per apartment	Rate (Cents / Unit)	Consumption ranges	Incentive descriptions
Each of the first 400 units	80.5	1–200 units	17.2 cents per unit on total consumption
Each of the next 600 units	93.9	201–300 units	16.2 cents per unit on total consumption
Each of the next 800 units	109.7	301–400 units	15.2 cents per unit on total consumption
Each of the next 800 units	140.5	> 400 units	No incentive
Each of the next 800 units	163.4		
Each of the next 800 units	173.8		
Each unit over 4200	175.0		
Electricity Charge (newly proposed)		**Energy Saving Rebate (newly proposed)**	
Monthly consumption per apartment	Rate (Cents / Unit)	Star–rating	Incentive descriptions
Each of the first 200 units	80.5	★★★★★	20 cents per unit on total consumption
Each of the next 300 units	93.9	★★★★	10 cents per unit on total consumption
Each of the next 400 units	109.7	★★★	5 cents per unit on total consumption
Each of the next 400 units	140.5	★★	Exclude minimum charge per bill (HK$ 18)
Each of the next 400 units	163.4	★	No incentive
Each of the next 400 units	173.8		
Each unit over 2100	175.0		

Note: 1 Unit = 1 kWh

It is understood that higher energy consumed households should bare higher rate of electricity charge, however, the existing household base energy saving rebate is not fair to larger apartments especially for AC use in the summer months. Obviously, incentive to reduce energy use in summer period is not being considered. Besides, the energy charge for bimonthly consumption taken between June–July or July–August might be charged differently if the total consumption exceeded one limit and charged in higher rate in the other level. Current energy saving rebate scheme is insufficiently encouraging for energy reduction especially in the summer periods.

Benchmarking with cooling energy index

Regarding to the limitation of existing energy saving rebate method, a new scheme is suggested to modify the existing one with cooling energy saving consideration. A 'Cooling energy index λ' determines from the monthly cooling energy consumption against the apartment floor area is proposed. This index value can provide an indication of level of energy saving rebate according to the monthly cooling electricity use in apartments.

The proposed scheme is adjusted in monthly, instead of bi–monthly, consumption. Also, the energy consumption is normalized by apartment floor area (m^2) to balance a fair rate between large and small flat size. Although the occupant load is found significantly correlated with electricity use in apartment as shown in Chapter 3, it is hard to identify the actual value among households. The same problem is not happened for apartment floor area, since it is standardized for public rental housings and can be easily confirmed by the Housing Authority.

A cooling energy index λ_m (kWh m^{-2}) in Equation 7.1, determined from the monthly cooling energy consumption $E_{c,m}$ for m = May to October and apartment floor area A_{fl}, is proposed as the benchmarking parameters. Higher value of λ indicates more cooling demands in corresponding apartment.

$$\lambda_m = \frac{E_{c,m}}{A_{fl}} \tag{7.1}$$

Taking $\lambda_{m,j}$ as a representative value of cooling energy demands for an apartment j from all public rental housing samples, and $\tilde{\lambda}_m$ as the distribution of monthly cooling energy consumption for all public housings with estimators of mean $\mu_{\lambda,m}$ and standard deviation $S_{d,\lambda,m}$ of the index, the cooling energy benchmark $B_{m,i}$ for *i*–th apartment is expressed in Equation 7.2. An apartment with $B_{m,i} \leq 1\%$ indicates the least cooling energy consumption, while $B_{m,i} = 100\%$ represents the highest cooling demands.

$$B_{m,i} = \int_{-\infty}^{\lambda_{m,i}} \tilde{\lambda}_m d\lambda_m \quad ; \quad \tilde{\lambda}_m \sim \tilde{\lambda}_m\left(\mu_{\lambda_m}, S_{d,\lambda_m}\right) \tag{7.2}$$

5–star cooling energy benchmarking system for Hong Kong public housings sector

A 5–star–rating cooling energy consumption benchmarking system is suggested in this chapter. This star–rating system is simple and easily recognized for layman usage. Following the assessment criteria of continuous benchmarking parameter by Blume (1998), the top 10% samples of cooling energy consumption benchmarking value ($B_{m,i} \geq 0.9$) is awarded with 1 star in the system, the next 22.5% ($0.675 \leq B_{m,i} < 0.9$) with 2 stars, the next 35% ($0.325 \leq B_{m,i} < 0.675$) with 3 stars, the next 22.5% ($0.1 \leq B_{m,i} < 0.325$) with 4 stars and the remaining bottom 10% ($B_{m,i} < 0.1$) with 5 stars.

Using the hybrid cooling energy simulation model and the database of base case cooling energy consumption in the public housing sector, i.e. estimators of monthly mean $\mu_{\lambda,m}$ and standard deviation $S_{d,\lambda,m}$ of the index, described in Chapter 4, Figure 7.1 graphs the cumulative percentile of cooling energy index $\tilde{\lambda}_m$ (kWh m^{-2}) for all public housing samples from May to October. The corresponding benchmark values $B_{m,i}$ using the 5–star–rating system are summarized in Table 7.3. It is reported that the ranges (μ_λ, $S_{d,\lambda}$) of cooling energy index for λ_{may}, λ_{jun}, λ_{jul}, λ_{aug}, λ_{sep} and λ_{oct}, are 0.43–3.14 (1.86, 0.30), 1.78–7.28 (4.68, 0.61), 2.42–10.71 (6.79, 0.92), 2.63–10.66 (6.86, 0.89), 2.93–7.44 (5.31, 0.50) and 1.27–3.79 (2.60, 0.28), and the limit of benchmark values between star–rating are (1.48, 1.72, 2.00 and 2.25), (3.90, 4.40, 4.95 and 5.46), (5.72, 6.46, 7.21 and 7.97), (5.72, 6.46, 7.27 and 8.01), (4.66, 5.08, 5.53 and 5.95) and (2.24, 2.47, 2.73 and 2.96) respectively.

