Dynamic Energy Demand Prediction and Related Control System for UK Households

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Abstract

Domestic energy consumption is not only based on the type of appliances, weather conditions, and house type; it is also highly depended on related occupancy profiles. In order to manage and optimise energy generation and the effective use of energy storage, it is important to be able to accurately predict energy demand in advance.

However, high-resolution (like below 1-min) occupancy profiles for domestic UK households are not ideally possible to be recorded or measured in nature. Therefore, an alternative approach to transfer particular electricity load to the number of active occupancy during selected time interval is identified by analysing the average electricity consumption of occupancy in this study.

Real load data analysis for three type of participated UK households is presented throughout the year. Then the seasonal synthetic high-resolution (30s) occupancy patterns for each household are generated independently. Weekday occupancy profiles are collected seasonally and used in a Markov-Chain model to produce particular occupancy daily activity sequence for each household. A stochastic model by using Markov-Chain Monte Carlo is presented to randomly generate high-resolution occupancy profiles in dynamic.

Then the predicted electricity loads are produced by mapping occupancy profiles to average electricity consumption. By validating the predicted results, it is found that maximum of sub-hourly aggregate result can mostly cover the measured demand in advance. Therefore, it is set the sub-hourly electricity demand boundary independently for each household during weekday throughout the year.

Heat demand for each household is simulated in sub-hourly resolution by using DesignBuilder with EnergyPlus throughout the year. Thus, sub-hourly energy demand of each household is applied in the control system of Bio-fuel Micro Trigeneration with Hybrid Electrical Energy Storage. The control system is designed and implemented by using Siemens software STEP-7 S-300 and WinCC. In addition, the predicted energy demands are utilized into the optimization of the control system. The comparison of optimized and general control strategies shows that optimized strategies by applying prescient sub-hourly energy demand can improve system efficiency significantly.

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Nomenclature

Abbreviations

AECO	average electricity consumption of occupant
ANN	artificial neural networks
BMT-HEES	bio-fuels micro-tri-generation with hybrid electrical energy storage
CHP	combined heat and power
CFD	computational fluid dynamics
ENN	Elman`s neural network
EEV	electronic expansion valve
RE	renewable energy
DHW	domestic hot water
HVAC	heating, ventilation, and air conditioning
TUS	time-use survey
MCMC	Markov-Chain Monte Carle
NIALM	non-intrusive appliance load monitoring
PID	proportional-integral-derivative
PLC	programmable logic controller
SAP	standard assessment procedure
SCADA	supervisory control and data acquisition
MPC	model predictive control
DCS	distributed control systems
GV	gas valve
WV	water valve
HX	heat exchanger

Symbols

Cw	Specific heat of water
E_{pre}	Predicted electricity demand
E_{off}	Off-peak electricity demand

N_{ACTIVE}	the number of active occupants
$P_{ZERO\text{-}OCCUPANT}$	minimum power consumption when nobody is active
P_A	actual data
P_F	predicted data
Q_{HC}	heat recovered amount
ΔT_{ACTIVE}	peak period
$\Delta T_{INACTIVE}$	off-peak period

Chapter 1. Introduction

1.1 The nature of energy challenges in UK

In terms of global warming and greenhouse gas (GHG) emission increasing, the UK Climate Change Act [1] set an objective of 80% CO_2 reduction by 2050, against with 1990 based level in 2008. However, the number of household was increased significantly towards to 1990 level with the booming of population. Meantime, it raised at approximate 1% proportion naturally, which means more energy consumption will be responsible by households [2]. In 2009, UK domestic end-users contributed approaching 29% of total energy consumption and 50% of greenhouse gas emissions, respectively [3]. It is also considered the primary energy source, like nature gas, coal and fossil is reducing gradually. Thus, the cost of energy will be another challenged factor which has a significant impact on the select and use of energy for domestic end-users.

To achieve this long-term objective and beat these challenges, one possible approach is using renewable energy (RE). As it can provide sustainable energy generation and reduce GHG emission significantly. In addition, an intermediate target of 15% RE generation by 2020 is launched by Department of Energy and Climate Change (DECC) in 2010 [4]. Meantime, the development of RE technologies for UK domestic end-users require effective use of energy and supply heat and electricity by reducing CO_2 emissions. Thus, the RE productions, such as micro combined heat and power (CHP), fuel cell, solar photovoltaic (PV) system and biomass boilers have a great potential market in UK [5].

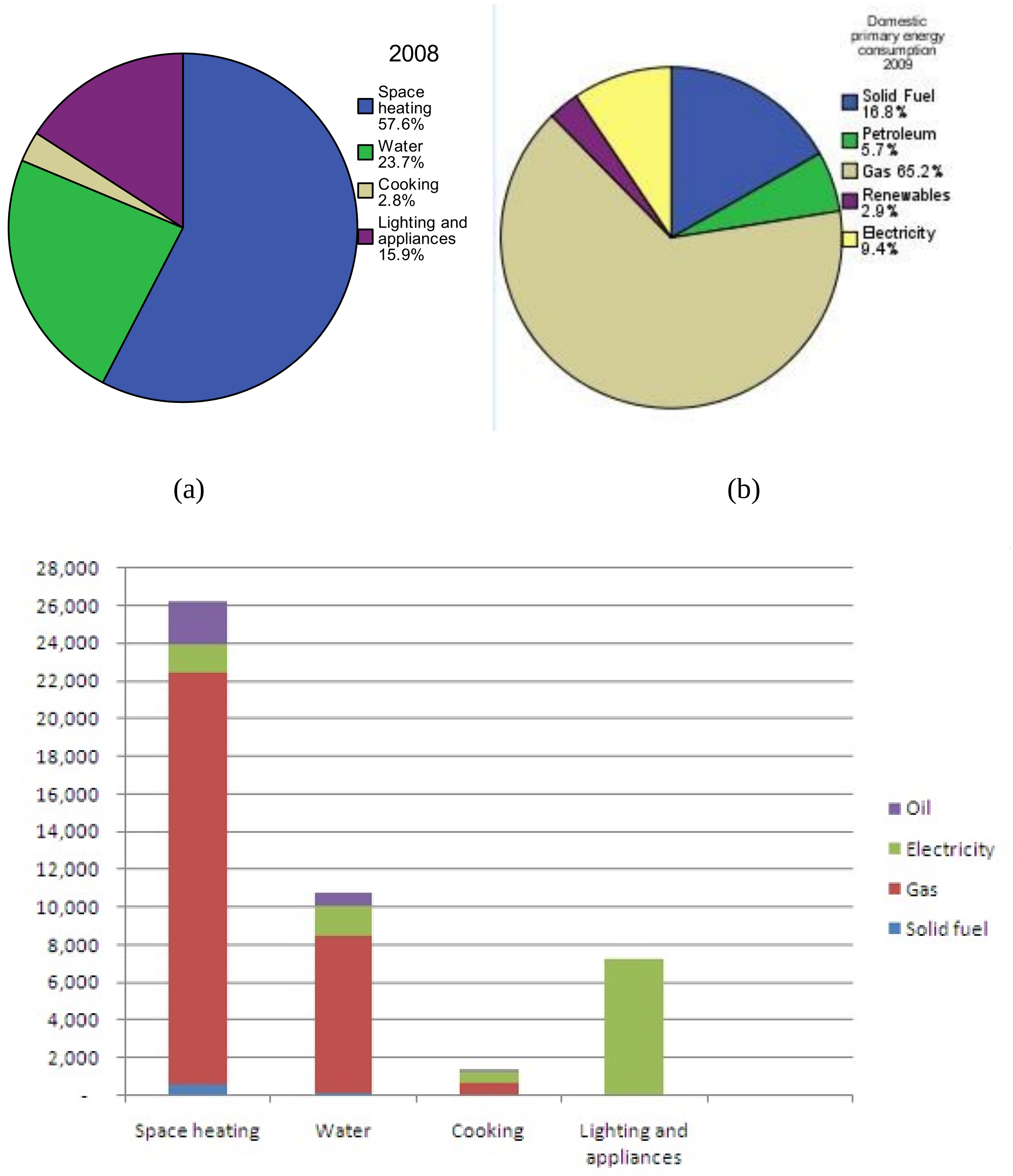
On the other hand, the cost of RE technologies has another significant impact for the consideration of both industries and domestic when replace current energy supply. In addition, compare with central gas system which is the most attractive energy production of UK domestic end-users currently, low-carbon technologies like bio-fuel micro CHP can provide heat and electricity synchronously without grid and nature gas supply, which has significant potential advantages for both efficient energy use and economic of energy cost. Alternatively, bio-fuels with non-toxic, sulphur-free, oxygenated and bio-degradable can be used by diesel engine with micro CHP system [6]. It can be a feasible solution for domestic end-users, which is mainly focused in this thesis to alter the energy use effectively and economically.

1.2 UK domestic energy demand

Domestic energy demand of each household has unique use patterns which refer to miscellaneous influential factors. These factors, which including occupancy compositions, house structure, house location, family income, weather conditions, occupancy behaviour, household income, vary from home to home. Consider with the feature of energy use, these factors can be divided mainly into two domains: behavioural domination and physical domination [7]. The former one is highly depended on how occupants spent their time at home but less-related to climate change and house design, which can be referred to electricity demand. The later one is none or less co-relation to occupancy behaviour, but strongly related house type seasonally. As it includes house design, house age and house structure, such as Detached, Semi-Detached, Terraced, Flat and Departments. Thus, it can be perceived as heat demand. The majority of cooling demand for UK family is fridge or refrigerator, which can also be categorized into electricity demand.

Details of UK domestic energy consumption by fuel in terms of primary energy equivalents in 2008 and 2009 are presented in Fig 1.1 [8]. The main energy consumption in 2008 (Fig 1.1 a) was space heating 57.6% and water 23.7%, lighting and appliances 15.9% and cooking 2.8%, respectively, and the ratio of heat to electricity approximates 4:1. Meantime, the data from Fig 1.1 (b) exposes that for primary energy consumption in UK, gas and solid fuel are the main options, also renewable energy has a huge potential market in the future;

In addition, Fig. 1.1 (c) shows the primary energy consumption for end use in 2009. The total heat is 34025 (9237+24788) thousand tonnes of oil equal to 395710 kWh (this total does not include the heat sold and renewable energy), and then the average of heat demand for each household is 17987 kWh/year [8, 9]. Therefore, average per day (kWh) is 49.28, and the average per hour (kWh) is 2.05. The total end-use energy demand is supplied primarily by gas and electricity (70% and 21%, respectively). It can be considered a significant impact of end-user`s demand with primary energy consumed [10].



(a) (b)

(c)

Fig. 1.1. (a) UK domestic energy consumption in 2008; (b) UK domestic primary energy consumption in 2009; (c) UK domestic energy consumption by end use and fuel in 2009, thousand tonnes of oil equivalent , respectively (data source from [8])

The total heating demand (kWh/year) and electricity demand (kWh/year) is presented in Table 1.1 [8].

Total heating (kWh/year)				Electricity (kWh/year)		
Minimum	Average	Maximum		Minimum	Average	Maximum
7600	12200	16800		1900	3200	4500
Average per day (kWh)	Average per day (kWh)	Average per day (kWh)		Average per day (kWh)	Average per day (kWh)	Average per day (kWh)
20.82	**33.42**	**46.03**		**5.21**	**8.77**	**12.33**
Average per hour (kWh)	Average per hour (kWh)	Average per hour (kWh)		Average per hour (kWh)	Average per hour (kWh)	Average per hour (kWh)
0.87	**1.39**	**1.92**		**0.22**	**0.37**	**0.51**
Heat to power ratio				4.00	3.81	3.73

Table 1.1. Overview of energy consumption for UK domestic end-users [8]

An investigation of energy use data collection from over 100 households in a year is presented by Staffell in [11]. Data set of these households from a range of 1 bedroom flats to 4 bedrooms detached houses shows that the average demand was 12.2 ± 4.6MWh/year of heat and $3.2 \pm$MWh/year of electricity in the UK [11].

The demand of micro-trigeneration system for domestic user depends on specific energy factors, which consists of the location and composition of residential house, house design, the particular heating system, the electrical appliances and occupancy behaviours, and related intensity of energy use [12, 13]. It is known that occupancy profile is the key factor in residential energy consumption. The composition and intensity of energy use, household size, and occupancy patterns including lifestyle, employment, income and age group, play important impacts in the end-use energy consumption [13].

Space heating takes account for around 66% of total domestic energy consumption in 2006, as shown in Fig 1.2 [14].

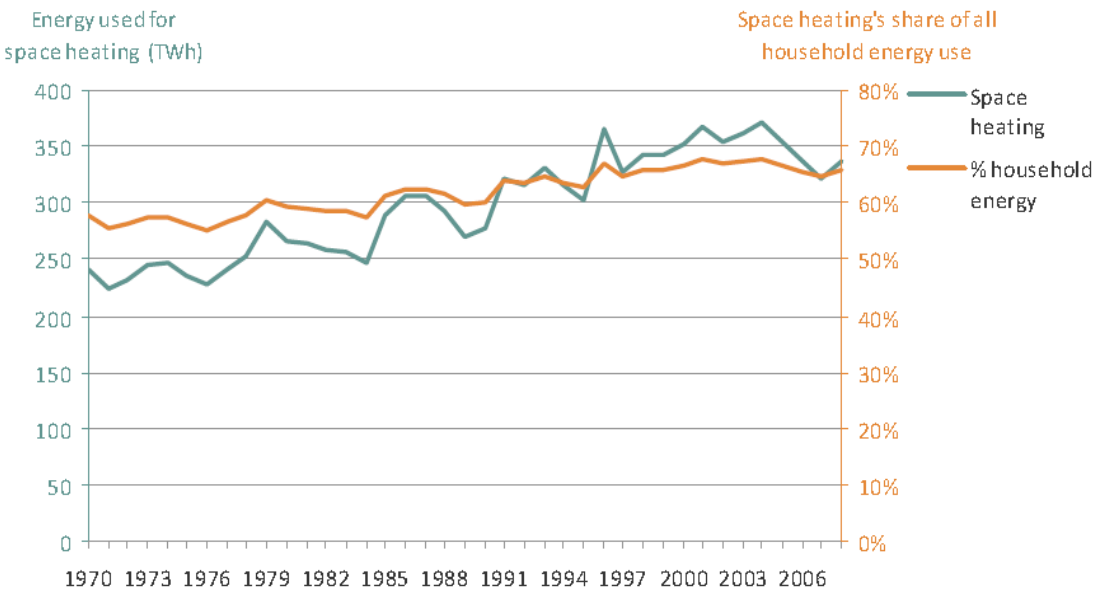


Fig 1.2. Household energy use for space heating (TWh) in UK from 1970 to 2006 [14]

From Fig. 1.2, the space heating`s share of all household energy use is growing from 48% in 1970 to 75% in 2003, which may describe recent phenomenon that the central heating energy system extensively applied in domestic dwellings, which allowed occupancy to heat the whole dwelling rather than individual rooms [14]. Meantime, it should be also noticed that the percentage of space heating in total energy use is decreasing since 2003, which may indicate the more efficiency energy system installed and new energy-saving dwellings built to achieve the carbon emission target by 2050.

The proportion of domestic energy use for water heating is significantly decreasing from 30% in 1970 to 17% in 2006 as shown in Fig 1.3 [14].

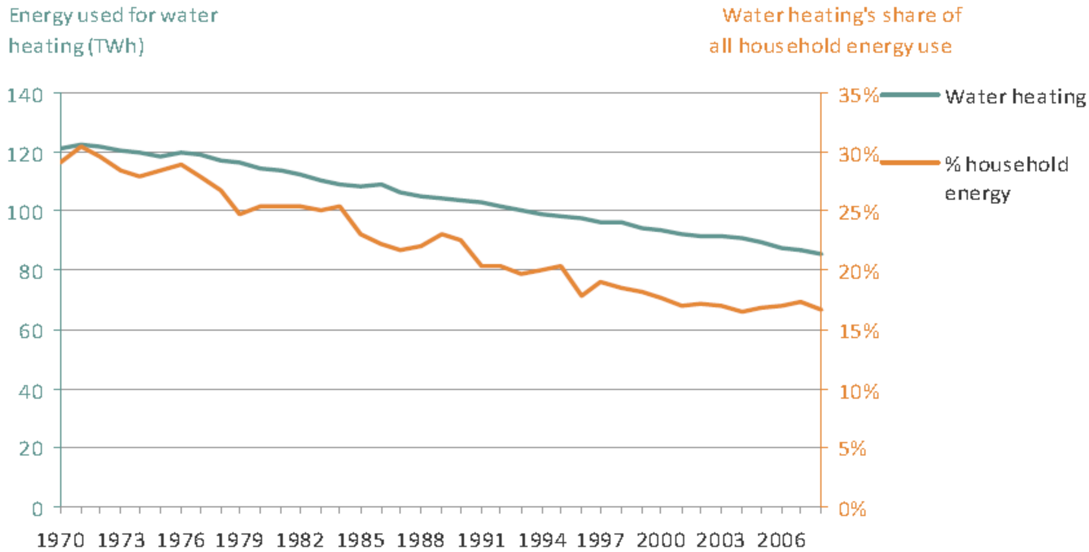


Fig.1.3. Household energy use for water heating (TWh) in UK [14]

Occupants require hot water for a variety of different purposes such as body cleaning, washing and drinking [7].With the technologies developing and more efficient energy system applied in domestic households, such as solar PV, water tank and advanced boiler, the heat loss from pipes and tanks are reduced significantly. Also with the greater utilize of dishwashers and showers, less hot water is consumed recent years [14]. Therefore, the energy consumption for domestic hot water will be continuously decreasing in near future with no doubt.

Because of the weather condition in UK, related cooling demand for UK households is mainly composed by fridge and refrigerator. These appliances are driven by electricity with a cyclic load from thermostatic temperature control [15], and also operated by occupancy with opening and closing activities, which can reflect on the variations of electricity load curve. Therefore, cooling demand for UK domestic householders can be represented by electricity demand. Moreover, consider with the energy consumption of these cooling appliances, and also with realistic stochastic fluctuations of occupancy activity, these appliances can be assumed as non-occupancy related appliances, effect of related operations can be neglected [16].

1.3 Bio-fuel micro trigeneration with electrical storage system for UK households

In order to address energy challenges for UK domestic end-users, a bio-fuel [17] micro-tri-generation system (BMT) [18] with hybrid electrical energy storage (HEES) system [19] is employed in this research, which is the main part of project funded by UK Engineering and Physical Science Research Council (EPSRC) with the grant EP/F061978/1. The demand side management including energy consumption prediction and related control system is the remainder part of this project that is presented in this thesis.

It is clearly that occupancy profile is the key factor for analysing and forecasting energy demand for particular household. In terms of the BMT-HEES installation for particular household, the primary part is to identify the system size including engine and electrical storage, which is highly related on the information of appliances, which including specifications, compositions and operations. Meantime, occupants require heating demand seasonally when they are at home regardless active or not, such as sleeping during mid-night in winter or hot water shower in summer.

Therefore, in order to manage and optimise energy generation and the efficient use of energy storage, it is important to be able to accurately predict energy demand within BMT-HEES for particular household.

1.4 Control system overview

Detailed energy demand profile is a significant prerequisite for effective use energy and demand side management in BMT-HEES system. With the prediction results of domestic energy consumption, both minimum and maximum power consumption can be identified. Therefore, the aim of control strategy is to have feasibility to meet the minimum requirement of energy consumption and also obtain flexibility to satisfy the maximum potential energy demand. The former one refer to general control system which set all related parameters primarily to control very unit including engine, valve, pump and energy storage when meet the energy demand requirements of electricity, cooling and heat. Later one related to optimization control strategies which not only make control system effectively generate energy and have ability to deal with system environment change like new appliances installation or occupants' holiday.

General control system contains several parts, which including control logic for engine, internal coolant water loop, external water loop, exhaust emissions, batteries and super capacitor. Initial parameters of each unit are set for opening and closing judgement. After that, general control strategy is implemented by using STEP-7 S300, Siemens software with PLC controller. Optimization control strategy is discussed to satisfy the potential demand requirements of domestic end-users by using predicted energy consumption results. Finally, a comparison of system efficiency between general control strategy and optimized control strategy is presented.

1.5 Contribution of this research

The aim of this thesis is to develop a novel solution to predict energy demand dynamically of domestic end-users then apply forecasted energy demand in intelligent demand side management with BMT-HEES.

The main objectives are followed:

To investigate the nature of high-resolution instantaneous electrical load and conduct a possible solution to generate synthetic appliance use and related active occupancy profile.

To develop a simple, extendable and applicable model of high-resolution energy demand prediction for domestic end-users.

To design and implement control system of BMT-HEES to meet the domestic energy demands.

Occupancy profile has played significant role in energy-using models, and with its unpredictable and complexity, particular for arbitrary domestic households, current research methods try to deduct its influence as much as possible when analysing and forecasting domestic energy use, such as using average data set. Based on historical average load of heating and electricity, massive methodologies have been developed to present roughly and predict the general energy demand for domestic end-users. However, accurate and intelligent of control strategies for particular domestic end-users require instantaneous data profiles, including consecutive high-resolution like below 30s time interval electrical load data, related occupancy profiles, appliances information. These instantaneous data sets cannot be derived from historical average data set or related sophisticated methodologies.

Especially for BMT-HEES system, the primary part is to decide the system size for particular household, which cannot be identified by average historical load. Meantime, high-resolution occupancy profiles need the occupants to record their activities frequently and continuously in every day, which are not ideally possible for arbitrary households. Therefore, to dynamically generate related consecutive occupancy profiles and then applied in dynamic energy demand prediction which based on high-resolution electrical load data sets is the main contributions of this thesis. The specific contributions are depicted below:

- A simple and applicable model to address synthetic appliance use based on high-resolution electrical load data by assuming a set of homogeneous appliances for different households.
- Based on real-time consecutive load data and related synthetic appliance use, the number of active occupants at each selected time interval are estimated dynamically, which can be used as input factors in miscellaneous energy-using models.
- Energy-using model is built-up by using estimated active occupancy profile to predict energy demand stochastically, which can present the potential minimum

and maximum energy usage and decide the system size of BMT-HEES for particular domestic household.

- The energy-using models can also be updated dynamically by input specific appliances of particular household to get more accurate results.
- With the results of accurate energy-using model, intelligent control strategies can make the BMT-HEES with high efficiency, energy saving and low emissions.

1.6 Outline of this thesis

In Chapter 2, a comprehensive literature review is presented including current methodologies of energy demand prediction within miscellaneous energy-use models, and related control unit and strategies. Chapter 3 discusses and describes a possible solution to generate synthetic high-resolution occupancy profile by analysing related appliance use. Chapter 4 presents the dynamic electricity prediction approaches by using Artificial Neural Network and Markov-Chain to dynamically generate electricity demand in a whole year. Chapter 5 conducts three different household models including Terraced, Large Terraced and Semi-detached in Design Builder with energy plus, then using estimated active occupancy profile to dynamically generate heating demand for each household in four seasons. Chapter 6 designs the general control system and set the initial parameters of each control units, then implemented it in Siemens STEP-7 S300. Chapter 7 concludes the main finding in this thesis and discusses the recommendations.

Chapter 2. Literature Review

2.1 Introduction

This chapter comprehensively discusses the current energy demand methodologies and related control strategies. Section 2.2 presents the nature of domestic energy demand in UK, and explicitly shows the relevant factors of electricity, then reviews related prediction approaches in electricity, and selects few of most popular forecasting methods to introduce in detail. Section 2.3 depicts the feature of domestic heat demand in UK, and discusses recent approaches on building heat consumption simulation and prediction. Section 2.4 reviews the control system requirements and challenges, discusses the control units such as PLC and related system environment like Siemens SCADA and WinCC. Also, the optimization control strategies are discussing, including effective control, intelligent control, control system feasibility and flexibility. Section 2.5 briefly concludes the summary of this chapter.

2.2 Domestic electricity demand analysis and prediction

2.2.1 The analysis of domestic electricity demand

Domestic electricity consumption is highly depended on three mains factors: (a) the type and number of electrical appliances, (b) the use of these electrical appliances by occupants and (c) the number of active occupants in dwellings [16].

A The type of electrical appliances in UK households

According to the pattern of use for appliances, firth et al identify the appliances into four categories: continuous appliances; standby appliances; cold appliances; and active appliances [16], and Richardson et al. in [20] investigate thousands households and list the most common appliances in two domains: non-occupancy related appliances and occupancy related appliances, which also including mean in-use power, mean standby power consumption and mean cycle length of each appliances, as shown in Table 2.1.

The non-occupancy related part contains the continuous and cycle appliance. These electrical appliance is always switched-on regardless the occupant is active or not. It should be noticed that the appliance with standby model may be changed to continuous category because of the occupant energy behaviour. In addition, the appliances with occupancy related which may be switched-on if there is at least an active occupant, which including standby appliance, most kitchen and house clean appliances, also with lighting.

Table 2.1 only lists the most common electrical appliances over fifty percentages installed in domestic dwellings, which are investigated from TUS data [21]. Some other appliances such as fax, dishwasher, tumble dryer, washer dryer, and chest freezer are not presented due to the poor percentages of them.

In addition, the in-use power consumption and cycle length of each appliance are set as a mean value in terms of the diversity of appliances in different households. It also should be known that the cycle length of each appliance is controllable by active occupant, which is determined by the demand of related activity.

Appliance domain	Appliance category	Category description	Appliance type	Mean in-use power (W)	Mean standby power (W)	Mean cycle length (m)
Non-occupancy related	Continuous	Continuously switched on and constant power consumption	Clocks	2.5	-	-
			Alarms	5	-	-
			Broadband modems	4	-	-
			Cordless telephone	1.5	-	-
			Answer machine	3.3	-	-
	cold	Cycling power consumption between zero and a set load level	Fridge / Refrigerator	200	8.8	190
Occupancy related	Standby	Actively switched on by occupants. When not in use, power consumption may be non-zero	Televisions-CRT	84	3.5	73
			Televisions-LCD	130	2	73
			Televisions-plasma	253	2.7	73
			TV Receiver box	27	10	73
			HiFi	100	8.2	60
			CD Player	15	4	60
			Desktop computer	140	7.1	300
	Active	Switched on by active occupant. When not in use, power consumption is zero, like cooking, washing, house cleaning, space heating and shower, etc.	Microwave	1250	-	30
			Kettle	2000	-	3
			Toaster	1000	-	3
			Hob	2400	-	16
			Oven	2125	-	27
			Washing machine	400	-	138
			Iron	1000	-	30
			Vacuum	2000	-	20
			Electric showers	9000	-	10
			Electric heaters	2000	-	240
	Lighting	Switched on when needed, when not in use, may still active, depends on the behavior of occupant	Lighting	200 (0-400)	-	N/A
	Total			24340		

Table. 2.1. The specification of most common electrical appliances in UK residential dwellings [16, 20].

Continuous appliances continuously consume electricity regardless occupant is active or not; it contains the most important appliances which need be always switched-on, like alarms, clocks, broadband modems, cordless telephone, answer machine. The reasons for these consecutive electricity consumptions are not only the energy consumption of these appliances are small, but occupants may need them at any time.

In addition, these appliances require continuous power supply. Meantime, in terms of the variation of system environment and climate, these appliances may be changed unsurprisingly.

Standby appliance or leaking electricity appliance is known as an electrical appliance remain consumes electricity after switched-off event [22]. The standby appliances with around 30 - 60W per home in 2000, account for approximately 3% of total electricity consumption [23], and it is also an estimation in Australia that standby energy consumption is responsible for 10% or higher than expected in 2006 [24].

Entertainment appliances, such as TV, CD/DVD player, computers and home stereo systems, collectively require power demand that is similarly close to continuous appliances when they are in use [15]. Also, most of these appliances have standby model when they are not in use, or sometimes completely switched off, which depends on the behaviours of occupants, like energy saving habits.

The most common sharing appliances are lighting, entertainment appliances and heating appliances. People may share appliance with others when these appliances are switched on. The proportion of energy consumption of sharing appliance depends on the number of active occupants at selected time. For example, when two occupants are active in winter evening, by assuming they stay in one room, they may use one or two electrical heater to recovery heat in terms of individual thermal comfort, but increasing number of occupants still in one room is unlikely cause the growing of electricity consumption, unless the occupancy move to another room where additional electrical heater is needed.

B The use of electrical appliances

The use of electrical appliances depicts what people do at home [15], which describes the occupant presence status and related behaviour. Detailed data set of electrical appliances use has a significant impact not only on modelling of electricity consumption [25], and also better understanding the nature of electricity demand.

On the other hand, the information of how people spend their time can be recorded as Time Use data [21] or captured from the load signatures in smart home which specific to the operation of appliances by using intelligent algorithms [26] or smart meters with sensors, which can help to determine the energy consumption straightforwardly, the frequency and intensity of use appliances [27].

A broad investigation of describing the activities of occupancy was presented in UK 2000 as known as Time-Use Survey [21], which conducts 1-day diaries recorded at a 10-min resolution of 2000 participated households [25]. TUS depicts detailed information of each investigated household, including location of households, number of occupants, and particular activity in weekday and weekend.

Overview of electricity consumption for UK household can be derived from TUS data, and also with stochastic occupancy profile generation. However, in terms of its simplification, especially only for 24-hours data set, the trends of appliance use for particular household cannot be presented which is the main drawback of this approach and is not suitable for analysing and forecasting the trends of appliance use.

The methodology named as Non-intrusive appliance load monitoring (NIALM) is developed by Hart from MIT in 1992 [28] in order to capture the feature of appliances to decide which appliance is exactly switched-on at a given time. This type of method, based on sensors and intrusive appliances installed at home, has significant impacts on understanding electricity consumption which has attracted many researchers to develop further research on load monitoring more precisely in recently years [29,30].

Indeed, although sensors, intrusive appliances, or smart meters installed in smart home is the trend of developing intelligent household in worldwide, the economic and inconvenient of these intrusive appliances installation for household are the principal shortages, which may disturb the occupant ordinary life and reject by the households with lower income [31].

Therefore, the load analysis in regular household without intrusive appliance or smart meters is the main issue in analysing electricity consumption.

In terms of the frequency and intensity of electrical appliance use in both domestic and commercial buildings, time-resolution has a great impact in building energy simulation. The most publicly available data sets including heating, electrical, cooling are practically based on one-hour resolution. One possible reason is one-hour resolution data is easily to record, which can present the primary overview of energy consumption. Another feasible aspect is the energy use for large-scale buildings is quite smooth rather than the frequent load fluctuation in domestic dwellings.

However, average record with low-resolution, such as one hour or thirty minutes, even 10 minutes, cannot capture the load fluctuation accurately, which can lead mismatch between demand and generation, especially for on-site generation without grid feed-in. For example, the records shown that there is a 3kW average power demand between 08:30-09:00, if the power output of on-site generation is set to 3kW to meet the energy demand, there may cause a system fault, like 6kW power consumption from 08:45:00 to 08:48:00. Because the data record is shown as an average value for selected period, and aggregated by instantaneous load in every second.

Meantime, the information of appliance use can also be influenced by the selection of time-resolution; Fig. 2.1 [16] and Fig. 2.2 [32] presents the two different feature appliances usages in 5-min and 1-min time-step. Comparing average load record resolution in Fig. 2.1 and instantaneous load profile in Fig. 2.2, the appliance use can be presented more unambiguously, also note with maximum power consumption is 1.8 kW and 7.18 kW, respectively. From Fig. 2.1 and Fig. 2.2, it also can be noticed the information of switch-on appliances is more sensitive with the time resolution, and the high-resolution load record can present more detailed use of appliances.

Moreover, more inaccuracy of average effects has also been reported in several literatures [33-37]. Hawkes and leach report that by analysing the influence of time-resolution in optimization modelling of micro-combined heat and power generation capacity, CO_2 emissions and life cost, results based on5-minutes time-step comparing with 1-hour time-resolution can significantly alter the optimization design of system capacity, environmental impacts and life cost [34].

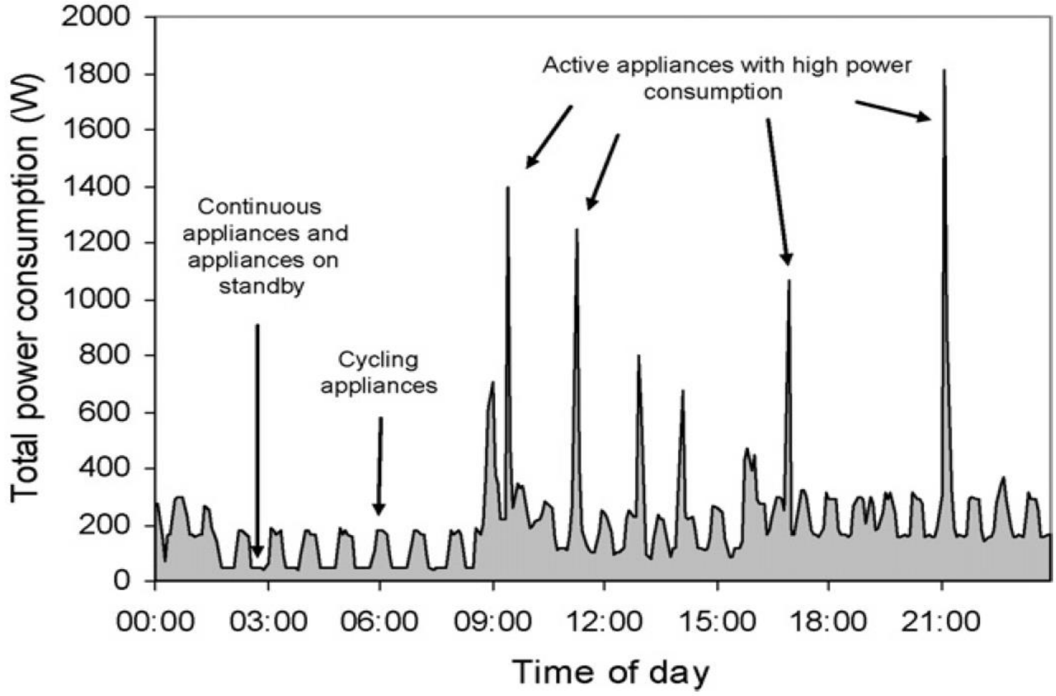


Fig. 2.1. 5-min resolution of electrical load record of typical household [16].

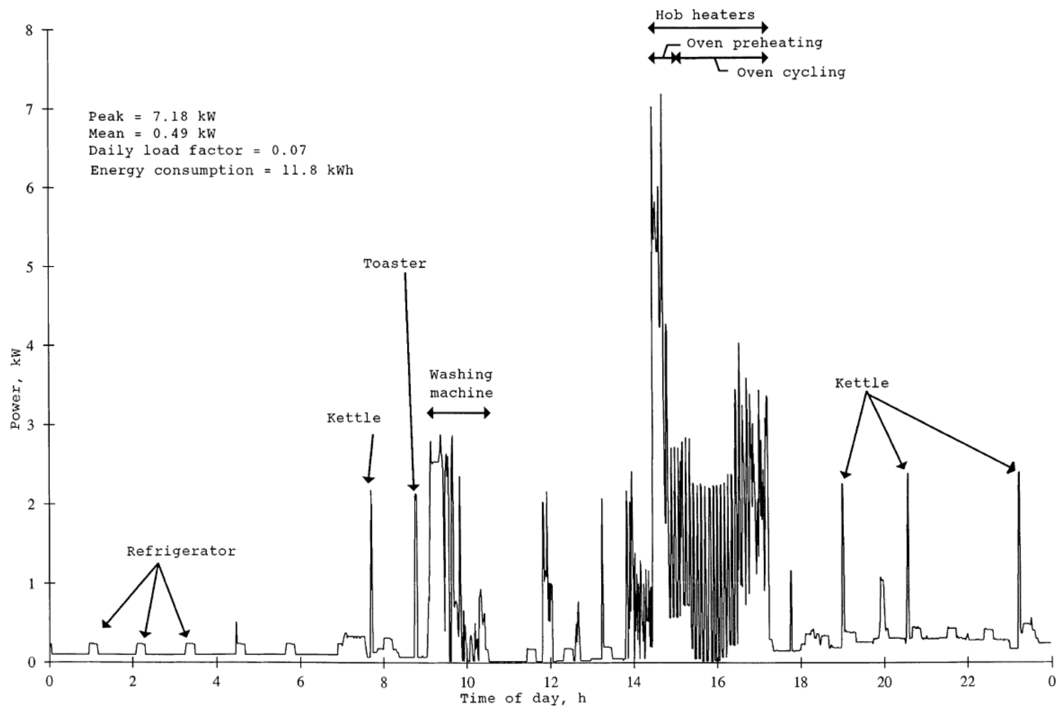


Fig. 2.2. 1-min resolution of an electricity demand profile from an individual household [32].

Wright et al. [33] investigate the difference of a load curve in selected time intervals, like 1 to 5 and 30 min, as shown in Fig. 2.3 by using hypothetical on-site generation models with import and export proportions analysis for 7 households, the results confirms that high-resolution load data like 1-min time step can briefly capture the details of load pattern, also considers with the data volume, they suggests that 5-min log period is reasonable time-resolution which can present exceptional accuracy of load pattern [33]. Similarly, Hoevenaars in [35] analyses the impact of time-resolutions in 1-s, 1-min, 10-min and 1 h time step from the simulations results with individual and hybrid renewable energy systems. They reports the spikes in the load is significantly influenced by time-resolution with hybrid system configurations, but renewable energy system with battery is less influenced rather than the systems with diesel engine [35].

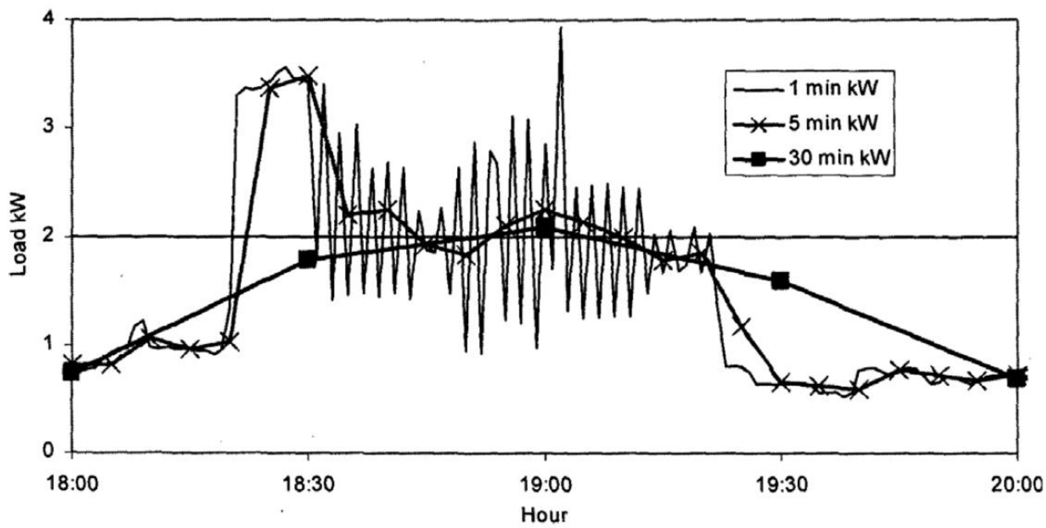


Fig 2.3. Comparison of 1, 5 and 30 min averaging at time of intensive loads for a typical house [33].

These researchers do not report the impact of time-resolution below 1 minute, as they consider 1-min resolution is the highest resolution level, which is recognized to cover most load curves in electrical consumption modelling. However, there are many events last less than 1 minute, like microwave, lighting, toaster, and iron, which will be disappear from these resolution and cause misleading in understanding nature of electrical demand.

Lawson [36] investigates the difference of time-resolution below 1 minute time step with instantaneous load record, like 2-s, 5-s, 8-s, 10-s, 30-s and 1-min, he reports that load recording resolution at 30s rate failed to capture a number of fast switching events comparing with higher recording resolution, such as 2-s, 5-s or 8-s. By analysing the load logging results, it is recommended the electrical load recording rate of 8 seconds and less can enable to capture of most switching events to reduce the degradation of the data obtained [36].

Latest research in April 2014, Cao [37] reviews the drawbacks of previous research on matching demand of end-users and on-site generation within different time resolutions, like 1-min, 15-min, 1-hour, by comparing the data set of hypothetical constant generations with the real load profile from Finland, the author reports the time-resolution can significantly alter the on-site generation and generate error when matching with demand profiles. Meantime, with the limitation of data set (only one day data with 1-min resolution), no further research is presented, and the conclusions suggest that 1-min resolution is the reasonable solution in electrical demand simulation to achieve close to real measure load [37].

C Active occupancy profiles

Domestic occupancy profiles, mainly in accordance with the use of electrical appliances, such as cooking, lighting, heating, and entertainment equipment, vary from different households [38]. Domestic electricity demand is not only depended on the presence of occupancy, which is active or not, and the number of active occupancy [39]. Richardson et al in [38] consider that occupancy profile is the key factor in energy-use models which cannot be neglected straightforwardly, and provide a definition of active occupant as “a person who is in the house and not asleep” [38]. However, with the complexity, diversity and uncertainty of occupancy profile with different households, as previous discuss, most current researchers neglect the effect of occupancy profiles by using average data set with low-resolution like above 5-min step.

Active occupancy profiles, applied in energy consumption models, can be obtained by people recording their activity as TUS data [21] or generated synthetically by using mathematic models [38]. The former one includes 24-hour dairies record with 10-min resolution, and later one is a stochastic model based on TUS data to generate occupancy profile randomly within 1-min resolution. However, with the limitation of TUS, which is intermittent data record, especially for particular household, TUS data only presents the overview presence of occupancy, but cannot provide the trend of occupancy activity, like occupancy habit, in individual households. Also, the consecutive occupancy profiles are not considered possible to collect, especially within high-resolution record, like below 1-min time step. Therefore, it is very imperative to generate estimated consecutive active occupancy profiles of particular household for energy-use models by using realistic record. On the other hand, the occupancy profile contains several important factors: the number of occupancy in the dwelling, housing stock, occupancy pattern, age group of occupancy, life style and time resolution scale.

D Household size

The composition of household decides the number of occupancy in the house. The average size of household is decreasing in UK since 1970, from 2.91 persons at 1970 to 2.31 at 2002 [40, 41], and expecting to 2.15 by 2031 [42]. Meantime, the proportions of one-person and two-person households have a significant increasing [42] due to the population growing and aging, also the number of households are increasing as approximately rate 1% proportion naturally every year [2], which means the proportion of one and two persons households will be the major part in near future. The composition of households in the UK in 2002 is shown in Fig. 2.4.

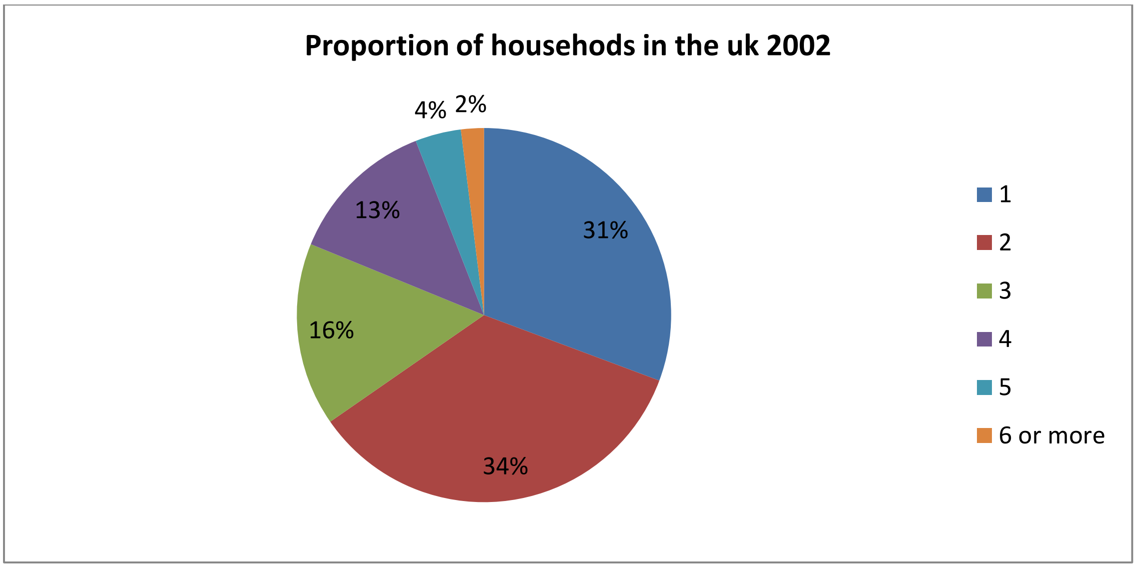


Fig. 2.4. Proportion of households with the specified number of occupancy [40].

E Housing stock

Because of the long physical lifetimes of UK domestic dwelling, the rate of replacement is approaching approximately 1% per year [42], also same rate with new builds which are low carbon properties to meet the criteria of Building Regulations [43]. In order to achieve the target of 80% CO_2 emission reduction, there is estimation that 70%-75% of new housing stock of UK by 2050 will be built with significant saving in energy efficiency and also reduction of CO_2 emission [44].

The current UK domestic dwellings can be perceived into five primary domains by considering the type of housing stock: a) Apartment and flats; b) Bungalows; c) Terraced Houses; d) Semi-detached houses; e) Detached houses [36].

F Occupancy patterns

Occupancy patterns, from small domestic dwelling to large commercial buildings, have significant attraction to researchers in recent years. Studies on the diversity of occupancy patterns in various buildings have shown the actual occupancy pattern is stochastic naturally of each independent building, when there is an at least occupancy occupied [45, 46]. Meantime, realistic occupancy profile is the crucial factor which can cause variance between original and simulated energy demand in domestic dwellings. [47].

In terms of the absence of continuous real-time occupancy profiles, the standard methods are using fixed design profiles to replace real one [48].Therefore, by classifying the type of employment of occupants, Yao in [7] generalizes the UK domestic occupancy patterns into five common domains, which are listed below:

- The household is unoccupied from 09.00 to 13.00. One of the occupants may have a part-time job in the morning.
- The household is unoccupied from 13.00 to 18.00. One of the occupants may have a part-time job in the afternoon.
- The household is unoccupied from 09.00 to 17.00. All of the occupants have a full-time job during weekdays.
- The household is unoccupied all day; the occupants are taking holiday.
- The household is occupied all the time. The occupants may have infant or younger child to look after, like child-minder, or is of retired couples or single.

However, the fixed occupancy profiles do not consider the variation during an occupied period, such as partially occupied [49]. Therefore, some researchers develop sensor to detect occupancy profile in building simulation [49, 50], the models in these papers provide personalized occupancy profile as particular weekday/weekend occupancy probability as a function of time for individual occupant [50]. There is one important aspect is neglected by these researchers, occupants may be inactive even the sensor has detected they are moving from one place to another but with zero energy consumption, which refer to the definition of active occupancy.

Thus, it can be noticed, active occupancy means a person is active and consuming energy. Sensors in the buildings can help to track the mobility of occupancy but cannot detect the utility of energy appliances, such as electrical appliances and heat appliances. Therefore, consider with the variation of the occupancy profile in different time and space [51], it is important to predict detailed and estimated occupancy activity profile in simulation of energy consumption in buildings [52].

G Age group of occupancy

The age of occupancy is another important factor which can affect occupancy behaviour and pattern slightly. In the case of the component of occupancy varies significantly in households, the occupancy with different age groups can be categorised into three determinations: adult, children and retired occupancy. The patterns of adult are highly related to related employments. Children consume less energy than others, and corresponding activities are most likely as lighting, fridge, and entertainment appliances, which can be assumed as zero in term of simple calculation in energy consumption. Retired occupancy is the person who may stay at home all day; they may occupy the household all the time. Therefore, detailed age group of occupancy can help better understand related occupancy pattern in the model of energy consumption for domestic dwellings.

H Lifestyle of occupancy

The lifestyle is another important factor within occupancy patterns, which decide the duration of staying at home for each occupant. For example, some people enjoy night life after work, and they may not stay at home at evening; others like outdoor sports when the weather condition is fine. Also, some people prefer staying at home after hours instead going outside. Different lifestyle can determine the occupancy pattern significantly, which is referred to occupancy habit.

I Impact of resolution in occupancy profile

The resolution of an occupancy profile is perceived mostly as 1 hour time step. Some researchers develop high- resolution occupancy patterns, such as 10-min in [38] and 3-min in [50] by using sensors installed each room to detect the activities of occupancy [53]. These records can dynamically present the mobility of occupancy, which can be used as great impact factor in heating energy consumption. However, the switch-on events of electricity appliances are more sensitive than mobility of occupants, and also sometimes, occupants are active but they do not consume any electricity. Therefore, the resolution of the occupancy profile has less impact rather than the number of active occupants.

2.2.2 Review of domestic electricity demand prediction methods

Low-carbon technologies like micro CHP generation and strategies such as demand side management require detailed electricity demand profiles to address what occupants do during at home and improve efficiency of electricity use [38]. The critical factor in analysing electricity demand is the appliances in different households, which has three determinations: composition, specification and operation. These determinations are various between different domestic end-users, which cause the most intractable issue within build-up model of analysing and forecasting electricity demand for particular household.

The prediction of domestic household electricity demand is a crucial factor in the term of improves energy performance. In order to accurately forecast the building electricity consumption, a large number of approaches have been carried out. However, with of the complex of building electricity consumption, like appliance types, occupancy patterns, and other related influent factors, the methodology in demand side prediction are significantly varied [54].

Meantime, there is another important factor in the prediction area, which has been ignored in most related literatures are data resolution. With the different data resolution, the data set such as electricity data can be divided into two regions, history average data like above 1-min resolution and dynamic data below 1-min resolution. These two regions require different influence factors, and majority researchers have proved that history average data can carry out the nature of particular building energy consumption by using particular methodologies. Seldom research concerns with dynamic load prediction because the occupancy behaviours have been convinced as unpredictable. Song in 2010 has demonstrated that 93% potential human outside mobility is predictable, and also indicated the reason an outstanding lack of variability in predictability, which is largely independent of the distance people cover on a regular basis [55]. However, the indoor human mobility or occupant activities in the domestic buildings are neglected by researchers because of its randomness.

Moreover, domestic energy demand pattern with less related factor is enough simple rather than large commercial buildings. In order to clearly understand the prediction methods for domestic end-users and also generate accurate demand results, it is important to take into account with the time-resolution scale.

Zhao et al. have classified the energy demand prediction methods into several domains, such as engineering techniques, statistical methods, neural networks, support vector machines and grey models. These approaches are focused on various buildings from a small room to big estates, and also varying from building`s sub-system analysis to regional or national level modelling [54].

With the complexity of energy demand pattern in different domestic households, especially with the uncertainty of occupancy behaviour, there is a significant challenge to provide precise demand prediction. Therefore, considered on the aim of prediction and related occupancy pattern, the methods of domestic electricity demand prediction have been divided into two categories: non-occupancy related models, and occupancy related methods.

A Non-occupancy related models

The non-occupancy related static models are simply built by correlating the historical electricity consumption or energy index with related influencing variables [54]. These models are widely used from long-term (up to yearly) to short term (up to hourly) load predictions, such as time series model, Fourier series model, regression model, fuzzy logic model and artificial neural network (ANN) model. These models need to collect sufficient historical data to build the relationship between input factors and output results. Because the time-resolutions in these models are quite low, historical occupancy details are not employed.

Time-series prediction model was the most popular one which has been utilized in many domains in the past decade [56]. The significant feature of time-series model is logical, because the history of energy consumption can be presented by a time series. Time-series models can capture the relationship between the hourly energy use and time variation given a set of time-series data. However, with the ideal prediction, the data should be linear, and the results of forecasting with nonlinear parameters are undesirable.

Dhar et al. [57] used a Fourier series model to predict the electricity demand in an institutional building. Fourier series models are based on the assumption that electricity use in most building is periodic. If dramatic changes happen, high-frequency Fourier components must be included in the models, thus dramatically increasing the computational cost.

Regression model is another widely used energy consumption prediction method by many researchers, it has been demonstrated to be effective for building energy predictions in a number of experiments [58]. There is a ratio for each parameter in regression model, which means the strength of impact. It is suited for predicting the average electricity consumption over longer periods such as days or months. For different buildings with different environment and weather conditions, much effort and time must be spent on selecting time resolutions and repressors to find a best fit model. Cho et al. in [59] present the prediction errors in the annual energy consumption based on 1-day, 1-week, and 3-month measurements are 100%, 30%, 6%, respectively, by using regression model. It is shown that the time-resolution of measurement can significantly influences the results in regression model.

Kucukali et al. in [60] propose an annual electricity forecasting model by using fuzzy logic approach to compare with regression model and time series model. The data in fuzzy logic model will be transformed from fuzzification to defuzzification reciprocally, and the boundary was set by the history load or from experienced experts in order to be utilized in IF-THEN rules. The errors were calculated as 3.9%, 5.3% and 7.3% for fuzzy logic approach, regression equation and time series methods, respectively. The validation shows that fuzzy logic method is a better solution in annual load prediction than regression and time series models.

In the past decade, many researchers have applied ANN to build artificial intelligence models in the prediction of building energy consumption. It has been proved that this type of intelligence model can be self-learned from various related factors, especially in solving non-linear issues [54]. Xiao et al. in [61] represent the short term load forecasting with rough set to wipe off the influence of noise data and weak interdependency data. With the rough set of Back Propagation (BP) neural network, it is believed that the method is better than the individual BP neural network and can achieve more accuracy. Beccali et al. in [62] detail a forecasting model based on an Elman`s neural network, the model is designed to predict, one hour ahead, the intensity of the electric current supplied to household users. Both weather data and electric intensity data have been used as input factors, and the MAPE is about 3.1%. The report also points that the humidity index is another importance for the evaluation of the household electricity consumption. Lopes et al. in [63] present a neural network based on the ART architecture (adaptive resonance theory), named fuzzy ART&ARTMAP neural work, it is adopted in the electric load-forecasting problem. This neural network has two remarkable performances; stability and plasticity (represents the capacity of learning new patterns without losing the memory or the patterns already trained). It aims to decrease the inaccuracy of the predicted results by a mechanism that distinguish the analogy and binary data, then process outputs individually. Also, it provides a significant decreasing on the processing time and enhanced outputs, when comparing with the Back-Propagation neural network. A number of important factors for electric load have been described, such as cloudy days, wind velocity, sudden temperature variation and non-conventional day effects (weekend, national holiday, strikes, etc.) , and the MAPE was only 1.62%.

In the application of building energy consumption prediction with ANN, it can be found that most methods are focused on short term (one hour to one day) and long term (one month to one year). Because these time-resolutions are quite low, ANN in these models can significantly neglect the influence of people behaviour and briefly concentrate with related factors, like weather conditions and history average data, therefore, the desirable results can be produced with very low MAPE. Meantime, ANN model in energy consumption prediction is using all relevant uncertain factors to predict one particular result. The algorithm of ANN is to generate most optimized output which is based on selected various inputs. However, the behaviour of people is quite random, which is a type of uncertain element. Although there is a literature [55] has proved around 93% outdoor human mobility can be predicted, nobody has published that if the indoor activity of the occupant can be predicted or not. Thus, it seems that using ANN in high-resolution building energy consumption is not ideally possible, which is needed to be proved.

In the reviews of these non-occupancy related prediction methods, it has been found these models are mostly static except ANN. The advantages of static prediction approaches are mainly identified as low cost, easy setup, and effectively forecast average energy demand from short term to long term. However, the static prediction scheme based on mathematical algorithm only contains single prediction model which has identified the relationship between the input-possible influence factors and output-energy demand, and cannot be changed since it is built up. The model cannot capture the recent data and update it automatically, because it is fixed. Moreover, a huge volume of historical data has been included in these models in order to achieve approximately real energy demand, and the data collection also including operational time are very difficult to handle for building the model. Furthermore, if the current building environment has significant modification, like appliances or occupancy change, the former prediction model is no longer effective or useful, because the relationship is altered.

Therefore, in order to predict domestic electricity demand in accuracy, like high-resolution load profile, it is very important to consider the system parameters dynamically, such as appliances and occupancy behaviours.

B Occupancy related methods

Daily appliance use in a domestic dwelling is highly dominated by the active occupants. The preference of occupant has significant impacts with the switch-on event for each appliance. To address these impacts and better understand electricity consumption, one possible solution is to use Time-Use data by assuming consolidated appliances for each investigated household. An example is Time-Use Survey (TUS) with 10-min resolution in 24 hours and collected from only two days including weekday and weekend which has been presented by UK government in 2000 [21] for thousands of households. Time-Use data can briefly depict the occupancy activity and generate the overview electricity demand for thousand households. However, TUS data only contains incidental occupancy activities which happened in one single day, so it cannot be used for particular household and always have an overestimation of electricity consumption.

On the other hand, high-resolution like below 1 min data including occupancy profile and load record is another known challenge which requires large amount data to describe occupancy activity and depict load fluctuation in recently years. Normally, there are three different solutions to generate detailed high-resolution occupancy profiles, which are TUS data, sensors and smart meters. However, firstly, the daily occupancy activity record with high-resolution will tremendously interrupt normal life of occupancy, where people should take notes for every activity, and it can deviate and delay preliminary action unsurprisingly; secondly, sensors can detect occupancy mobility but cannot provide specific appliance usage; thirdly, smart meter technology only offer the total electricity consumption and cannot recognize particular switch-on event of appliances. Therefore, the high-resolution real-time occupancy profiles are not ideally possible to be captured or recorded currently.

In order to reduce the influence of occupancy behaviour, “bottom-up” models are employed by many researchers, which can break down the electricity consumption to different single switch-on event. The most commonly bottom-up model developed by Capasso [64], which combined detailed related factors to present the electricity consumption of an arbitrary number of households, is cited by most researchers in recent years.

Similarly, complex bottom-up models like Patterro [65] using large amounts of input data and particular assumptions to stochastically determine the hourly electricity consumption. These models are complex and both of them did not concern the behaviour of occupants which is quite important in electricity demand prediction. Another bottom-up model developed by Yao [7] simulating the hourly building energy load profile by analysing different occupancy patterns and particular components of energy appliances, like electrical appliances, domestic hot water, space heating, etc.

These bottom-up approaches analogously adopt Time-Use data to identify the installed proportion and usage possibility of each domestic appliance then generate more accurate overview electricity demand for domestic end-users. However, because of the imperfection of Time-Use data, which only contains few days pattern, these methodologies cannot track the trend of occupancy activities. Because it requires a large amount of data sets including daily occupancy profile and detailed appliance use.

In addition, these models focus on short-term energy profile prediction show that by adding various relevant input factors and particular assumptions, hourly energy load profile can be generated randomly for arbitrary households. However, demand side management requires more specific electricity load detail, such as minutes load even second load to optimize the system performance, like time-shifting approach to delay or forward electricity use.

Therefore, advanced methodology such as bottom-up combined Markov-Chain in Widen`s model [66] and bottom-up combined calibration in Richardson et al. model [25] are developed in order to address detailed electricity consumption with high-resolution, like 1-min. These models shows the synthetic electricity demand data can stochastically present the electricity use of end-users by using Time-Use (TU) data which involves detailed occupants activities, and the aggregate simulation results show well comparison with measured data in validation.

Richardson et al. [38] modelled 1-min resolution occupant status, which marked as active and inactive, based on UK Time-Use data with non-homogeneous Markov chain, and the validation in Richardson model has shown the Time-use data can be used to generate stochastically synthetic occupancy presence. Widen model in [66] combined bottom-up method with Markov-chain to model domestic lighting demand with three-state in 1-min resolution, and the transition probabilities are also determined from a detailed set of time-use data in Swedish households, also the model adjust the parameters to make the load curve to fit the real measure loads.

Widen model is extended and improved in [15] to generate synthetic occupancy patterns and related electricity consumption by using Markov-chain combined with bottom-up methods with various appliances presence, the model still used time-use data in Sweden as primary resource to generate 1-min resolution domestic electricity demand with concerned detailed appliances and sharing activity of occupancy. These models have proved time-use data which presents detailed occupancy activities has advantage aspects in high-resolution modelling like 1-min, and the results can match well with original data from the validation.

However, the time-use data, which has widely used in these models, are collected from thousands of households and recorded only in one or two days. Firstly, these data cannot present the consecutive occupants activities, which can describe the favourite behaviour of each occupant in particular household. Secondly, occupancy behaviours are frequently changed by many reasons, such as weather condition, employment, holiday, illness. These time-use data also cannot be identified these variations. Last by most important, the time-resolution of current time-use data is lower than nature of appliance use, the switch-on events of electrical appliances are frequently occurred in seconds, the 1-min or 10-min resolution cannot capture the variation of appliance use. However, perhaps unsurprisingly, high-resolution below 1-min occupancy activities profiles require significant amount data and significantly influence the occupancy normal life are not ideally possible currently. Therefore, synthetic occupancy activity profiles blow 1-min resolution is very crucial and of considerable benefit in the context of energy-use modelling [38].

With the discussion above, it can be clearly found there is a research gap in high-resolution electricity demand prediction for particular household, which is to dynamically identify the individual occupancy profile. Traditional TUS data can only provide average national possibility of occupancy activity and not for single household, especially within consecutive occupancy profiles. With the limitation of real-time occupancy profile generation, it is very important to develop a novel method which can generate synthetic occupancy profile to replace real one in domestic electricity demand prediction.

2.3 Domestic heat demand analysis and prediction

2.3.1 The feature of domestic heat demand

Domestic heat demand is highly related with house design, household`s size, climate, and the efficiency of its heating systems including space heating and domestic hot water, etc. [7], and unlike electricity demand vary from occupancy, these factors are usually fixed physically for particular households. Therefore, the heat demand of UK households can simply be categorised in two domains: house heating demand - outside and occupancy heating demand - inside, the first one can be represented by a rating system launched by UK Government which known as Standard Assessment Procedure (SAP), and the later one concerns the internal environment in the house, which can be depicted as thermal comfort.

A Standard Assessment Procedure (SAP)

The SAP system is adopted by UK government to assess the energy performance of dwellings by calculating the following factors [67]:

- Materials used for construction of a domestic building
- Thermal insulation of the dwelling fabric
- Air leakage ventilation characteristics of the building and ventilation equipment
- Efficiency and control of the heating system(s)
- Solar gains through openings of the domestic building
- The fuel used to supply space and water heating, ventilation and lighting
- Energy for space cooling, if applicable
- Renewable energy system or technologies
- Climate data
- Household sizes

- Heat loss

The Calculation in SAP system is based on energy balance taking into account the listed factors which contribute to energy efficiency [68]. Also, each factor which is related to the particular feature of the domestic building is calculated independently in rating system, such as: household size, ownership, efficiency of electrical appliances, individual heating patterns and temperatures [68]. Official housing stock assessment is published by Energy Saving Trust for UK households with newly version in 2011 [69]. A large number of dwellings is investigated and calculated, and related SAP profile is shown in Fig. 2.5.

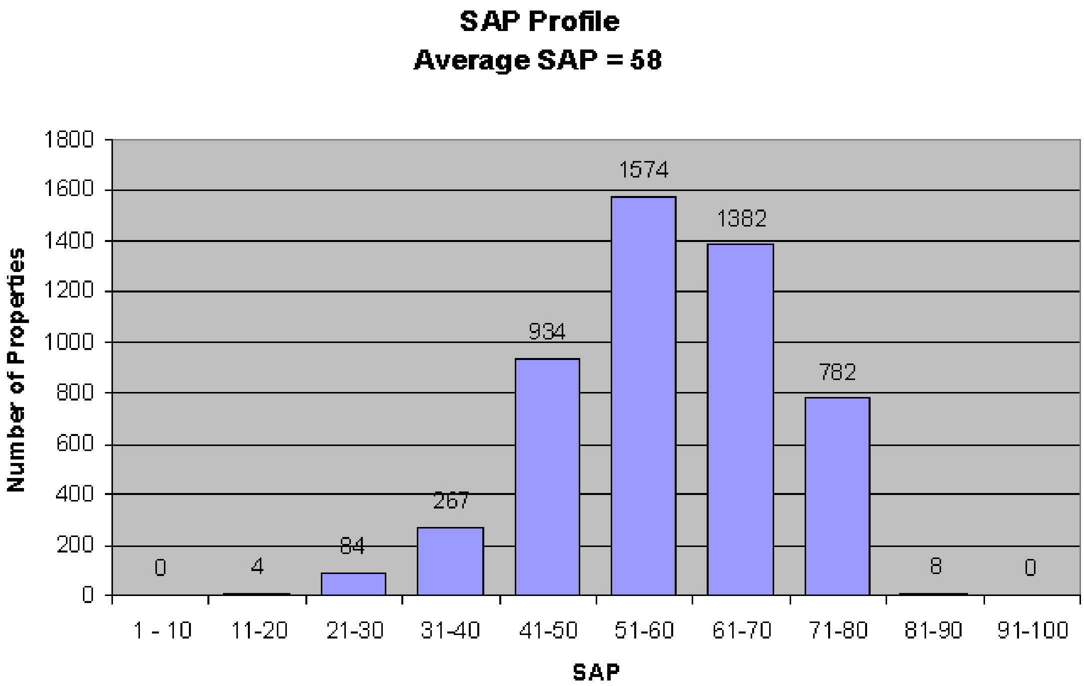


Fig. 2.5. An example of SAP profile for thousands participated UK households in 2011 [69].

The SAP system provides a range scale of 1-100 for each investigated dwelling after calculation, the dwelling with a high number mean the running cost is low. From Fig. 2.5, the majority of this housing stock has a SAP rating of between 40 and 70, with only about 7% of dwellings with SAP ratings below 40 and very few with over 80. The average SAP value was 58 in 2011.

In order to quickly understand the energy efficiency of dwelling, the SAP energy rating on Energy Performance Certificates (EPCs) are categorised into seven bands, from A to G, similar to those that are used for energy efficient appliances. Therefore, SAP energy rating profiles are now often presented to show the breakdown of stock into these seven bands, which is shown in Fig 2.6. The most energy efficient dwellings with lowest energy cost are in band A, and band G is the group of properties that have least energy efficient appliances and have highest fuel bills [70]. An example of listed properties in Fig. 2.6 is shown the majority of UK dwellings are band E and D, and the average SAP is 58. It can be seen clearly that the potential improvement of energy performance for UK dwelling is enormous. There are over 40% properties in UK have lower energy efficiency, and the SAP of around 80% dwellings have a lower rating under 70.

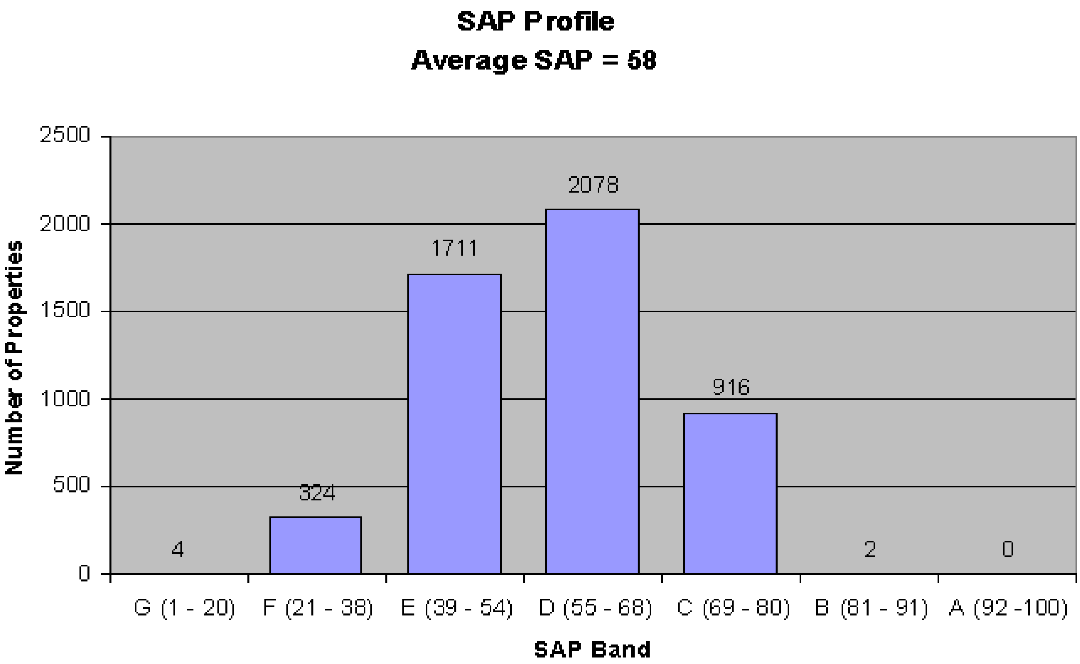


Fig. 2.6. An example of SAP energy rating on Energy Performance Certificate for UK households in 2011 [69].

On the other hand, the SAP rating calculation is highly depended on the age of property, over 40% of UK properties which are built pre 1919 have a SAP rating of less than 41 [71], and even 9% properties in England have a SAP rating below 30 [72]. Accordingly, 60% of the newly built dwelling since 1990 have a SAP rating greater than 70. Meantime, the higher SAP rating means lower CO_2 emissions, therefore in order to achieve the target of CO_2 emission reduced 80% by 2050, it is very important to rebuild the energy system of these properties which have SAP rating lower than 70. It means the innovate technologies such as renewable energy within micro-CHP system and solar PV, will have great potential market in the near future. This revolution can also be seen from the comparison of SAP profiles between 2009 and 2015 as depicted in Fig 2.7. The average SAP is increasing from 58 in 2009 to 66 with the hypothetical profile in

2015. However, even with optimistic estimation in 2015, there are still a few dwellings with SAP rating under 50, and around 20% properties with SAP rating below 60. This phenomenon shows the tough target to treat these old homes, which should be need special consideration for these unachieved dwellings with how to improve related energy rating to a reasonable level [69]. Also, it has been proposed that by 2050, the mean SAP rating should be improved to 80 (the level of new building after 2010), and also make sure all existing dwellings have a SAP rating greater than 58 (average in 2011) [73].

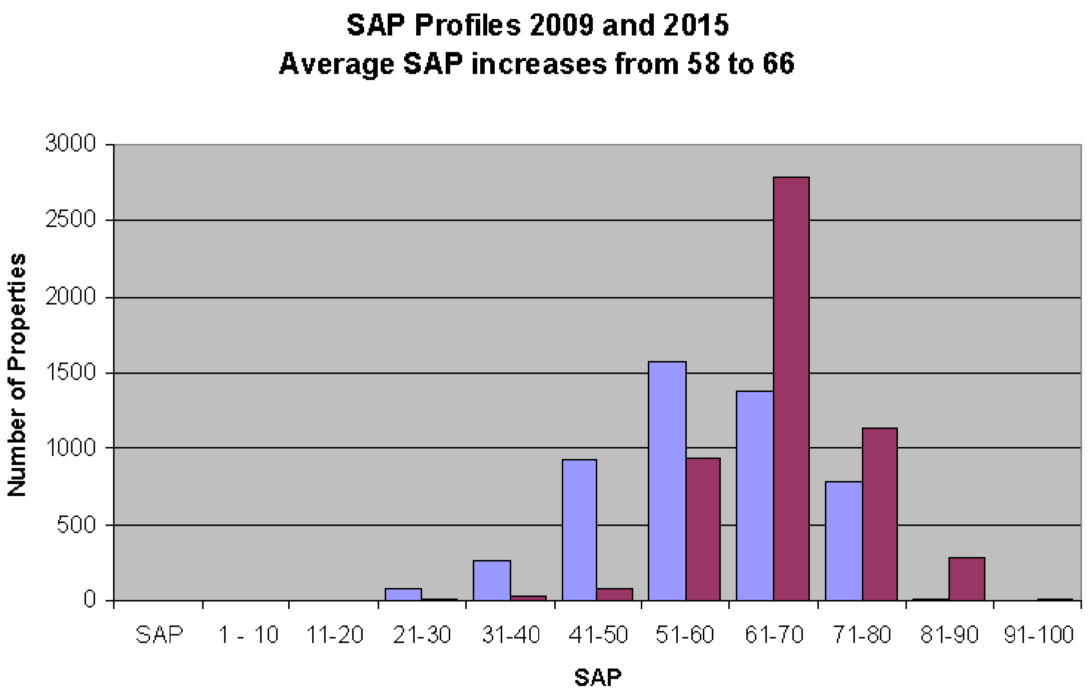


Fig 2.7. A comparison of SAP profiles between 2009 and future prospective in 2015 [69].

B Thermal comfort

Thermal comfort is defined in British Standard BS EN ISO 7730 as: '*that condition of mind which expresses satisfaction with the thermal environment*.' [74]. Thermal comfort is an internal indicator which can describe the psychological state of people. It refers to the indoor temperature of the environment which is not detrimental to their health but can make people feel comfortable, not too hot or too cold [74].

Thermal comfort varies from person to person in different age groups. The comfort level temperature of an adult is lower than elder persons and children. As a reasonable expectation, the number of people over the age of 75 is increasing as fifty percentage rating by 2031, which requires longer period heating during the dwellings are occupied and higher average indoor temperature to make them feel comfortable [41].

Meantime, the comfort temperature is highly related with climate change and building energy efficiency, with the global warming and new efficient technologies applied in domestic dwellings, the internal of temperature of domestic dwellings rose from 13 ℃ to 19 ℃ in the period from 1970 to 2001 [75]. Another investigation depicts the average internal temperature of majority households are 19 ℃ in 2010, varying from 18 ℃ to 22 ℃ [76]. Therefore, an acceptable, comfortable level of internal temperature is adopted as 21 ℃ for living rooms and 19 ℃ for all other areas of UK households.

2.3.2 EnergyPlus

Reducing energy consumption of domestic dwellings is a critical issue in terms of the growing greenhouse gas emissions and energy expenditures. However, analysis of domestic energy consumption is a tough task as it requires detailed relative factors among the buildings type, internal energy system, weather conditions, construction materials, and occupancy activities. [77]. Unlike with electricity consumption, heat consumption is quite difficult to be recorded or measured, because it is consisted by space heating, domestic hot water and thermal comfort of occupancy, which are continuously varied by indoor and outdoor temperature.

However, as the previous discussion, heat consumption related "fixed" factors, such as house design, household`s size, climate, and the efficiency of its heating systems including space heating and domestic hot water, etc. [7], it is therefore easy to simulate by proper methods because of its less randomness.

In the past four decades, many researchers and engineers have developed various models in the simulation of building heat consumption, like Computational Fluid Dynamics (CFD) [78] and EnergyPlus [79], which are the most popular methods to evaluate building energy consumption for both industrial and domestic [78], especially before building construction and retrofitting [80]. CFD and EnergyPlus are known effective approach for predicting various heat parameters, such as space heating, solar gain, thermal comfort, indoor air quality, heating, ventilation, and air conditioning (HVAC) system performance, etc. in different types of dwellings [81].

In addition, CFD method is mainly contributes to evaluate ventilation and environment of buildings [82], and EnergyPlus, which is the U.S.DOE building energy simulation program, is a type of engineering prediction tools and widely employed in the building energy consumption for modelling building heating, cooling, lighting, and other energy flows [83]. Therefore, in the application of heat consumption prediction, EnergyPlus program is the primary selection for both commercial and domestic buildings.

DesignBuilder is a type of modelling software which using EnergyPlus simulation engine, it provides a range of environmental performance data including hourly or sub-hourly heat and electricity consumption, internal comfort, solar gain, and HVAC component size. [84]. The users can friendly model whole buildings stock with visualisation and OpenGL EnergyPlus interface, and by input individual occupancy profiles of domestic building, related internal temperature, surface temperature, solar gain, radiant heating or cooling, thermal comfort level, energy and power costs, can be calculated and represented hourly or daily by DesignBuilder with EnergyPlus simulation [82].

DesignBuilder is a type of powerful software which can significantly model statistic energy consumption for domestic dwellings. Consider with lowest time-resolution of DesignBuilder is sub-hourly. It is, therefore, used mainly for heat demand calculation and prediction. The most models in DesignBuilder is using fixed occupancy profile to simulate energy consumption currently, but demand side management requires dynamic heat consumption results and also related energy demand should be predicted accurately, therefore, detailed and dynamic occupancy profiles are needed to replace particular fixed patterns then generate dynamic energy consumption results.

2.4 Control system design and analysis

2.4.1 Control system overview

The tri-generation system has a series of advantages, i.e. high efficiency of primary energy generation, reduction of greenhouse gas emissions and a lower cost of energy services. With these benefits applied in general units, there are two significant issues should be considered: the synthesis of system configuration which including system capacity and scale, and the operational strategy which contains control planning, energy flow rates and electrical loads [85]. These issues should be concerned for a new trigeneration appliance, but for a particular well-defined trigeneration system, the control strategy is the only issue which should be tackled.

Control valves are the most popular terminal control appliances in the industry. A study in analysing the effect of friction in control valves is presented in [86],eight different models including four physical principles and four empirical ones are designed and implemented in Simulink/Matlab, by comparing the different friction coefficients and input signals, the behaviour of the values is involved the operating in open loop. Synthesis of general control system involves a number of valves and controllers, such as Proportional-Integral-Derivative (PID) controller, Electronic Expansion Valve (EEV) and Programmable Logic Controller (PLC). The multiple valves and controllers are utilized in various systems to fulfil the desired functions (e.g. cost, energy efficiency).

- PID: PID controller has been used diffusely in engineering systems in the past decade, such as process control, motor drives, magnetic and optic memories, automotive, flight control, instrumentation, etc. [87]. A number of studies have been developed with PID controller including linear and nonlinear. Roskilly et al. [88] presented a robust PID controller for robotic manipulators. Piazzi et al. [89] developed a noncausal approach for PID control to solve the shortage of PID controller which shows it is difficult to achieve the desirable performances both in the set-point following and rejecting the load disturbances at same time. Su et al. [90] promulgated an enhanced nonlinear PID (EN-PID) controller that presents the advanced performance than the traditional linear fixed-gain PID controller.
- EEV: Electronic expansion valve can calculate the evaporator outlet pressure and temperature, and also the measurement of outlet superheat at a particular set-point value can be adjusted. There is a novel research by using EEV for deriving high-performance, adaptive control algorithms in finned-coiled, dry-expansion evaporators for refrigeration systems [91]. In this case, the author derived and implemented a detailed distributed evaporator model based on finite volume spatial discretization in a particular simulation environment.
- PLC: PLC is an advanced appliance which can be programmed by a technician to determine the requirements levels and the related time of equipment. PLC program is typically designed for regulating the interaction between the physical inputs and outputs of the pumping applications in most manufacturing systems. Abdallah In [92] shows a PLC control implementation in a medium capacity controlled heating system, which is designed and regulated by using PLC and frequency control, and the whole control system is operated by internal temperature from zero to maximum and from maximum to zero for the required range of time. A control system of the

cryogenic facility for JT-60 NBI system is presented in [93] by utilized the PLC and SCADA (Supervisory Control and Data Acquisition) systems. In this case, PLC is proved that it can be suitable for a large scale control by optimizing the function block diagram structure in the programming.

Therefore, with the boundary of in designing the control strategy from minimized to maximized depends on the energy demands (heating, cooling and electricity). For each subsystem in a particular trigeneration unit, various valves and controllers can be employed diffusely according to the temperature of stream and exhaust gas, also including the electrical loads.

2.4.2 Engine and thermal control system

Temperature feedback is the main issue which must be concerned in the design of engine and thermal control system. Considering the complex and flexibility of a particular thermal system, PID controller is more advanced in regulating the rate of flow for the reheating stream in the control loop. In addition, PLC can collect the temperature feedback of the PID controller and monitor the start-up and shut-down functions. However, many significant issues have not been well identified in the literatures. Every PID controller requires a series of settled parameters based on the experimental data which cannot be modified when the PID controller is chosen. Moreover, the fault tolerance is also another weakness for the PID controller, if one of the valves does not work correctly, the whole system will be suspended. In the last ten years, the emergence of automatic tuning and use of model predictive control require well-tuned PID controllers at prime level.

2.4.3 Electrical storage control system

There is a trend for using a super capacitor as the electrical storage in engineering systems in recent years [94-96], such as voltage sag compensator and intermittent renewable storage. The super capacitor can supply energy storage for the sudden load and some uncertain requirements. The energy density of the super capacitor is more powerful than the traditional capacitors and batteries, and super capacitor is already utilized in motor drives, Uninterruptible Power Supply (UPS) systems and electric vehicles [96]. The author in [96] presented a fuzzy logic control strategy to generate the power command for the super-capacitor bank (SCB), the configuration of SCB is proposed in Fig.2.8, followed two types of control strategies, the primary control which satisfies the power command, the secondary control which supply triggering pulses for the buck-boost converter.

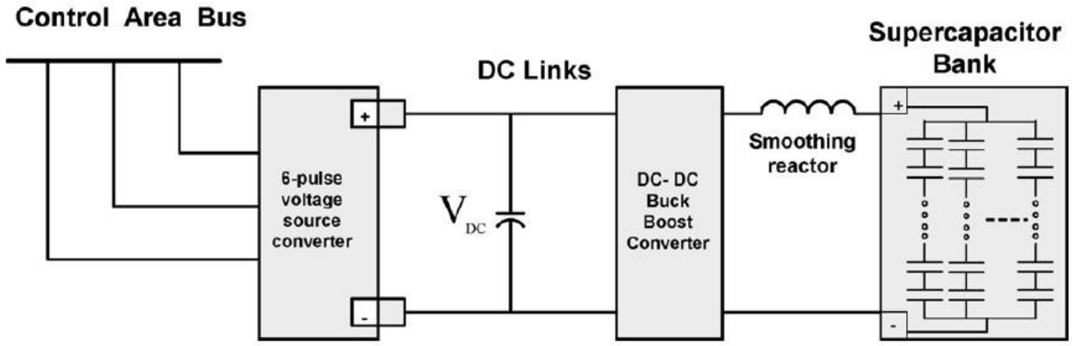


Fig. 2.8 Configuration of super-capacitor bank in a control area [96]

The state of charge (SOC) is a significant issue in the control of electric/hybrid storage applications. A method for reducing the measurement noise model and data rejection of Kalman filter (EKF) is presented in [97], which can improve the estimation of SOC and also revise the model errors in terms of the nonlinear behaviour of battery. Blood et al. in [98] present an electrochemical experiment in order to characterize the SOC of lead-acid battery in term of its potential plate production quality control and battery conditions. A new SOC estimation method is presented in [99], which can eliminate filtering divergence resulting from dubious to correct for the initial value by employing the adaptive Kalman filtering.

2.4.4 Refrigerating control system

Cooling in a typical trigeneration is aims to recover the waste heat where is provided by the exhaust gas. In term of the growing warm climates, the cooling demand in summer is the predominant energy usage in various buildings, such as school, office building, hospital and hotel. An investigation for cooling strategies on thermal performance is addressed in [100], by describing the building and other parameters, cooling strategies combined the pre-cooling and intensive night cooling are presented. In this case, it has been proved that for a building in warm climate regions, the improved cooling control strategy can decrease cooling demand which is lower than expected while working hours.

2.4.5 Optimization control system analysis

For a typical trigeneration in a mature energy market, system size, system performance, energy price (subject to high variability and volatility) and the quantities of energy services demand (daily and seasonal alterations) determine the profitability of the operation. Most literature studies in the optimal control strategy of the trigeneration system always utilize a set of variable loads depicted by employing the temporal evolution of thermal, electrical and cooling demands [100]. Steady-state and set-point are the most important issues for the methods of continuously operating processes by using linear control models, such as Real-time optimization and Model Predictive Control (MPC). However, the application of nonlinear MPC is very limited for the transient processes (e.g. batch processes, continuous processes) [101].

Most studies or practices have proved that input, output and state constraints are the most important elements which have been diffusely employed to develop a series of control design methods in linear systems. The stability, desirable performance and constrains of these systems have been identified by a nonlinear control law. In recent years, there is the most popular standard for constrained multivariable control method in related linear systems, which is MPC or simply MPC in the process industries.

During the MPC working period at every sampling time, it can gather feedback of the present measurement or system state and resolve the open-loop optimal control problem in a limited time horizon to identify the operating sequence of values for control system in the future. Therefore, control procedure will be a reiteration after the first sequence is identified at each sampling instant.

Control emphasis is disparate on each element for every application, indeed, for the same application, the control emphasis is usually diverse for operations from time to time. Lu in [102] developed an explicit triangle coordinates to represent the control emphasis as shown in Fig. 2.9.

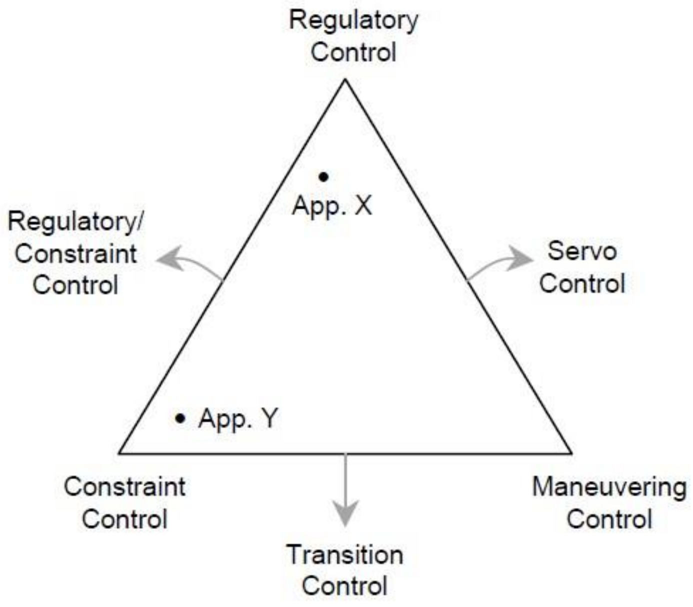


Fig. 2.9. Control emphasis description [102]

In Fig.2.9, every vertex of the triangle presents a “pure” form of control, and each side defines a combination of two controls. Moreover, each point inside the triangle indicates a combination of three types of controls with independent relative emphases. For example, because of the unique set of objectives under particular different operations, the control strategy of the application X may not suitable for the application Y in the triangle. However, in a typical integrated system, the various control strategies will be chaotic, so there is a significant demand for developing a method to conclude all three control emphasis into one control procedure; therefore, MPC is introduced and proposed before each “pure” control is clarified the problem [102].

Before developing the MPC framework for a particular system, the structure of the control system should be analysed and discussed. Tatjewski in [103] describes a functional multiplayer control structure implemented by distributed control systems (DCS), which is presented in Fig. 2.10.

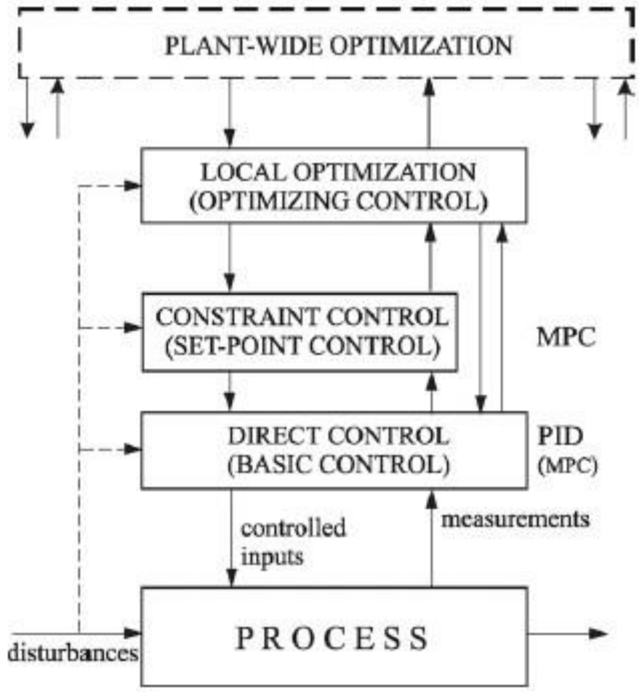


Fig. 2.10. The hierarchical control structure [103]

Safety is the most important issue for the control system, same as the quality of a product. The fundamental safety of dynamic control procedure in the production is determined by the direct control layer or basic control layer. The direct control layer composes the various controllers or valves, which is the only connection to the production, also with the input variables.

Many literatures have presented the robust and auto-tuning control strategies, such as [104]. PID controller as its advantage in acceptable stable performance is still dominant in the basic control layer. Also, modern DSC systems can provide a series of computational advanced approaches comparing with the limitation of PID performance, advanced control algorithms have been designed and implemented by modified PID in the particular MPC algorithms.

Constraint control or set-point control in the higher layer is depicted by advanced feedback controllers with the set-point values. For the multivariable and non-linear processes system, the set-point control algorithms should manipulate with high control performance. The impact of the constraint control layer is directly connected with the development of basic control algorithms and local optimization control algorithms. However, seldom literature has mentioned the distinction between the direct control (basic control) layer and constraint control (set-point control) level. With the development and widely usage of DMC algorithm and other MPC type algorithms in current industries, there is a potential demand for separating the advanced control and basic control, which has been minutely presented in [105].