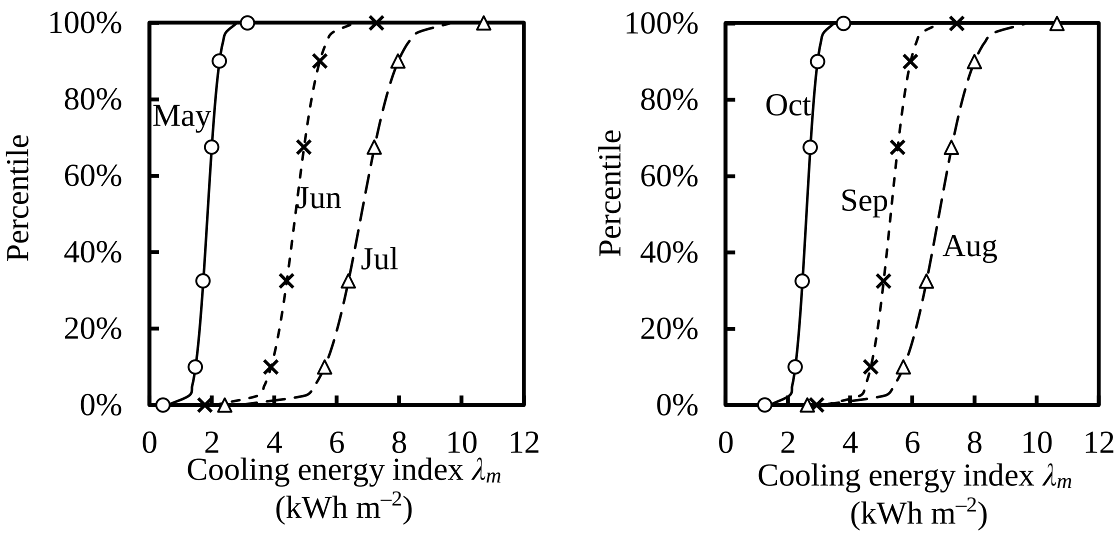


Figure 7.1 Distribution of per–area cooling energy consumption for all public housing samples from May to October

Table 7.3 Benchmarks with star–ratings of cooling energy index λ_m in each month for all public housing samples

Star–rating	Benchmarking value	May	Jun	Jul	Aug	Sep	Oct
★★★★★	$B_{m,i} < 0.1$	$\lambda_{may} \le 1.48$	$\lambda_{jun} \le 3.90$	$\lambda_{jul} \le 5.61$	$\lambda_{aug} \le 5.72$	$\lambda_{sep} \le 4.66$	$\lambda_{oct} \le 2.24$
★★★★	$0.1 \le B_{m,i} < 0.325$	≤ 1.72	≤ 4.40	≤ 6.37	≤ 6.46	≤ 5.08	≤ 2.47
★★★	$0.325 \le B_{m,i} < 0.675$	≤ 2.00	≤ 4.95	≤ 7.21	≤ 7.27	≤ 5.53	≤ 2.73
★★	$0.675 \le B_{m,i} < 0.9$	≤ 2.25	≤ 5.46	≤ 7.97	≤ 8.01	≤ 5.95	≤ 2.96
★	$B_{m,i} \ge 0.9$	> 2.25	> 5.46	> 7.97	> 8.01	> 5.95	> 2.96

Description of new energy charge system with cooling energy reduction incentives

A new electricity charge and corresponding rebate scheme is proposed to enhance cooling energy saving incentive in summer months as shown in Table 7.2. The new electricity tariff is changed from bimonthly to monthly meter–readings, thus the total monthly consumption limit in each level is halved from original value, i.e. the fist level would be replaced by 'Each of the first 200 units' and the next level would be 'Each of the next 300 units', while the energy charging rate in each level remains unchanged.

The cooling energy index λ_m in each month, determines via Equation 7.1, is compared with the benchmark values in Table 7.3 to match the level of star–rating. The awarded star–rating corresponds to the incentive for cooling energy saving rebate listed in Table 7.2. The level of incentive is determined as: 1 star for no incentive, 2 stars for excluding the minimum charge per bill which is HK$18, 3 stars for 5 cents rebate per energy unit (i.e. 1 kWh) on total demands, 4 stars for 10 cents per unit on total demands and 5 stars for 20 cents per unit on total demands. The cooling electricity use for each month $E_{c,m}$ is predicted in Equation 7.3, which is the difference between the total electricity use on that month E_m and the average electricity use from November to April $E_{N\text{–}A\_ave}$ as listed on the most updated apartment electricity bill. It is assumed that electricity use for space heating is negligible in all public rental apartments because of the mild climate temperature in Hong Kong (HKO 2014).

$$E_{c,m} = E_m - E_{N-A\_ave} \quad ; \quad \begin{cases} m = May \quad to \quad Oct \\ E_{N-A\_ave} = \dfrac{\sum_{m=Nov}^{Apr} E_m}{6} \end{cases} \tag{7.3}$$

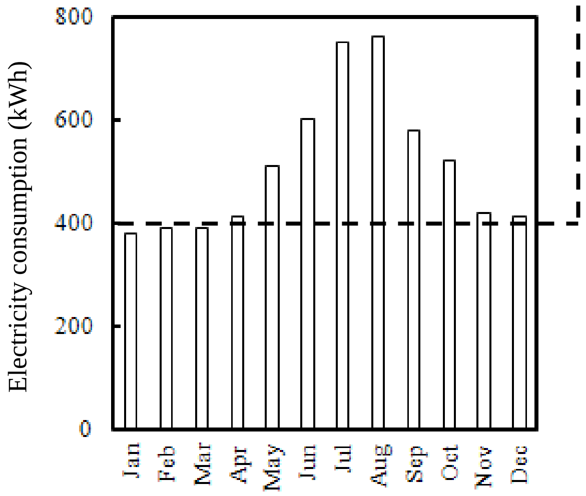
Application example for the proposed energy saving rebate scheme