In addition, it should also be noticed that the constraint control layer cannot be always operated if there is no demand for the set-point control layer. Moreover, this layer cannot fully isolate the direct control layer from the optimization layer—as is depicted in the structure of Fig. 2.10. Meantime, optimization of set-points for feedback controllers is responsible for the performance of the next level of the hierarchy, the local optimization layer, which is directly above the regulatory control.

In [106], the author details a networked linear MPC approach based on neighbourhood optimization for a set of continuously linked processes. By utilizing the predictive state observer, the flexible errors of the structure of the sub-process can be corrected primarily during the modelling. Another study has utilized genetic and sequential quadratic programming algorithms to tackle the constrained optimization air temperature control issue [107]. For each sampling period (a prediction horizon of 1h with 1-min), set-point value is tracked, and effort of control is minimized by calculating the controller outputs [107]. Therefore, the future behaviour of a greenhouse environment in the north of Portugal is optimized. The greenhouse climate is described by the mathematical models, and also the controller should be responsible for predicting the greenhouse environmental conditions over a specified time interval.

A Optimization of Thermal control system

A multi-objective optimization problem is presented by Fares et al. in [108] to identify the optimal layer thickness and optimal closed loop control function for a symmetric cross-ply laminate subjected to thermo-mechanical loadings. An optimization procedure is designed to maximize the critical combination of the implemented boundary load and temperature levels and to minimize the laminate dynamic response subject to constraints on the thickness and control energy.

A novel formulation of multi-objective corresponding power and voltage control for power system is specified in [109]. In this study, the load boundaries and operational boundaries are considered to obtain the power loss, voltage deviation and the voltage stability index of the system. Mathematic formulation is detailed to deal with the multi-objective formulation of the problem. Therefore, a pseudo-goal function is employed to eliminate the use of weighing coefficients. The inequality boundaries are applied into the fitness function by pseudo goal feature which guarantees that the selected optimal approach is suitable. An optimization approach, which aims to maintain a flexible and efficient method for the optimization and coordination of power system controls, is applied in a power system simulation software package is presented in [110].

B Optimization of Energy Storage control system

A composite framework for the optimal design and control of metal-hydride storage under hydrogen desorption operation is described in [111]. The features of this framework include a specified two-dimension dynamic process model, a design and operational dynamic optimization approach and a multi-parametric model predictive controller method. In this case, the mathematical model, optimization and dynamic simulation are also implemented by designing a robust MPC controllers and employing an optimized PI controller.

A novel control method, optimized by genetic algorithm, is presented in [112] to operate stand-alone hybrid renewable electrical systems with hydrogen storage. In this study, it is an aim to optimize the control of the hybrid system, minimize the whole consumption and optimize the usage of the spare energy. When the amount of energy load is higher than the demand which generated by the renewable sources (wind, PV and hydro), the control strategy will provide the most economical approach to satisfying the energy deficit.

C Optimization of cooling control system

For the cooling or refrigerating system, there is an enormous potential demand to depress the operating cost and increase the energy efficiency with advanced control method. An adaptive optimal control model for building cooling and heating sources is presented in [113], optimization control strategy is implemented for the building cooling source system in a commercial building in Changsha, China. This optimization control strategy can reduce the energy consumption of the cooling source system by 7%. Yao Y et al. in [114] develop a mathematical model for the optimization operation of the cooling system, which based on the energy analysis of the primary dynamic appliances that consists of chillers and pumps. In this case, a term named “System Coefficient of Performance (SCOP)” is introduced to analyse the efficiency of energy usage of one central cooling system. Optimization issue is depicted minutely as the maximization of SCOP while providing the comfort conditions in the air-conditioning zones during the operation for the whole cooling system [114]. The optimal approaches deal with the condenser water flow rates and the chilled water temperature to ensure the desirable system energy efficiency, and the compatible optimal control model is consists of the optimal control model, parameter identification and optimal algorithm. The optimal control model contains the objective function and constraints, and the model for parameter identification describes each component in the optimal control model with fuzzy self-tuning oblivious factor method; genetic algorithm is employed to explorer the optimum values for the discrete and continuous variables [114].

2.4.6 Control system considerations and challenges

The feasibility and flexibility of the design of optimization control strategies are the primary concerns in a particular trigeneration system. On the other hand, economics also should be considered by comparing the various approaches, and only the one can be selected by satisfying the lowest cost of utility demands. Moreover, process operability as another important issue should be analysed. Grossmann in [115] considered that the operability relates to the capability of process, which should tackle the issues of flexibility, controllability, reliability and safety simultaneously.

The feasibility of control system concerns a process should be suitable for the operability including the undesirable outcomes and fulfil the criteria to ensure smooth operations. Flexibility is about the ability of control system to satisfy feasible operation as parameters vary. Steady state and set-point require the control system should be flexible within dynamic modifications [116]. Typically, the design of a particular control system is based on its general conditions/operating conditions, which are most likely to occur. However, this control system cannot dispose the sudden accident, if the process parameters have been amended, this control system will lose efficacy, and there will be some failures for the operation and the system profitability will be deprived.

An advanced control strategy can tackle more process conditions at a desirable level, and also it should have an additional capability to handle the unanticipated future changes and improve the system ability to operate more smoothly [116]. For a particular trigeneration system, the control system design is a very tough task, and various elements should be taken into account. An undesirable control system will not be able to obtain the best economic return and also lose in gaining the preferable system operability. The future climate change and human activities should be considered to satisfy the utility demands of each subsystem (power, heat and cooling). Over-design approach in control system is a possible solution to defeat these critical challenges [117], which can expand system size and amplify the range of operation with some process parameters. Therefore, the feasibility of control system is proved, and the control system is suitable for handling a wide range of operation conditions. Mostly, the over-design technique is more expensive and impractical, and it can be an alternative option for the design of control system.

2.4.7 Optimization control system implementation –WinCC

The control system for BMT system is implemented by Windows Control Centre (WinCC) which is a PC-based process visualization system invented by the company Siemens in Germany. WinCC is utilized as a stand-alone SCADA system or as a Human Machine Interface (HMI) for process control system, such as SIMATIC PSC7.

SIMATIC WinCC, which has been widely used in general control system implementation, is a PC-based operator control and monitoring system for visualizing and operating processes, system flows, machines and productions in all sectors [118]. WinCC has a simple single-user station through to distributed-multi-user systems with redundant servers and multi-site approaches with Web Clients with its powerful process interfaces and reliable data archiving. WinCC also provides the fault-tolerant solutions for instrumentation and control operation [118].

A PLC-based control system is presented in [119], which employed WinCC to monitor the dynamical industrial process. In this study, the PLC is primarily utilized for collecting process data and implementing auto-tuning PID controller as well as sequence control strategies. Wu et al in [120] introduce a stable and reliable Pu-Er Tea automated fermentation system by using Step S-300 and WINCC 6.0. An automatic control of Deep-Hole Chrome-Plated System basing on WinCC is presented in [121].The author employs WinCC to implement the communication between PLC and host computer. Tag has been set up by Step7-300 with an independent name, type and address, and the address can provide a one-to-one relationship between tag and a particular address in S7-300. WinCC is configured to dominate the control system. In addition, the product serial number is employed to provide the data query according to the customer demand and the data query weakness of WinCC.

Xiong et al. in [122] use WinCC to provide the testing circuit and acting switches of switch appliance flexibly, and also monitoring the dynamical testing process. The author depicts hardware architecture of the monitoring and control system, as shown in Fig.2.11.

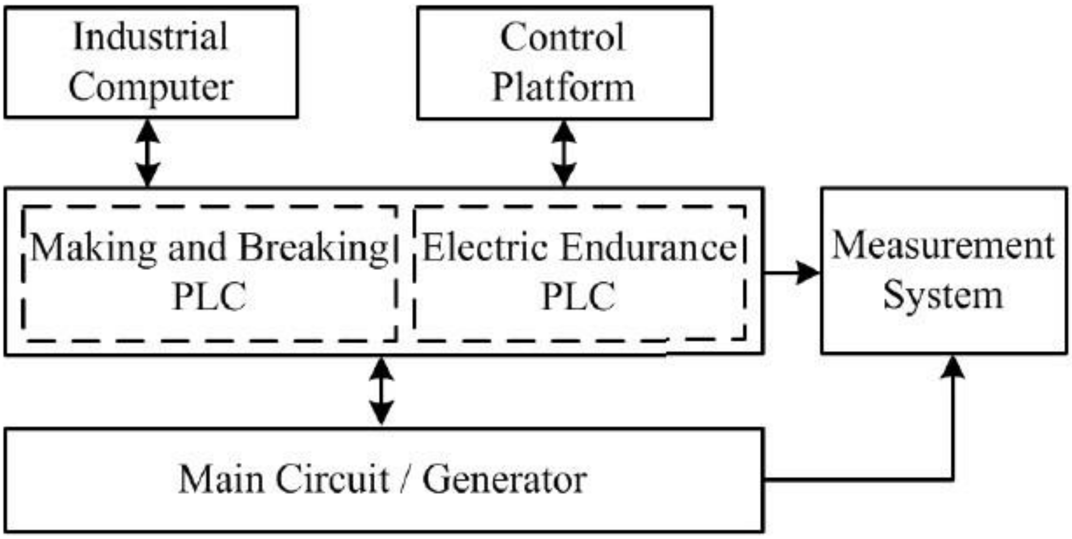


Fig. 2.11 Hardware architecture of monitoring and control system [122]

The industrial computer serves as general control computer and operated by WinCC, the operator can dominate a series of parameters for testing, e.g. type of product, power, duty, main circuit, time and action switch, and so on. PLC acts as the main controller communicated with the main circuit and generator. Indicator lights for each state are presented by the control platform. The result of the experiment indicates the monitoring control system with PLC and WinCC has high reliability, convenient operation, friendly interface and robust flexibility by operating successfully in a particular system.

2.5 Summary

This chapter has briefly introduced the feature of domestic energy demand in detail, especially for electricity and heat. It is known that the time-resolution of data and related occupancy profiles are the most important factors and difficult parts in energy demand prediction and analysis. Meantime, synthetic occupancy data in high-resolution and recorded occupancy patterns in low-resolution are two primary considerations which have significant impacts in both electricity and heat demand analysis and forecasting. With the output of energy demand, control system design and optimization strategies are also discussed.

Chapter 3. High-resolution synthetic occupancy profiles generation

3.1 Introduction

People may consume energy when they are active at home. Occupancy profiles, therefore, have a significant impact in the prediction and analysis of domestic energy demand. Also, because of the randomness and complexity of occupancy activities, accurate energy demand prediction requires high-resolution occupancy patterns. However, it is not possible to record people`s daily life in minutes because it can disturb the normal activities of end-users significantly. The highest resolution of Time-Use Survey (TUS) data [9] of UK to record occupancy activities of domestic households are based 10-min currently, which is not ideally represented occupant patterns accurately. Another solution is using smart meter to capture the appliance use, but the latest smart meter only can record the usage of electricity, not for capturing the use of appliances recently.

Therefore, specifically address the appliances use for electricity and heat demand, which can briefly represent how occupants spent their time at home, is a possible solution to replace real-time occupancy patterns. Consider with the frequency usage of both electricity and heat appliances, electricity appliances are selected as the primary concern to investigate domestic occupancy profile. TUS data can present overview appliances use of arbitrary household by using same occupant profiles, also with collective appliances set of thousand households. Therefore, it is selected as the most popular data sample in electricity demand analysis and prediction recently. However, occupancy profiles in different household are various. Average or random occupancy profiles applied in particular household will cause a significant difference in energy demand prediction and analysis.

Meantime, the efficient use of energy and demand side management for each particular household requires miscellaneous detailed electricity demand data. Therefore, it is imperative to be able to produce a simple model to analyse the appliance use of end-user for arbitrary household.

Although the high-resolution record of appliance use has same tough issue with occupancy profile, the load fluctuation can accordingly represent the switch-on event of appliance use. Meantime, load profile with low-resolution cannot present accurate appliance use. Therefore, it is critical to analyse high-resolution load profile in order to generate synthetic use of appliances to represent domestic occupancy profiles. The method estimates the highest possibility of switched-on events for most common appliances by analysing high-resolution load record to replace real-time appliance use.

Three participating households are involved in this study. High-resolution load records based on 5s with four seasons in a year are available for both of these dwellings, which is from Robert`s project [54]. This chapter presents the detailed analysis of electrical peak load for each household, and the synthetic use of appliances are described seasonally to represent related occupancy profiles for each property. Section 3.2 presents main related factors of domestic electricity consumption. Section 3.3 describes the calculation of average electricity consumption of occupancy for each household. Section 3.4 depicts the generation of high-resolution domestic occupancy profiles, and section 3.5 briefly summarized this chapter.

3.2 The feature of domestic electricity load

The feature of domestic electricity consumption can be categorized into following factors: (a) the composition of appliances; (b) specification consumption of each appliance; (c) the use of appliances; (d) occupancy patterns; (e) time resolution; (f) weather conditions. These factors are mainly presented in the following sections.

3.2.1 Electrical appliances

The type of electrical appliances is presented from Fig 3.1, which shows the most common appliances in UK domestic households and the appliances with proportion over 0.50 and mean cycle power over 100w (red part) are selected in this research. These appliances based on related occupant behaviour are categorized into following domains:

A Continuous and standby appliances

Continuous appliances contain a series of electrical appliances which are continuously switched on and consumed power consistently, such as clocks, alarms, broadband modems, cordless telephone, answer machine, and TV receiver box. Standby appliance including fridge and other standby appliance which are operating in standby mode when they are not in use. The total energy consumption of these appliances is typically fixed in most domestic dwellings, and it can be identified during an off-peak period when occupants are inactive. In this research, the average power consumption of continuous appliances for three participated households are 80W.

Appliance category	Appliance type	Dwelling configuration Has appliance? Randomise	Proportion of dwellings with appliance	Mean cycle length (m)	Mean cycle power (W)
Cold	Chest freezer	NO	0.163	14	190
	Fridge freezer	YES	0.651	22	190
	Refrigerator	YES	0.430	18	110
	Upright freezer	NO	0.291	20	155
Consumer Electronics + ICT	Answer machine	YES	0.900	0	0
	Cassette / CD Player	YES	0.900	60	15
	Clock	YES	0.900	0	0
	Cordless telephone	YES	0.900	0	0
	Hi-Fi	YES	0.900	60	100
	Iron	YES	0.900	30	1000
	Vacuum	YES	0.937	20	2000
	Fax	NO	0.200	31	37
	Personal computer	NO	0.708	300	141
	Printer	YES	0.665	4	335
	TV 1	YES	0.977	73	124
	TV 2	YES	0.580	73	124
	TV 3	YES	0.180	73	124
	VCR / DVD	YES	0.896	73	34
	TV Receiver box	YES	0.934	73	27
Cooking	Hob	YES	0.463	16	2400
	Oven	NO	0.616	27	2125
	Microwave	YES	0.859	30	1250
	Kettle	YES	0.975	3	2000
	Small cooking (group)	YES	1.000	3	1000
Wet	Dish washer	YES	0.335	60	1131
	Tumble dryer	NO	0.416	60	2500
	Washing machine	YES	0.781	138	406
	Washer dryer	YES	0.153	198	792
Water heating	DESWH	NO	0.170	20	3000
	E-INST	NO	0.010	5	3000
	Electric shower	YES	0.670	3	9000
Electric Space Heating	Storage heaters	NO	0.028	360	10200
	Other electric space heating	NO	0.026	240	2000
Lighting	Lighting	YES	1		

Fig. 3.1. The component of domestic electrical appliances [41]

B Cooling appliances

Cooling appliances like fridge and refrigerator have cycle capacity that reflect on daily load curve and been dominated by internal thermostatic temperature. Meantime, the working cycle of appliance is also described the frequency of opening and closing by active occupant. In order to avoid miscellaneous situation in load analysing, the effect of occupancy can be simply neglected. Thus, it is assumed that cold appliances have fixed load curve during a whole day.

C Active appliances with occupancy related

These appliances may be active when there is more than one occupant is active, and also the probability will be increased when the number of active occupants grown. These appliances include kettle, printer, personal computer, CD player, HI-FI, TV, Iron, electrical heating and lighting.

Cooking and cleaning activities are also related with active occupancy but have more sensitive with a particular period. For example, the most cleaning activities are happened during evening peak time, because the occupants normally do not have plenty time in the morning. Cooking appliances include microwave, oven and small cooking, and cleaning appliances contain the washing machine, dish washer, vacuum, respectively.

Meantime, majority entertainment appliances have less contribution to energy consumption (compare to appliance with load above 100W), such as Stereo, HiFi, and CD/DVD player. The load of these appliances are summarized into Stereo appliance. TV appliance has been set with fix load and cycle length to generate the use of appliance separately.

D Heating appliances

Domestic heat appliances including electrical heater and shower are also considered in this research, but domestic hot water with electricity boiler is not concerned. It is also assumed the electrical heaters are installed in each bedroom.

E Other appliances

Cooking and cleaning appliances are selected from most common appliances in UK households, and dishwasher because of lower fraction is not considered in this research.

3.2.2 Occupancy pattern

The energy use is highly depended on the occupancy of household, including a number of occupancies, occupancies pattern and energy use behaviour. Occupancy pattern, which involves a series of factors, such as employment status, age group and lifestyle, is a type of useful information in terms of analysing and forecasting the use of energy. Energy use behaviour concerns the waste of energy use. In order to produce ideal prediction result, therefore, it is assumed that all of the occupants in this research have good energy use behaviour. It means the active electrical appliances should be switched off if not in use. Table 3.1 has listed the information on the occupancy of the three different households from Robert`s project [54], which are also investigated in this study.

Adult occupant has a significant impact on electricity consumption of household, such as most active appliances. Meantime, children consume less electricity, like fridge, light, and other appliances which may be operated. The electricity consumption of children is neglected in this research in order to produce ideal performance in electrical load analysing and prediction.

Household	**House 1**	**House 2**	**House 3**
Category	Mid-Terraced	Mid-Terraced (Large)	Semi-Detached
No of occupants	2	2	5
No of Bedrooms	3	7	3
Age groups (In years) >65		2	
30-40	2		2
2-10			2
<2			1
Employment (Adults)	Both adults in full-time employment	One adult in part-time work and the other is retired	Both adults in full-time employment
Lifestyle	Work and socially active	Work and restful retirement	Family based
Energy Supply	Central gas	Central gas	Full electricity

Table. 3.1. Details on the occupants of the households in this study [54]

In order to analyse the whole electricity demand of household, it is crucial to analyse the adult behaviour, similarly as occupancy pattern, which including the age of occupant, employment status, and daily life.

In the first, work and rest model for occupant in different age has a huge difference. For example, occupant over 55 years always wakes up early than the occupant between 30-40 years, because they are mostly retired and always getting up early. It means in these households the first peak time of electricity consumption in the calendar day will be early than other age group, and also same as the last peak time in the evening.

In the second, employment status has limited and separated the daily time of occupant. For the occupant who has a full-time job in weekdays, the house must be unoccupied during the working time, like from 9am to 5pm, same as occupant has a part-time job.

Otherwise, if there is electricity consumption during working hour in weekdays from history load, the occupant should be off at that time, which can be categorized as weekend pattern.

In the last, daily life has given the occupant daily favourite behaviour. Occupant prefers socially active means they choose to active outside rather than stay at home. Same as occupant is family based, because they have children, occupant spent most time at home rather than outside activity, especially in the evening time.

Therefore, from the analysis of occupant patterns, an overviewed electricity daily consumption and active profile of occupant for each household can be shown. On the other hand, because real-time detailed occupant profile is not available in this study, so it is imperative to generate synthetic occupant profile for energy-use modelling.

3.2.3 Weather condition

Occupant behaviour is changed seasonally, and different weather condition can also have a great impact on the particular occupant behaviour, especially in weekend. For example, occupant always choose to stay at home if there are heavy rains or strong winds, and also, hot weather will increase the frequency of use of kettle and fridge.

However, with an overview of whole electricity consumption in both of weekday and weekends for UK domestic households, particular weather condition has less impact than season change. Thus, in order to address the impact of the climate change on electricity demand, weather condition is categorised into four seasons by month in a calendar year. The classification of the season by monthly is as shown in Table 3.2, which are same as data set from Robert`s project.

Spring	**Summer**	**Autumn**	**Winter**
March, April and May	June, July and August	September, October and November	December, January and February

Table 3.2. Classification of seasons by months of the year [54]

3.2.4 Selection of load resolution

Historical load has a significant impact on analysing electricity demand and also with the occupant behaviour. Meantime, electricity consumption is highly depended on the data set resolution. For example, if the data set is formed as short-term (resolution less than one hour) or long-term resolution (more than a day), it should be historical average load, even including the very short-term data set as five minute resolution.

These types of demand records can present the general overviewed electricity usage but cannot describe the appliance use and occupant behaviour. Figure 3.2 has shown the load variations from three different time resolutions, which are 5s, 30s and 1 min, data set from Robert`s project [54]. From figure 3.2, it can be seen clearly the load records not only are missing due to increasing time resolution, and also the peak value is dropped accordingly. Meantime, partial switched-on events of appliance are hidden when the time interval is above 30s.

High-resolution electrical data set requires significant amount data and resource to collect which are ideally not possible in most current researches. However, the efficiency of energy use and optimisation of control strategy require accurate electricity data. Load record with above one minute time interval has covered and impaired the peak value of electrical load, which cannot be tracked to get the maximum of electricity use.

On the other hand, the missing and impairing peak value can mislead the system design and control side management, especially for tri-generation with energy storage system. Robert [54] has proved that the load resolutions below 5s, like 2s, 4s, are mostly same. It is considered with the possibility of related factors, 5s is a persuasive resolution which can be used to analyse the nature of the domestic load [54].

Figure 3.2 has shown the comparison between 5s, 30s and 1-min instantaneous load patterns during an identical single peak period. It can be seen 30s resolution can capture most peak load. Regard to real-time occupant activity, it is selected 30s resolution to analyse the average electricity consumption for each occupancy in these three households.

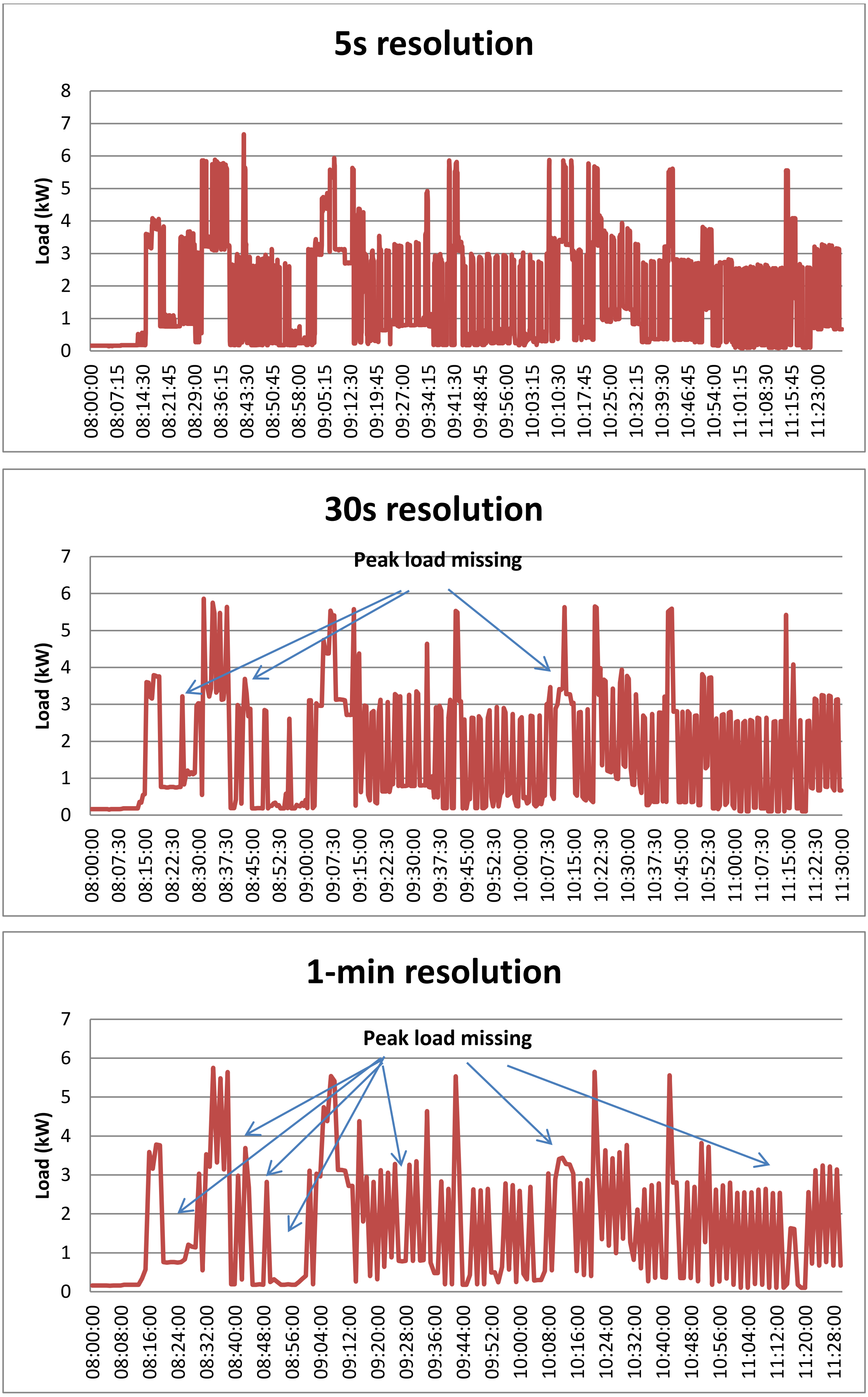


Fig. 3.2. The real load curve from three different time resolution, 5s, 30s and 1-min.

3.3 Average electricity consumption of occupant (AECO)

Active occupant is defined as "a person who is in the house and not asleep" [8]. When occupants are active in the house, they may use the electrical appliances or share with other occupants. Sometimes, they did not consume any electricity, for example, reading at summer afternoon, these type of conditions are neglected in this research. The number of active occupant at each particular period is the critical factor for analysing and forecasting electrical demand. Also, the number of switched-on appliances and in-use appliances are another significant issues in analysing domestic electricity consumption. However, the appliances in different household have a huge difference, of which are also unknown component in Robert`s project [54]. Therefore, it is very important to use most common appliances as shown in Table 3.3 to replace the real composition of appliances. These appliances are selected with above 100 W in UK households. The related load consumption and cycle length are set to a fix value via considered the average data from the literature [41]. For each appliance, two parameters are set to the mean value, which are Power (P) and cycle length (T). Therefore, it is generated hypothetical detailed list of appliances for this study.

Because of the complexity and uncertainty of occupant behaviour, it is not ideally possible to investigate and record how occupants spent their time at home within particular time interval, like thirty-second in this research. Meantime, appliance statuses including switch-on and in-use events are also not possible to record unless using smart meter to record every appliance. Therefore, generate synthetic occupant activity is paramount, which can help to understand the electricity usage simply and analyse the load effectively. In addition, high-resolution load record can present the most information of how people use electrical appliances. So it is possible to generate synthetic appliance status to replace the real one by analysing the load, which can represent the load variation.

By analysing the Average Electricity Consumption of Occupant (AECO), the hypothetical number of active occupant can be identified. It is defined the Average Electricity Consumption of Occupant as "the average of electrical load in certain time interval of each occupant". Also, the selected examples of households both have two adults, which are same as most common UK households. Thus, the AECO of households with two occupants have been presented in this study.

Appliance type	**Minimum mean power consumption (W)**	**Maximum mean power consumption (W)**	**Mean cycle length (Min)**	**Ratio of occupant use**
Continuous appliance	50	$P_{CONTINUOUS}$ = 80	N/A	0
Standby appliance	30	$P_{STANDBY}$ = 100	N/A	0
Fridge	0	P_{FRIDGE} = 200	T_{FRIDGE} = 100	0
TV	0	P_{TV} = 250	T_{TV} = 73	0.5
Stereo	0	P_{STEREO} = 500	T_{STEREO}= 60	0.5
Microwave	0	$P_{MICROWAVE}$ = 1500	$T_{MICROWAVE}$ = 30	1
Kettle	0	P_{KETTLE} = 2000	T_{KETTLE} = 2	1
Toaster	0	$P_{TOASTER}$ = 1000	$T_{TOASTER}$ = 3	1
Hob	0	P_{HOB} = 2400	T_{HOB} = 16	1
Oven	0	P_{OVEN} = 2200	T_{OVEN} = 27	1
Desktop computer	7.1	P_{PC} = 300	T_{PC} = 300	1
Washing machine	0	$P_{WASHING}$ = 400	$T_{WASHING}$ = 138	1
Iron	0	P_{IRON} = 1000	T_{IRON} = 30	1
Vacuum	0	P_{VACUUM} = 2000	T_{VACUUM} = 20	1
Electrical heater	0	P_{HEATER} = 3000	T_{HEATER} = 240	0.5
Lighting	0	$P_{LIGHTING}$ = 400	N/A	0.5
Electrical shower	0	P_{SHOWER} = 9000	T_{SHOWER} = 10	1
Total	87.1	25880		

Table. 3.3. Specification of most common electricity appliances in UK households.

Consider with the sharing activities, such as lighting, TV, Stereo, and electrical heater. It is assumed that these appliances are shared with all occupants. When calculating the number of in-use appliances, the ratio of these appliances are divided by the number of occupants. For example, for a two adults households, TV is shared as the ratio of 0.5.

Other appliances, like microwave, vacuum, etc. are operated by occupancy independently. The ratio of occupancy use for these appliances is 1. When generating the detail of in-use appliances, the total number of appliance use is summarized by adding related ratio of occupancy use.

3.3.1 Non-active occupant of AECO

In order to address occupant behaviour accurately, it is crucial to find out the maximum load during the unoccupied period, such as sleeping time or working time. This type of load is consisted by continuous appliance, cold appliance and standby appliance. $P_{ZERO\text{-}OCCUPANT}$ can be calculated and observed clearly from load record, as shown in equation (3-1), which is from 0.08 kW to 0.35 kW of participated households.

$$P_{ZERO-OCCUPANT} = P_{CONTINUOUS} + P_{STANDBY} + P_{FRIDGE} \quad (3\text{-}1)$$

For every time step $i = 1\ldots M$, if load P_i is below $P_{ZERO\text{-}OCCUPANT}$ at time i (from 00:00:00 to 24:00:00 for every 5 seconds in each weekday, where M is equal to 17280). Therefore, it is assumed that there is non-active occupant at home or they are asleep. It does not mean the real occupant status in the household, because sometimes occupants were active but they did not use any electrical appliances, or occupant use some appliances with lower load when fridge is in sleeping cycle. This type of effect is neglected in this research. Therefore, the number of active occupant N_{ACTIVE} at time i can be similarly determined from (3-2)

$$N_{ACTIVE}(i) = \begin{cases} 0, & P_i \leq P_{ZERO-OCCUPANT} \\ \geq 1, & P_i > P_{ZERO-OCCUPANT} \end{cases} \quad (3\text{-}2)$$

If the load P_i is above $P_{ZERO\text{-}OCCUPANT}$, it means at least one occupant is active, and this occupant is using appliance, then the status of occupancy can be identified.

For the time process from i to j, $i = 1, \ldots, M$, and $j = i+1,\ldots, M$, the time period of occupancy is inactive and active can be presented by (3-3), and time interval is 5s.

$$\Delta T = \begin{cases} \Delta T_{INACTIVE} = 5 \times \sum_i^M (j-i) \ , N(i,j) = 0 \\ \Delta T_{ACTIVE} = 5 \times \sum_i^M (j-i) \ , N(j,j) \geq 1 \end{cases} \quad (3\text{-}3)$$

Therefore, the whole time of calendar day is separated by peak period as identified as ΔT_{ACTIVE}, and off-peak period same as $\Delta T_{INACTIVE}$.

3.3.2 Method of load analysis with AECO

Occupancy status is highly depended on related pattern. There are some most common scenarios of household occupancy pattern in the UK, which are as follows: (a) unoccupied period is from 09.00 to 14.00, the occupants have the part-time job during morning; (b) unoccupied period is from 12.00 to 18.00, the occupants have the part-time job during afternoon; (c) unoccupied period is from 09.00 to 17.00, the occupants have the full-time job; (d) the house is occupied all the time, it means it is weekend or occupants have infant or children to look after, also the occupants may be retired and always stay at home; (e) the house is unoccupied all the time, which means the occupants are taking holiday.

For households with two occupants, if appliances are in-use, it should be at least one occupant is active, and also the occupant may share appliances, like lighting, TV, Stereo, and heating appliances. It is important to address the AECO of one active occupant, which can set the boundary of electrical load to identify the number of active occupants. Therefore, the author analyses the possibility of switched-on event with each appliance during certain time interval (5s of each period), and then generates the number of in-use appliances with 30s resolution. With the details of synthetic in-use appliances, it can present the proportion of the number of in-use appliances at each selected time interval. It also should be known that the possibility of switched-on event is hypothetical, which is used to replace unknown real-time status. By analysing the number of in-use appliances, synthetic occupancy status can be identified.

Real-time load of each household can be divided into four domains: (a) weekday off-peak load; (b) weekday peak load; (c) weekend off-peak load; (d) weekend peak load. Occupants who have complex patterns like one occupant has a full-time job, and another has a part-time job may have more peak time daily. Meantime, the peak load during weekend can be happened at any time from occupants getting up in the morning to they are asleep in the night. By analysing the nature of the load, the synthetic appliance status can be generated by using most common appliance, as listed in Table 3.3.

In order to find out the AECO of the household which has two adults, the key issue is to identify the load boundary for one active occupant. For the load fluctuations, the author defines $\varDelta P_i$ and $\varDelta P_j$ as:

$$\Delta P_i = |P_{i+1} - P_i|, \ i = 1, \dots, N \quad (3\text{-}4)$$

$$\Delta P_j = \left|P_{j+1} - P_j\right|, \ j = i+1, \dots, N \quad (3\text{-}5)$$

From time *i* to *j* at ΔT_{ACTIVE}, if

$$\Delta P_i = \Delta P_j, \quad j = i+1, \dots, N \quad (3\text{-}6)$$

then

$$\Delta t = (j - i) \times 5 \quad (3\text{-}7)$$

Compare ΔP_i and Δt in table 3.3, and choose the most approximate appliance with *P* and *L* to replace real-time appliance. If there is no appliance fix ΔP_i and Δt, firstly select two conjunction of appliances. Then three appliances and step to step until *P* and *L* are fixed. Then for each 5 seconds, the switched-on and in-use appliance status can be generated.

Because of the load record limitation with Robert's project [54] in weekend, weekday load has been chosen as a primary source. The off-peak load during weekday can address the load boundary of non-active occupant consumption, and peak load is used to analyse and produce hypothetical appliance use. The peak load in weekday is highly depended on the occupant patterns. It means the peak load of households in which occupants who have full-time job living during weekday has two parts, morning peak and evening peak. Thus, it is selected these two peak parts in each weekday to analyse and generate the synthetic appliance use for each investigated household. With the analysis results of synthetic in-use appliances, average appliance use for one occupancy can be identified. Therefore, the load boundary for one active occupancy and two occupancies can be discovered.

In this study, one weekday in each season for every participated household is chosen, and also with the limitation of load record, only one of peak period for each select weekday is analysed, the details are following.

3.3.3 Real-time electrical load analysis

A House1 Spring weekday evening peak load analysis

House1 is built-in central gas supply energy system, and two adults with a full-time job. It means during the working hour; there are nobody stays at home. By analysing the electrical load from 00.00 to 06.00 and 09.00 to 17.00, the electricity consumption of non-occupancy related $P_{ZERO-OCCUPANT}$ can be identified as 0.34 kW, which means the load of peak period is above 0.34 kW. The first example is selected as one Spring Friday evening, and the load is shown at Figure 3.3.

From Figure 3.3, it can be seen the occupants are active from 18:23:25, and consume 0.41 kW at that moment. It can be assumed lighting plus non-occupant related appliances. Then the occupants are inactive at 18:58:55. Evening peak time starts at 19:30:05 with 0.46 kW and ends at 22:23:30 with 0.31 kW. Thus, It can be identified that ΔT_{ACTIVE} is mainly from 19:30:05 to 22:23:30. From 19:30:05 to 20:39:05, the load fluctuations can be assumed simply as single appliance switched-on event. Also, the load variations are changed frequently from 20:39:15 to 21:42:10, which can be addressed as main occupant activities. Thus, this peak period is selected to analyse synthetic appliance status and list the possibility of different appliance conjunction during occupant active period. The details are followed.

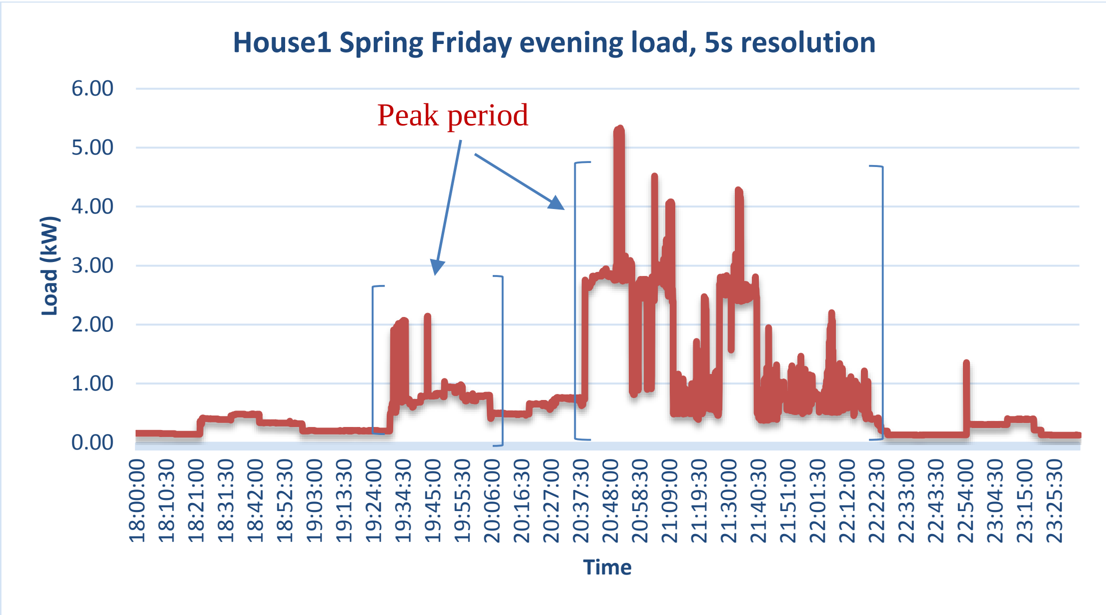


Fig. 3.3. An example of load in the evening peak time in spring weekday (house1)

Specifications of appliances are listed in Table 3.3. Details of the load at each five seconds are presented in Table 3.4, and the load variations less than 100W are hidden.

Date	Time	Load		Date	Time	Load		Date	Time	Load
2009/3/6	20:39:10	0.73	↓	2009/3/6	20:52:30	2.74	↓	2009/3/6	21:03:05	2.46
2009/3/6	20:39:15	2.76		2009/3/6	20:52:55	2.84		2009/3/6	21:05:15	2.95
2009/3/6	20:41:05	2.65		2009/3/6	20:53:20	3.04		2009/3/6	21:08:55	2.51
2009/3/6	20:41:10	2.72		2009/3/6	20:53:35	3.16		2009/3/6	21:09:00	4.05
2009/3/6	20:41:50	2.71		2009/3/6	20:53:40	2.80		2009/3/6	21:10:05	4.05
2009/3/6	20:41:55	2.82		2009/3/6	20:53:50	2.95		2009/3/6	21:10:10	2.38
2009/3/6	20:49:40	2.75		2009/3/6	20:54:50	3.00		2009/3/6	21:10:35	0.88
2009/3/6	20:50:10	2.81		2009/3/6	20:55:55	2.98		2009/3/6	21:10:55	0.49
2009/3/6	20:50:15	2.95	↓	2009/3/6	20:56:00	0.87	↓	2009/3/6	21:12:20	1.16
2009/3/6	20:50:30	2.77		2009/3/6	20:56:50	1.30		2009/3/6	21:21:35	2.47
2009/3/6	20:50:35	5.28		2009/3/6	20:58:10	0.89		2009/3/6	21:22:15	2.25
2009/3/6	20:50:40	5.16		2009/3/6	20:58:15	2.56		2009/3/6	21:22:20	0.76
2009/3/6	20:50:45	5.31		2009/3/6	21:01:15	2.61		2009/3/6	21:27:00	2.69
2009/3/6	20:50:55	5.12		2009/3/6	21:01:20	0.90		2009/3/6	21:33:40	4.29
2009/3/6	20:52:15	5.21		2009/3/6	21:01:25	1.40		2009/3/6	21:35:35	2.41
2009/3/6	20:52:20	2.87		2009/3/6	21:02:55	1.13		2009/3/6	21:40:20	0.50

Table. 3.4. Information of example load in five second resolution of house1 weekday.

In Table 3.4, the load is changed over 50W every five seconds during selected peak time, which is not ideally possible in real-time for two adults. Thus, this type of load record can be identified as bad data. However, it can be still analysed by average similar load during a selected period.

There is 0.73kW power consumption at 20:39:10, which can be determined as lighting and TV appliances are operated. From 20:39:15 to 20:56:00, around 2 kW power consumption which last 16 minutes may be one single appliance or conjunction of two or more appliances, considered with the mean power cycle length has listed in Table 3.3, it can be assumed as Hob is operated during that time. Meantime, the load has a slight variation less than 100 W, which can be assumed as lighting event at same time. At 20:50:35, around 2.5 kW is increasing for one and half minute, which can be estimated as microwave and toaster are switched-on. Same as TV in-use from 20:53:20, and kettle is switched-on from 20:58:15 to 21:01:15. From 21:03:05 to 21:10:10, around 1.5 kW is consumed continuously, this can refer to Oven appliance activity, and also, there is around 1.7 kW last one minute as well, which can be assumed as iron appliance. From 21:27:00 to 21:40:15, around 2kW load is consumed, which can be estimated as vacuum for cleaning purpose. Therefore, the estimated appliance status identified by switched-on appliance is listed in Table 3.5 during principal occupant activities period, non-occupant related and entertainment appliances are not presented.

From Table 3.5, it can be seen that the majority of the number of switched-on appliances during spring weekday evening peak period is one. Consider with the sharing appliances, like Lighting and TV, it can be assumed that for most peak time during weekday evening, the average number of in-use appliance for each 5 seconds is two.

Time	**Load (kW)**	**Switched-on appliance**	**In-use appliance**	**number of synthetic appliance**
20:39:10	0.73	N/A	Lighting, TV	1
20:39:15	2.76	Hob	Lighting, TV, Hob	2
20:50:35	5.28	Microwave, Toaster,	Lighting, TV, Hob, Toaster, Microwave	4
20:53:20	3.04	Desktop Computer	Lighting, Hob, TV, Desktop Computer	3
20:58:15	2.56	Kettle	Lighting, TV, Kettle	2
21:03:00	2.81	Oven	Lighting, TV, Oven	2
21:09:00	4.05	Iron	Lighting, TV, Oven, Iron	3
21:21:35	2.47	Microwave	Lighting, TV, Microwave	2
21:27:00	2.69	Vacuum	Lighting, TV, Vacuum	2
21:33:40	4.29	Microwave	Lighting, TV, Vacuum, Microwave	3

Table. 3.5. Estimated partial appliance status during selected spring evening peak period for house1.

Then it is collected all the information of in-use appliances during this peak period and reforms them into 30s resolution. The specification of in-use appliances is presented in Fig 3.4, which shows the number of in-use appliances in each 30s during selected weekday evening peak period.

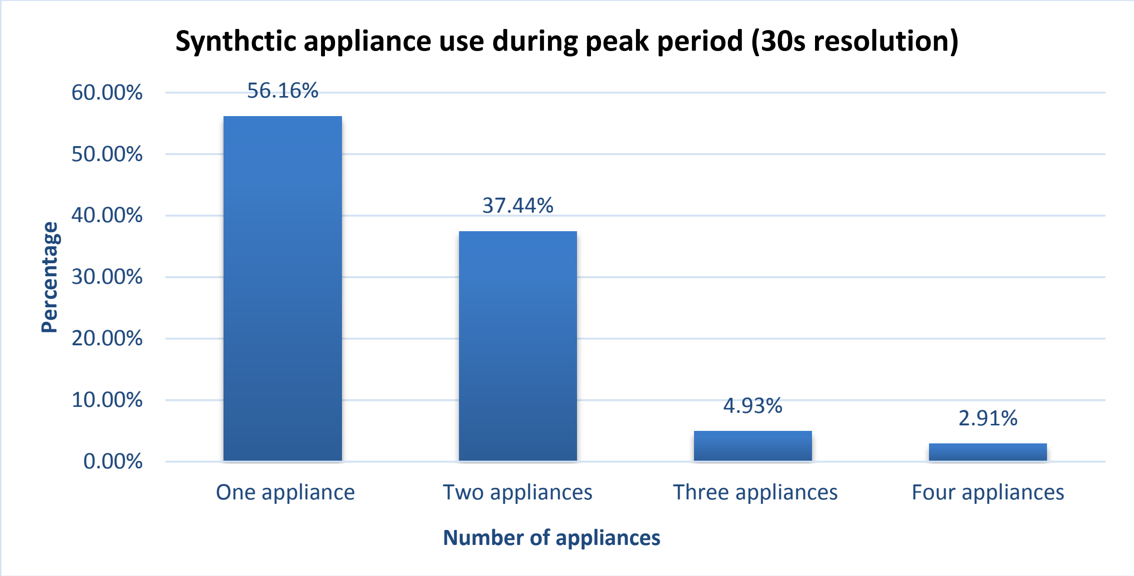


Fig. 3.4. The number of synthetic appliance use during spring weekday evening peak time of house1 with 30s resolution.

From Fig 3.4, it can be seen clearly that for most of the time, the number of in-use appliances is one and two, which has over 90% percentage. Consider with the real-time activities, it is shown that the average number of in-use appliances during this spring weekday evening for one occupancy is two in this example.

B House1 Summer weekday morning peak load analysis

Another example load period is chosen from one weekday morning in summer, and the real load with five second resolution has been selected, which can be seen in Figure 3.5. From Figure 3.5, it can be known clearly that there are two peak periods in this weekday morning, which are from 06:55:00 to 07:00:00 and 07:27:00 to 07:30:00. Meantime, people always do some cooking activities and then go for work during normal weekday morning, and they may not have enough time for cleaning or other activities, such as vacuum and iron. During the selected period, the maximum load is 5.97 kW, and the minimum load is 0.3 kW. On the other hand, the electricity shower is not possible to be used because its load is around 9kW, and it is summer morning, lighting appliance is not in use either. Therefore, these two short-cut peak periods with 5s resolution are analysed, the detail is followed.

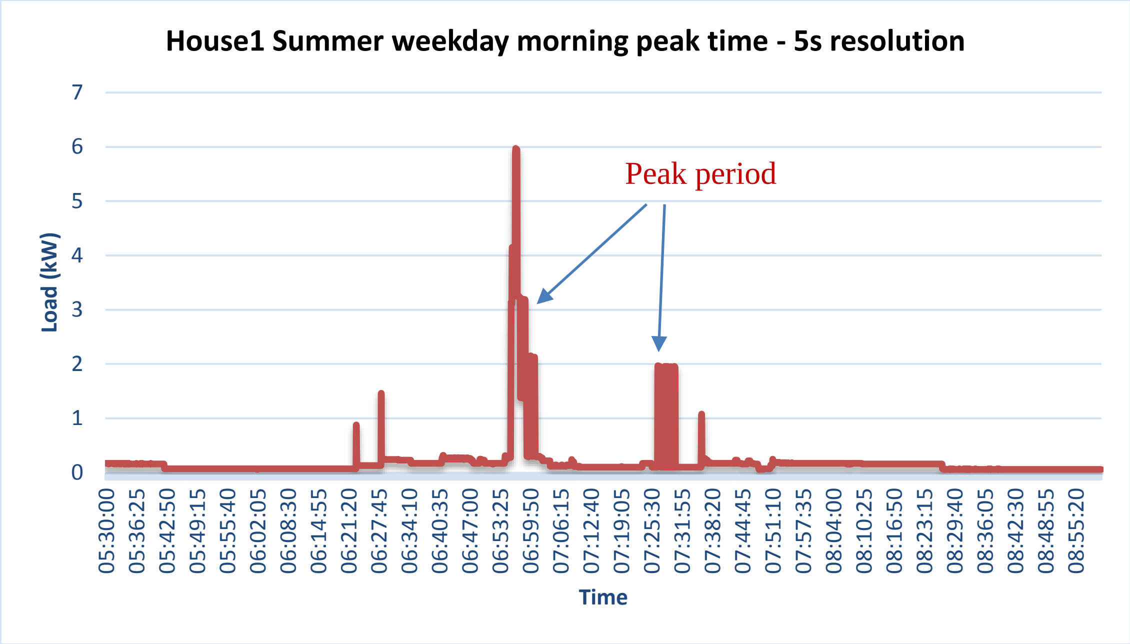


Fig. 3.5. An example of load in the morning peak time in summer weekday (house1).

It is also known the load of kettle is 2 kW – 3 kW and it typically last minutes to boil water, which has fitted the real-time from 06:55:50 to 06:57:50. Thus, it can be identified that the kettle may be operated during these two minutes with a high possibility. It is also noticed that during 06:56:05 to 06:57:05, there is another appliance or some appliances have been used as the load is about 1kW (4.14-3.14) to 2.8kW (5.97-3.11) only for one minute, so it can be assumed as toaster and microwave. Also, from 06:57:10, it can be easily seen that Stereo appliance is switched-on. From 06:57:50 to 07:00:00, there is no kettle operation, because it has been already used and the load is wave not constant. Consider with the mean cycle of toaster is an around three minute, it can be assumed that toaster has a high possibility to be switched-on from 06:56:05 to 06:58:45.

From 06:58:10 to 06:58:25, there is appliance which consume about 1.8 kW is switched on only for 15 seconds, considered the cycle of appliance, the most possible appliance is microwave, which is controllable appliance and cost right power. Meantime, same as from 06:58:50 to 06:59:05, and 06:59:30 to 06:59:45, both of them last 15 seconds, similarly like previous microwave in-use cycle, thus, the author can assume that microwave has been switched on during these periods. Therefore, the detail of synthetic appliance use is presented in Table 3.6, and in order to avoid the disruption of half number, the author rounds off all numbers as integer.

Time	Load (kW)	Switched-on appliance	In-use appliance	number of synthetic appliance
06:56:00	3.11	Kettle	Kettle	1
06:56:30	4.14	Toaster	Kettle, Toaster	2
06:57:00	5.95	Microwave	Kettle, Toaster, Microwave	3
06:57:30	3.25	Stereo	Kettle, Toaster, Stereo	3
06:58:00	1.38	N/A	Toaster, Stereo	2
06:58:30	1.37	Microwave	Toaster, Stereo	2
06:59:00	2.15	Microwave	Microwave, Stereo	2
07:00:00	2.15	Microwave	Microwave, Stereo	2

Table. 3.6. Synthetic appliance use in summer weekday morning peak time (House1).

It is calculated the number of synthetic in-use appliance in both 5s and 30s resolution, where the detail of zero appliances is hidden, and the result is provided in Fig 3.6.

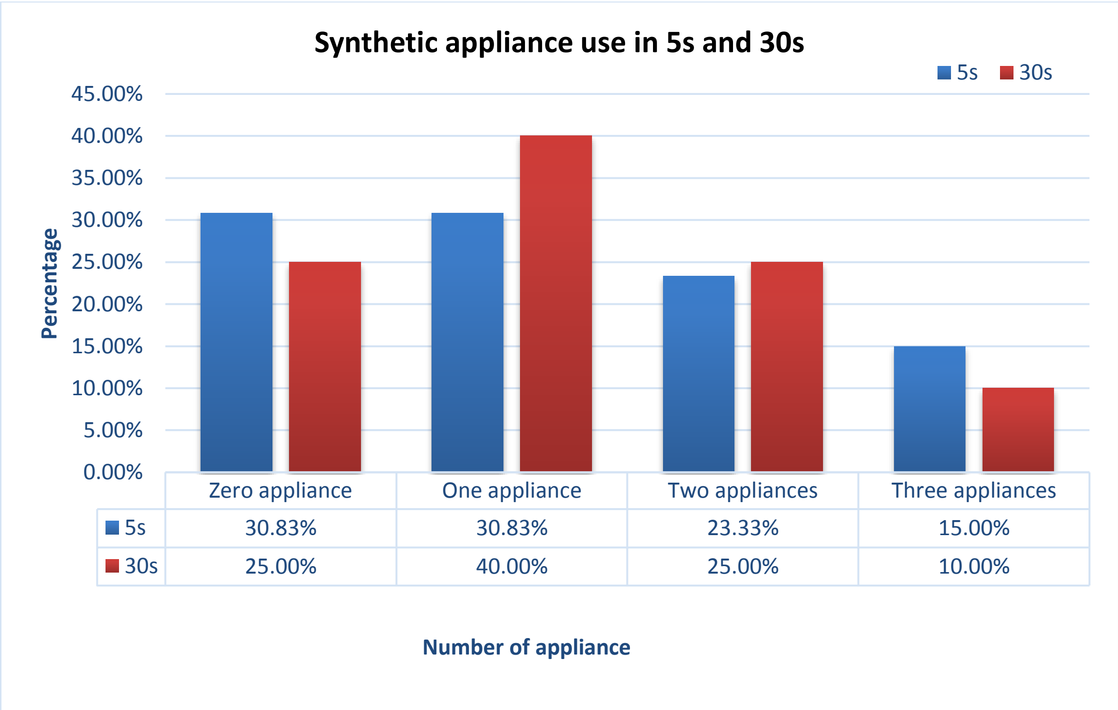


Fig 3.6. The number of synthetic appliance use during summer weekday morning peak time of house1 with 5s and 30s resolution.

From Fig 3.6, it can be seen clearly that the majority of in-use appliances is still one and two appliances during summer morning peak period, even the time resolution is increasing significantly.

C House1 Autumn weekday evening peak load analysis

In order to address the appliance use in different season, an example load is present in Fig 3.7, which shows particular load pattern during autumn Wednesday evening with 5s resolution.

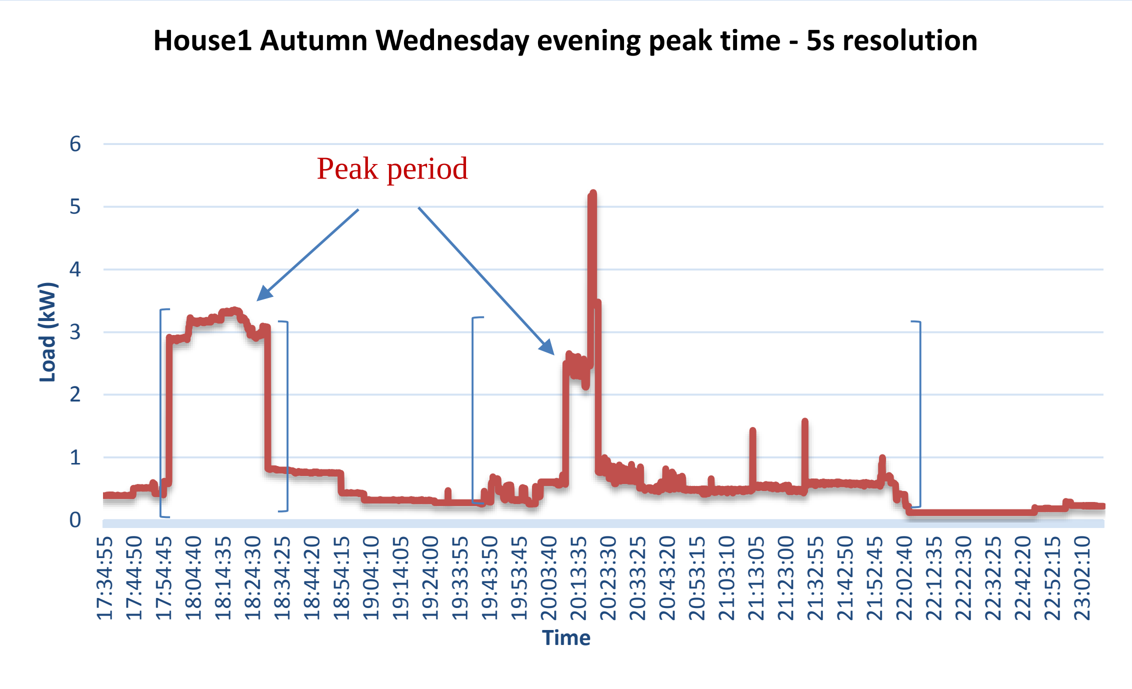


Fig. 3.7. An example of load in the evening peak time in autumn weekday (house1).

There are two main peak period, which are from 17:54:45 to 18:34:15, and 19:43:30 to 22:02:40, as shown in Fig 3.7. The first peak period has lasted about thirty minutes which consistently consumed around 3kW. It can, therefore, be assumed as single or two appliances are operated at that time, like cooking appliances. The load below 1 kW can be assumed as $P_{ZERO\text{-}OCCUPANT}$ (as identified as 0.39 kW in this case) plus lighting and TV appliances. Therefore, it is selected the load which above 1 kW during these two particular peak period to analyse the synthetic appliance use. The switch-on event of synthetic appliances (excludes lighting and TV) during this selected peak period is presented in Table 3.7 as followed.

Time	Load (kW)	Switched-on appliance	In-use appliance	number of synthetic appliance
17:56:50	2.92	Oven	Lighting, TV, Oven	2
18:03:25	3.11	Desktop computer	Lighting, TV, Oven, Desktop computer	3
20:09:40	2.5	Vacuum	Lighting, TV, Vacuum	2
20:18:00	5.17	Microwave	Lighting, TV, Vacuum, Microwave	3
20:19:00	3.45	Toaster	Lighting, TV, Vacuum, Toaster	3

Table 3.7. Synthetic appliance use in autumn Wednesday evening peak time (House1).

The details of synthetic appliance use in both 5s and 30s resolution is depicted in Fig 3.8.

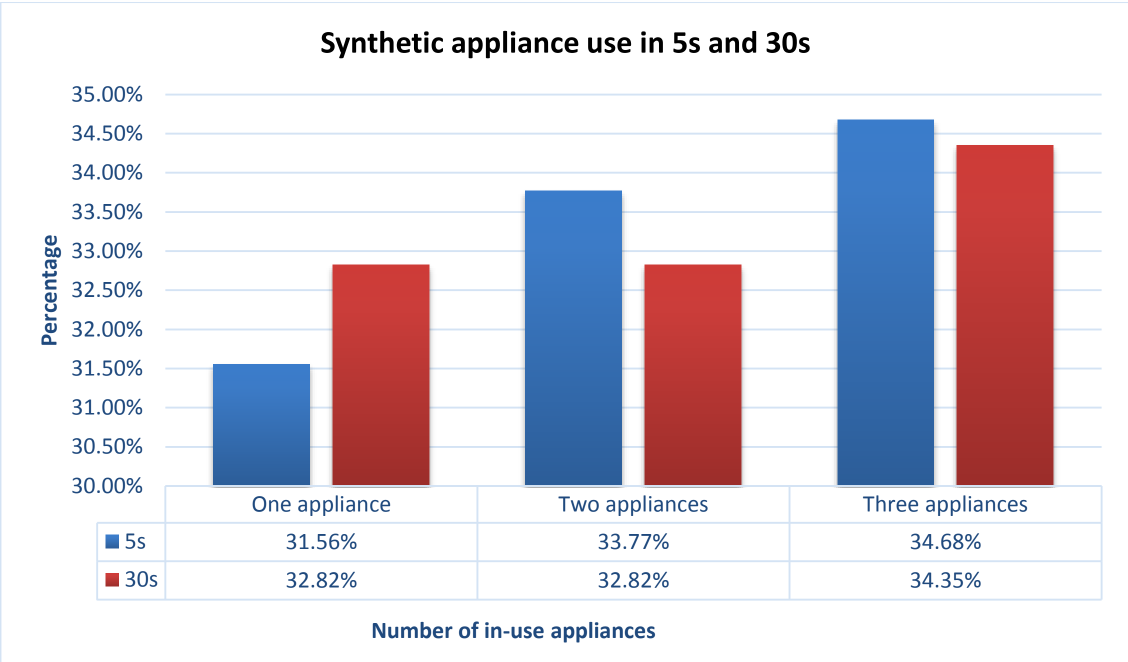


Fig. 3.8. The number of synthetic in-use appliance during autumn Wednesday evening peak period of house1 with 5s and 30s resolution.

Fig 3.8 reveals that one and two in-use appliances still obtain the main electricity consumption during autumn weekday evening peak time, as shown 65.33% and 65.64%, respectively, even with increased time-resolution like from 5s to 30s.

D House1 Winter weekday evening peak load analysis

Winter is a special season in the analysis of electricity consumption for this particular household. Because of its central gas supply system, it means occupancy may not be able to use electrical heater to recovery the temperature of the indoor environment.

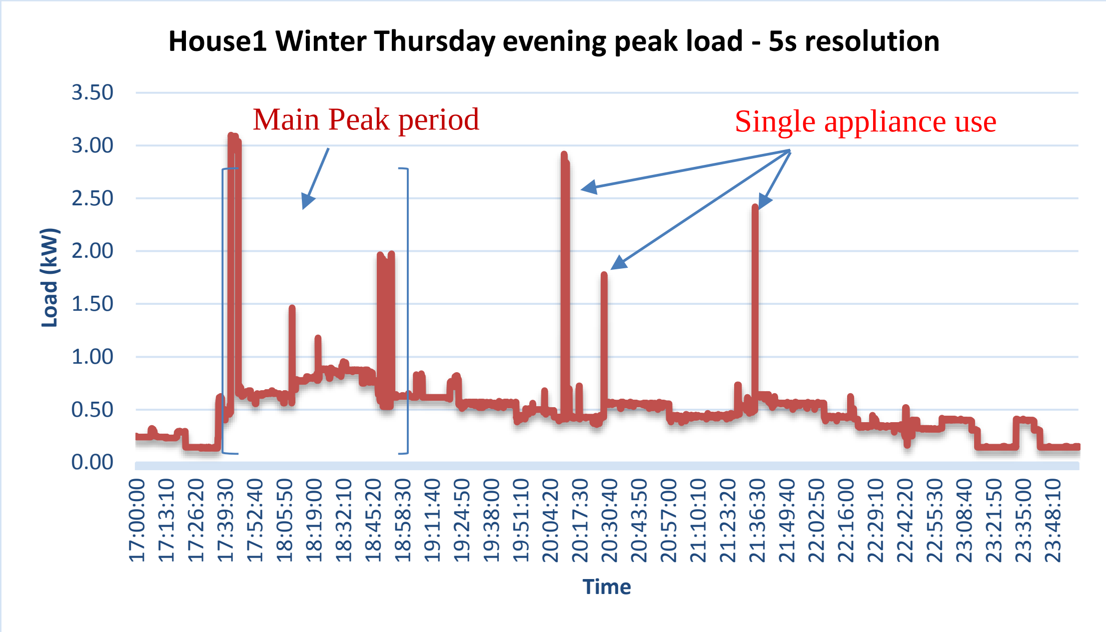


Fig. 3.9. An example of load in the evening peak time in winter weekday (house1).

An example of peak load during winter Thursday evening is present in Fig 3.9, and the $P_{ZERO\text{-}OCCUPANT}$ is this case is 0.3 kW (from afternoon off-peak load). Therefore, the peak period is obviously from 17:39:30 to 23:11:45. Because lighting appliance should be switched-on continuously during winter evening, and the load of lighting vary approximately from 0 to 0.4 kW. Meantime, there are some individual peak loads as shown in Fig3.9, which can be frequently identified as single appliance switch-on event during this peak period. In terms of avoiding this disruption, it is selected the main peak period which from 17:42:00 to 18:54:00 as peak load pattern to generate the synthetic in-use appliance sequence. The details are presented in Table 3.8 and Fig 3.10.

Time	Load (kW)	Switched-on appliance	In-use appliance	number of synthetic appliance
17:42:20	3.10	Kettle	Lighting, Kettle	2
17:45:40	0.65	TV	Lighting, TV	1
18:48:50	1.96	Microwave	Lighting, TV, Microwave	2
18:50:45	1.88	Microwave	Lighting, TV, Microwave	2
18:51:40	1.89	Microwave	Lighting, TV, Microwave	2
18:52:30	1.89	Microwave	Lighting, TV, Microwave	2
18:53:25	1.88	Microwave	Lighting, TV, Microwave	2

Table. 3.8. Synthetic appliance use in winter Thursday evening peak time (House1).

Fig 3.10 provides the specification of synthetic in-use appliance in both 5s and 30s resolution.

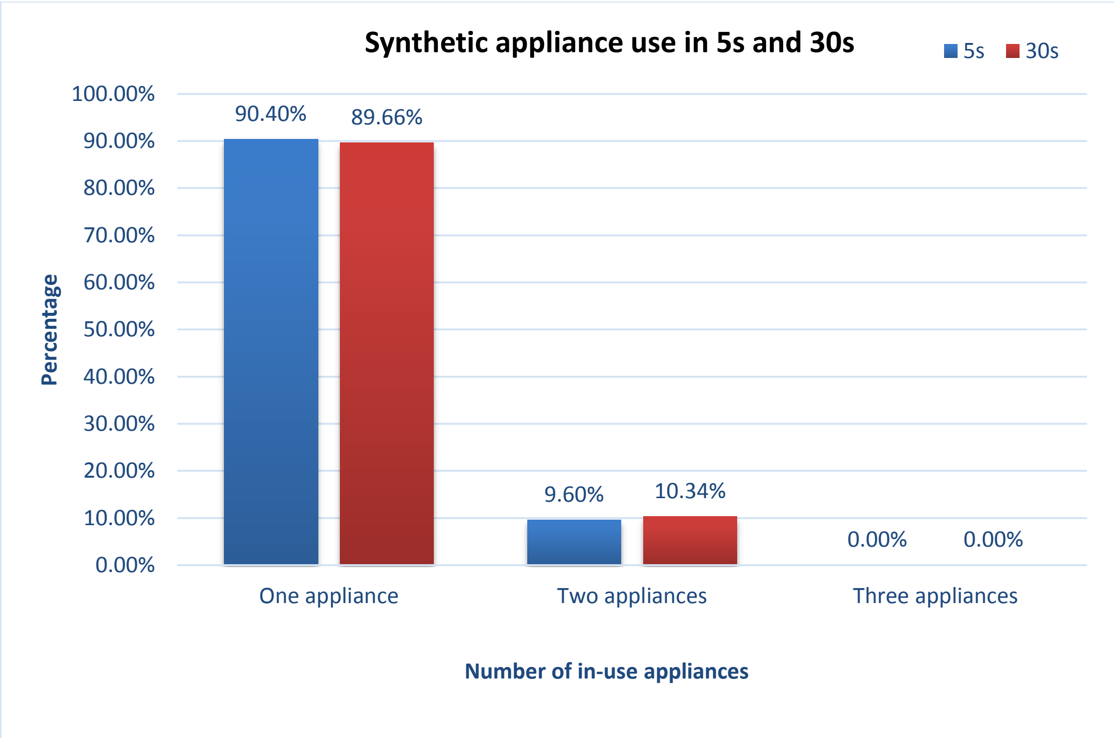


Fig. 3.10. The number of synthetic in-use appliance during winter Thursday evening peak period of house1 with 5s and 30s resolution.

In the winter case, Fig 3.10 reveals that one and two appliances have completely domain the peak period, which are nearly same with other seasons.

E Summary of House1 weekday peak load analysis

With the peak load analysis result of each season for house1, it can be found that for the household with central gas supply, the number of in-use appliances during most peak period is one and two. Meantime, consider with the number of occupancy in the household, in the case of house1 is two adults, and the sharing activities, thus it can be simply assumed that the maximum in-use appliance at each thirty seconds for one occupancy is two.

Therefore, for a particular household with two adult occupants, the power of non-active occupant can be identified as $P_{ZERO\text{-}OCCUPANT}$, which contains standby appliances, continuous appliances and cooling appliances; the power of one active occupant can be calculated by the conjunction load of any two installed appliances; and if the load is above the power of one active occupancy, it should be two active occupants.

In order to validate this finding, the author selects other two households, which are large Terraced House and Semi-Detached house, as the example to identify the synthetic appliance use during the peak period. For each household, summer and winter weekday peak periods are picked as primary sources to analyse the in-use appliances.

F House2 weekday peak load analysis

House2 is a large Terraced (7 bedrooms) dwelling with two elder occupants who are over 65 years old, and the occupancy pattern is one with part-time job and child-minders for another. An example of weekday electrical consumption is presented in Fig 3.11. As previous discussion, the age group can influence the energy consumption of occupancy. In this particular case, these occupants wake up at 05:15:35, which is much earlier than the former occupant in house1, as 06:21:20. Meantime, the evening peak period is quite short because they go to bed very early.

From Fig3.11, it can be identified that the occupancy who has a part-time job is from 10.00 to 15.00, and the whole day electricity consumption can be divided into two main parts, morning peak period and afternoon peak period. Cooling appliance like fridge can be readily revealed during an off-peak period. The load fluctuation in morning peak period is much more sensitive than another one. Therefore, it is selected as the primary energy consumption source to analyse and generate the synthetic appliance use. The detail of synthetic appliance use for this case is presented in Appendix, and the specification of in-use appliances is depicted in Fig 3.12. The $P_{ZERO\text{-}OCCUPANT}$ in this case is identified as 0.4 kW.

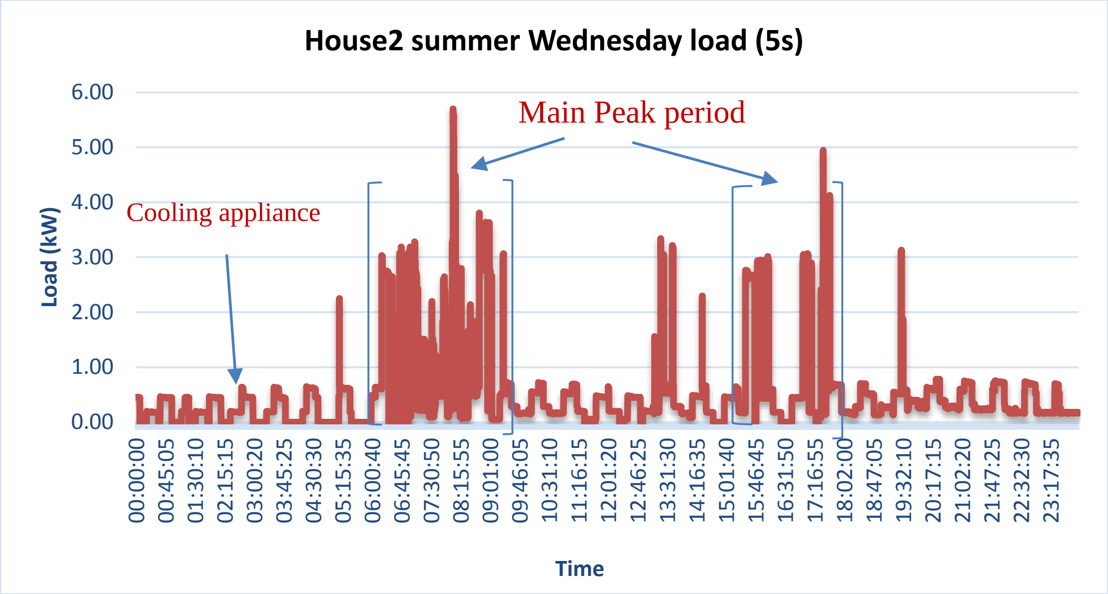


Fig. 3.11. The whole day load detail in summer Wednesday of House2

Because some bad data has interrupted the whole load record, therefore, some of the good load data is selected to analyse and generate the synthetic appliance use, which is given in Fig 3.12.

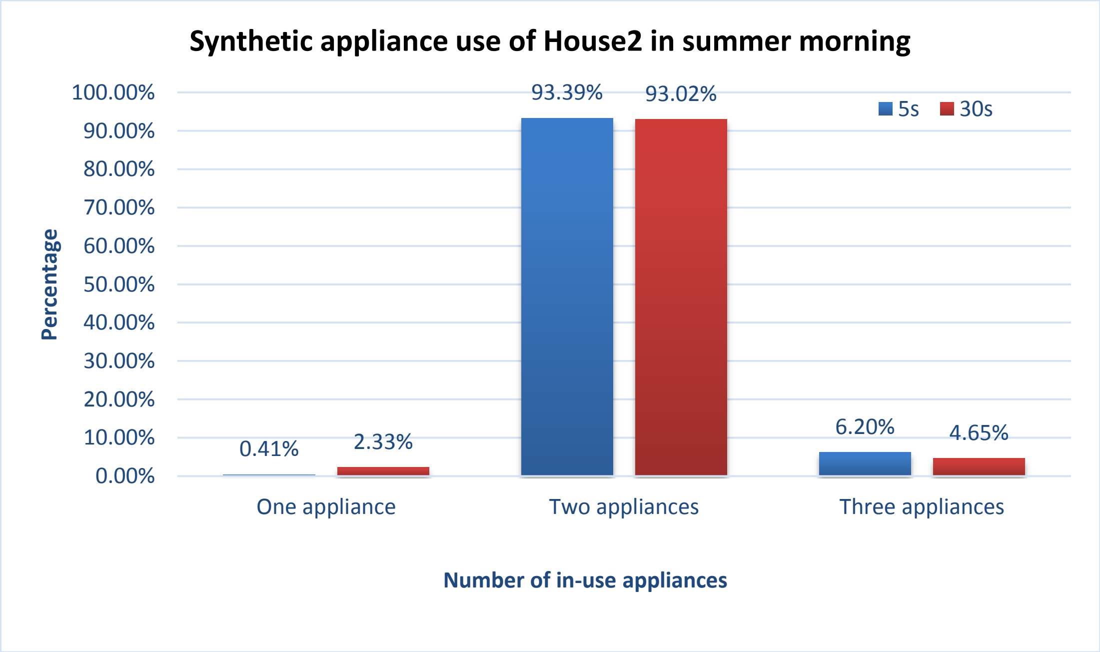


Fig. 3.12. Partial synthetic appliance use during morning peak time (House2)

The partial results of synthetic appliance use during summer morning peak period still reveals that the two appliances have still dominated the main electricity consumption.

Another example is selected from winter Thursday evening load, as shown in Fig3.13. The energy system in House2 is central gas supply with radiator. However, it can be found that there is a cycle appliance or some appliances are used during this selected peak period, which can be directly identified as an electrical heater with auto-control model. Because the occupants in this household are both retire and the occupant may want to save energy cost due to their income, and also consider with the type of child-minder pattern in this household, the programmable heater with cycling utilization is reasonable. The $P_{ZERO\text{-}OCCUPANT}$ in this case is identified as 0.36 kW.

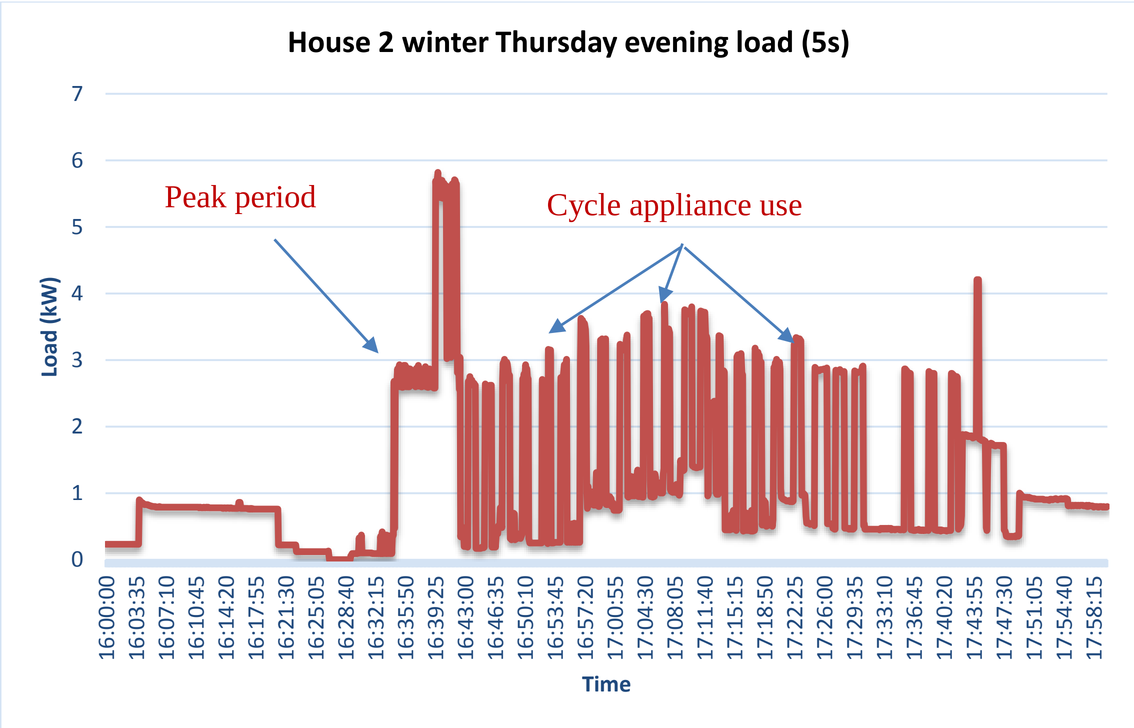


Fig. 3.13. Peak loads in winter Thursday of House2.

The sunset in UK during the winter season is normally around 5pm, which means lighting appliances are always switched-on in this case. The peak period from Fig 3.13 is selected from 16:34:30 to 17:31:00.

The specification of synthetic appliance use is presented in Appendix, and the detail of in-use appliance is depicted in Fig 3.14.

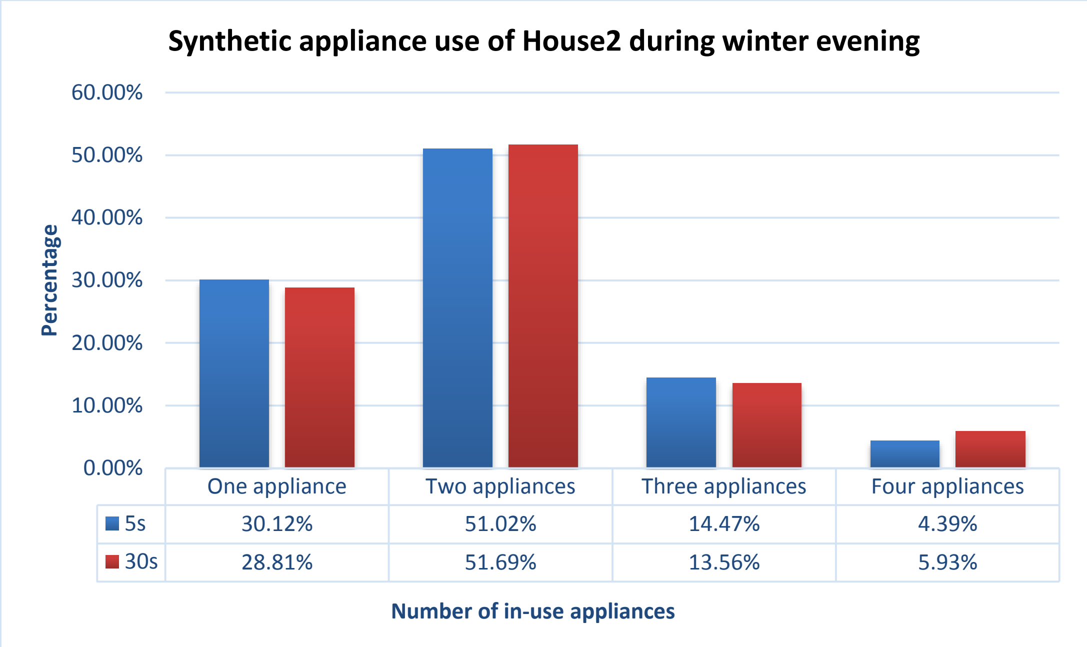


Fig. 3.14. Synthetic appliance use during weekday evening peak period (House2).

The selected two cases from house2 present that two appliances have highly responsibility of electricity consumption during winter weekday evening peak period, which is same with house1.

G House 3 weekday peak load analysis

House3 is a Semi-Detached house with two adults whom both have full-time jobs, and electricity is the only energy supply for both heat and electricity in this household. Therefore, the load of this case can fully present feature of appliance use. Meantime, without radiator, the electrical load during winter should be much higher than others. The author still picks summer and winter weekday to analyse the load during a peak period.

An example of one weekday load is presented in Fig 3.15, which is picked from one summer Wednesday of house3. There are two main peak periods in this case for this household, morning peak period and evening peak time, which have matched the related occupancy pattern as both of occupants have full-time jobs.

The morning peak period is chosen as a primary resource to estimate the synthetic appliance use for this case. The results of appliance use are presented in Appendix, and the percentage of in-use appliances is depicted in Fig 3.16.

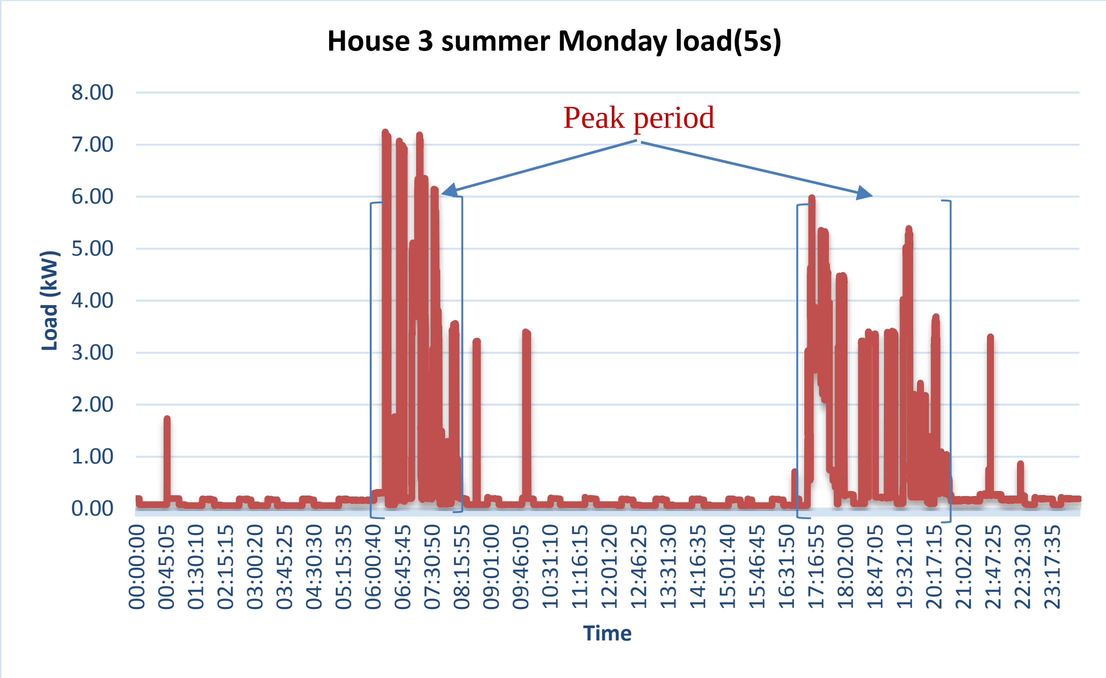


Fig. 3.15. Detail of whole day load of house3 in summer Wednesday.

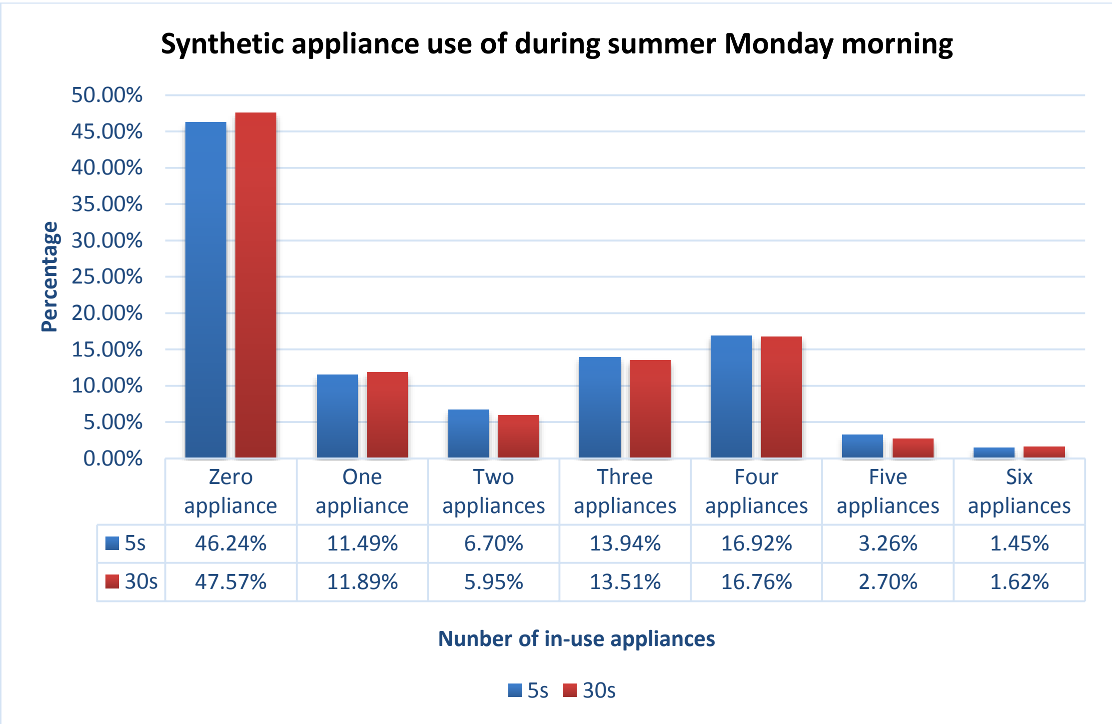


Fig. 3.16. Estimated appliance use during Monday morning peak period (House3).

Although the energy system of this household is whole electricity supply, the result of estimated in-use appliance still reveals that the majority of appliance use is below two of them in summer, which is same with other households.

Another example of weekday load is selected from winter Christmas holiday, which is the highest energy consumption during the full year, the details of load are depicted in Fig 3.17.

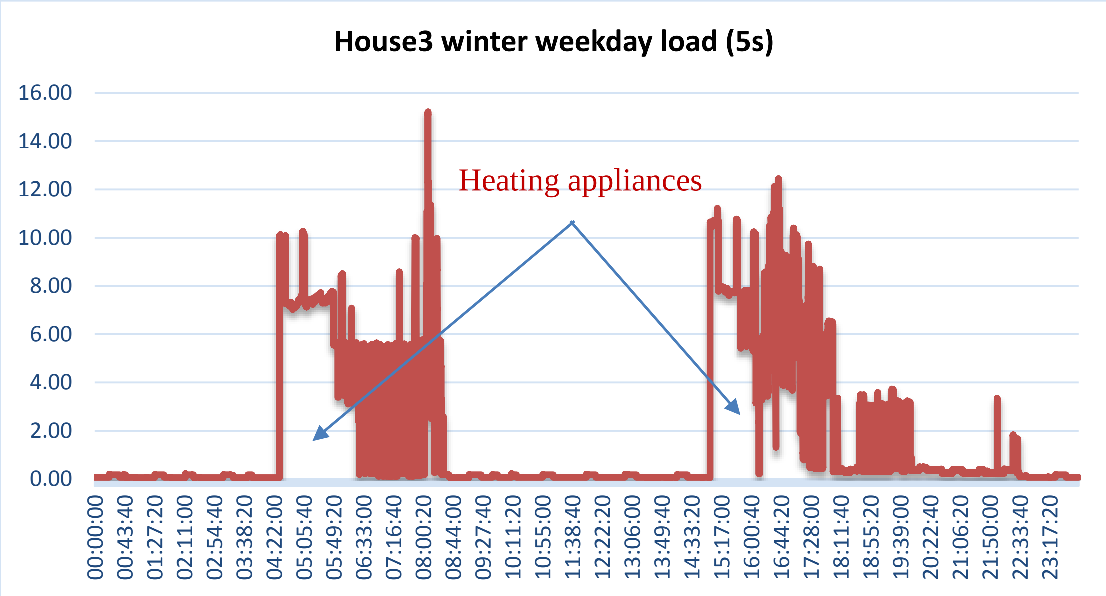


Fig. 3.17. An example of particular weekday load at 28th Dec 2009 of house3.

During Christmas holiday, occupants generally choose to stay at home for family activities. Because there are three children in this house and one is an infant, it is very important to keep the house warm in terms of avoiding the little one catch a cold, which can be reflected in Fig 3.17. The heating system is automatically operated at 4am in the morning. Meantime, although it is a weekday, occupants did not need to work, so this case can be categorized into weekend pattern.