To demonstrate the application of the cooling energy consumption benchmarks system, a case study household with floor area of 39.3m^2 and monthly electricity usage profile (kWh) from January to December of [380, 390, 390, 410, 510, 600, **750, 760,** 580, 520, 420, 410] is adopted for calculation. From the electricity profile, the average electricity use from November to April is found to be 400 kWh per month. Taken the electricity demand of July and August as base scenario, the corresponding cooling energy demands (kWh), cooling energy index λ (kWh m^{-2}), star–rating, original charge by CLP method (HK$), adjusted charge by new energy saving rebate scheme (HK$) and the charge difference (HK$) are summarized in Table 7.4. A flow diagram of detailed calculations, taken an example of Test 2, is illustrated in Figure 7.2.

Table 7.4 Comparison of electricity charge by CLP and proposed new methods

Cases	Month	Electricity consumption (kWh)	Cooling energy demand (kWh)	Cooling energy index, λ (kWh m^{-2})	Star–rating	Original charge (HK$)	Proposed charge (HK$)	Charge difference (HK$)
Base	Jul	750	350	8.91	★	1481	735	0
	Aug	760	360	9.16	★		746	
Test 1	Jul	700	300	7.63	★★	1360	662	36
	Aug	700	300	7.63	★★		662	
Test 2	Jul	650	250	6.36	★★★★	1272	542	135
	Aug	670	270	6.87	★★★		596	
Test 3	Jul	600	200	5.09	★★★★★	1163	432	280
	Aug	620	220	5.60	★★★★★		450	

Household floor area = **39.3**m^2



Step 1:
Calculates average electricity consumption by Eq. 7.3, from November to April
= **400** kWh per month

Step 2:
Cooling electricity demands in Test 2
Jul : 650 – 400 = **250**kWh
Aug : 670 – 400 = **270**kWh

Step 3:
Calculates cooling energy index by Eq. 7.1
Jul : 250 / 39.3 = **6.36**kWh m^{-2}
Aug : 270 / 39.3 = **6.87**kWh m^{-2}

Step 4:
Check benchmarking value in Table 7.3 for star–rating
Jul : ★★★★
Aug : ★★★

Step 5:
Check incentives from the newly proposed energy saving rebate scheme in Table 7.2
Jul : 10 cents per unit rebate
Aug : 5 cents per unit rebate

Step 6:
Calculates electricity charge corresponding to the awarded incentives

Jul :
Original electricity charge
200×0.805 + 300×0.939 + 150×1.097 + 18 (min. charge)
= 625.2 HK$

With 10 cents per unit rebate
200×0.705 + 300×0.839 + 150×0.997 (no min. charge)
= **542.2** HK$

Aug:
Original electricity charge
200×0.805 + 300×0.939 + 170×1.097 + 18 (min. charge)
= 647.2 HK$

With 5 cents per unit rebate
200×0.755 + 300×0.889 + 170×1.047 (no min. charge)
= **595.7** HK$

Figure 7.2 Application procedures for proposed energy saving rebate scheme

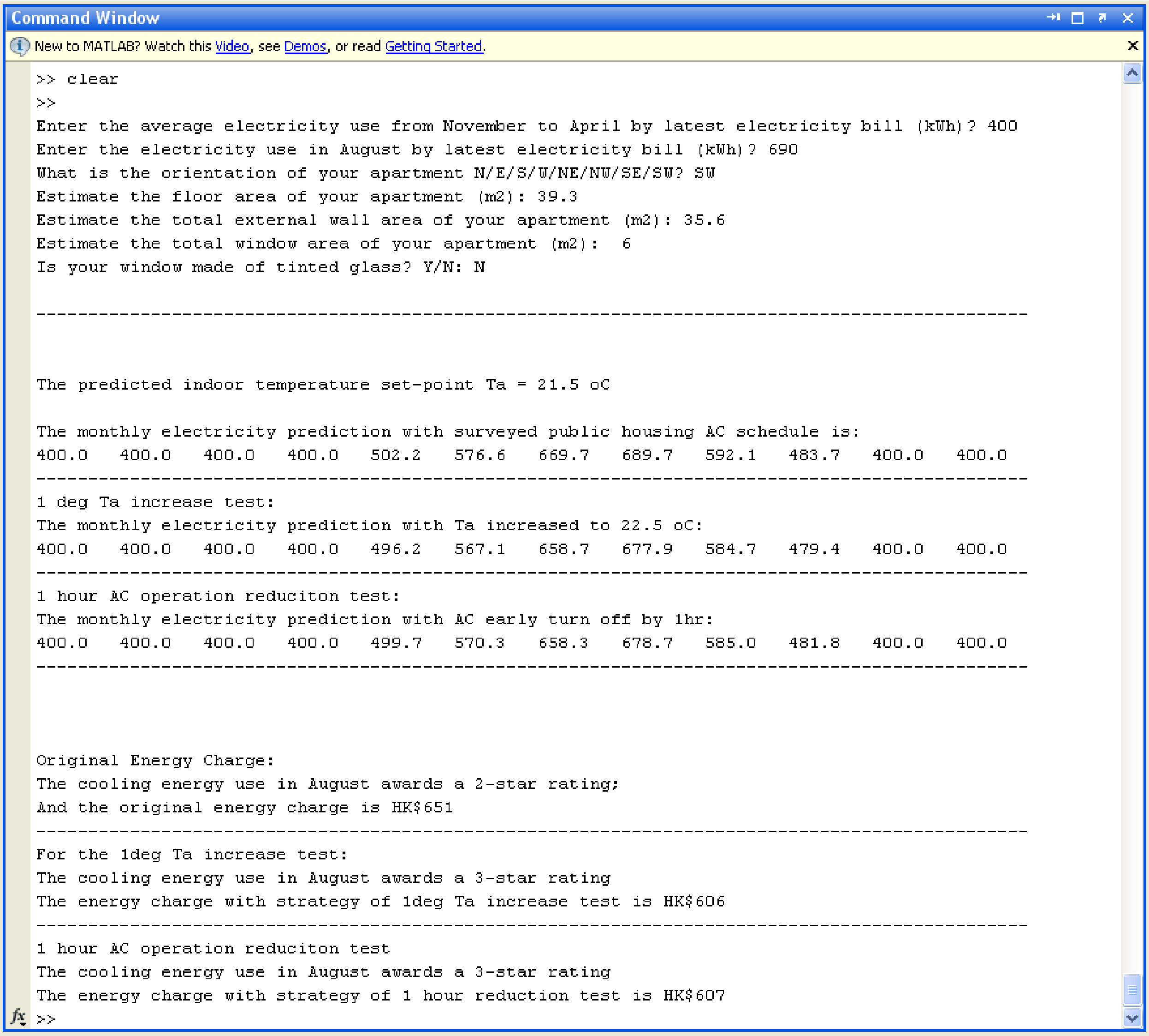
In Table 7.4, only 1 star is awarded to the base scenario for both July and August cooling energy use, i.e. no incentive is given to the household, therefore no charge difference is reported between the two energy charging schemes. For Test 1, the electricity consumptions for July and August are both reduced to 700kWh, where 2 stars are marked for each month. In this case, energy charge is excluded from the bill minimum charge per month (HK$18.0). The total energy charge in two months is estimated as HK$1324, with HK$36 incentives as compared with the original energy charge. The cooling energy use in July/August is further reduced to 650/670kWh and 600/620kWh in Test 2 and Test 3. The energy charge in Test 2 reserved a total of HK$135 as compared with original fee, where bill in July earns an incentives of '10 cents per unit rebate on total demands' with 4 stars rating, while 3 stars are rated in August with incentive of '5 cents rebate per unit on total demands'. Detailed calculation procedures can be followed by Figure 7.2. An energy saving rebate of '20 cents per unit on total demands' is given in Test 3 with 5 stars rating in both July and August and a maximum charge difference of HK$280 is recorded.