In order to address the appliance use in this household during selected peak period, it is crucial to identify the load of heating system. The heaters in this house apparently have programmable model which can be auto-controlled by timer or in-door temperature. Meantime, as there is few load from 9am to 2pm, it can be found that the heating system is only auto-controlled in the night time, which is dominated by internal timer. During winter time, occupants always operate heater to maintain their thermal comfort, and even pre-heats the house when they are away. Therefore, before analysing the appliance use during afternoon peak period, the load of whole heating system should be identified, and the author assumes that one room only can be allocated one heater. The specification of this type of morning load is depicted in Fig 3.18.

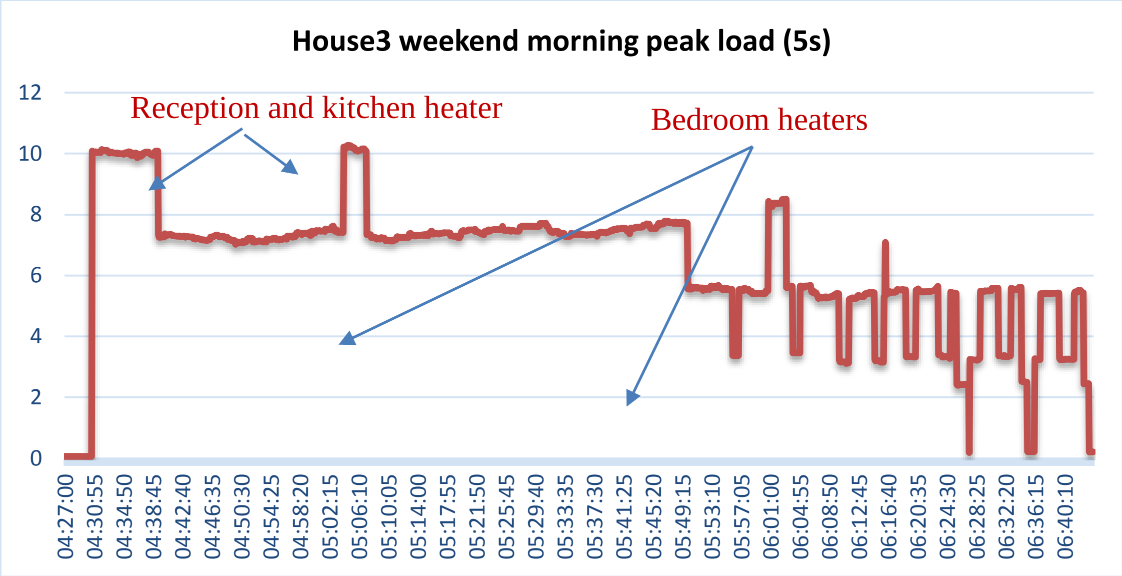


Fig. 3.18. Morning peak load from Fig 3.17 of house3 at 28th Dec 2009.

There are 3 bedrooms in house3, and it should have reception room and kitchen, it is assumed that the heating system are auto-controlled in these five rooms when occupants are asleep. The heaters in both reception and kitchen did not need to keep the temperature normal, so they are only operated few time to preheat the room, which can be found in Fig 3.18 with two arrows. Meantime, it can be noticed that the heat load is dropped from 7.7 kW at 05:49:55 to 5.5 kW at 05:50:00, and from 5.5 kW at 05:55:55 to 3.3 kW at 05:56:00. Therefore, the load of heaters in reception and kitchen can be identified as 1.4 kW (10.2 kW minus 7.4 kW then divide 2) for each. Meantime, the heater in the bedroom of infant is 3kW and 2.2 kW in others, as shown in Table 3.9.

Electrical heater	**Load**	**Ratio of occupant use**
Reception room	1.4 kW	0.5
Kitchen	1.4 kW	0.5
Bedroom1 (parents)	2.2 kW	0.5
Bedroom2 (young child)	2.2 kW	1
Bedroom3 (infant)	3 kW	1
Total heat load	**10.2 kW**	
Average heat load per room	2.04 kW	

Table. 3.9. Load specification of electrical heaters in house3.

The detail of appliance use is presented in Appendix, and the percentage of in-use appliances for including and excluding heating appliances are shown in Fig 3.19 and Fig 3.20.

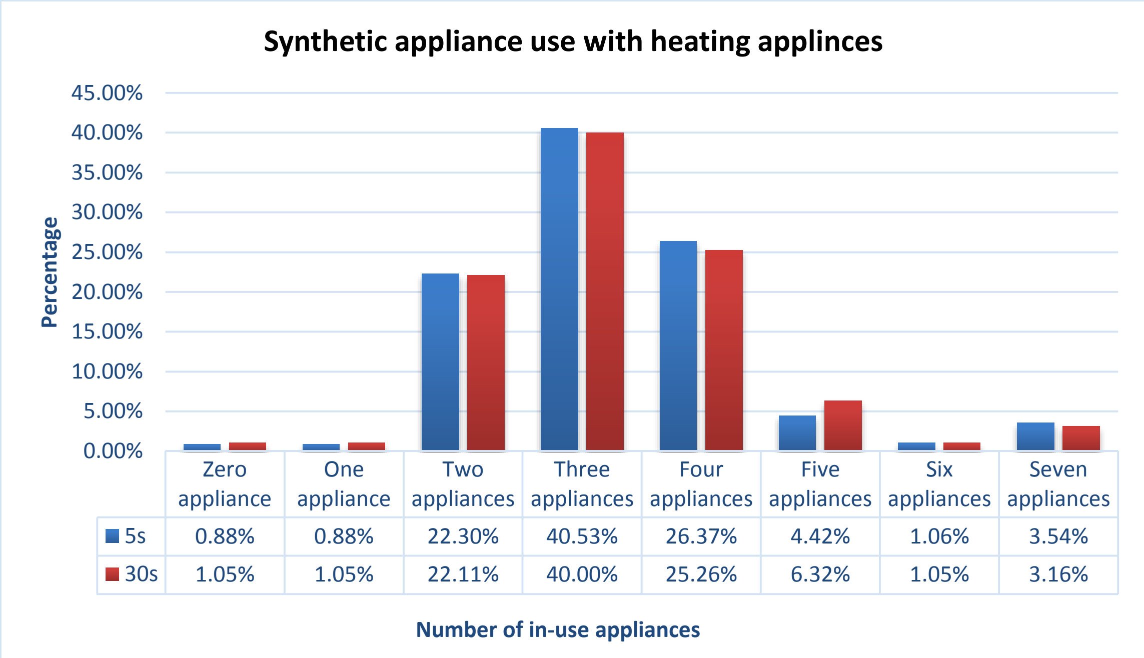


Fig. 3.19. Specification of estimated in-use appliance including heating appliances during winter weekday afternoon peak period of house3.

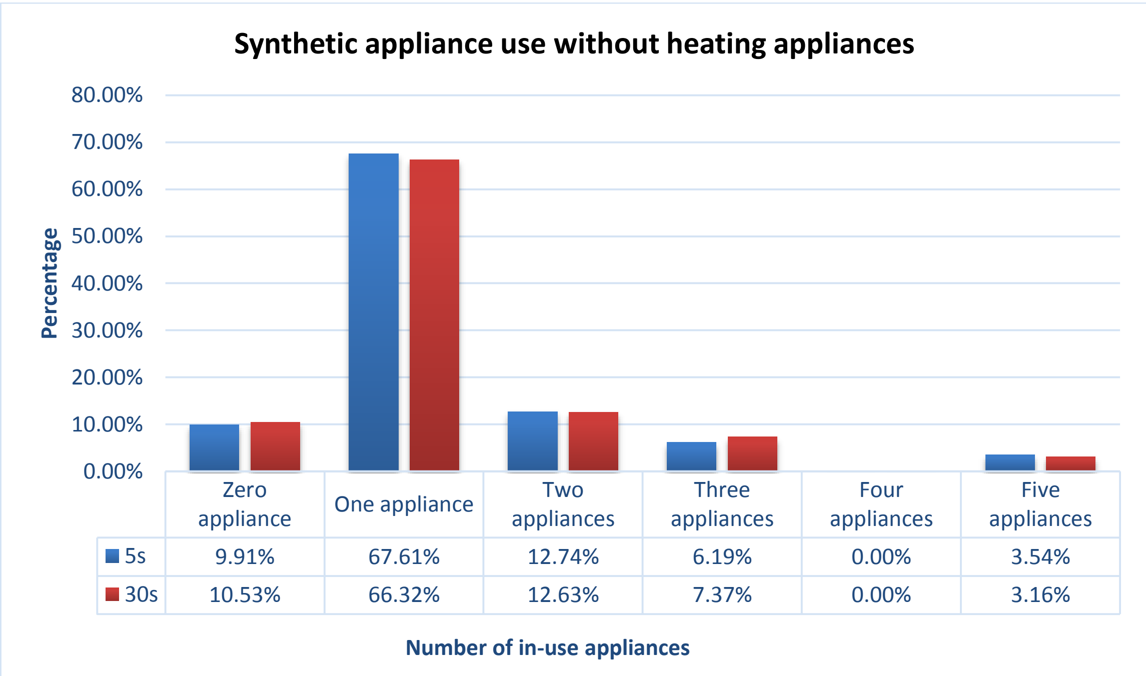


Fig. 3.20. Specification of estimated in-use appliance excluding heating appliances during winter weekday afternoon peak period of house3.

3.3.4 Load boundary of AECO

When an appliance is occupied, it means there is at least one occupancy is active at that time. Occupancy may share appliance in real-time, like TV, lighting, CD player, etc. Meantime, it is not ideally possible to identify the number of active occupancy in real-time within high-resolution occupancy profile.

Therefore, the author defines synthetic active occupancy as “a person is active and occupy appliance” to replace real-time active occupancy. The synthetic active occupancy depends on two features, active and appliance use which refers to the number of in-use appliances.

Considered the time-resolution in this research is 30s, it can be assumed that for one occupant, the maximum number of switch-on appliances during every 30s is two.

In addition, from the real-time load analysis in section 3.3.3, the results can mainly be concluded in two domains:

- For a household with central gas supply, the number of in-use appliances during most active periods is two.
- For a household with whole electricity supply, the number of in-use appliances during most active periods is two, which excluding heat appliances like electrical heaters, electrical boiler, and shower.

Therefore, for a household with two occupants, it can be assumed that during the most peak period, the maximum in-use appliances for one occupancy is two.

Then the author calculates all the conjunction of any two appliances which have been listed in Table 3.3, (excluding lighting appliance, heating appliances like electrical heater and shower), as shown in Table 3.10.

Minimum consumption	Maximum consumption	Average consumption
0.24 kW	4.6 kW	2.53 kW

Table. 3.10. Load calculation of any two appliances.

As the range of load consumption for two appliances is from 0.24 kW to 4.6 kW, the author picks the average 2.53 kW as the load boundary for one active occupancy and two active occupants.

Meantime, the power consumption of non-occupancy related is from 0.08 kW to 0.4 kW. Therefore, the load boundary of one active occupancy is from 2.61 kW to 2.93 kW, in order to simply calculate the number of active occupancy, the author sets the load boundary of one active occupancy as 3 kW, which is presented as follow:

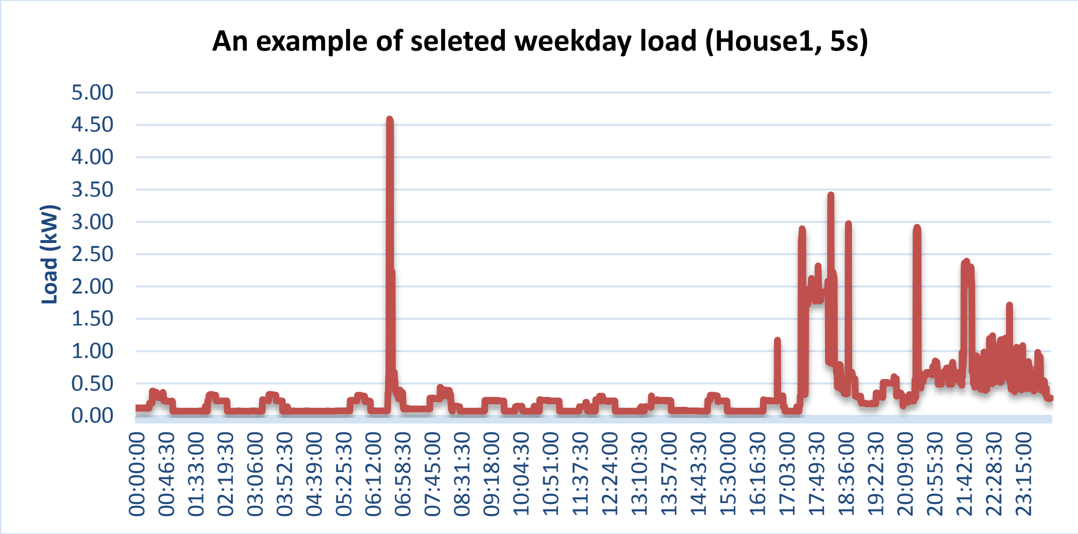
The power consumption P_i at any time *i* for any household with two occupants:

- During summer:
  - Non-active occupant: $P_i \leq 400W$
  - One active occupant: $400W < P_i \ \leq 3\ kW$
  - Two active occupants: $P_i > 3\ kW$
- For the other seasons, where $P_{HEAT\ APPLIANCE}$ is the average heat load
  - Non-active occupant: $P_i \leq 400W + P_{HEAT\ APPLIANCE}$
  - One active occupant:

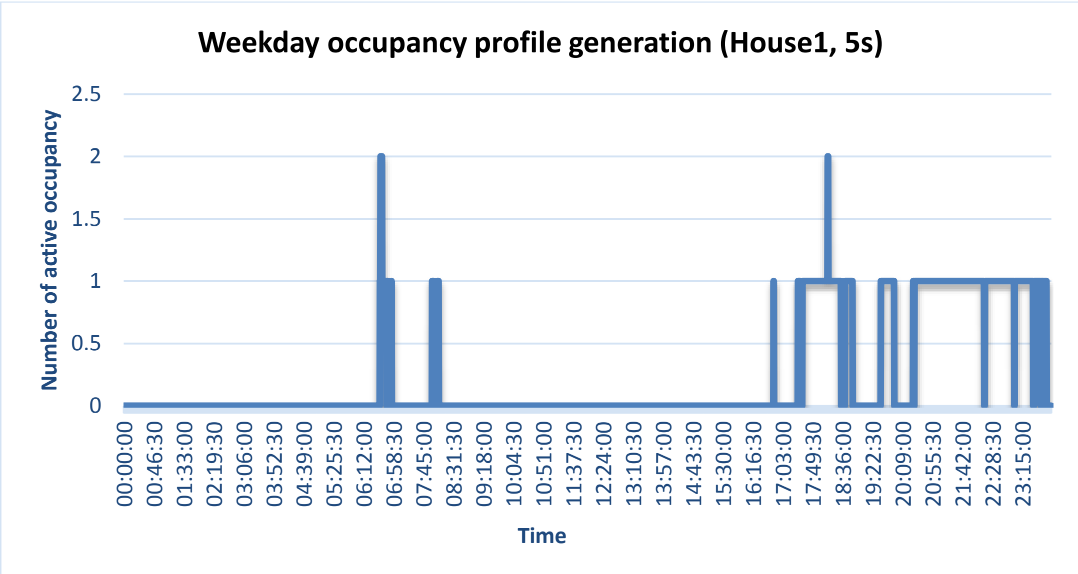
    $(400W + P_{HEAT\ APPLIANCE}) < P_i \ \leq (3\ kW + P_{HEAT\ APPLIANCE})$
  - Two active occupants: $P_i > 3\ kW + P_{HEAT\ APPLIANCE}$

3.4 High-resolution synthetic occupancy profiles generation

With the identification of load boundary for arbitrary household with two occupants, any load can be converted into a number of active occupancy. Therefore, high-resolution historical occupancy profiles can be generated by applying the load boundary into selected electrical consumption. A typical example of an occupancy profile in one single day is present in Fig 3.21, where particular load pattern in shown in Fig 3.21 (a), and converted into synthetic occupancy profile is depicted in Fig 3.21 (b)



(a)



(b)

Fig. 3.21. An example of daily estimated active occupancy profile generation (House1, 5s resolution), (a) rea-time load; (b) synthetic occupancy pattern converted from (a).

From Fig 3.21, it can be seen that each single load can be converted into particular number of active occupant. Therefore, the estimated occupancy profile of each household in a whole year can be generated applying AECO to the particular electricity load pattern.

3.4.1 Occupancy profiles of Mid-Terraced House (House1)

The synthetic occupancy profiles of house1in four seasons are presented from Fig 3.22 to Fig F.3.25.

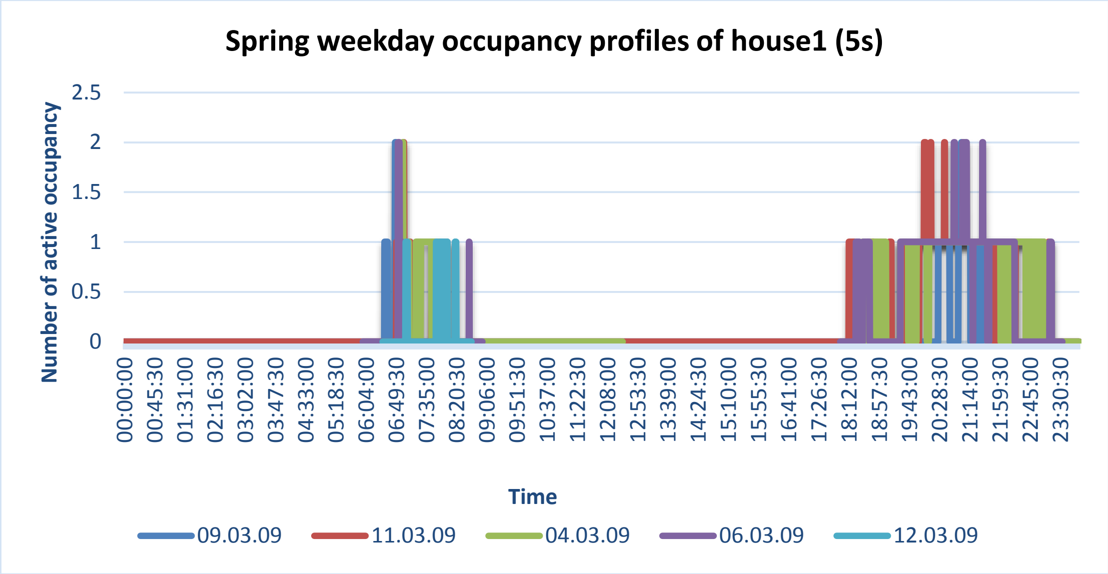


Fig. 3.22. Spring weekday occupancy profiles of house1 in 5s resolution.

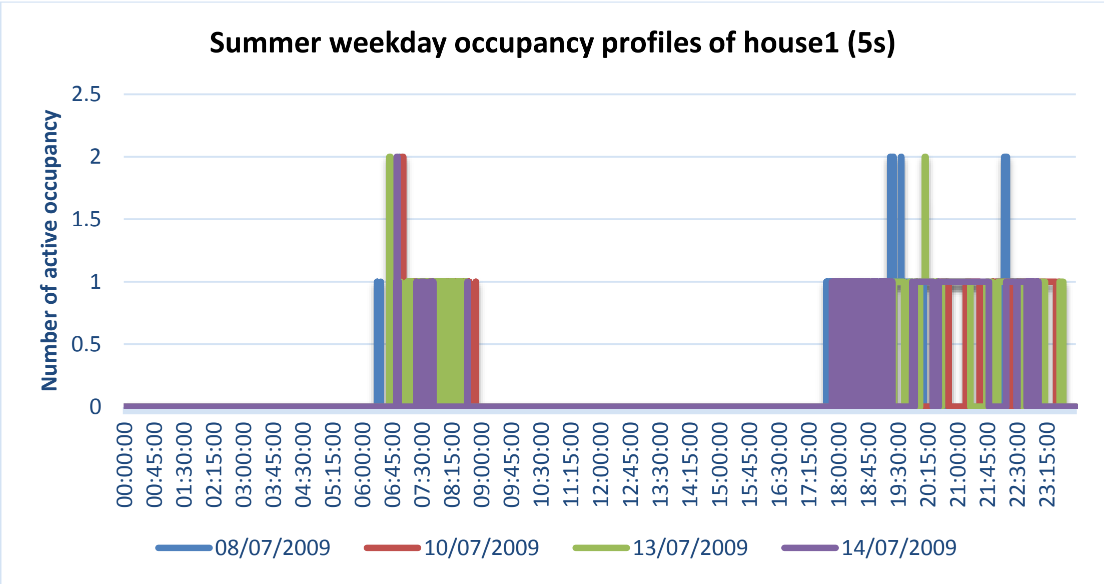


Fig. 3.23. Summer weekday occupancy profiles of house1 in 5s resolution.

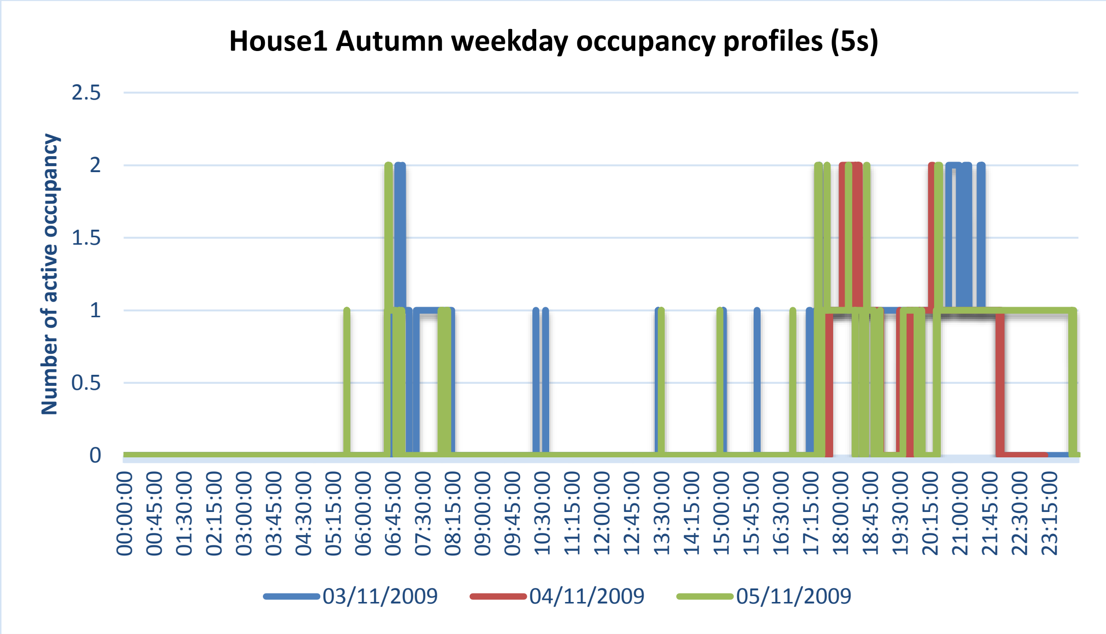


Fig. 3.24. Autumn weekday occupancy profiles of house1 in 5s resolution.

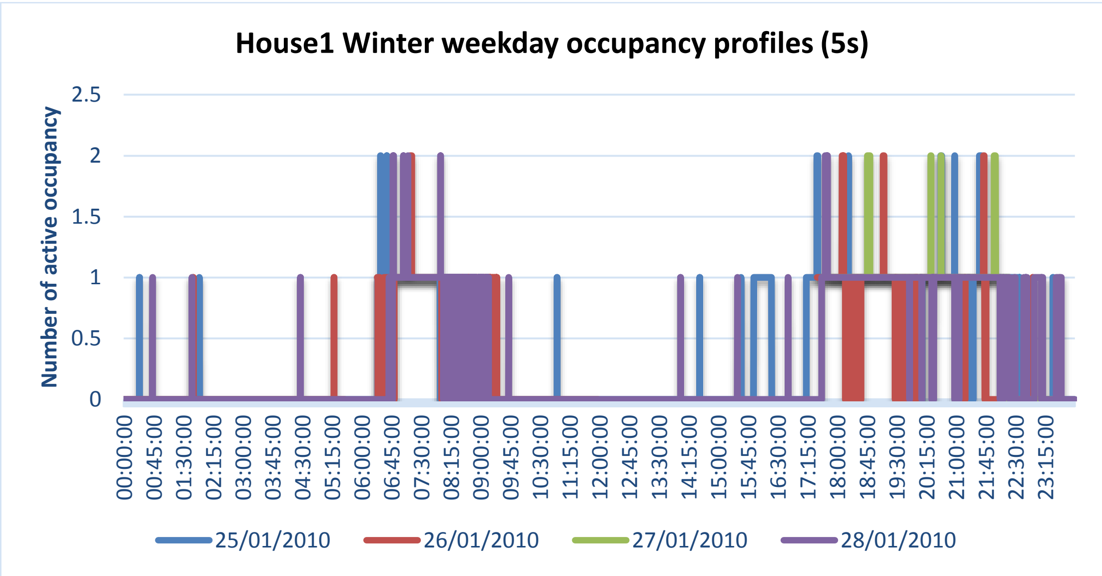


Fig. 3.25. Winter weekday occupancy profiles of house1 in 5s resolution.

From Fig 3.22 to Fig 3.25, the occupancy profiles of house1 in each seasons are depicted above. It is very clear that occupancy during spring and summer have very routine daily life, which has shown two complete peak period during morning and evening. There are some single activities in autumn and winter profiles, and it can be noticed they are in November and January, considered with related temperature, it can be identified as single heating appliance switch-on event. The total occupancy profiles have well proved the occupancy in this mid-Terraced house both have full-time jobs during weekday.

3.4.2 Occupancy profiles of Large-Terraced House (House2)

This type of household has two elder occupants, and one adult has a part-time employment, and the other is retired. Seasonally synthetic weekday occupancy profiles for house2 are predicted from Fig 3.26 to Fig 3.29.

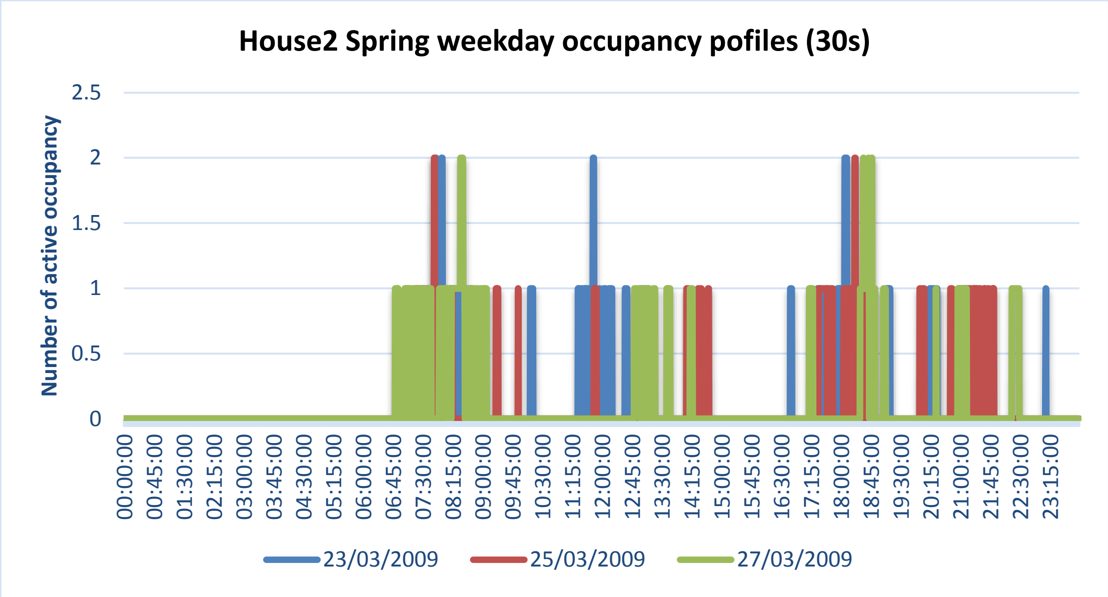


Fig. 3.26. Spring weekday occupancy profiles of house2 in 30s resolution.

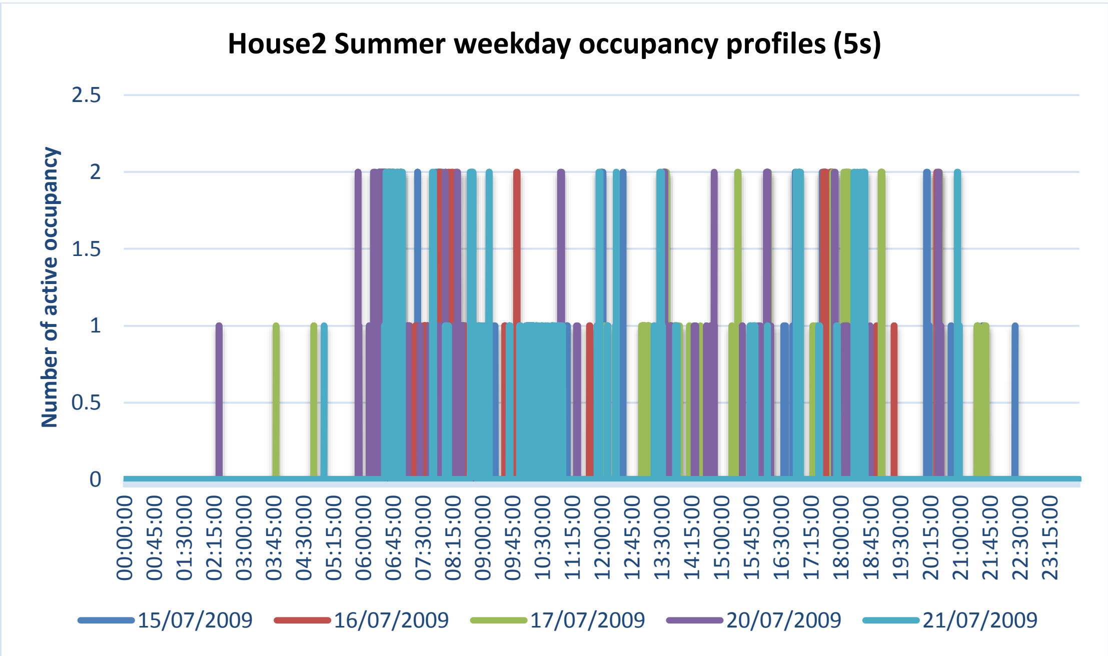


Fig. 3.27. Summer weekday occupancy profiles of house2 in 5s resolution.

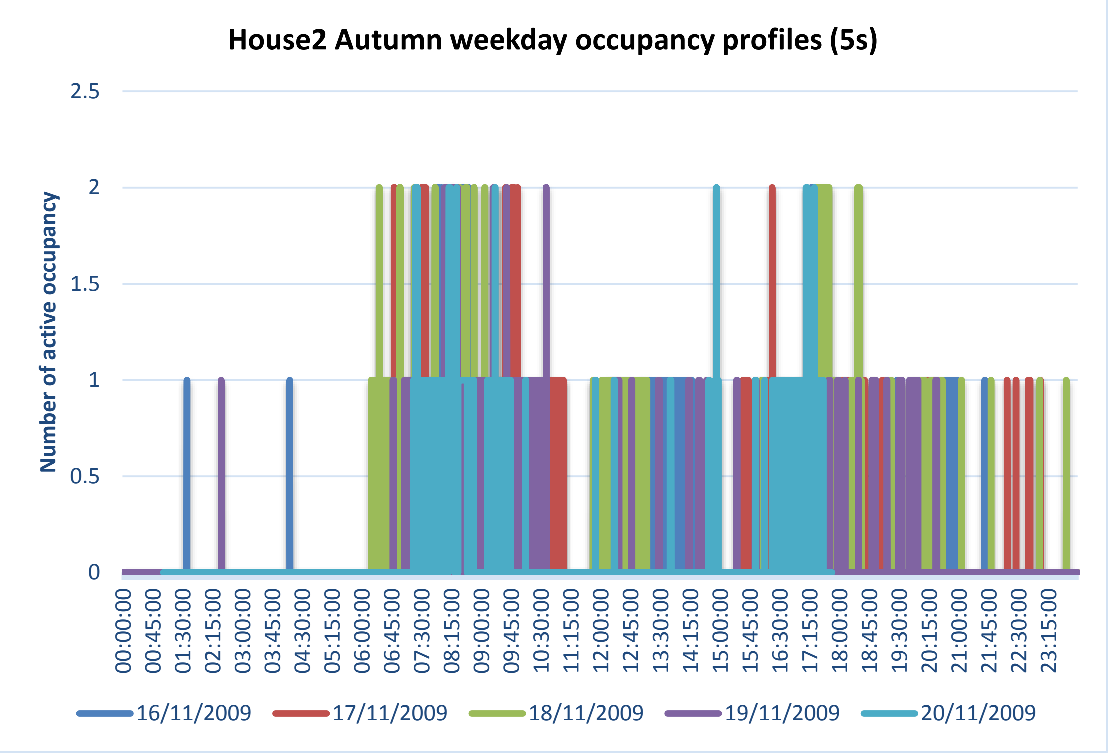


Fig. 3.28. Autumn weekday occupancy profiles of house2 in 5s resolution.

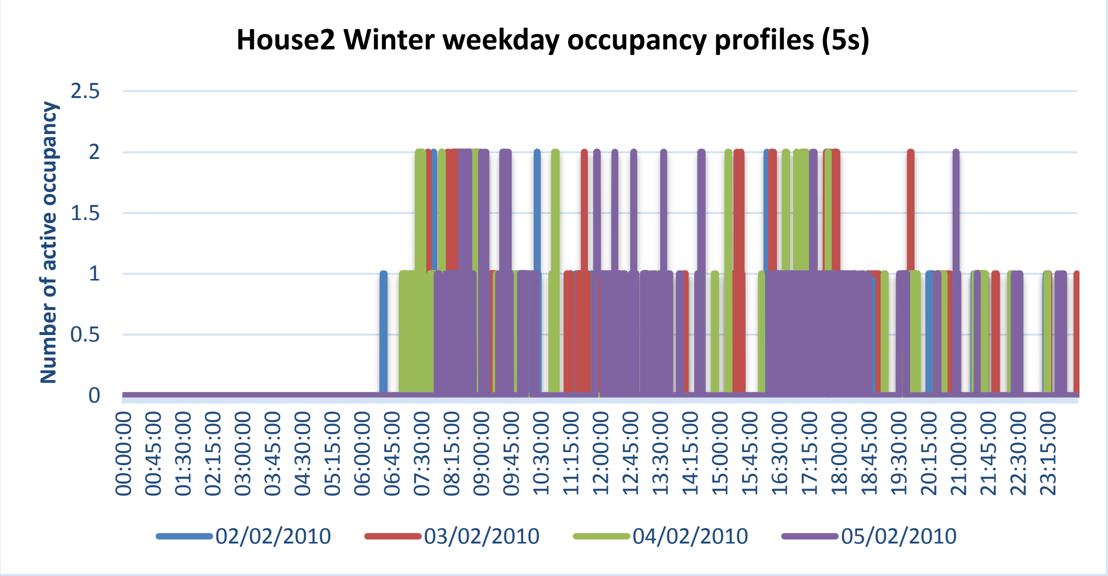


Fig. 3.29. Winter weekday occupancy profile of house2 in 5s resolution.

Fig 3.26 to Fig 3.29 show the occupancy pattern in this household is much more complicated than previous one. Because the occupancy can be active at any time. Meantime, there are some missing original data and bad data in this data pattern. Thus, the occupancy patterns in each season seem quite confused, which will make the difficulty in both load analysis and prediction parts.

3.4.3 Occupancy profiles of Semi-Detached House (House3)

House3 is a type of Semi-Detached stock, which has two adults whom both have full-time jobs, and also with three kids, one of them is an infant. The details of the occupancy profiles for this household are provided from Fig 3.30 to Fig 3.33.

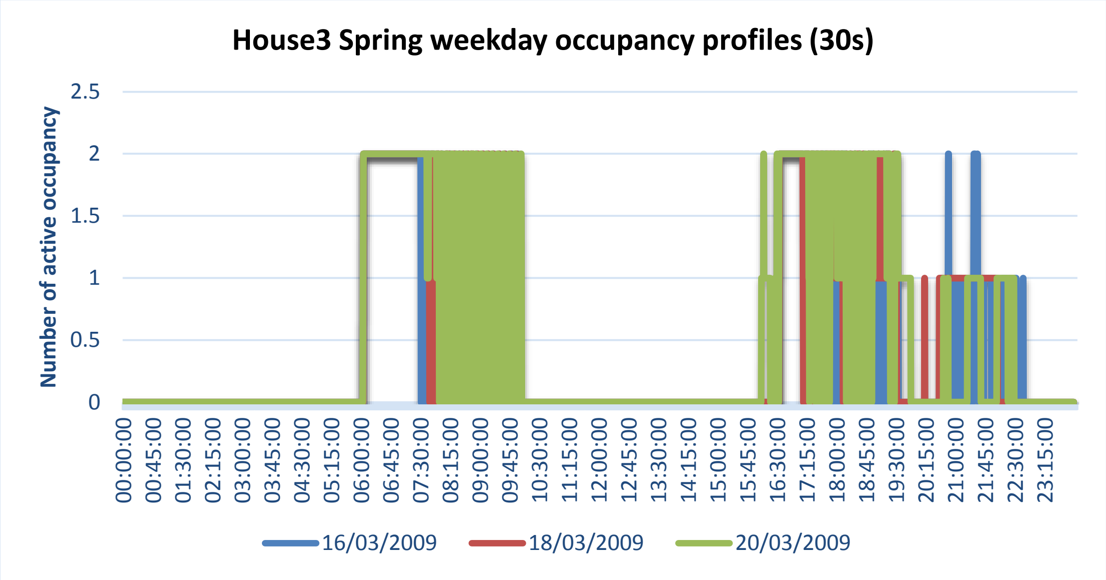


Fig. 3.30. Spring weekday occupancy profiles of house3 in 30s resolution.

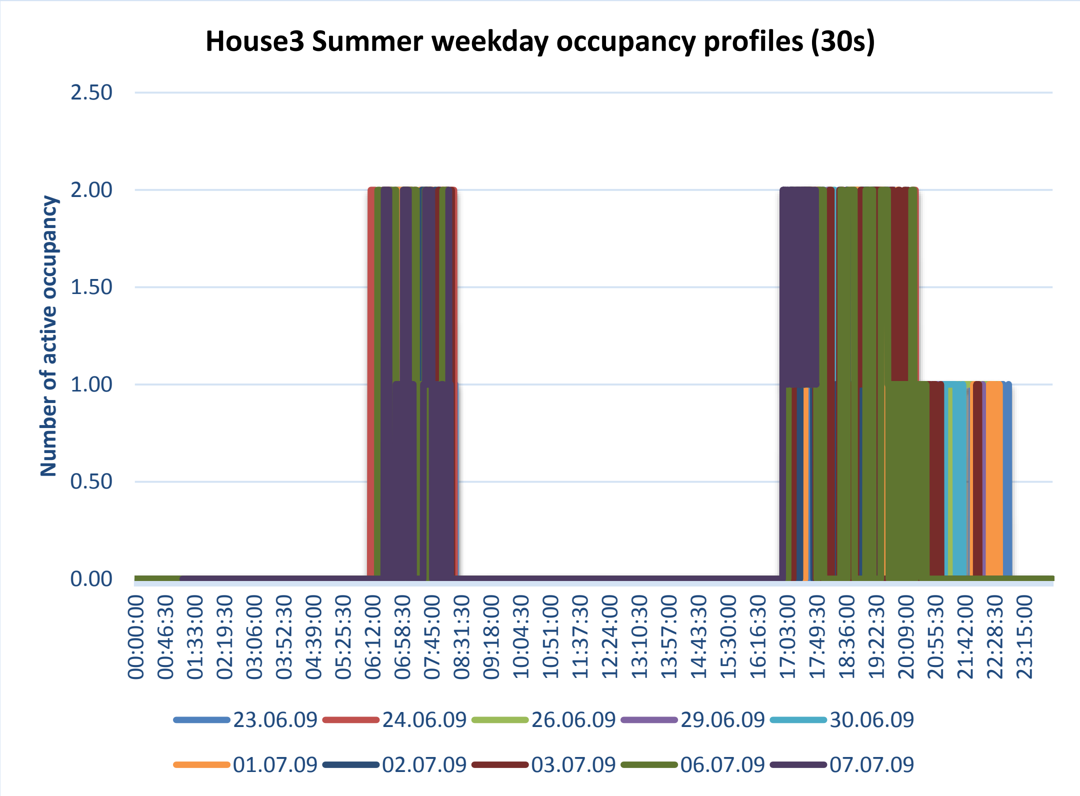


Fig. 3.31. Summer weekday occupancy profiles of house3 in 30s resolution.

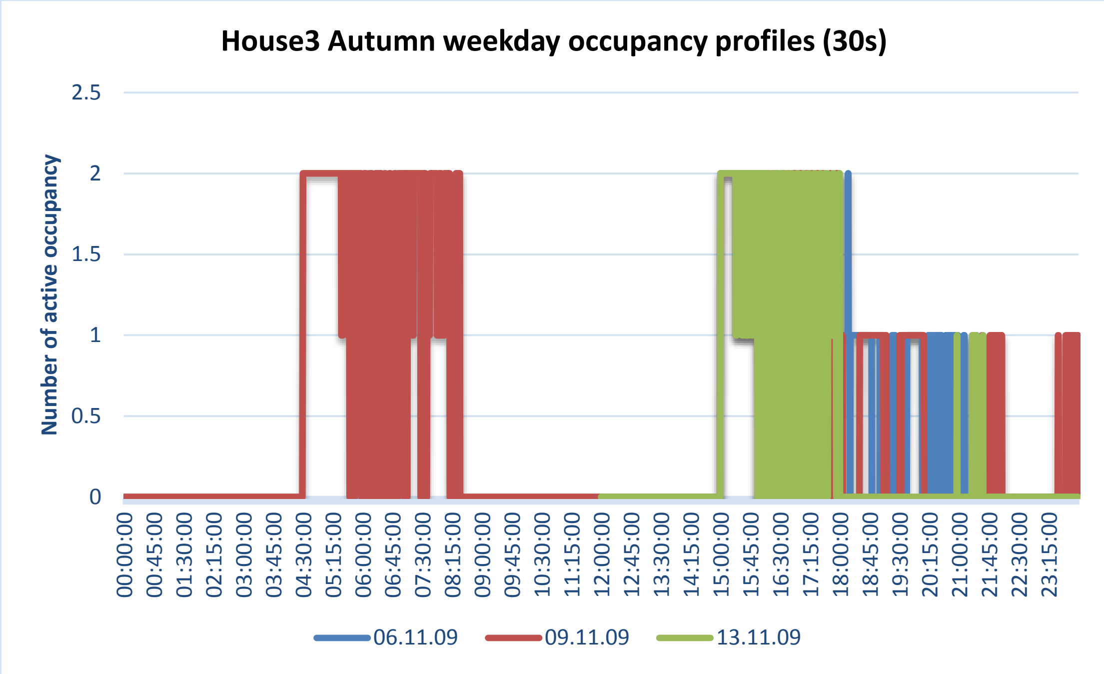


Fig. 3.32. Autumn weekday occupancy profiles of house3 in 30s.

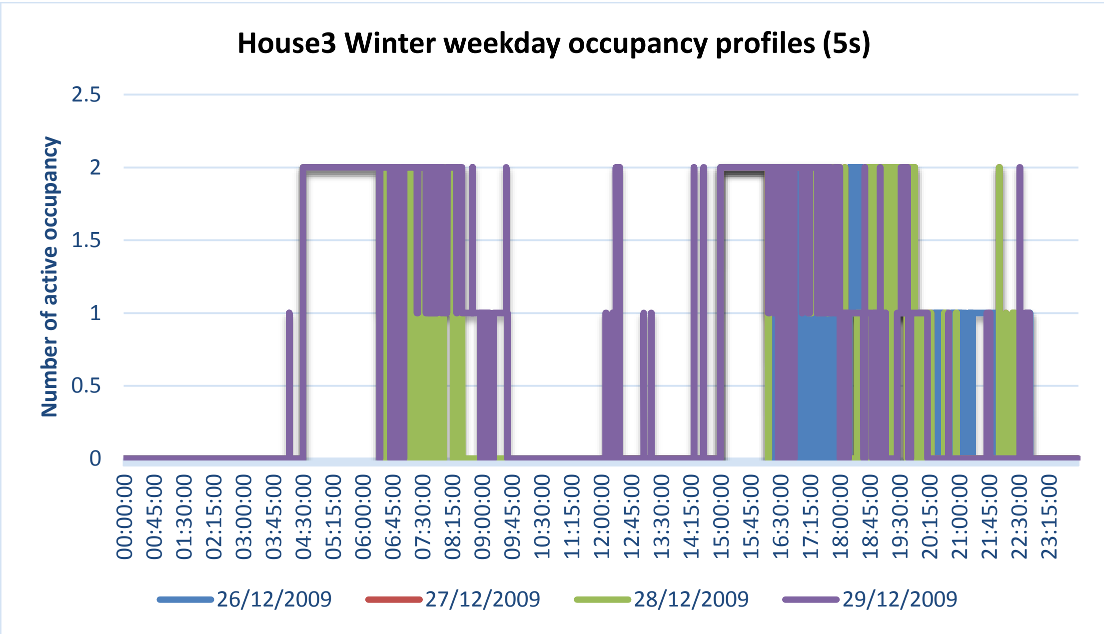


Fig. 3.33. Winter weekday occupancy profiles of house3 in 5s.