An average cooling energy reduction of 145kWh in each month can only reserve HK$318 (21.4% of the primary fee) by using the original charging scheme, while applying the proposed charging scheme almost doubles the money saving to HK$599 (40.4% of primary fee). Cooling energy use has been proven to be occupant behavioural dependent in Chapter 6, where greater incentives are definitely more encouraging for cooling energy reduction in apartments. The example in this section demonstrates the macroscopic application of the hybrid cooling energy simulation model established in this study.

7.4 Energy charge prediction tool for public housing residents

Energy simulations are often connected with government strategies and policies for environmental protection, which seems too far from layman use and consideration. What the public really do care is the balance between level of comfort and the charge for the upcoming electricity bill in their own apartments. A cooling energy simulation tool, written in Matlab with user–friendly interface, is therefore developed in this section to assist the public in understanding their cooling energy usage status. Improvement on electricity savings can be visualized via the recommendation of cooling energy reduction strategies. Besides, the energy charges for current and improved cooling energy usage are displayed and benchmarked with star–rating in accordance to the energy saving rebate scheme suggested in previous section.

Figure 7.3 illustrates the prototype of the energy charge prediction tool for public housing residents. The program is divided into 3 parts: Part 1 aims to collect information of apartment characteristics and electricity use; the monthly electricity profiles for current and improved energy usage are presented in Part 2; while Part 3 determines the energy charge in corresponding cooling energy usage status and suggests star–rating for the cooling energy demands in August with respect to the proposed energy benchmark system.



```
Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.
>> clear
>>
Enter the average electricity use from November to April by latest electricity bill (kWh)? 400
Enter the electricity use in August by latest electricity bill (kWh)? 690
What is the orientation of your apartment N/E/S/W/NE/NW/SE/SW? SW
Estimate the floor area of your apartment (m2): 39.3
Estimate the total external wall area of your apartment (m2): 35.6
Estimate the total window area of your apartment (m2):  6
Is your window made of tinted glass? Y/N: N

-----------------------------------------------------------------------------------------------



The predicted indoor temperature set-point Ta = 21.5 oC

The monthly electricity prediction with surveyed public housing AC schedule is:
400.0    400.0    400.0    400.0    502.2    576.6    669.7    689.7    592.1    483.7    400.0    400.0
-----------------------------------------------------------------------------------------------
1 deg Ta increase test:
The monthly electricity prediction with Ta increased to 22.5 oC:
400.0    400.0    400.0    400.0    496.2    567.1    658.7    677.9    584.7    479.4    400.0    400.0
-----------------------------------------------------------------------------------------------
1 hour AC operation reduciton test:
The monthly electricity prediction with AC early turn off by 1hr:
400.0    400.0    400.0    400.0    499.7    570.3    658.3    678.7    585.0    481.8    400.0    400.0
-----------------------------------------------------------------------------------------------




Original Energy Charge:
The cooling energy use in August awards a 2-star rating;
And the original energy charge is HK$651
-----------------------------------------------------------------------------------------------
For the 1deg Ta increase test:
The cooling energy use in August awards a 3-star rating
The energy charge with strategy of 1deg Ta increase test is HK$606
-----------------------------------------------------------------------------------------------
1 hour AC operation reduciton test
The cooling energy use in August awards a 3-star rating
The energy charge with strategy of 1 hour reduction test is HK$607
>>
```

Figure 7.3 Interface of the layman usage energy charge prediction tool

Part 1: Data collection

The electricity data required for energy benchmark and the housing characteristics necessary for cooling energy prediction are collected in this part. According to Equation 7.3, the average electricity use from November to April and one of the tested months in summer, taking August in this case, are required to estimate the cooling energy index for benchmark evaluation. Since August is usually the hottest month within a year in Hong Kong, it is being selected as the test month with 690kWh of electricity demand, while the average demand from November to April is assumed as 400kWh in this case study.

Regarding to the input parameters listed in Chapter 4, the housing characteristics including the apartment orientation, floor area A_{fl} (m^2), total external wall area A_e (m^2), window area A_{wd} (m^2), glazing U–value U_{wd} (W $K^{-1}m^{-2}$), shading coefficient S_c, external wall U–value U_{wl} (W $K^{-1}m^{-2}$) and vertical shadow angle σ_v are necessary in the hybrid EP–ANN simulation model to determine the cooling energy consumption in apartment. Since some of these parameters are not familiar to public understanding, only the first four data are required from the respondents, and the values are take as orientation facing South–west, A_{fl}=39.3m^2, A_e=35.6m^2 and A_{wd}=6m^2 in this example. The glazing materials are expressed in terms of tinted glass (U_{wd}=5W $K^{-1}m^{-2}$, S_c = 0.67) or clear glass (U_{wd}=6.3W $K^{-1}m^{-2}$, S_c = 0.94) choices with mean value of U_{wd} and S_c taken in Table 5.1. The external wall materials and vertical shadow angle are assumed to be 2.6W $K^{-1}m^{-2}$ and 75.3^o respectively, prior to the common practice for existing public housings design (Lam 2000, Cheung et al. 2005). It is noted that the indoor temperature T_a is excluded from the scope of data collection, which will be evaluated in the next section.

Part 2: Prediction of electricity profiles

Since occupants seldom recognized the indoor temperature set–point T_a in the apartments, this tool can automatically estimate T_a based on the parameters input in Part 1. An array of T_a ranges from 10^{o}C to 35^{o}C with 0.5^{o}C step difference is pre–set at the indoor temperature input. Using this T_a array and the housing characteristics recorded in Part 1, series of monthly cooling energy profiles with different temperature set–points are evaluated by the hybrid simulation model using the public housing air–conditioning operation schedule expressed in Chapter 6. Meanwhile, based on Equation 7.3, the cooling electricity demand in August $E_{c,Aug}$ is found to be 290kWh, which is the difference between electricity use in August and the average electricity demand from November to April. The optimal indoor temperature and electricity profile for the sampled household are thus determined by the least difference compared between $E_{c,Aug}$ and the August prediction among the series of cooling energy profiles. With current input values in Part 1, the corresponding T_a is determined to be 21.5^{o}C with cooling electricity demand of 289.7kWh and total electricity demand of 689.7kWh in August as shown in Figure 7.3. Besides, the program is designed to terminate itself if the predicted indoor temperature is exceeding the pre–set temperature range [10^{o}C, 35^{o}C].

Figure 7.4 demonstrates the situation for a predicted too hot temperature set–point, T_a >35^{o}C, with electricity consumption input in August of 450kWh. This energy input might be reliable for energy saving household who seldom operate their air–conditioners in summer period, but the pre–determined PUB AC operation schedule does not matched with such usage pattern and the program is terminated to exclude any misleading predictions. Similarly, Figure 7.5 presents the condition for a predicted too cold temperature set–point,

T_a < 10°C, with electricity demand in August increases to 1200kWh. Such huge monthly cooling demand, i.e. 800kWh, in a single apartment is too rarely happened and it can be attributed by mistake inputs or too long AC operation hours. A warning box is displayed to announce the unmatched AC schedule with the tested household and stops the simulation process.

Apart from the prediction of original electricity profile, Part 2 in Figure 7.3 also summarizes the profiles with cooling energy reduction strategies of increasing existing T_a by 1°C and decreasing AC operation by 1 hour using the implication in Section 6.6. It is reported in the case study that the electricity consumption in August reduces to 677.9kWh and 678.7kWh, respectively by increasing T_a to 22.5°C and early turn off AC by 1 hour.