Fig 3.30 to Fig 3.33 depict all estimated occupancy profiles in this type of household pattern in four seasons. Although occupancy profile in 5s will present occupancy activities in more accurate, with the consideration of real-time daily activity for each occupancy, 30s resolution can capture most of the occupancy activities and cover all peak periods.

3.4.4 Summary of occupancy profiles generation

Because of the data log from Robert`s project [54] for each season only have one week load, therefore, the seasonally occupancy profile is assumed to be presented by weekly profiles. Meantime, the occupancy profiles during peak period in different resolutions such as 5s and 30s are nearly most same, and also considered with the utilization in simulation, therefore, 30s time interval is picked as main resolution in this study.

From the integration of occupancy profiles in several days, daily occupancy activities of particular household can be identified. For example in Fig 3.31, the occupancy profile shows that the occupants regularly wake up at 6am in the morning, then have breakfast between 6am to 8am, and leave home around 08:15 every day. Meantime, the house is usually unoccupied after 08:15 until 17:15. The evening peak period is from 17:15 to 23:00 for most time, which means the occupants normally go to bed before 11pm. Therefore, it can be found that the more daily load is logged, the more accuracy of an occupancy profile can be presented.

Although this type of occupancy profile is synthetic, which is estimated by number of in-use appliances, but it can be factually present the occupancy activity independently. Meantime, high-resolution like below 30s occupancy profile is not possible to record or collect because it will obviously interrupt occupancy`s daily. However, with this approach, synthetic high-resolution occupancy can be generated, even in 5s resolution because it is depended on related load pattern. By adding newly record, occupancy patterns can be updated dynamically, which is quite important in the energy demand prediction part.

The most important aspect of this method is that it can identify individual occupancy profile for particular household, not by using average occupancy profile like Time-Use data which has less accuracy to represent related occupancy activity.

High-resolution occupancy profile can be used in many applications, such as demand side management, energy demand prediction, auto-control of appliances, etc. Meanwhile, the AECO analysis can be used in arbitrary household to identify their particular occupancy patterns.

3.5 Summary

Average electricity consumption of occupancy is fully discussed in this chapter, by selecting universal electrical appliances, analysing related synthetic appliance use, then estimated active occupancy profiles are generated for each selected household. The methodology of AECO analysis can be extended into other applications, such as heating or cooling load, also daily, weekly, even seasonally high-resolution occupancy profiles can be provided for arbitrary household. Occupancy ordinary life and their daily schedule timetable can be identified by using AECO approach, which is very important for managing energy consumption.

Chapter 4. Dynamic electricity demand prediction for UK domestic users

4.1 Introduction

The prediction of domestic building electricity consumption was a very popular research topic in the last decade, as it can promote better building daily operation and optimize related control strategies in demand side management. Domestic electricity consumption is highly depended on related occupancy patterns, and because of the diversity of occupancy patterns in different households, real-time electricity consumptions are very complex, and vary from house to house. Meantime, daily occupancy activities are not ideally possible to collect or record for particular household. Therefore, some prediction methods choose to neglect this type of factor, such as time series, Fourier series, regression, and fuzzy logic. These models based on mathematical algorithms only contains a single prediction model which has identified a relationship between input possible influence factors and output energy demand. Thus, they are only be used to forecast low-resolution average electrical consumption, such as hourly, daily, monthly or yearly.

However, demand side management and related control system for domestic end-users require accurate prediction results. Therefore, occupancy patterns that can address how residents spent their time at home play a vital role in high-resolution electricity demand prediction methods. These methods, such as bottom-up models and stochastic methods, are currently using Time-Use data. Time-Use data is a type of one-day survey and collected from thousands of households to represent related occupancy patterns. Also, it is assumed the occupancy patterns are same in every day, which are not ideally possible in real life. Meantime, as the previous discussion, high-resolution real-time occupancy patterns, like below one-minute, are not likely to be recorded. Because it can be extremely interrupt the ordinary life of occupancy, which can lead undesirable or unreal results. Therefore, synthetic occupancy pattern is a possible solution to replace real-time activity in the context of electricity demand prediction.

On the other hand, historical load, which contains general electricity usage, is another important factor in electricity demand prediction. High-resolution historical load can accurately present electricity demand for particular household, and typically determine the electricity storage size when the end-uses decide to install. Historical load in prediction part can be categorized into two domains: average and instantaneous. Mostly, the former one is usually used in static prediction models with low-resolution load, and these models cannot be modified when it is built up. Therefore, they cannot capture the variation of a household environment, like occupancy or appliances alterations. Meantime, the results of these models can only present historical general electrical usage for a fixed period by assuming the system is fixed without any modifications. To solve these limitations, dynamic prediction models using instantaneous load is becoming major concern in recent years. These type of models require both continuous occupancy profiles and instantaneous load in high-resolution. However, the former one is not possible to record currently. Therefore, most researchers are using fixed profiles derived from Time-Use data to replace real-time occupancy pattern or even neglecting related occupancy profiles. Meantime, fixed occupancy profiles cannot represent the actual occupancy activities for particular household, which will lead inaccuracy prediction results and cause extra cost in demand side management.

To fill this research gap, high-resolution dynamic synthetic occupancy profiles (30s) presented in chapter 3 are utilized in this chapter. Two selected dynamic prediction methods for forecasting thirty seconds time-resolution electricity demand are employed in this research, which are Artificial Neural Network (ANN) model and Markov-Chain model. The former one is using historical uncertain related factors to produce exclusive result as presented in section 4.2.The later one is employing particular inputs to generate electricity consumption stochastically, which is presented section 4.3. The prediction and validation of the occupancy profile and related electricity demand are presented separately from section 4.4 to section 4.7. In the last, the comparison between most popular prediction bottom-up model and stochastic model as employed in this research is presented in section 4.8.

4.2 Artificial Neural Network model

Artificial Neural Networks (ANN) has been acknowledged as human neurons because of its individual characters such as pattern recognition, perception, and motor control, many times faster than the fastest digital computer in existence today [123]. Haykin in [123] presents that: "*A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use*".

4.2.1 Function of ANN

A neural network has to be configured by a set of direct or relaxation inputs, a number of neurons and a set of outputs. Each set of input produces the desired set of outputs. Fig. 4.1 has shown a nonlinear model of a neuron, which has three parts like inputs signals $x_{0...n}$, summing junction $v_k$by synaptic weights and activation function to produce output y_k.

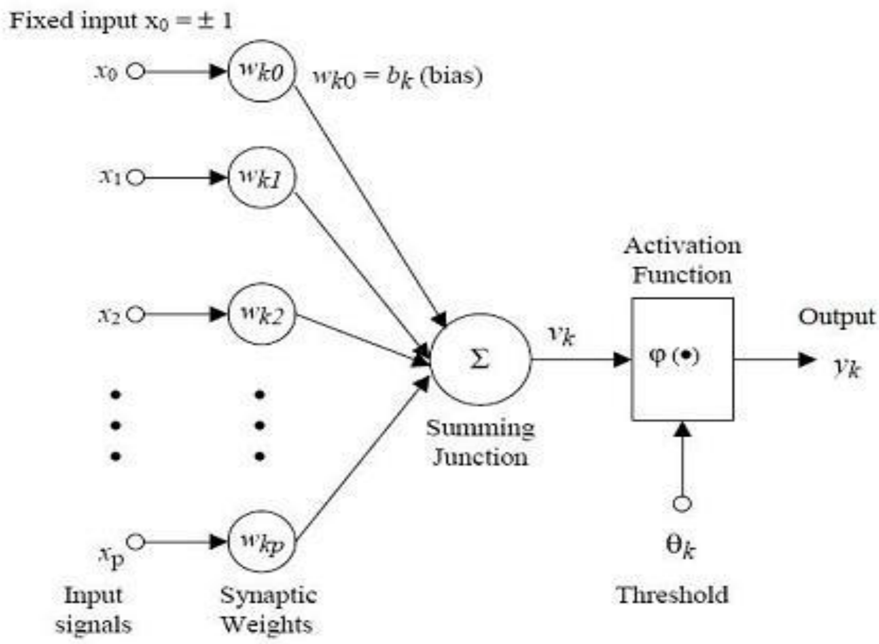


Fig.4.1. Nonlinear model of a neuron [124]

Where the fixed input signals $x_0, x_1, x_2 ... x_n$ multiply the synaptic weights severally, and have a summing function in order to compare to the θ with the activation function, and then produces an output.

From this model the interval activity of the neuron in summing junction can be shown:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \tag{4-1}$$

The output of the neuron, y_k, would, therefore, be the outcome of some activation function on the value of v_k [124].

There are various methods to set the strengths of the existing connections. Normally is to set the weights explicitly, by using prior knowledge, another way is to set the weight randomly in initial, and then train the neural network by using some learning rule to teach patterns and change the weights by itself. If the output is same as the desirable, the training will be terminated; otherwise, the weight will be adjusted until get the desirable result. Three primary training rules are listed as:

- **Supervised learning -** the network is trained by providing it with input and matching output patterns.
- **Unsupervised learning -** output unit is trained to respond to a set of input patterns.
- **Reinforcement learning -** This type of learning may be considered as an intermediate pattern of the above two types of learning.

The activation functions vary for each learning methods; there are four typical activation functions, which are sigmoid function, tan function, Sigmund function and step function. These activation function plays as a squashing function, and produces the outputs as individual values which are between (0 and 1, or -1 and 1) [124].

ANN is one of the most modern dynamic forecasting methods in energy demand prediction field, as its model can be updated dynamically by adding new data. The relationship between input and output factors in ANN model can be auto-trained, which can capture system environment variations, like appliance changes.

Electrical appliances are operated by active occupancy and consumed electricity for a while, which is identified as cycle length for particular appliance. Thus, the previous electrical load has a high influence with the current load. A recurrent neural network is employed in this study. It has a context layer which can obtain the previous output from the hidden layer and feed back to the input for training the neural network.

4.2.2 Elman`s neural network model

Elman`s Neural Network (ENN) contains a context unit, which can hold the information of the last inputs, such as weight and attribute. The context unit can memory the value of output and send back to the hidden neurons as another input. It can be recognized as lag algorithm, which can produce the dynamic prediction.

The feature of Elman`s recurrent network is the lag and storage of its context layer, it can be very sensitive with the history states, also with the internal recurrent character, the network can deal with the information dynamically. It can produce arbitrary precision to any non-linear mapping. Fig.4.2 has presented a typical topology of Elman`s recurrent neural network.

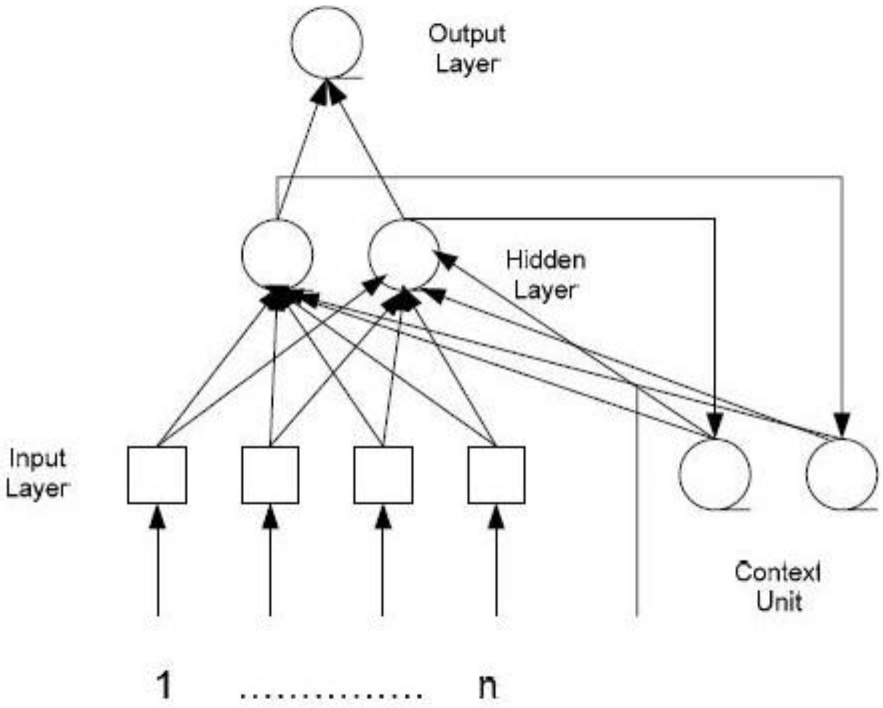


Fig. 4.2. Elman`s recurrent neural network [125]

There are four layers in Elman`s recurrent network, which are input layer, hidden layer, context unit and output layer. Each layer contains multiply neurons which can be recognised as input neurons, hidden neurons and output neurons [125].

- **Input layer**: An input neuron receives inputs from the original data, and each input neuron represents a type of related factor and connects with every next neuron of hidden layer. There are 19 inputs in this network, each input factors which will be discussed later.
- **Hidden layer**: The hidden neuron in this layer receives inputs from the input neurons and the context neurons, then sends outputs to both the output layer and the context layer. The number of the hidden neurons is set as 18, by using cut-and-trail methods.
- **Context layer**: The context unit in the context layer can store the output from the hidden layer and feedback as inputs to the hidden layer to re-train network. The number of the context neurons is equal to the hidden layer.
- **Output layer**: The output neuron in this layer receives the training results then exports final outputs. The number of the output neurons depends on the output

of data structure, and in this network there is only one output which is the predicted electrical load.

Each input neuron receives value from original inputs data and set connection to next layer (hidden layer in ENN) with individual weight, and then every hidden neuron produces output result to output neuron to decide the final value. The number of the input neurons is decided by related factors, and weight of each input neuron represent the importance relevance for every input factor. The optimal number of hidden neurons is selected by the following rules:

$$l < \ n - 1 \tag{4-2}$$

$$l < \ \sqrt{(m+n)} + \ a \tag{4-3}$$

$$l = \ \log_2 n \tag{4-4}$$

Where n is the number of input layer neurons; l is the number of hidden layer neurons; m is the number of output layer neurons; a is a constant between 0 ~ 10. In fact, the selection of the number of hidden neurons is to identify the number of ranges firstly, and then use cut-and-trial to modify and confirm the final number of hidden neurons.

Training for Elman`s neural network is followed by following steps [125]:

1. Network initialization

Identify the sequence of system input (*U*) and output (*O*), confirm the number of input neurons *n*, hidden neurons *l*, and output neurons *m*, and initialize the weight between context layer and hidden layer ω^1, the weight between input layer and hidden layer $\omega^2$and the weight between hidden layer and output layer ω^3; initialize the threshold value of hidden layer *a* and output layer *b*, in this project, we give it as 0 and 1, and give study rate and activation functions.

2. Calculate the output of hidden neuron

$$X_k = f(\omega^1 x_c(k) + \omega^2 u_{k-1}) \ \ k = 1,2, \dots, m \quad , \tag{4-5}$$

$$X_c(k) = \ X_{k-1} \ \ k = 1,2, \dots, m \tag{4-6}$$

X_0 is the initial output of hidden layer, X_k is the output of hidden neurons with n dimension; u is the input vector with r dimension; X_c is the feedback vector with n dimension; $f(*)$ is the activation function, in this project, it has been selected as:

$$f(x) = \frac{1}{1+e^{-x}} \tag{4-7}$$

3. Calculate the output of output neuron *Y* (predicted output)

$$Y_k = g(\omega^3 x_k) \tag{4-8}$$

Where $g(*)$ means the transmit function; it is the linear set of hidden layer output.

4. Error calculation

Based on the predicted output Y_k and expected outputO_k, calculate the error.

$$e_k = Y_k - O_k \quad k = 1,2, \dots, m \tag{4-9}$$

5. Weight modification with learning indicator

$$E(\omega) = \sum_{k=1}^{n} (Y_k(\omega) - O_k(\omega))^2 \tag{4-10}$$

6. Decision-making. Estimate the iteration is finished or not, if no, return step 2. If finish, calculate the Mean Absolute Percentage Error (MAPE)

$$MAPE(\%) = \frac{1}{N} \sum_{i=1}^{N} \frac{\left|P_A^i - P_F^i\right|}{P_A^i} \times 100 \tag{4-11}$$

Where P_A is the actual load, P_F is the predicted load, and *N* is the number of data.

MAPE is a measure of accuracy of an approach and widely used in the prediction validation and trend estimation. The MAPE percentage primarily shows the accuracy of prediction model, which is used to indicate the validity of predicted model dealing with different data set. In this research, the MAPE is employed as the indictor in the prediction validation to determine whether the selected prediction methods are desirable.

4.2.3 Input factors of Elman`s network

The nature of domestic electrical load are highly related four type of factors: (a) historical load; (b) the number of active occupancy; (c) component of appliance; (d) domestic appliance use;

Firstly, historical load factor contains the load of the previous day and the average load of last week at same time. Secondly, the number of active occupancies is generated by using AECO analysis for each household. In the third, the number and type of appliances are still selected from Table 3.3. Last but most important, because domestic appliance use cannot be predicted instantaneously, it is employed appliance use weight to instead this type of factor, which can be identified by following equation:

Appliance use weight = Appliance load (kW) × Appliance activity possibility

Where the appliance activity possibility is selected from Richardson model [25] which is derived from UK Time-Use data. In Time-Use Survey data, the appliances based on related occupant behaviour are categorized into seven domains:

- **Cooling**: Including fridge and other cooling appliances.
- **TV**: Watching television, and a TV receiver box is also included when this type of activity is active.
- **COOKING**: Performing cooking activities, including microwave, oven, toaster, kettle and hob.
- **LAUNDRY**: Doing laundry, washing machine is active.
- **IRON**: Ironing
- **HOUSECLEAN**: Cleaning the house by using a vacuum.
- **Occupant related**: These appliances may be active when there is more than one occupant is active, and also the probability will be increased when the number of active occupants grown. These appliances include printer, personal computer, CD player, HiFi, electrical heating and lighting.

The Time-Use Survey data is collected from thousands of households in UK, and at each specified time, how many households are using specific appliances can be represented by the activity possibility profiles. An example of cooking activity profile is presented in Fig. 4.3. It can be clearly shown when the number of active is growing; the possibility of appliance use is increasing. Because the Time-Use data only classifies appliance use into seven domains, it is assumed that the appliance in the same category has identical switch-on possibility.

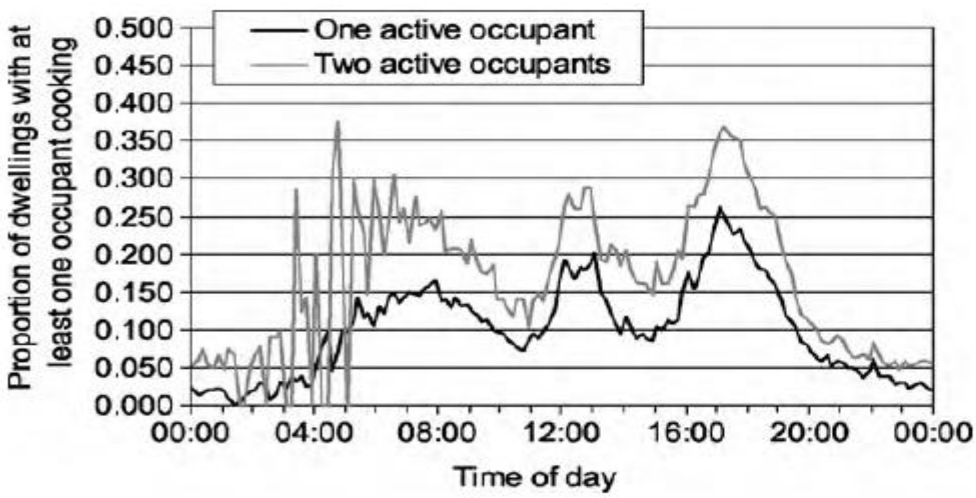


Fig. 4.3. Weekday cooking activity profile for one or two active occupants [25].

Therefore, the input factors in this Elman`s network can be identified as following:

- The load of the previous day at same time(kW)
- The average load of last five days at same time(kW)
- The synthetic number of active occupancy
- Fridge
- TV and TV receiver box
- Microwave
- Oven
- Toaster
- Kettle
- Hob
- Washing machine
- Iron
- Vacuum
- Printer
- Personal Computer
- CD Player
- HiFi
- Electrical heating
- Lighting

4.2.4 Matlab implementation

Matlab`s neural network toolkit has been employed to implement and train the models. The step of implementation is followed:

a) Data normalization, to normalize all the data between 0 and 1.
b) Data classification. Including produce data sequence randomly, selects the normal training data, validation data and test data.
c) Neural network build-up. Because of the complexity of layers and the number of neurons in each layer, there is no scientific model and formula to identify the number of neurons. It is typically used experienced method or cut-and-trail, set the transmit function of hidden or context layer.
d) Initial the training parameters.

e) After training, invoke the results; input the test data, starting a testing process.
f) Data de-normalization.
g) Error and results analysis, classification, figure generation.

The program code is presented in Appendix, and an example of model processing is shown at Fig. 4.4.

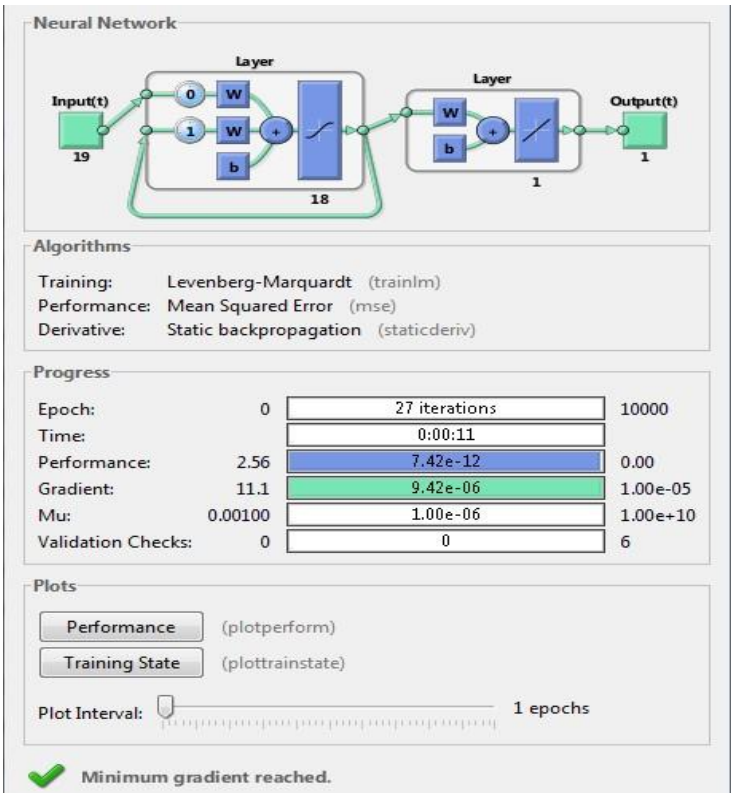


Fig. 4.4. Simulation of Elman`s network in Matlab.

4.2.5 Results and discussions

Because all day load prediction needs huge database and will cause extremely long time in the simulation, thus it is selected peak periods from weekday with each participated household, three example of results are presented from Fig. 4.5 to Fig. 4.7.

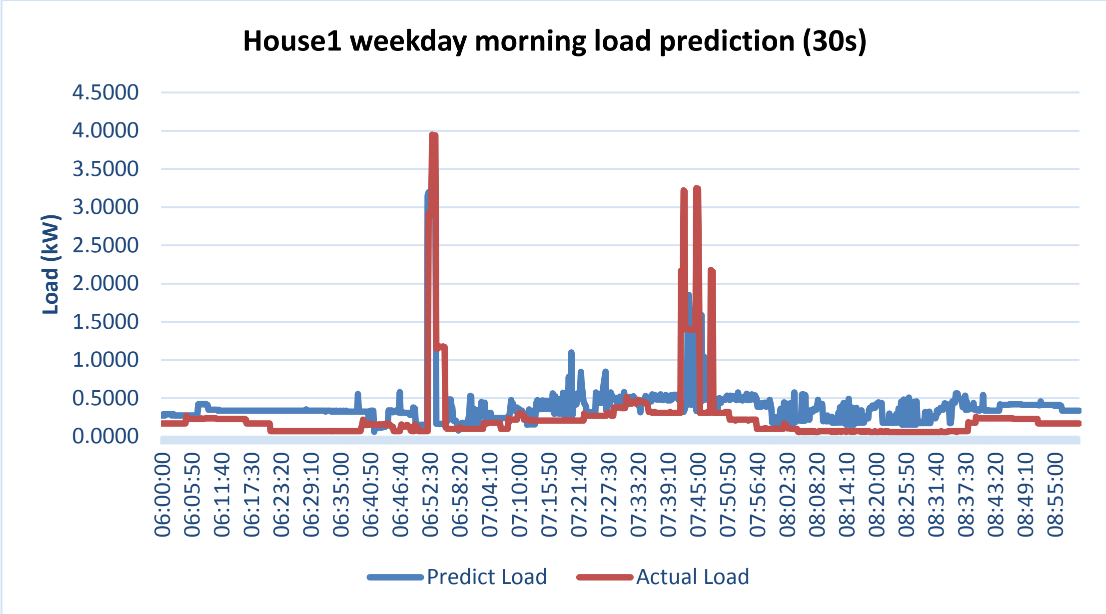


Fig. 4.5. Weekday morning electricity load prediction from 06:00 to 09:00 of house1

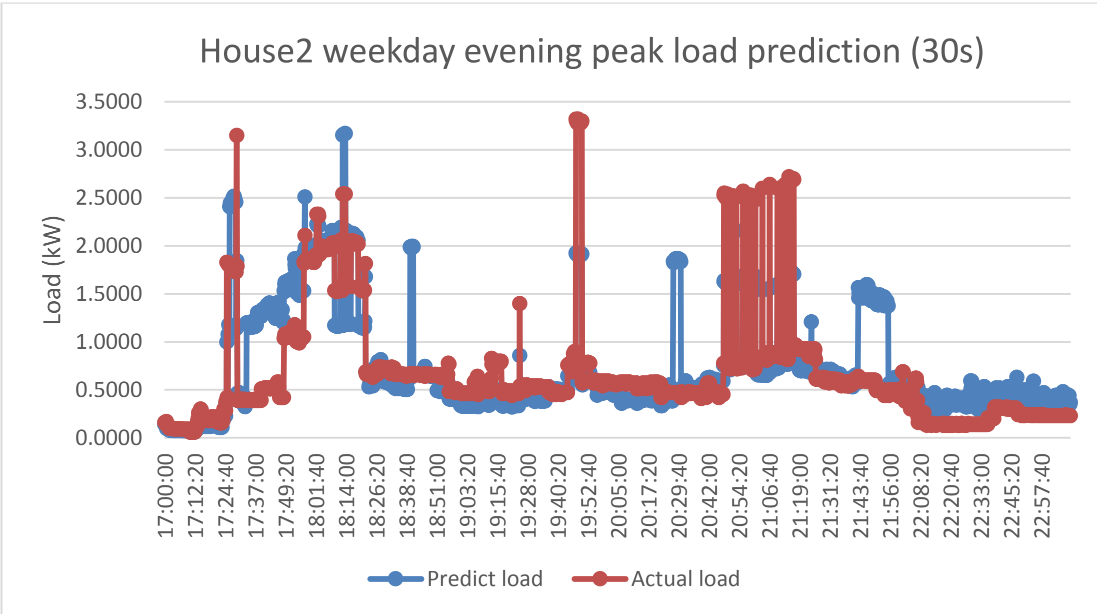


Fig. 4.6. Weekday evening electricity load prediction from 17:00 to 23:00 of house2

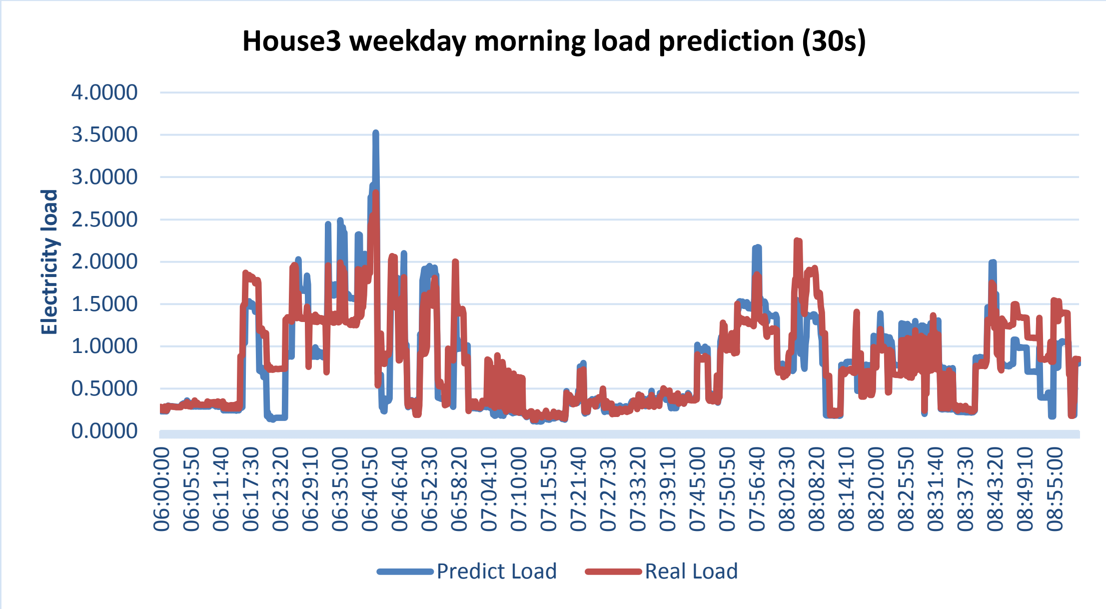


Fig. 4.7. Weekday morning load forecasting from 6am to 9am of house3.

Although the results show that peak load curve can be predicted roughly, MAPE of each simulation is over 15%, which is not suitable for dynamic prediction.

The first reason is the number of active occupancies. Because this type of input factor is given from history record in the training process. However, after training process, it is unknown in output results generation, which is also should be predicted. It can be used historical average number of active occupancy to instead predicted one, which will cause a difference, because occupancy profile may be various every day.

The second reason is the weight of appliance use. The current weight used in this model is derived from Time-Use data, which is the average active possibility of thousand households. The appliances use in different household may have some diversity. For particular household, real-time appliance use should be seriously considered.

Because of the uncertainty of occupancy profiles and related appliance use, the ANN model, which using uncertain factors to generate unique result, is not an ideal solution for dynamic electricity consumption.

Therefore, another model is selected to stochastically produce active occupancy profile and related electricity consumption.

4.3 Stochastic model: Markov-Chain

Markov-Chain is a traditional stochastic method and applied in many applications, like energy consumption. Richardson et al. [38] present a domestic building occupancy model for energy demand simulations with a two-state non-homogeneous Markov-chain. The transition probabilities in that research are generated from Time-Use Survey data in the UK. Widen et al. [66] provide a combined Markov-Chain and bottom-up method to modelling of domestic lighting demand with a three-state non-homogeneous Markov-chain, where the transition probabilities are determined from Time-Use data in Swedish households. These two methods have identified that Time-Use data can be successfully used in a stochastic model to generate domestic specific electricity demand profiles.

However, as the previous discussion, although Time-Use data can be used in many energy demand simulation models, it cannot present individual occupancy pattern for particular household. For example, the Time-Use data shows that there is a peak period during an afternoon every weekday, but the occupants in selected household both have full-time jobs which are not able to be active at that time.

Meantime, the most important aspect is Time-Use data only contains one day or two days occupancy data. Therefore, this type of discontinuous data cannot provide daily occupancy preference. In terms of the diversity of occupancy pattern varies from day to day and house to house; individual occupancy pattern should be seriously considered in the stochastic model. The advantage of using individual occupancy pattern in the stochastic model firstly is more realistic. It also contains consecutive information of how occupancy spent their time at home during selected periods, which are very necessary to indicate particular occupancy pattern independently.

Therefore, with the previous analysis of AECO, particular occupancy pattern is used in a stochastic model by employing Markov-chain method. It is used particular inputs, as historical electrical load and occupancy pattern, to generate electricity consumption stochastically.

4.3.1 Model description

In terms of the complexity and randomness of occupancy behaviours, and also the detailed realistic occupancy activities profiles are not possible to be obtained. Therefore, some researchers developed synthetic occupancy profile to replace the real pattern, where a mathematical method named Markov Chain is employed to resolve this type of problem. Markov Chain is defined as "*A stochastic model describing a sequence of* *possible events in which the probability of each event depends only on the state attained in the previous event"* [126].

The principle of Markov-Chain is throughout discussed in the literature previously. A Markov-Chain X is a discrete time stochastic process $\{X_0, X_1, \ldots, X_n\}$with the property that the distribution of X_t given all previous values of the process. $X_0, X_1, \ldots, X_{t-1}$ only depends upon X_{t-1}, then for any set A, the transition probability P at state t, can be written as [127]:

$$P[X_t \in \ A|X_0, X_1, \ldots, X_{t-1}] = P[X_t \in A\ |X_{t-1}] \tag{4-12}$$

A two states non-homogeneous Markov-chain model assumes that a person presents two status: inactive and active. The former one presents the person is asleep, away, or stay at home but did not consume any electricity, such as reading in a summer afternoon. Another status depicts that the person occupies any appliance in the home. Three states Markov-chain has divided inactive presence into absent, present and inactive. These classifications are based on known occupancy pattern, such as from Time-Use survey. As this type of survey is collected from thousand households, the occupants can be active at any time, which is not realistic for individual household.

With the analysis of AECO, the occupancy presence in particular household can be identified. Therefore, the states can be selected to the number of active occupants. For the participated household in this research, it can be presented in three states non-homogeneous Markov-chain model, which are zero active occupancy, one active occupancy, and two active occupancies. The occupancy must be one of these states in each time step, $i = 1, \ldots, N_i$.

When the time step i is moving from i to j, $j = i + 1, \ldots, N_i$, occupancy presence holds a transition probability which shows the forwarding from state m to n, therefore, the probability of staying in state m can be presented by $p_{mm}(i)$, and the probability of moving from state m to state n can be indicated by $p_{mn}(i)$, respectively. $p_{mm}(i)$ and $p_{mn}(i)$ can be identified from historical record, which indicates that at each time step i, how many days in total are staying at state m, then depicting the number of days when moving from m to n. Therefore, for a three-states Markov-chain, the states and transition probabilities can be represented in Fig. 4.8.

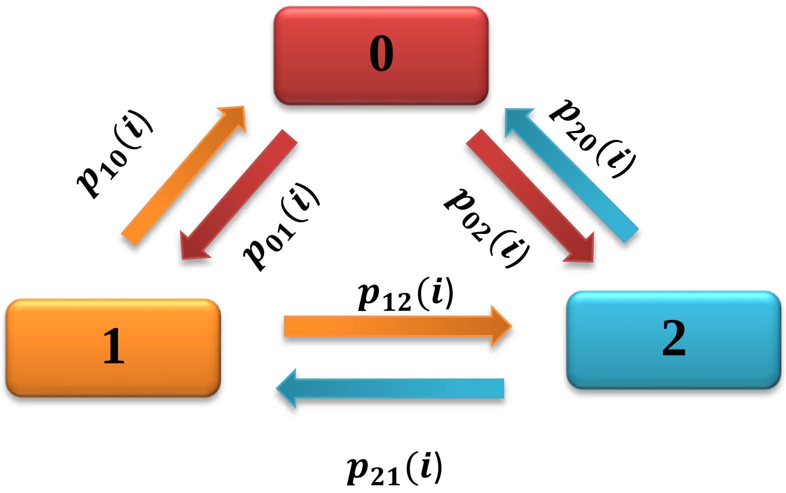


Fig. 4.8. Three occupancy states: 0 = zero active occupancy, 1 = one active occupancy, 2 = two active occupancy, and transition probabilities in Markov-chain occupancy presence model for the household with two occupants.

Therefore, at each time step i, the transition probability p_i can be ordered into a 3x3 matrix, as shown:

$$p_i = \begin{bmatrix} p_{00}(i) & p_{01}(i) & p_{02}(i) \\ p_{10}(i) & p_{11}(i) & p_{12}(i) \\ p_{20}(i) & p_{21}(i) & p_{22}(i) \end{bmatrix} \tag{4-13}$$

Now, the whole transition probabilities sequences of occupancy presence for each household can be linked in high-resolution as selected 30s in this study.

For example in the application of occupancy presences, we simply assume that there is a household which has one adult occupant, and his presence has been recorded within10-min resolution record in past 14 days. Therefore, for each ten times in per day, the occupancy activities can be linked in a Markov-Chain, as 2 × 2 matrix, and his presences are simply divided into two domains: asleep and active. Therefore, for every continuous 30s record, which is named as “states”, it held a 2 × 2 “transition probability matrices”, as shown in Table 4.1 and Table 4.2.

Number of active occupants		Number of occurrences in the history record (day)		Transition probability
At 06:00:00	At 06:00:30			
0	0	8	8+4=12	8/12 = 0.75
0	1	4		4/12 = 0.25
1	0	1	1+1 = 2	1/2 = 0.5
1	1	1		1/2 =0.5

Table. 4.1. A simple example of transition probability matrix calculation for one occupancy household in one day at 06:00:00-06:00:30.

In Table 4.1, the number 0 means this occupancy is asleep at that time, and 1 presents there is one active occupant, and number 8 means in the past 14 days, there are 8 days, this occupancy is asleep at 06:00:00 and very likely still be asleep at 06:00:30, then this is represented by 0.75 probability in occurrences. Alternatively, if this person is asleep at 06:00:00, there are 4 days shows that he is awake at next 30 seconds at 06:00:30, and the probability is slightly presented as 0.25. Therefore, for one person, the detailed 2 ×2 transition probability matrix is shown in Table 4.2.

Active occupants	Next state (at 06:00:30)	
	0	1
Current state (at 06:00:00)		
0	0.75	0.25
1	0.5	0.5

Table. 4.2. A simple example of transition probability matrix for one occupant household.

Markov-chain is a well-established stochastic method of data generation [127], and all existing status can be captured and linked with transition probability in each state.

Therefore, the occupancy states in this type of application can be particularly linked and modelled in different time-resolution by using Markov Chain. The example we present is simple and related transition matrix is quite stable. Therefore, it cannot be used to capture the future variation.

In order to stochastically generate occupancy presence for each household, the Markov-Chain Monte Carlo (MCMC) method is employed. MCMC methods are defined as "*a class of algorithms for sampling from probability distributions based on constructing a Markov chain that has the desired distribution as its equilibrium distribution*" [128].

All sequences are generated by following Metropolis-Hastings algorithm, which is given by [129]:

a) Initialize the iteration counter *j* = 1 and set the initial value of the chain $\theta^{(0)}$.

b) Initialize the component counter *i* = 1, where $i, j = 1, \dots, d$.

c) Move the *i*th component of the vector of states of the chain to a new value $\emptyset_i$ generated from density $q_i\left(\theta_i^{(j-1)}, \emptyset_i\right)$.

d) Calculate the acceptance probability of the move $\alpha_i\left(\theta_i^{(j-1)}, \emptyset_i\right)$, where

$$\alpha_i(\theta_i, \emptyset_i) = min\left\{1, \frac{\pi_i(\emptyset_i)q_i(\emptyset_i, \theta_i)}{\pi_i(\theta_i)q_i(\theta_i, \emptyset_i)}\right\}, \qquad (4\text{-}14)$$

And

$$\pi(\theta) = \pi_i(\theta_i)\pi(\theta_{-i}) , \qquad (4\text{-}15)$$

Where π_i is the full conditional density of θ_i.

Meantime, the move determined by q_i only changes θ_i , so $\theta_{-i} = \emptyset_{-i}$ and

$$\frac{\pi(\emptyset)}{\pi(\theta)} = \frac{\pi_i(\emptyset_i)}{\pi_i(\theta_i)} \qquad (4\text{-}16)$$

If the move is accepted, $\theta_i^{(j)} = \emptyset_i$ .If the move is not accepted, $\theta_i^{(j)} = \theta_i^{(j-1)}$ and the chain does not move.

e) Change the counter from i to i +1 and return to step c) until $i = d$.When $i = d$, go to step f).

f) Change the counter from *j* to *j* +1 and return step b) until convergence is reached.

The implementation of MCMC in this study is following:

Firstly, the initial state is set as 00:00:00 at each day. The historical data shows that all occupants are asleep at that time, and they are also asleep in the next 30 seconds. So the initial occupancy presence is zero active occupancy with $p_{00}(1)$ as 1, and other probabilities are 0. Then in each step during Markov-Chain moving from i to j, an uniform random number between 0 and 1 is picked to compare with existing transition probabilities to decide which state is taking place. For a Markov-Chain with 30s resolutions, there are 2880 states in one day, and occupancy presence at each state is represented as $s(k)$,

Where $s(k) \in \{0,1,2\}, k = 1, \dots, 2879$.

Therefore, the details of one day state generation are shown as following:

Step 1. Initial state setting as $s(1) = q$, which q is determined by realistic occupancy profile.

Step 2. Set integer number k as index, where k is from 1 to 2879.

Step 3. For k from 1 to 2879:

Step 4. Generate random real number $R \in [0,1]$.

Step 5. If $0 \leq R < p_{q0}(k)$, then $s(k+1) = 0$

Step 6. Else if $p_{q0} \leq R < (p_{q0} + p_{q1})$, then $s(k+1) = 1$

Step 7. Else if $(p_{q0} + p_{q1}) \leq R$, then $s(k+1) = 2$

Step 8. Next k, repeat step 4 to step 8.

With the loop continuously processing, one occupancy presence in a day is generated, and then the algorithm can produce an arbitrary number set of possibilities by choosing simulation times with finite existing states.

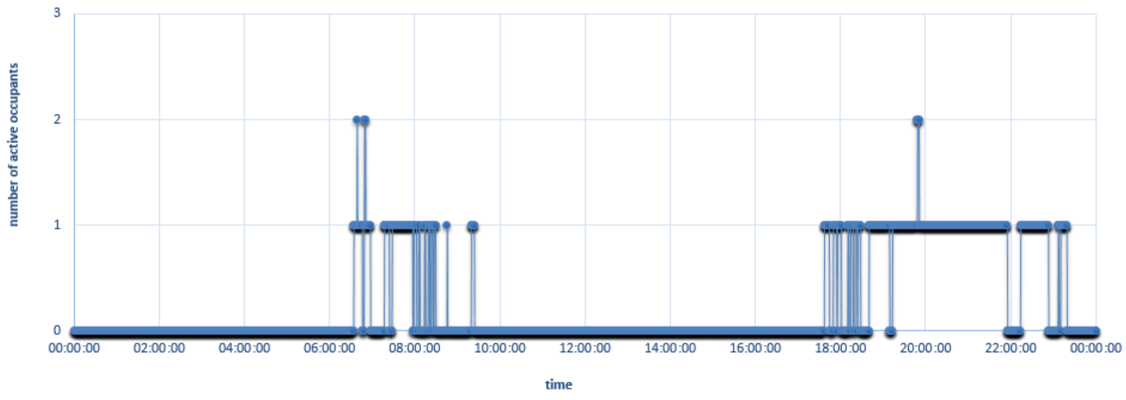
When the stochastic occupancy profiles of household with two occupants are generated, the load boundary of AECO is used to transit synthetic occupancy presence to average occupancy electricity load. Then calculation of the average electricity consumption for each number of active occupancy is given.