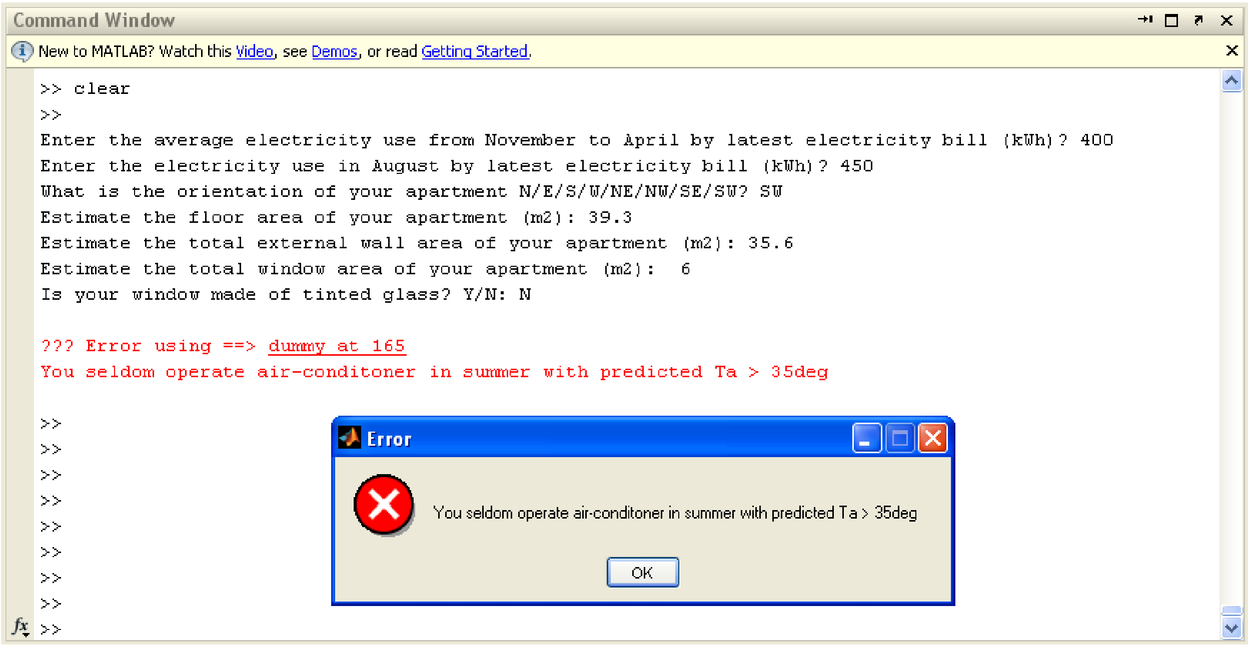


Figure 7.4 Warning interface for a predicted too hot indoor temperature set–point

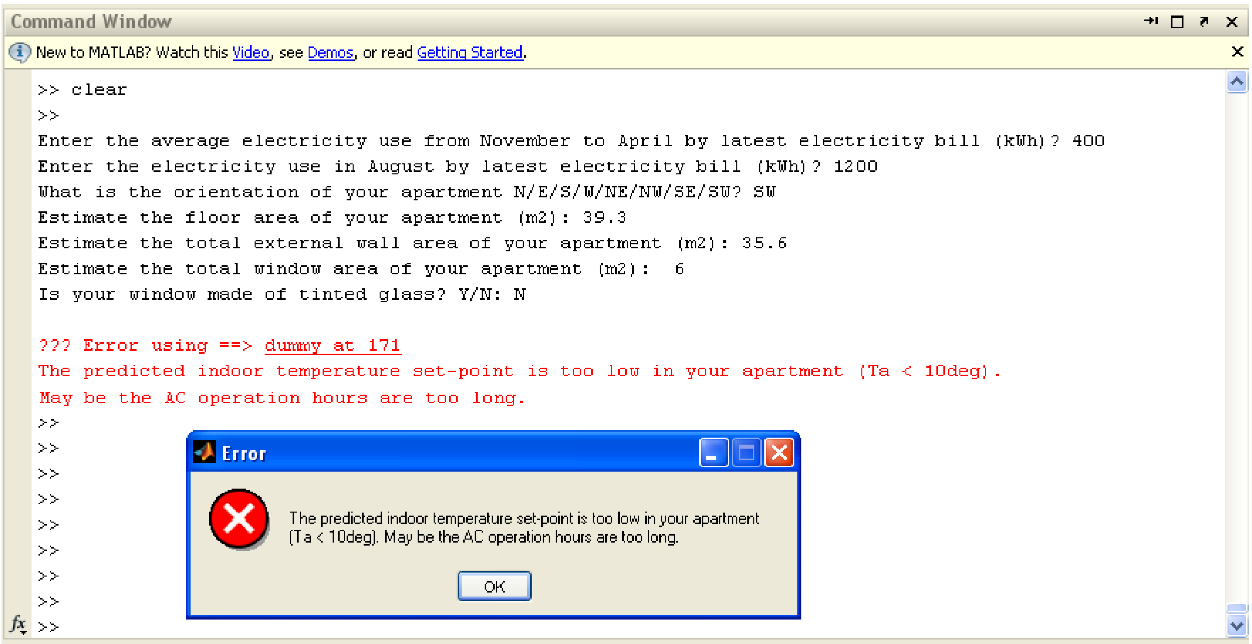


Figure 7.5 Warning interface for a predicted too cold indoor temperature set–point

Part 3: Calculation of energy charge

By implementing the newly proposed energy saving rebate scheme, Part 3 of the program benchmarks the cooling electricity use in August with star–rating and calculates the energy charge (HK$) according to the awarded incentive.

According to the cooling electricity profile simulated in Part 2 and the apartment floor area recorded in Part 1, the corresponding cooling energy index in August λ_{Aug} is determined by Equation 7.1 and compared with the benchmark values in Table 7.3. Case study for the original cooling energy demand in August awards a 2–star–rating, where the minimum charge of electricity bill is excluded, and the charge is calculated as HK$651. Considering both of the cooling energy reduction strategies, the cooling energy index in August is improved to achieve a 3–star–rating, which enjoys the incentives of 'excluding minimum charge' and '5 cents per unit rebate'. The energy charges estimate via strategies of increasing T_a by 1^{o}C and reducing AC operation by 1 hour are HK$606 and HK$607 respectively.

Applying the proposed hybrid cooling energy simulation tool, the prototype of this energy charge calculator is applicable for public users in determining the cooling energy performance and electricity fee for existing and energy saving scenarios in their apartments. It also demonstrates the application in generalizing the complex simulation tool for public usage. This idea can be a research direction on cooling energy reduction in occupant behaviour dependent buildings.

7.5 Summary

This Chapter demonstrates the applications of the proposed hybrid cooling energy simulation tool. The macroscopic applications is expressed via example for energy saving potential of various strategies for new town planning and development of new energy saving rebate scheme for summer months, while the microscopic application is described by the energy charge prediction tool for layman usage in individual apartment.

Taking an example of new town planning, the cooling energy use for public housing development with cooling energy reduction strategies by material selections, construction designs and occupant's energy saving behaviour adjustments are studied. The findings reveal significant cooling saving potential via occupant behaviour including increase of indoor temperature set–point and reduce air–conditioner operation hours. The power supply company is suggested to establish more incentives to attract occupant in saving energy especially during the summer months.

A new energy saving rebate scheme is proposed to improve the current energy charge system with incentives to enhance cooling energy saving in summer months. A 5–star cooling energy benchmarking system for public housings is developed to identify the level of cooling energy index λ, determined by cooling electricity demand and apartment floor area in the sampled household, with respect to the incentive levels given in the new energy rebate scheme. Higher energy rebate rate is awarded to 5–star–rating households, while no reward for apartments which labelled with 1–star–rating. The proposed scheme is demonstrated via case studies. It shows that the new charging scheme doubles the money saving as compared with the original scheme for the same amount of energy reduction. It is expected that occupants would take action on cooling energy saving practices by earning higher rebate rate on their electricity bills.

With regards to promote cooling energy saving in residential buildings, a tool is developed to help residents in estimating the energy charge prior to the new energy saving rebate scheme. The indoor temperature set–point and monthly electricity profile can be evaluated by collecting the basic information of energy use and housing characteristics from the sampled apartment. Energy charge with incentives is estimated in August (the hottest month during a year) according to the awarded star–rating via the benchmarking system. Besides, the electricity profile and star–rating for cooling energy saving strategies of higher indoor set–point temperature and shorter AC operation hour are recommended. This tool provides immediate responses to occupant's inputs and easy to operate. It could be an effective reference for residents to acquire the cooling energy usage status for existing and improved cases.

The above examples proved the flexibility of the proposed hybrid model for both large scale and individual basis cooling energy simulations. Its application is also extended to assist establishment of cooling energy reduction policy, enhancement of energy charging scheme and promotion of energy saving practice for layman use.

Chapter 8

Conclusion

This thesis proposed a flexible cooling energy prediction tool for residential buildings. This prediction tool is available for both single and multiple zones simulations with quick and accuracy responses, which is especially beneficial in forecasting building cooling energy consumption with various strategies implementation. The proposed tool also flexibly integrates with several sub–programs to maximize its simulation functions, including a probabilistic approach to evaluate occupant's air–conditioning (AC) operation schedule and an energy demand calculator with visualized benchmarking system for layman understanding, so that more realistic simulation results with occupant behaviour consideration and specific energy saving recommendations on individual cases become possible.

Energy conservation is one long lasting topic in relation to a number of research areas. Building energy use comprises remarkable portion in world energy expenditure, where the heating, ventilation and air–conditioning (HVAC) system records the highest contribution among the other contributors in buildings. In addition, cooling energy use is found more significant than heating consumption in buildings due to global warming with increasing trend of outdoor temperature. According to the literature reviews in this study, occupant behaviour plays an important role on total cooling energy demand, where this effect is in particular obvious in residential building as compared with the office and commercial premises. Proper prediction of AC usage patterns in residential building is of the most important issue to be solved before accurate cooling energy consumption is identified. Besides, the cooling energy reduction strategies reported in literatures are often related to building materials selection, construction designs, HVAC system efficiency and control on energy price. However, study on encouraging or supporting occupant's cooling energy conservation is found limited. Research work on this direction may help strengthen resident's energy saving awareness, in which to maximize cooling energy saving potential in residential sector.

Building energy simulation tools available in existing field can briefly be classified into physical model and statistical model categorized under bottom–up analysis method. Pure physical approach can provide detailed thermal energy performance results to the target building, but the input process is relatively complex with lengthy simulation time which may not applicable for non–professional usage and not feasible for large scale simulation. In contrast, pure statistical approach is superior to its simulation speed and non–linear relationship analysis such as occupant behaviour. However, pure statistical models require large database for model training and causal relationships between input and output data are not explicitly necessary. Regarding to the limitations in each model, an integrated approach which hybridizing the strength of both physical and statistical models can be an alternative for improvement. Detailed thermal performance outputs are available for multi–simulation with quick response time and simple parameter input process. The hybrid model provides an alternative in evaluating cooling energy consumption in buildings, in particular superior for city scale energy forecast with different energy saving strategies implementation.

Energy usage for different building types can be varied. An electricity consumption survey has been conducted in Hong Kong residential sector, targeted on the public rental housings (PRH), government subsidized housings by home ownership scheme (HOS), private housings (PRI) and some luxury private housings equipped with clubhouses (PRI_{CH}). Housings characteristics and electricity consumption in both tenant (apartments) and communal (public places including clubhouses) areas are recorded. The electricity consumption in tenant and communal areas are normalized by corresponding highest correlation parameter and compared among housing types. Energy consumption with descending order of sequence for PRI_{CH} > PRI > HOS > PRH is observed. HOS and PRH are further re–grouped as public housings (PUB) due to the similarity in block design constructed by the government. Energy consumptions for residential sector varied by housing mix ratios between PUB, PRI and PRI_{CH} are forecasted. The PUB is reported as the most energy efficient housing type and is recommended for future housing development plan in satisfying the increasing population.

A hybrid EP–ANN cooling energy simulation tool is proposed in this study. Four typical residential block layouts in Hong Kong including slab, trident, harmony and new cruciform are selected for in–depth cooling energy evaluation. Series of hourly envelope heat gains are simulated by EnergyPlus (EP) based on the building characteristics of the four housing blocks. From the simulation cases, the input parameters and corresponding output values are randomly extracted to construct the input/output database, which is further used for artificial neural network (ANN) training. The total cooling energy demand can be evaluated by adding the envelope heat gain (by ANN), ventilation and internal heat gain (by physical expressions and findings in literatures), together with consideration for occupant AC operation schedule and system coefficient of performance. The goodness–of–fit between EP and ANN performance is confirmed by hourly variation of Mean Bias Error (MBE=0.073) and Root Mean Square Error (RMSE=0.046). Besides, the prediction performance of the proposed hybrid model is satisfactorily validated via peer research study, government energy statistics and actual electricity consumption in 39 existing apartments. Slightly higher cooling energy consumption is predicted among these validation cases, where possible explanations are attributed to the unrealistic fixed AC operation schedule and unknown indoor temperature set–point in current stage.