4.3.2 Model implementation and simulation

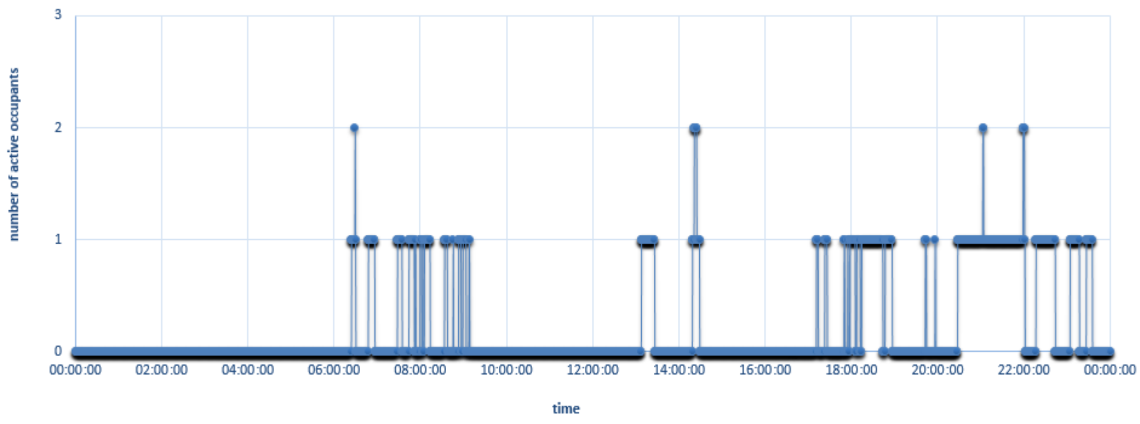
The model is made in Microsoft Excel workbook and using Visual Basic to implement the algorithm of stochastic occupancy presence generation. The program code is presented in Appendix.

Four examples of simulation results with house2 during spring weekday are presented in Fig.4.9 and Fig. 4.10. It can be seen clearly that each result has shown different occupancy pattern, however, all of these results are generated from same occupancy presence matrix.

Therefore, the occupancy profiles for each household have been divided into four seasons in terms of to identify the difference of the active pattern independently.

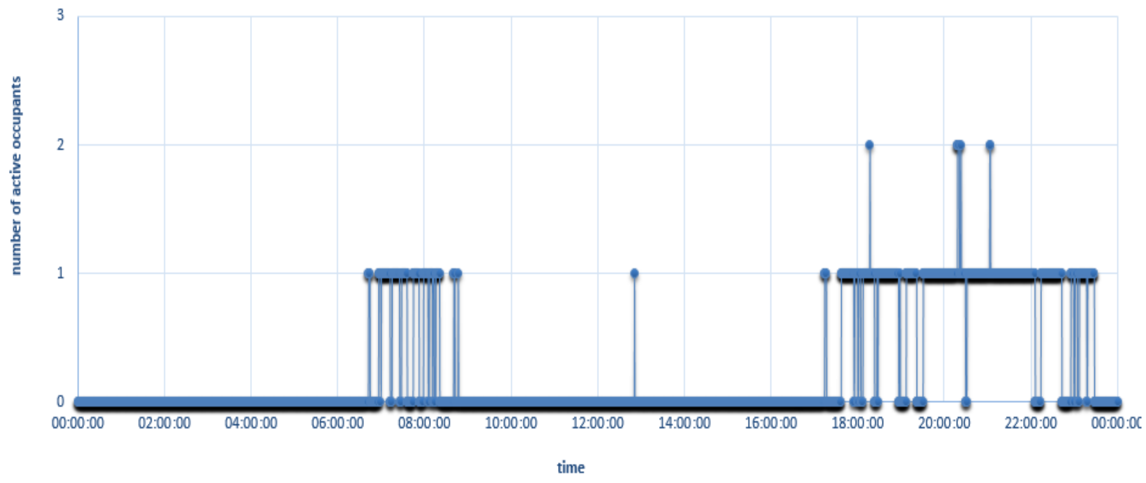


(a)

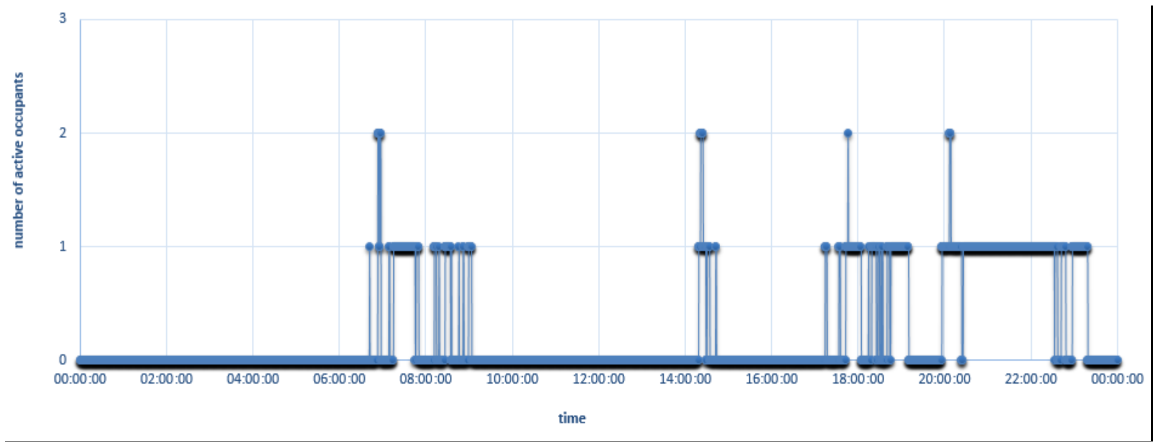


(b)

Fig. 4.9. Two examples of simulation results with house2 spring weekday.



(c)



(d)

Fig. 4.10. Two examples results from occupancy presence simulation (house2 spring weekday).

From Fig. 4.8 to Fig. 4.10, although the occupancy profile is generated randomly, it can still found that there are two peak periods, morning and evening. Also, because one occupancy in this household has a part-time job, the activity of this occupancy can still be captured. The stochastic simulation results show that this model not only can presents historical activity, also can generate unknown presence which based on pasted record.

As the previous discussion, people may consume electricity when they are active. The synthetic occupancy presence in this stochastic model is generated by real-time load. It means the occupancy is active in real-time if the simulation result shows there is at least one active occupancy. Therefore, the simulation results generated from this stochastic model can not only limit the daily peak period of occupancy, and also can present the range electricity consumption, as same with load boundary of AECO.

In order to implement this stochastic model to dynamically predict electricity consumption of participated households. Firstly, it is important to generate random occupancy profiles which can adequately cover historical activities of selected occupancy. In the second, accurate electricity load within high-resolution is proved as not ideally possible to forecast currently. Thus, the average electricity consumption for each occupancy is used to replace the synthetic occupancy profiles which are stochastically generated by Markov-chain model. Also, the average electricity consumption is generated from all historical load by setting same load boundary with AECO at each selected time-interval, like 30s in this study. Thus, dynamic occupancy patterns of different households are shown in the following.

4.4 Dynamic occupancy profiles prediction for UK households

With the output of the stochastic model with Markov-chain and Markov-chain Monte Carlo, occupancy profiles for each participated household can be stochastically produced. The existing model, which using historical profiles can statically represent what happened in the past, is fixed. However, occupancy profiles may vary at each calendar day with different households, even same household. Therefore, it should be proved that this stochastic model can capture the variation of occupancy profiles when the fresh data is updated.

Meantime, because of the uncertainty of occupancy behaviour, it is not possible to accurately forecast how occupants spent their time during high-resolution period, like below 1 minute. However, the occupancy preferences and daily activities during peak periods can be generated by stochastic model, which is very important in the occupancy profile prediction. It can identify what type of appliance or activity the occupancy operate or involve. Also, the results should be validated to find out the MAPE range.

Because of the lack of original data, the weekend profile is cannot be proved and validated. Thus, the weekday profiles of each household are chosen as primary sources in the prediction and validation.

On the other hand, historical occupancy data structure is another important factor in stochastic prediction simulation. For example, if the data is collected from only one day, the transition probability is 100% for each state. The results of the simulation will undoubtedly reappear what happened at that day with 0% error. Also, it will not be presented what may happen in the future.

Therefore, the number of collected days in the data sample is a crucial aspect, which should be seriously considered in the prediction parts. Table 4.3 listed the number of collected weekday seasonal data from each household.

Occupancy data	Spring	Summer	Autumn	Winter
Mid-Terraced (House1)	Two whole days and three half days	Four whole days	Two whole days and one half day	Two whole days and two half days
Large-Terraced (House2)	Three whole days	Five whole days	Four whole days and one-half day	Four whole days
Semi-Detached (House3)	Three whole days	Five whole days and five half days	One whole day and two half days	Two whole days and two half days

Table 4.3. The detail of occupancy data logs with each household in every season.

Table 4.3 reveals the detail of occupancy data, which shows that occupancy data in summer has more collected days rather than other seasons for each household. In order to identify the dynamic feature of the stochastic model in this study, it is therefore for each household, the prediction of occupancy profile is selected from summer weekday profiles as example, and the other seasons are shown in Appendix.

Thus, the examples of dynamic occupancy profile prediction for each selected household within 30s resolution are presented as followed.

4.4.1 Occupancy profiles prediction of Mid-Terraced household (House1)

The two occupants in Mid-Terraced household are both have full-time jobs, which means the main occupied period is morning peak time and evening peak time during a weekday.

Firstly, the dynamic feature of this model should be identified. All historical profiles are presented to find out which day has individual activity; secondly, take this unique profile off from data sample; in the third, separately simulate the remainders and all day together to discover the difference in these results.

Therefore, all historical profiles of house1 in summer weekday is shown in Fig. 4.11.

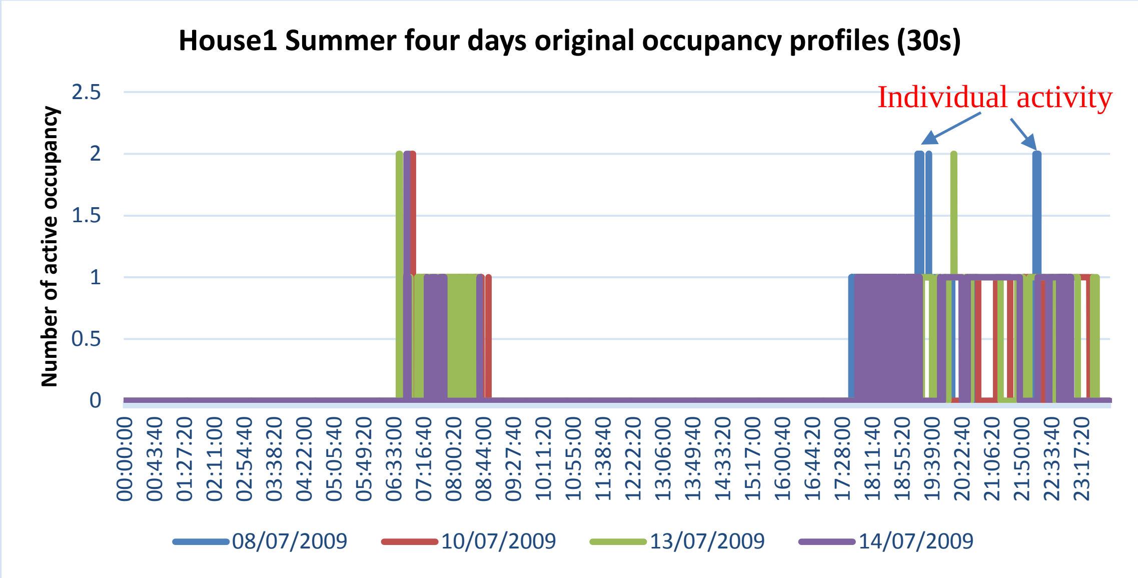


Fig. 4.11. House1 summer weekday occupancy profiles of four days in 30s resolution.

Fig. 4.11 reveals that there are some individual activities which are not covered with other days. Thus, the profile of this single day is taken off from whole data sample as shown in Fig. 4.12.

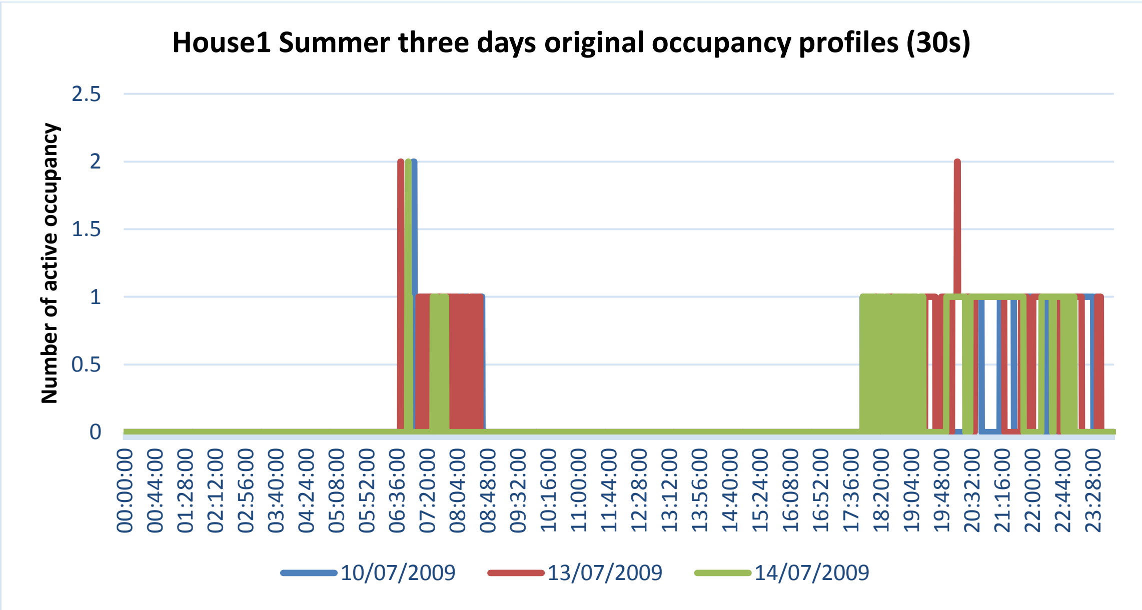


Fig. 4.12. House1 summer weekday occupancy profiles of three days in 30s resolution.

Then, this three days profiles are used to randomly generate synthetic occupancy activities, an example result is shown in Fig. 4.13.

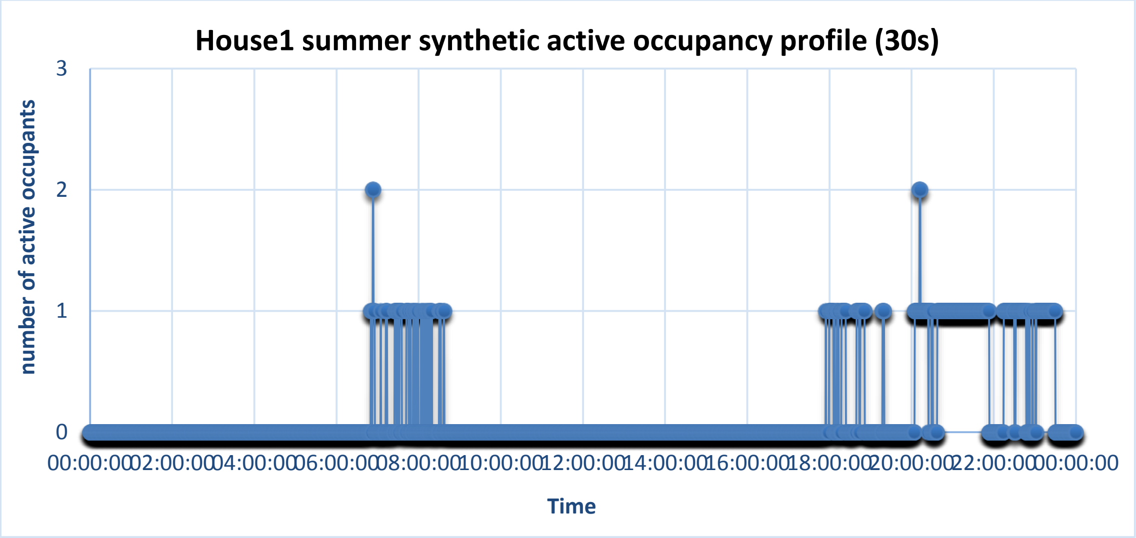


Fig. 4.13. An example summer weekday occupancy profile generated from three days data sample (House1, 30s).

Simulation result generated from four days data sample is depicted in Fig. 4.13.

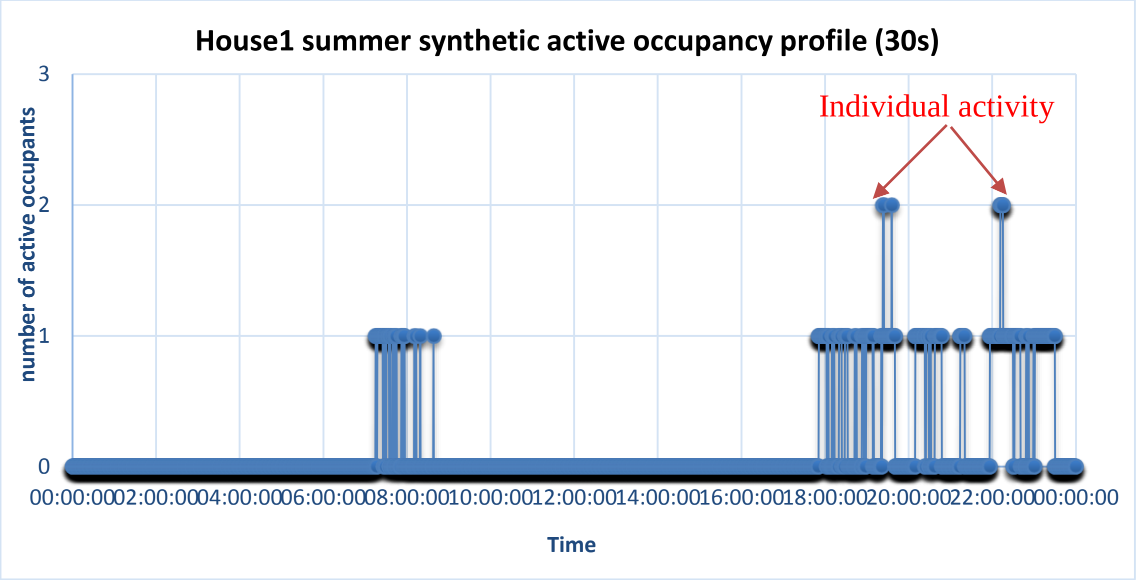


Fig. 4.14. An example summer weekday occupancy profile generated from four days data sample (House1, 30s).

Fig. 4.14 shows that the stochastic model in this study can dynamically capture the system variations by adding fresh data to update current transition probability matrix.

4.4.2 Occupancy profiles prediction of Large-Terraced household (House2)

In order to validate the finding from the previous simulation in section 4.4.1, it is selected house2 summer weekday profiles as data sample. A total of five weekday occupancy profiles is presented in Fig. 4.15.

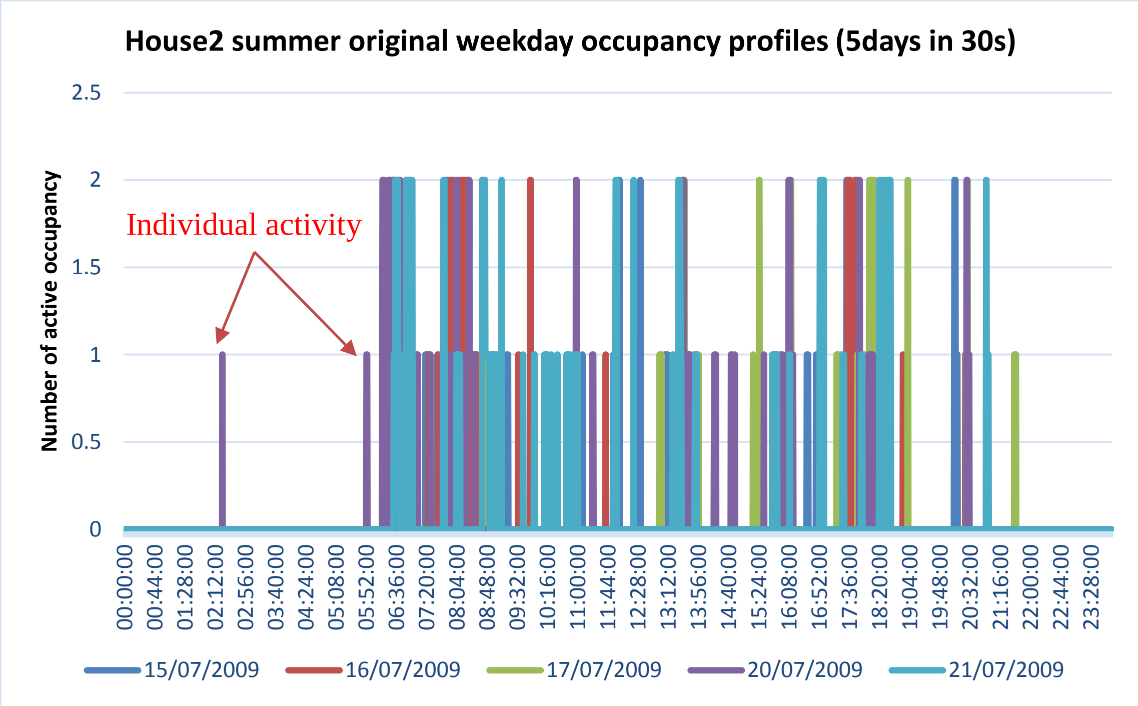


Fig. 4.15. House2 five weekdays occupancy profiles (30s)

Fig. 4.15 reveals that there are some individual activities happed in 20.07.2009. Therefore, the profile of this day is wiped out, and the original profiles of remainders are shown in Fig. 4.16.

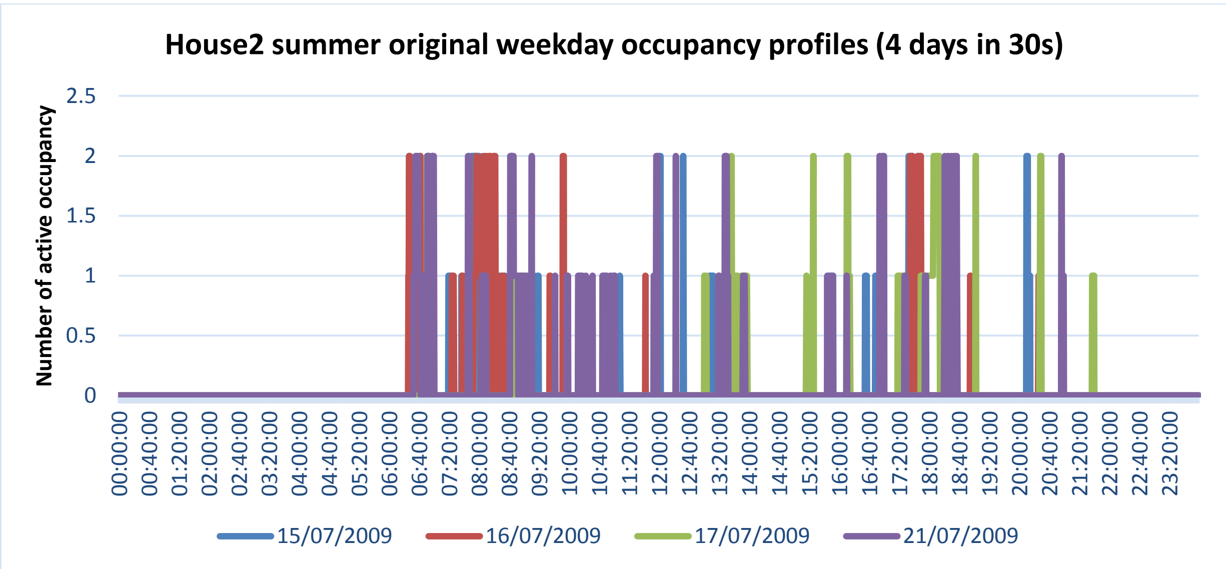


Fig. 4.16. House2 summer four weekdays original occupancy profiles in 30s resolution.

The first simulation is generated by four original weekday occupancy profiles. The result is shown in Fig. 4.17, and secondly simulation output with five weekdays is shown in Fig. 4.18.

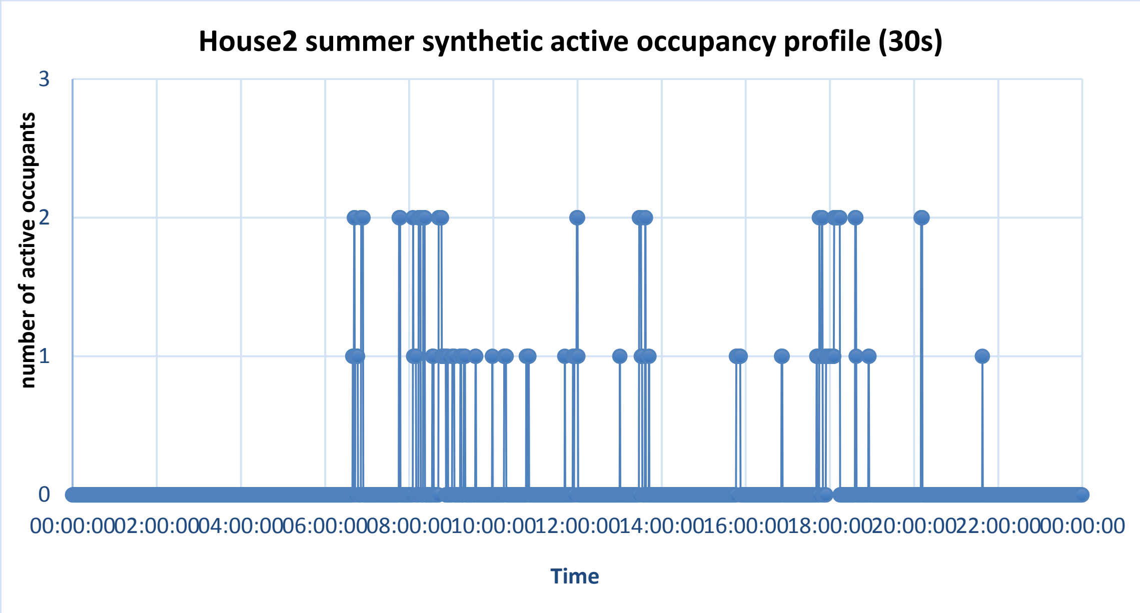


Fig. 4.17. An example summer weekday occupancy profile generated from four days data sample (House2, 30s).

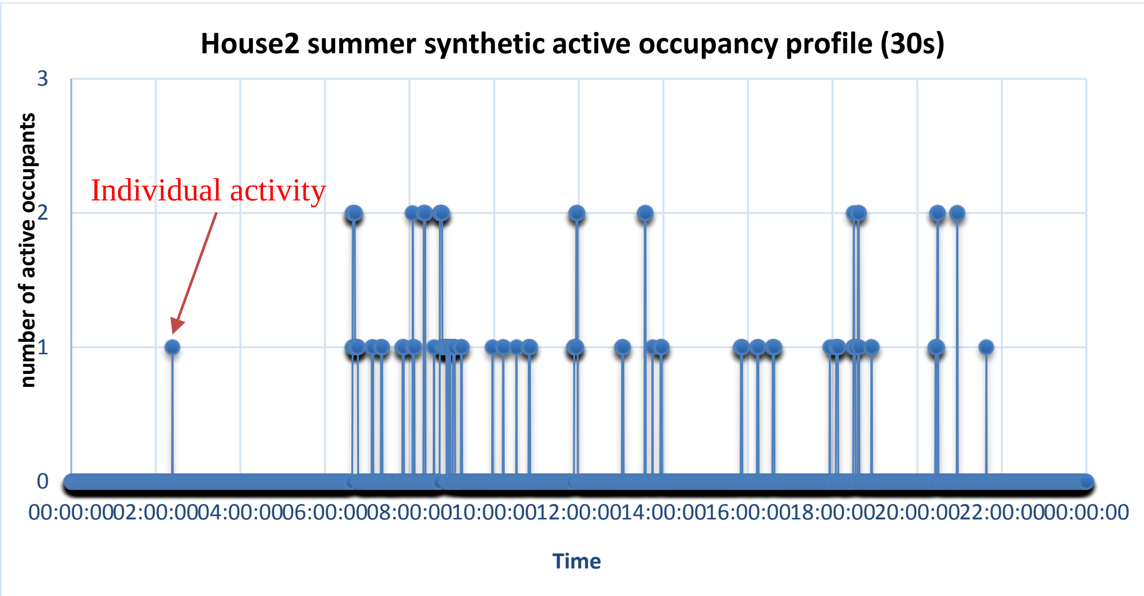


Fig. 4.18. An example summer weekday occupancy profile generated from five days data sample (House2, 30s).

From Fig. 4.17 to Fig. 4.18, individual activity can be identified. The simulation results of house2 prove that this stochastic model can dynamically capture the system variations, such as appliance change or occupancy activity modification.

4.4.3 Occupancy profiles prediction of Semi-Detached household (House3)

Another important feature of this stochastic model is to identify that if the model can generate unknown activity from existing profiles. Not only reappear the previous activities, which is very crucial aspect in prediction part. In order to prove this feature, the original data profiles should be more complicated which need collect multiple weekday profiles rather than only one or two days. Consider with the data profile in this study, the longest data profile is from house3 summer season, which has five whole days and five half days data. Therefore, this type of data sample is used to verify if this stochastic model has a predicted feature.

In the first, synthetic occupancy profiles are generated randomly in multiple times, example results are shown from Fig. 4.19.

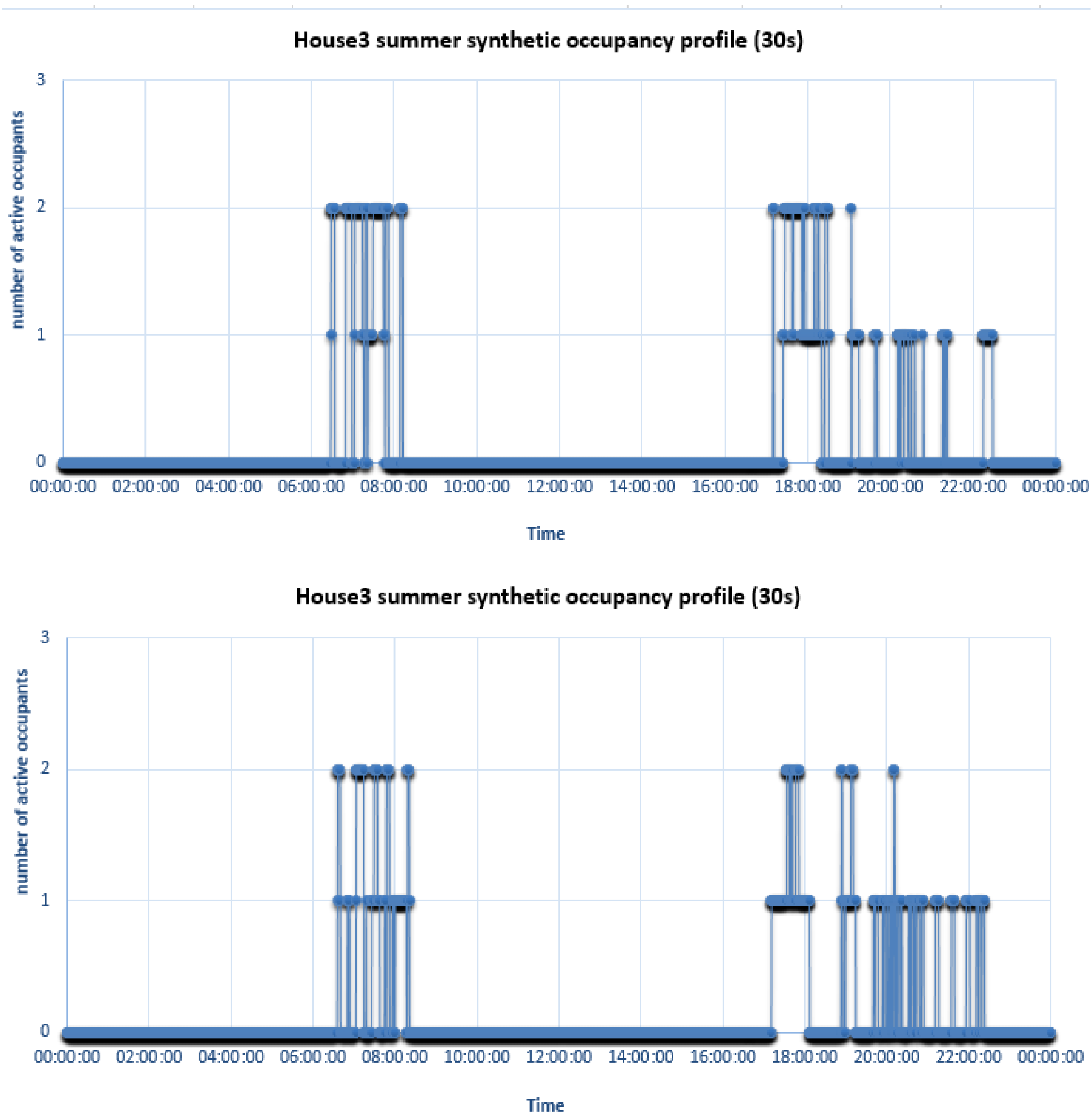


Fig. 4.19. Examples simulation results of summer weekday occupancy profiles (House3, 30s)

In order to address unknown activity, it is important to check original occupancy profiles. Also, it is very difficult to identify this type of activity from whole day profile, thus a comparison between original profiles and predicted results should be narrowed into a short period, like few hours. Meantime, as the data missing can cause misleading results, the historical load in a selected period for comparison should be continuous.

From Fig. 4.19, it can be found two primary peak periods during summer weekday in house2. The occupancy activities in the evening is more complicated than morning. Thus, evening peak period is selected as an example to find out if the model can generate unknown activities as shown in Fig. 4.120.

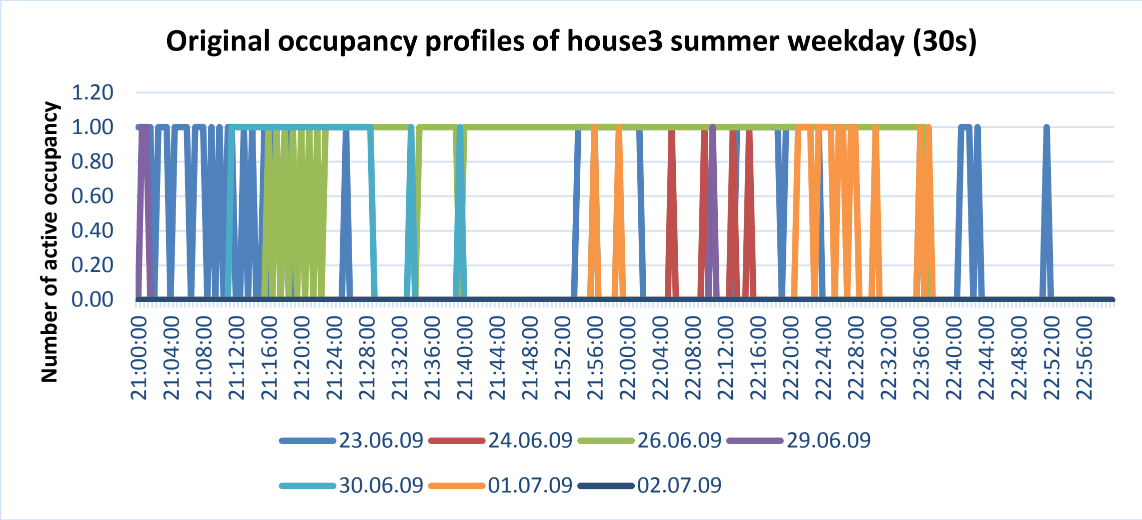


Fig. 4.20. Two hours original occupancy profiles picked during house3 summer weekday

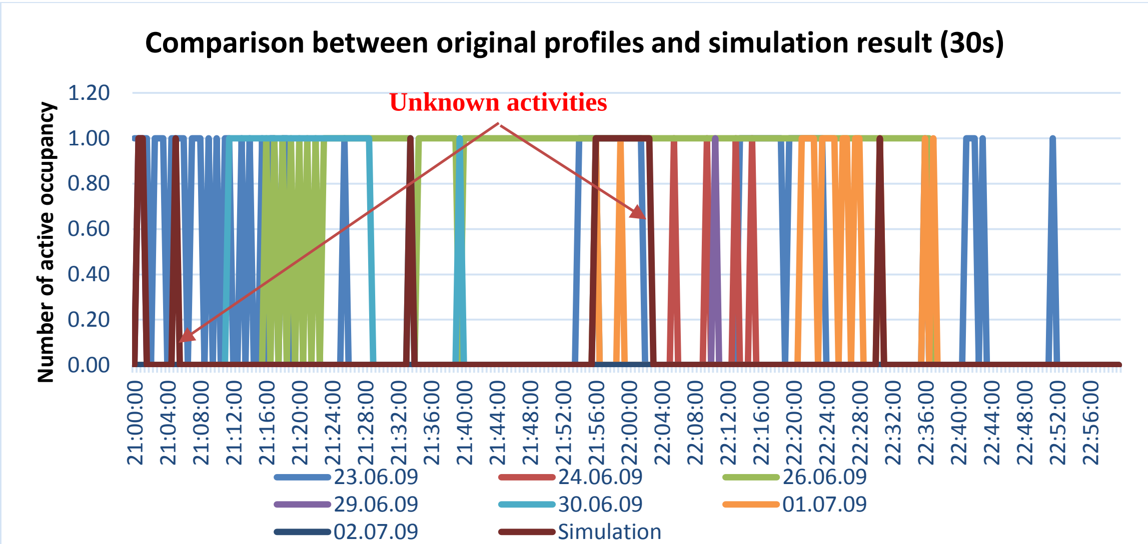


Fig. 4.21. Comparison between original occupancy profiles and simulation result (house3)

Fig. 4.21 reveals that the simulation can generate unknown activities based on existing known profiles, which is quite important in prediction part. Because the most other research methods can identify the peak period of particular household, but what will be happen during the peak period is unknown. With this stochastic model, it is not only can capture what occupants have done in the past, and also generate what the identical occupants will mostly do in the future. Therefore, the prediction feature of this stochastic model is verified.

4.5 Validation of occupancy profiles prediction results.

The most important part of prediction model is validation, which is to prove if the model is reliable. The stochastic model in this study is employing Markov-chain and Markov-chain Monte Carlo methods to randomly generate synthetic occupancy profiles. Therefore, the simulation result is not expected to be identical curve with unknown original profile in the prediction domain.

Because the simulation results contain both existing profiles which are already happened in the past and unknown profiles which are predicted activities. Thus, the first step in the validation is to discover that if the simulation results can trace back to original data by comparing simulation average with history average. Meantime, the mathematical function of this stochastic model can generate infinite possible profiles based on finite state, so the simulation iteration time is another crucial factor which should be seriously considered. Also, all possible patterns may not be generated entirely by low-count loop. With this feature, it can be easily seen with the growing data sample, the error between history and simulation will be increasing accordingly.

Therefore, the methodology in verification in this study is made from following steps: (a) to identify the influence of simulation iteration count then find out a possible fixed number of iteration times in simulation; (b) by calculating the MAPE to prove if the model can review historical profiles, which is the independent occupancy activity feature for each household; (c) Repeatedly adding fresh collected data of each day to updating the model, to find out the trend of error percentage.

4.5.1 Validation of Mid-Terraced household (House1)

In the first, suitable iteration counts from 100 times to 1000 times in the simulation are presented in house1 model, as shown in Fig.4.22 to Fig. 4.24. All the simulation results are based on original weekday profiles of house1, which are collected from four whole weekdays.

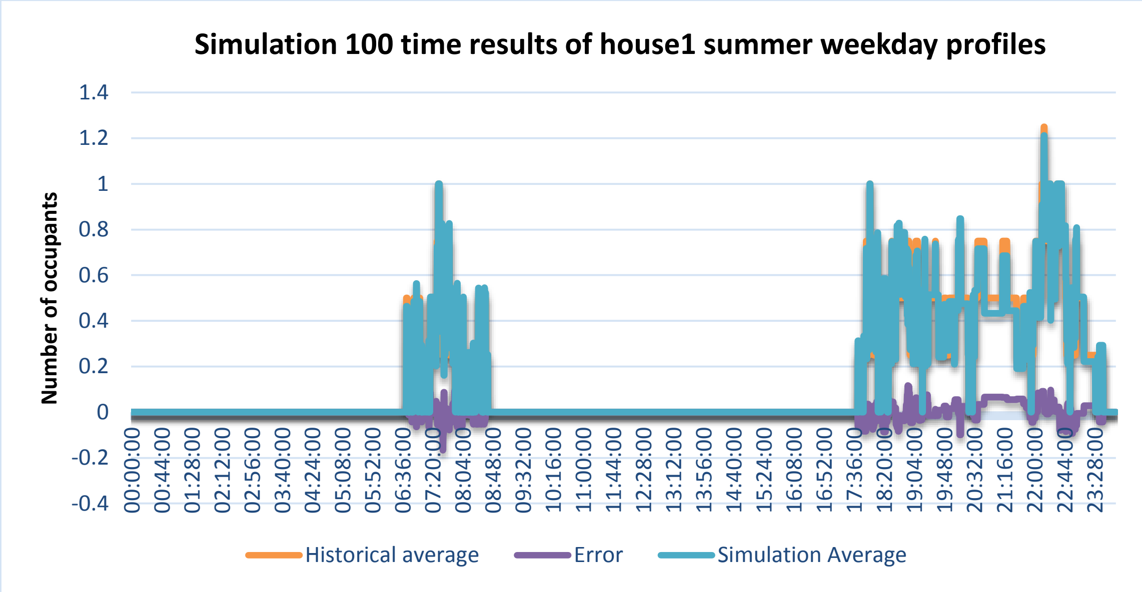


Fig. 4.22. 100 time simulation results of house1 summer weekday profiles.

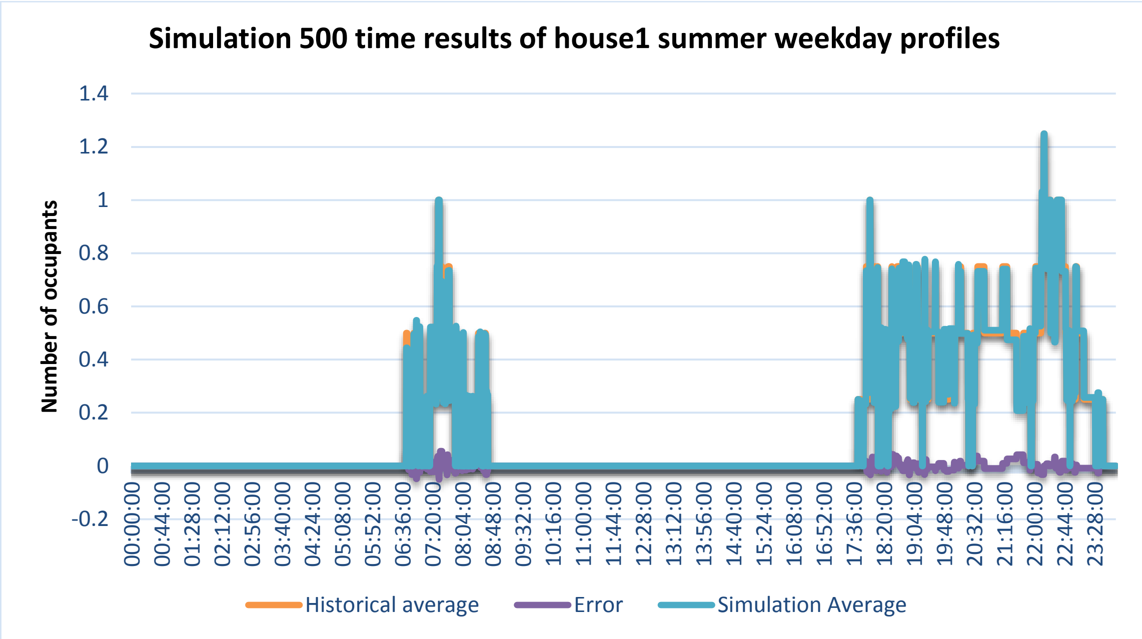


Fig. 4.23. 500-time simulation results of house1 summer weekday profiles.