Findings from application examples

Impact on cooling energy consumptions for distribution of individual apartment and entire residential sector by sensitivity change of materials selection and construction designs are investigated. Remarkable cooling saving potential in public housing sector, up to –13.7%, is reported by replacing existing settings with light–weight concrete for external wall and tinted single glazing for window. Solar heat reduction strategies incorporate between window area and shading shadow angle are emphasized, where saving potential of –5.58% is highlighted. Energy impact based on mix ratio of small (<30m^2), medium (30–50m^2) and large (>50m^2) apartment sizes is studied. Cooling energy use is found more efficient in larger apartment using the same occupancy schedule, and construction of medium and large size flats is recommended. Significant energy saving in apartment with reduced external wall area is demonstrated. However, more details on construction criteria and regulations are necessary for consolidate recommendation, which is out of the scope in current study. Lastly, the impact on whole building cooling energy consumption via orientation effect on the four typical public housing blocks is evaluated. It reveals that energy impact by orientation is closely related to building shape, where the impact is less sensitive for buildings with envelope evenly distributed in all directions, while the variation is remarkable for non–uniformly shaped buildings. The analyses in this section can be useful references for future public housing designs and development plans.

Cooling energy demands which correlate with occupant behaviours in terms of thermal comfort criteria and AC operation patterns are studied. Extensive surveys on occupant's thermal comfort conditions in 54 apartments and 217 interviewees have been conducted. The 'Neutral' thermal comfort zone for residential environment with indoor temperature boundaries of 24–26^{o}C and mean relative humidity of 76% is evaluated from the results of physical measurement on the thermal comfort related parameters and subjective responses on occupant's instantaneous thermal perception. Besides, the cooling energy impact due to variations of indoor temperature set–point and hourly outdoor temperature data is studied. About 7% reduction of total cooling energy demand is recorded for each 0.5^{o}C increase in indoor temperature set–point within the neutral thermal comfort zone. If the outdoor temperature is on average increased by 1^{o}C, corresponding indoor temperature set–point should be adjusted from 24^{o}C to 25.5^{o}C in compensating the excessive cooling demand.

Another survey has been conducted in 30 apartments with 109 interviewees to investigate occupant's AC operation patterns with different demographic and socio–economic backgrounds. The results are grouped into 6 categories including housing types, income groups, age groups, education levels, job natures and AC energy saving levels. A probabilistic approach, using the means and standard deviations of surveyed AC operation time periods, is proposed to model the actual AC usage pattern in each group. Satisfactory prediction performance between the proposed model and surveyed data is confirmed (α=0.05, K–S test). Significant reduction on residential cooling energy consumption is observed by replacing the original fixed AC schedule with the probabilistic AC schedule used in the hybrid cooling energy prediction tool. The indoor temperature set–point, used in previous simulations, is adjusted from 24^{o}C to 23^{o}C to match the cooling energy consumption comparable to government energy statistics. The analyses are responding prior to the argument for higher cooling energy prediction in model validation section. The application of the improved model is expressed via two energy saving strategies including (i) reduce AC operation hour(s) by setting timer at night and (ii) enhance occupant's AC energy saving awareness. Cooling energy saving potential of 14.0% and 34.1% is evaluated respectively for strategy of earlier turn off AC by 3 hours and practicing the 'high' energy saving AC schedule.

Effectiveness of various cooling energy strategies is compared and a supporting energy calculation tool for layman use is proposed in the last assessment in this thesis. By integrating the previously discussed cooling energy saving strategies on material selections, construction designs, indoor and outdoor temperature variations and occupant's AC operation patterns, the energy saving potentials for future public housing development plans in Hong Kong are evaluated. The largest energy saving potential refers to indoor temperature set–point adjustment and follows by the variation in AC operation schedules. The findings in this assessment exclusively highlight the effectiveness on cooling energy saving regarding to occupant's thermal comfort needs and AC usage patterns.

A two–step algorithm is proposed to encourage resident's AC energy saving awareness. Firstly, a new electricity charging scheme with incentive of higher rebate rate in summer months is suggested. A cooling energy index is proposed as a benchmarking parameter quantifying the monthly cooling energy performance per apartment and adopts in a simple 5–star benchmark rating system. More energy efficient households would be awarded with a higher star–rating with a better energy rebate rate. Secondly, a layman usage cooling energy calculator is developed for residents to estimate the cooling energy performance in their apartment. The indoor temperature set–point and monthly electricity profile can be estimated by several simple inputs from occupant. Besides, improvements on electricity and money saving are available with recommendations on raising set–point temperature and reducing AC operation hour. The presented energy calculation tool can be an effective reference encouraging occupant's energy conservation awareness in apartments.

Perspective on future research direction

Energy conservation in building can be achieved by advanced building characteristics and improved system efficiency, however the most critical contributor is attributed by occupant behaviour and their conscious in energy saving. Potential energy saving can be observed via research works on building physical and system mechanical improvements, but these strategies are beyond the concerns by end–users which results with little contribution to the total energy demands. The hybrid cooling energy simulation model proposed in this study shows not only the flexibility in handling city scale energy forecast with sensitivity change of building parameters, but also capable in evaluating energy impact on occupant behaviour variation. Most importantly, the final products are attempted to bridge the gap between sophisticated research analyses and end–user energy saving actions. This issue shall be highlighted as a direction in future cooling energy study to maximize the energy saving potential. The outputs presented in this study can be a useful reference in constructing framework to initiate occupant energy saving awareness by research level knowledge. Further works on the causal relationship for AC operation patterns in residential sector are recommended to evaluate the criteria of incentive on energy saving.

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