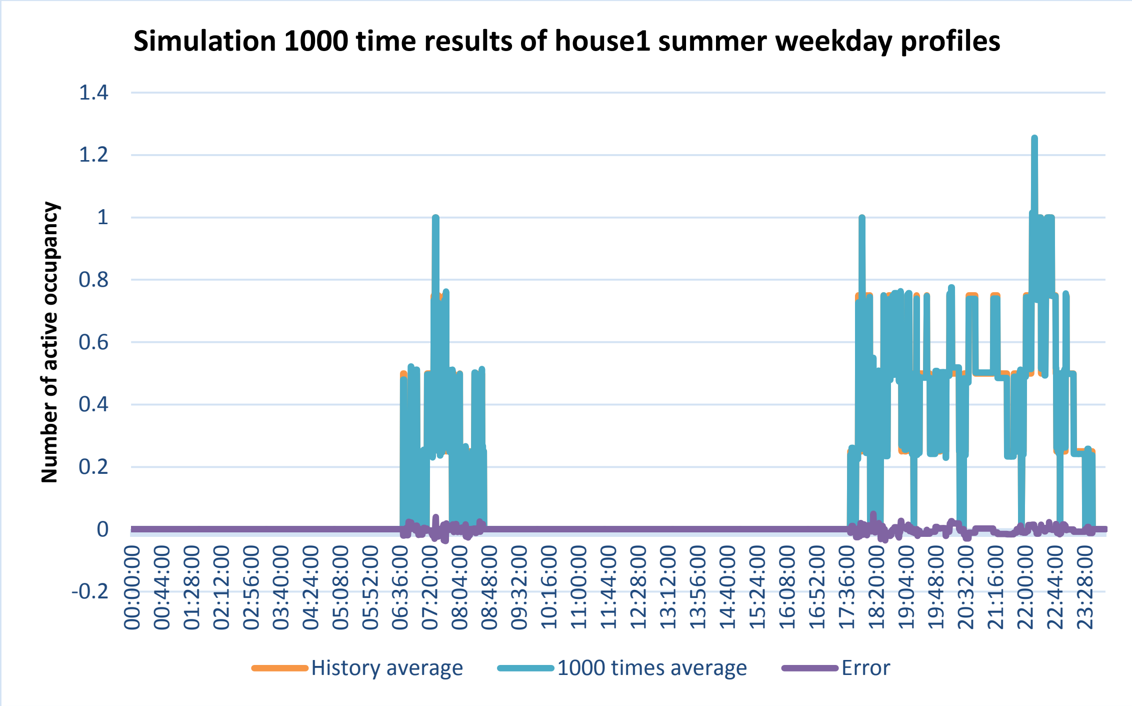


Fig. 4.24. 1000 time simulation results of house1 summer weekdays.

From Fig. 4.22 to Fig. 4.24, it can be found that the error is decreasing significantly due to the simulation time growing.

The detail of MAPE results in different simulation times is presented in Fig. 4.25, which is from 100 time to 1000 time. All simulation based from original four weekday occupancy profiles.

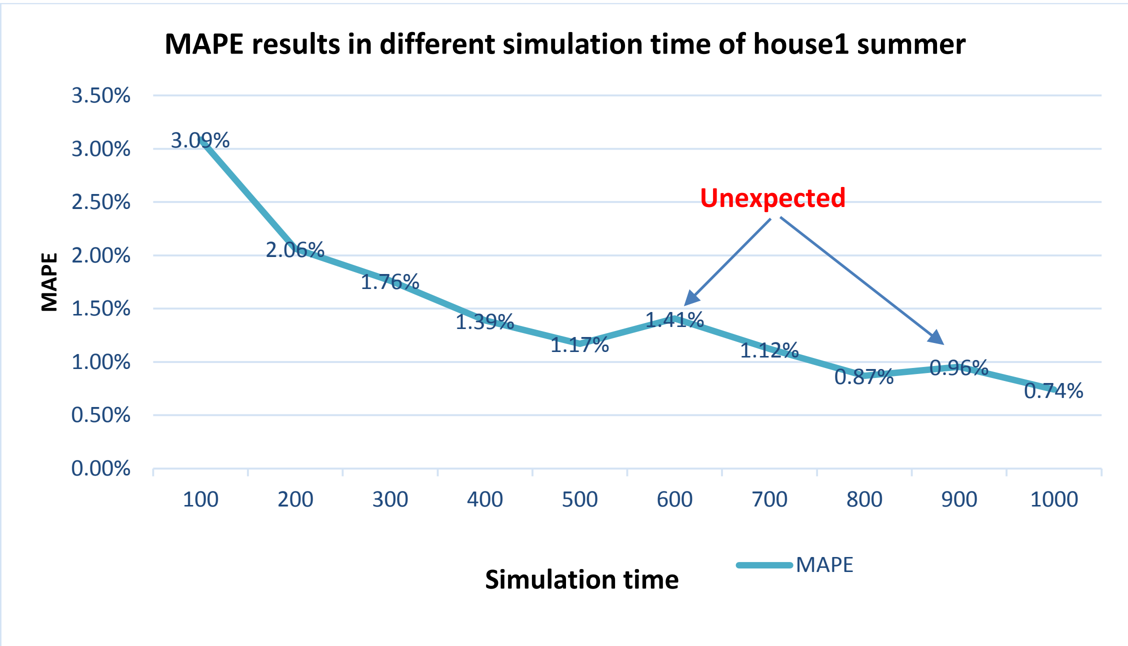


Fig. 4.25. MAPE results from 100 simulation times to 1000 simulations of house1 summer (4 days original data sample).

From Fig. 4.22 to Fig. 4.24, it can be seen that the simulation results can match very well with historical profiles. Thus, it is very important to generate individual occupancy pattern for particular household, in terms of the diversity of different household. As the simulation results contain both existing profiles and unknown activities, the predicted results are shown as error. When the simulation times are increasing, the error is decreasing, which is one of particular feature of Markov-chain model.

The detail of MAPE results in different simulation times is depicted in Fig. 4.25, which shows the individual MAPE of each simulation times. Because the results are generated randomly, so there are two unexpected results which are from 600 simulation times and 900 simulation times. The simulation times are shown up to 1000, because the simulation times above 500 will cause from 15 minutes to 1 hour to produce results in this stochastic model, which is one of limitation in this study.

However, the MAPE in 1000 simulation times is only 0.74%, which is quite good match with other related simulation models in literatures. Consider with the number of original weekdays is only four days in this example, which is a quite small data sample. Therefore, it should be validated the feature of MAPE variation when the data sample is growing. Meantime, 1000 times is selected in the rest of the simulation.

4.5.2 Validation of Large-Terraced household (House2)

The occupancy pattern in house2 is much more complicated than house1, because the occupants in this household do not have fixed daily activities, such as morning peak and evening peak period. One occupancy has par-time job, and another one is, which means the occupancy can be active at any time during the whole day.

The simulation results still capture very well with historical profiles, and these simulations are based on five whole weekday profiles.

Same validation procedure is processed within house2 summer weekday profiles, 100 time and 1000 time simulation results are presented in Fig. 4.26 and Fig. 4.27, respectively.

From these two Figures, the error is apparently reduced, which can prove the previous finding.

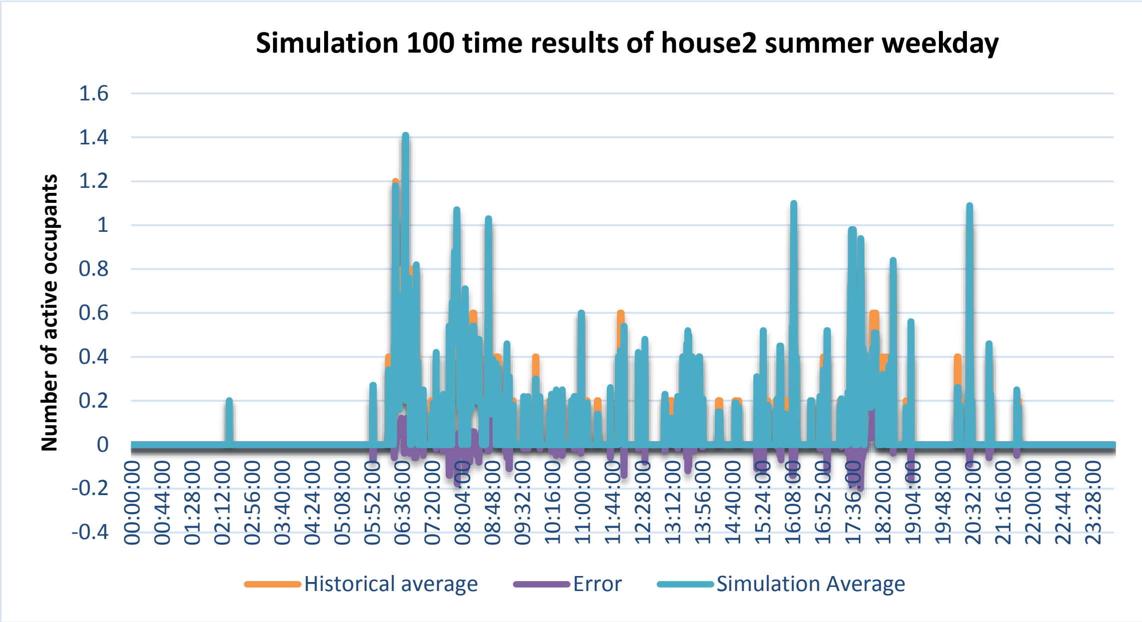


Fig. 4.26. 100 time simulation results of house2 summer weekday profiles.

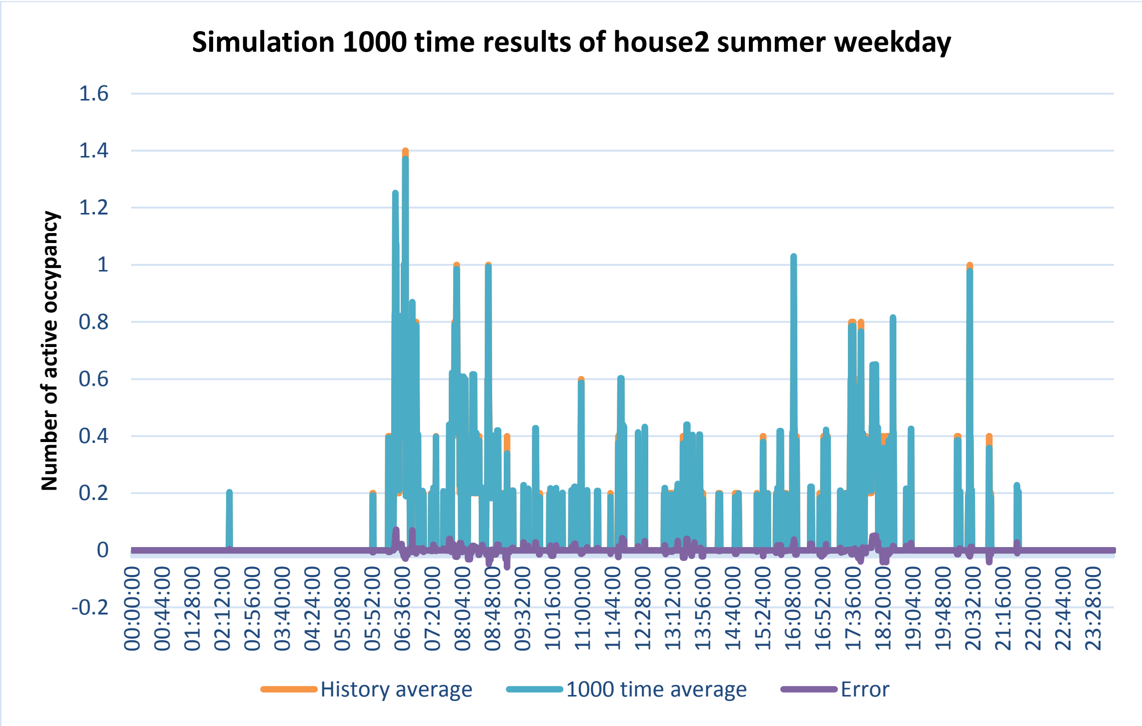


Fig. 4.27. 1000 time simulation results of house2 summer weekday profiles

The MAPE results in different simulation time iteration are depicted in Fig. 4.28. It still can be found that when the increasing time iteration, percentage error is decreasing accordingly, which is another type of validation for the finding of the previous section.

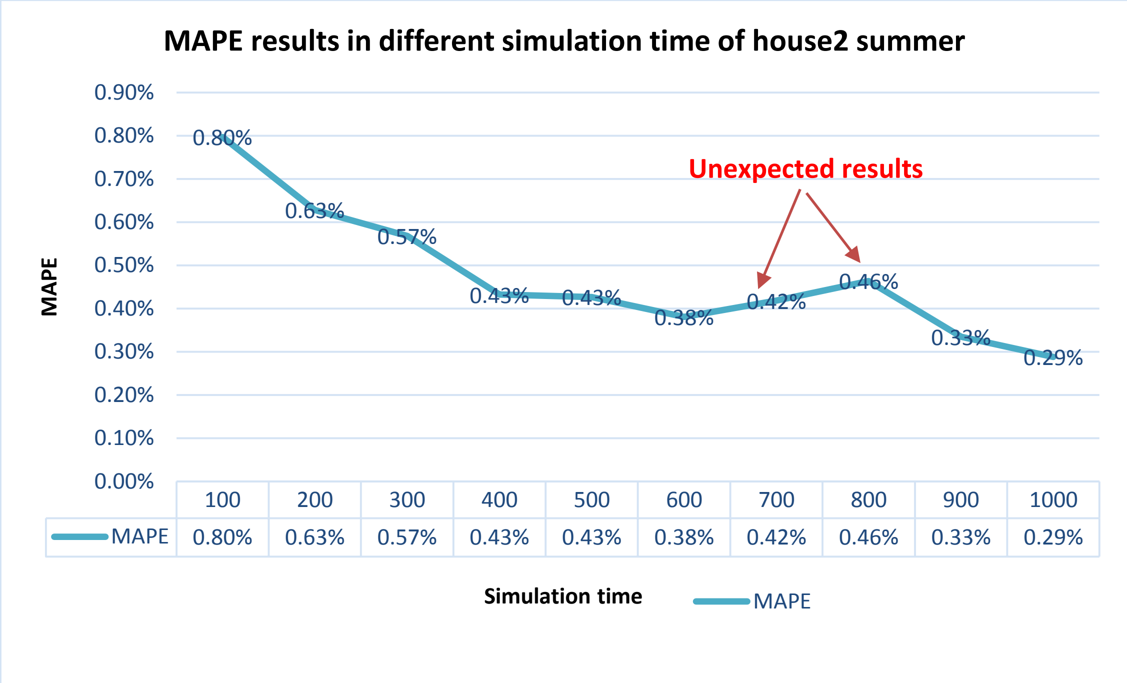


Fig. 4.28. MAPE results from 100 time to 1000 time simulation of house2 summer (5 days original data sample).

Another interesting finding in Fig. 4.28 is MAPE at 100time and 1000 time are only 0.80% and 0.29%, respectively. It is more accurate when comparing with the same results with house1. However, as they are two different households with independent occupancy patterns, it cannot be concluded that the model will be more accurate when the number of data collected days is increasing. This feature should be verified in same household, which is presented as followed.

4.5.3 Validation of Semi-Detached household (House3)

From previous simulation outputs of house1 and house2, it can be confirmed that 1000 time is suitable simulation iteration count. Thus, 1000 time simulation results of house3 based on different number of original weekday profiles are presented.

The occupancy in this type of house both have full-time jobs, and the data sample is consisted by five whole days and five half days. Therefore, the validation in 1000 time based on five original days and ten days are presented in Fig.4.29 and Fig. 4.30, respectively.

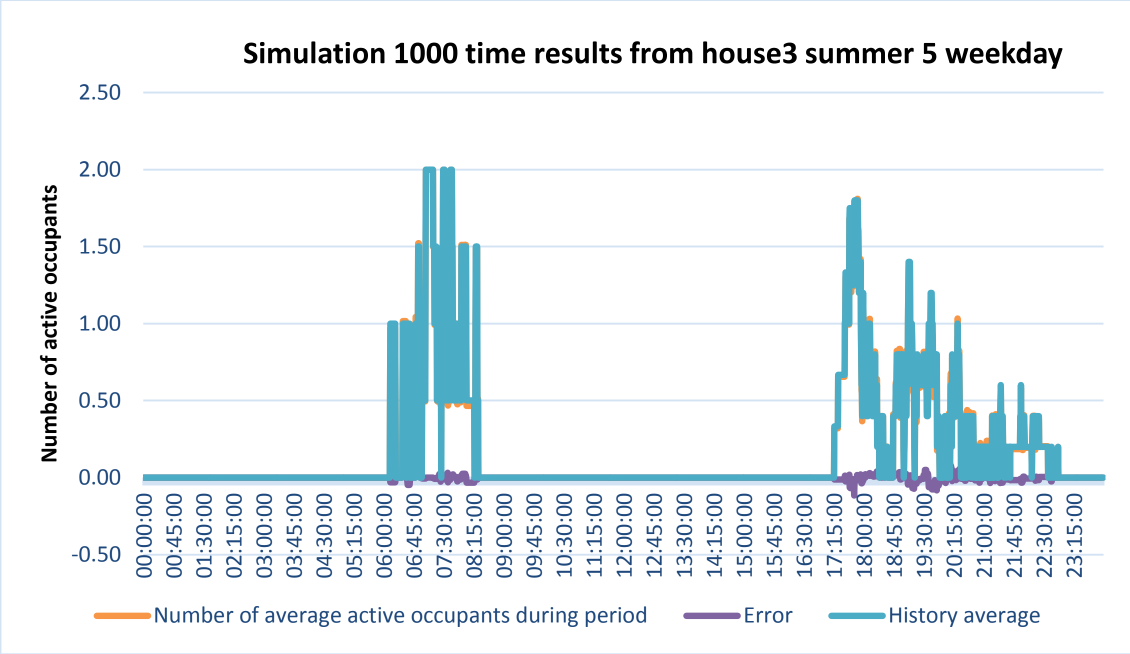


Fig. 4.29. 1000 time simulation results of house3 summer weekday profiles based on five whole weekday data sample.

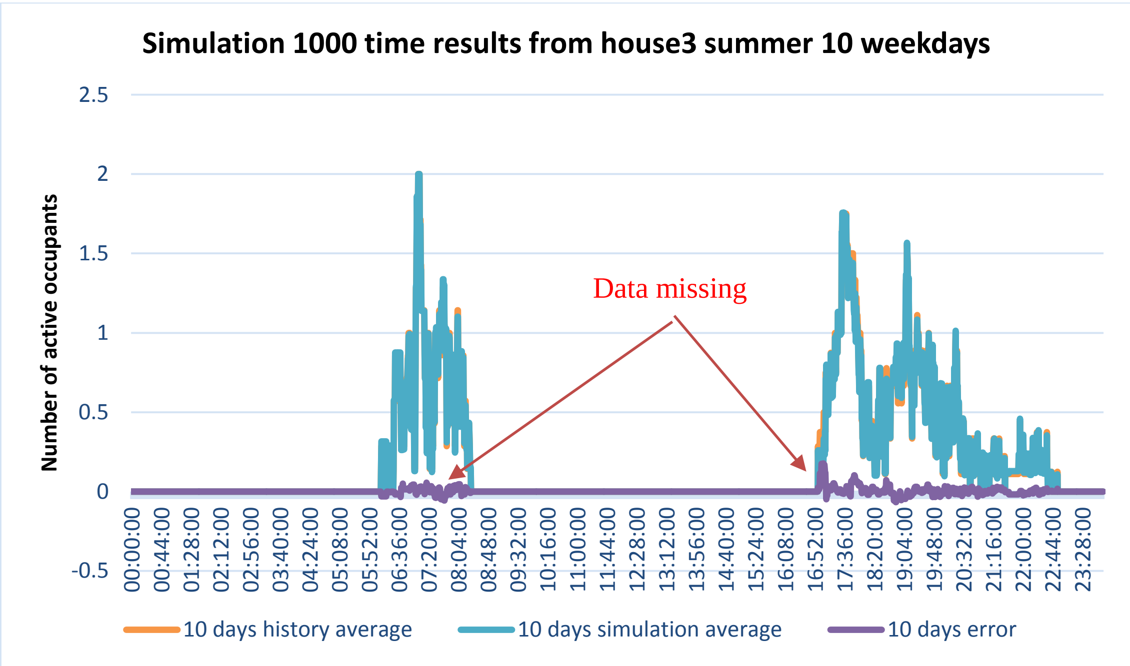


Fig. 4.30. 1000 time simulation results of house3 summer weekday profiles based on five whole days and five half days data sample.

Because the data from half day sample can interrupt the transition probability in Markov-chain matrix. Therefore, error is accordingly increasing where the data is missing, as shown in Fig. 4.30.

Because the lack of original data collection, it cannot be proved that after collecting particular days occupancy profiles, the error percentage will hold doubtless trend. Although the trend of error percentage is unknown or unpredicted in this study, but the model can dynamically capture the occupancy activities when the fresh profiles are added. Meantime, data missing in this model can insignificantly lead increased error percentage as shown in Fig. 4.30, the model is still reliable for prediction and validation.

4.6 Electricity consumption prediction for UK households

In terms of instantaneous high-resolution electricity consumption is proved as unpredictable. Therefore, with the simulation output of dynamic occupancy profile, the number of active occupancy can be simply mapped to related historical average electricity consumption. The mapping procedure calculates the load boundary of AECO at each selected time interval, like 30s in this study. Then transit occupancy patterns to related load profiles.

It is selected same load boundary for each household when transiting number of active occupancy to related electricity consumption. Thus, the number of data collection days N, at each selected time interval i with load P_i, can be divided into three categories by comparing the load boundary of AECO, as shown below.

$$N_{SUMMER} = \begin{cases} N_0\,, P_i \leq 400W \\ N_1,\ 400W\ < P_i \leq 3\ kW \\ N_2, P_i > 3\ kW \end{cases} \tag{4-17}$$

Where N_{SUMMER} means the number of occupancy during the summer,N_0, N_1, and N_2 display the number of days which has the same load range.

Similarly, the number of days in other seasons can be identified as:

$$N_{OTHER} = \begin{cases} N_0\,, P_i \leq (400W + P_{HEAT\ LOAD}) \\ N_1,\ (400W + P_{HEAT\ LOAD})\ < P_i \leq (3\ kW + P_{HEAT\ LOAD}) \\ N_2, P_i > (3\ kW + P_{HEAT\ LOAD}) \end{cases} \tag{4-18}$$

Where the $P_{HEAT\ LOAD}$ is selected as average heat load at each selected time interval, which can be identified from non-occupancy related time period, and this type of load is highly related with weather conditions, like indoor and outdoor temperature. Sometimes, $P_{HEAT\ LOAD}$ may equal to zero. N_{OTHER} means the number of occupancy during spring, autumn and winter.

Therefore, the average load P at each time interval in different category can be identified as following:

$$P_{AVERAGE} = \begin{cases} P_0, \quad P_0 = \frac{\sum_1^{N_0} P_i}{N_0} \\ P_1, P_1 = \frac{\sum_1^{N_1} P_i}{N_1} \\ P_2, P_2 = \frac{\sum_1^{N_2} P_i}{N_2} \end{cases} \tag{4-19}$$

Where P_0, P_1, P_2 is the average power consumption at each time interval i for zero occupancy ,one active occupancy and two active occupants, respectively.

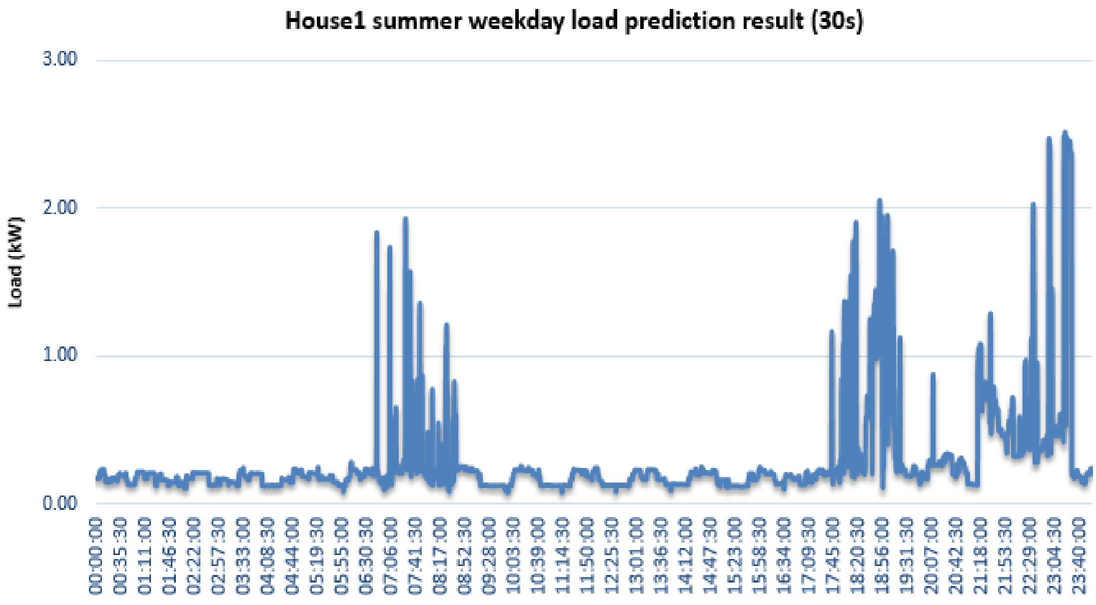
Therefore, in order to generate estimated electricity consumption for each household, stochastic occupancy profiles for every season are produced, then for particular simulation result of synthetic occupancy profile, electricity load at each time step can be directly generated by mapping with related number of active occupancy with individual average power consumption.

For each participated household, the author picks the summer patterns as examples, and the results in other season are presented in Appendix.

4.6.1 Electricity consumption prediction of Mid-Terraced household (House1)

Two examples of load profiles prediction results are shown in Fig. 4.31, the electricity consumption is randomly generated by mapping with synthetic occupancy profiles.

These results in Fig. 4.31 reveal that the occupancy in this household has two peak periods, after wake up in the morning and get home in the evening. Simulation results show the breakfast and dinner time are probably held early at 7am and 7pm, respectively. Meantime, occupancy normally go to bed very late around 11pm.



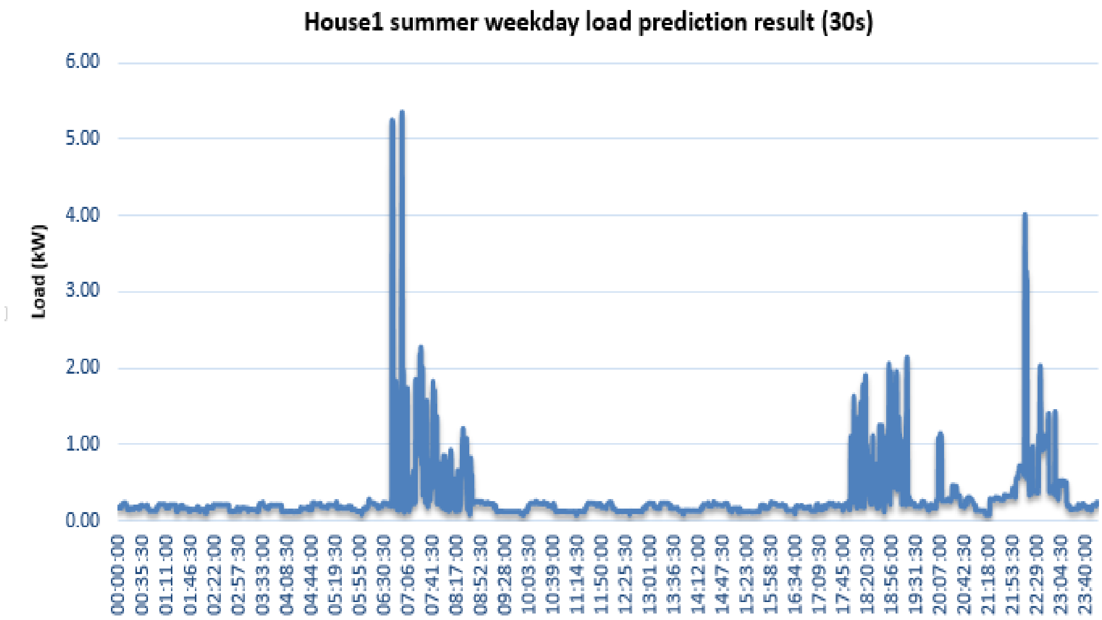


Fig. 4.31. Two examples of electricity consumption prediction of summer weekday (house1)

4.6.2 Electricity consumption prediction of Large-Terraced household (House2)

Fig. 4.32 shows an example of estimated electricity load profile of house2 in summer weekday.

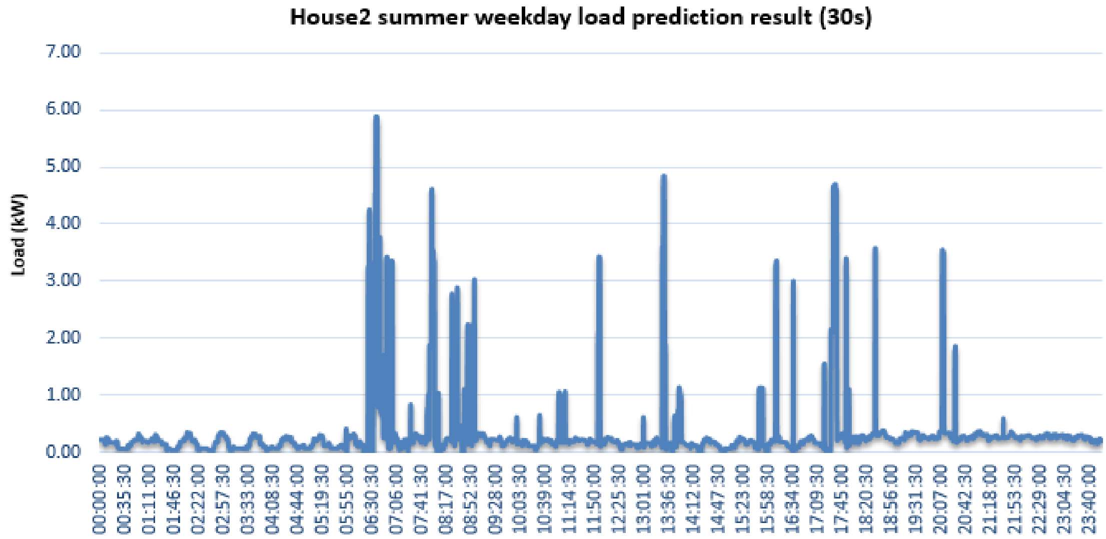
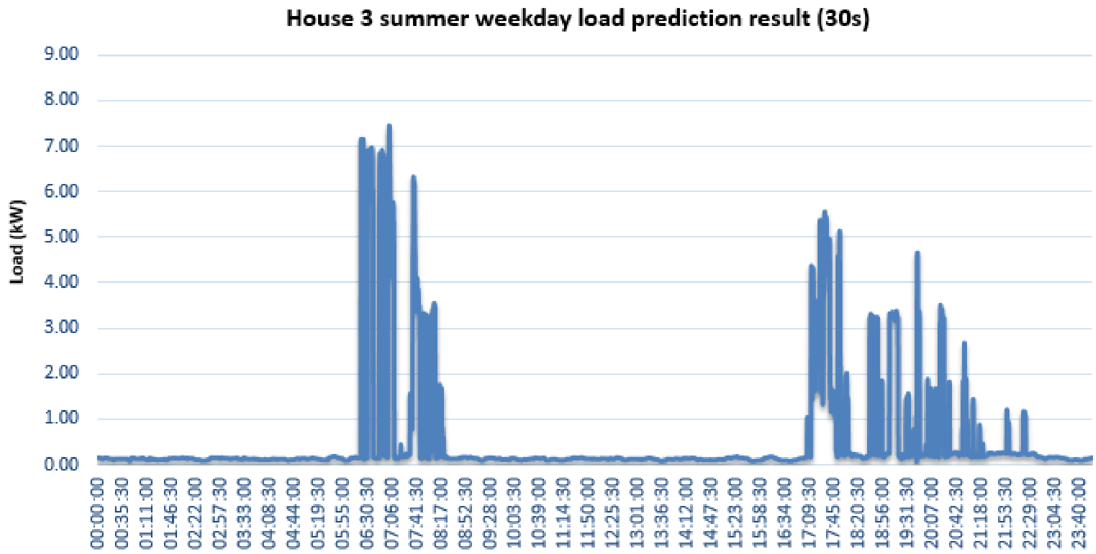


Fig. 4.32. An examples of electricity load profile of summer weekday (house2)

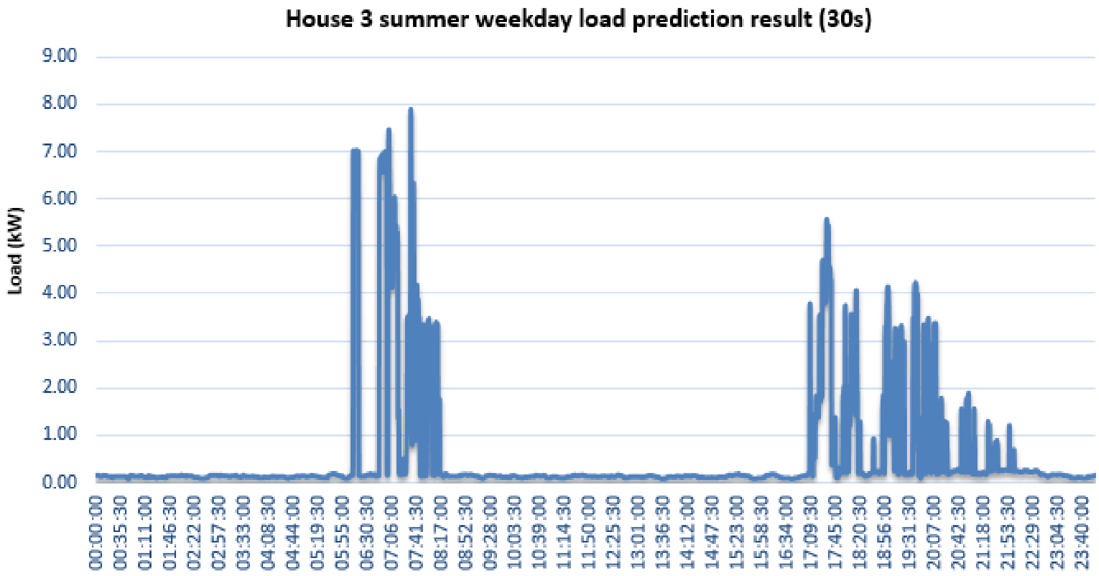
As the occupancy in this large-Terraced house is partially employed, and even one occupancy is retired for child-minders. The simulation result can capture these load variations, which reveal that electricity demand in this household does not have consecutive peak load curve instead of single peak load. The outputs show good correlation between the stochastic model and original occupancy patterns.

4.6.3 Electricity consumption prediction of Semi-Detached household (House3)

Two examples of the simulation results provided by load prediction models are presented in Fig. 4.33, which shows the stochastic electricity consumption of house3 in summer weekday.



(a)



(b)

Fig. 4.33 Two examples of electricity load profiles of summer weekday (house3)

There are three kids in this household; two are above ten years old and another one is an infant. In this study, the electricity demand of young children is not concerned and calculated, but it does not mean children consuming zero electricity. In fact, children in this household may switch on many appliances, which is the reason the electricity load in house3 is much higher than house1.

4.6.4 Summary of electricity consumption prediction

As the stochastic prediction of electricity consumption is based on related occupancy profiles, therefore, the domestic loads of each household in full seasons are produced by mapping independent AECO load boundary.

The simulation results show that high-resolution electricity demand can be directly generated for individual household particularly, and different household in each season has unique load pattern which should be considered seriously. Once load transition, which is processed from active occupancy to electricity consumption, is achieved. High-resolution electricity demand in a full year for particular household can be provided.

4.7 Validation of electricity consumption prediction model.

The prediction results for each day are stochastic load profiles, they are, of course, not expected to be same load curve with original electricity demand. The aim of prediction electricity demand in this study is to find out if the stochastic model can provide similar electricity consumption in advance with measured original load, like sub-hourly or hourly, even minutely. It is a quite important aspect in demand side management, like time-shifting control.

Also, because each household has individual occupancy profiles which have been applied in their particular stochastic models. Therefore, it is not necessary to compare the electricity demand with each household. In the validation part for each household, in the first, aggregate results are validated to compare with history average load in order to identify the model is still accurate. Then hourly, sub-hourly and minutely verifications are processing to find out if the model can address electricity demand in advance, and how accurate time-resolution it is.

4.7.1 Daily aggregate validation

Aggregated verification outputs with 30s resolution for each household in the summer are presented separately in this section, as shown from Fig. 4.34 to Fig. 4.36. MAPE is calculated independently for every daily result by aggregating all simulation daily results then comparing with historical daily demand. It is noticed that the MAPE is increasing when mapping occupancy profiles to related electricity load, this is a normal aspect for aggregate verification because there is non-relationship between averaged historical to averaged number of active occupancies. For example, MAPE in 1000 times occupancy profile simulation of house1 during summer weekday is 0.74%, and then for electricity load with same occupancy profile is 6.08%, as shown in table 4.2.

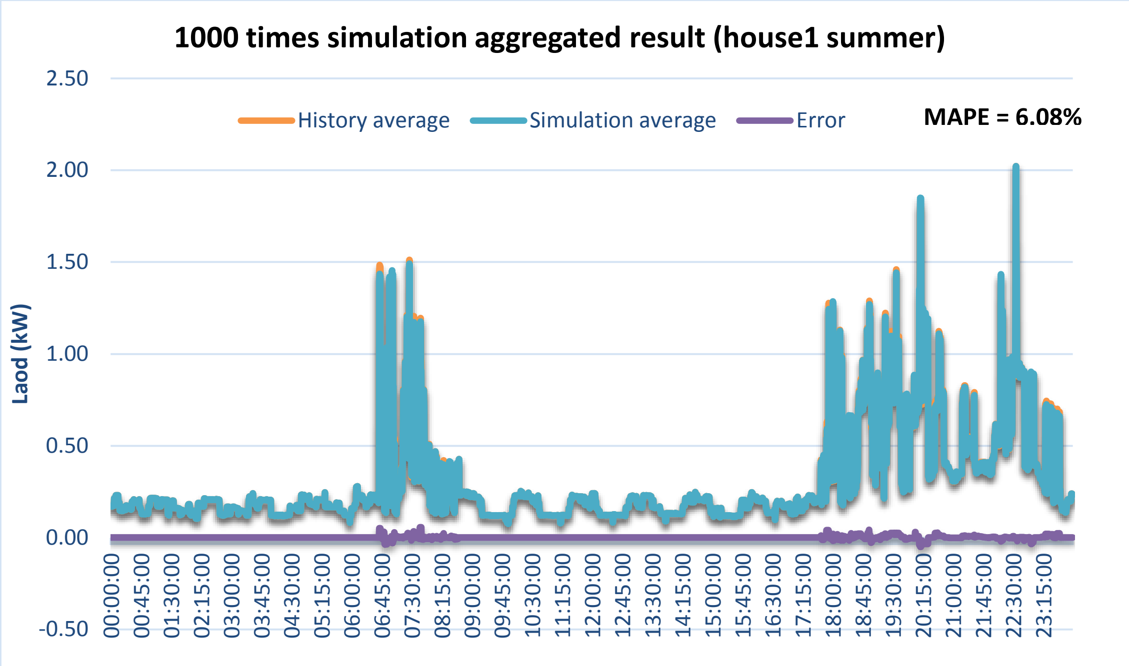


Fig. 4.34. Aggregate verification output of house1 summer weekday (based on four weekdays)

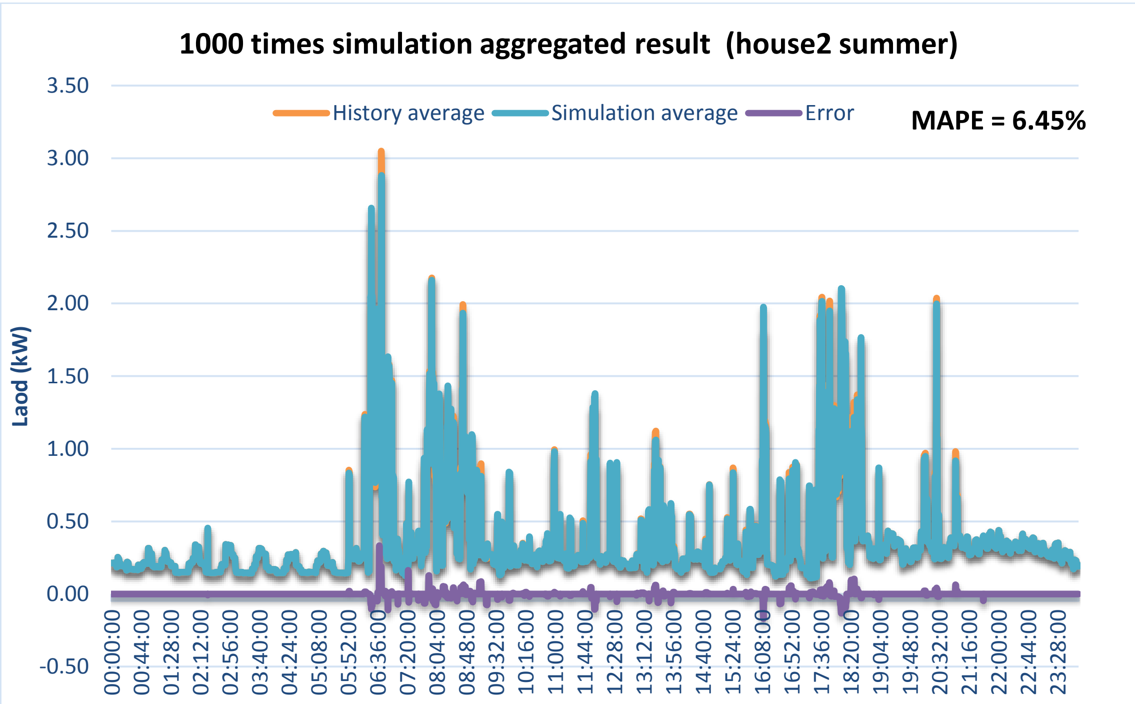


Fig. 4.35. Aggregate verification output of house2 summer weekday (based on five weekdays)

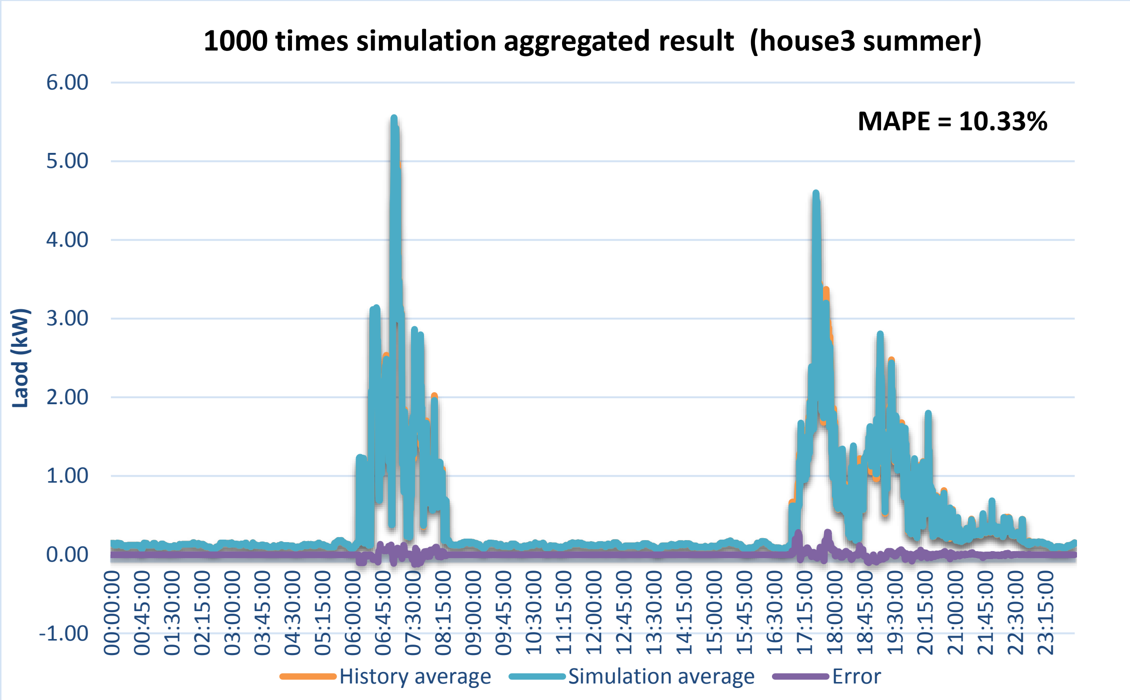


Fig. 4.36. Aggregated verification output of house3 summer weekday (based on ten weekdays)

Household weekday	Historical daily demand (kWh)	MAPE in 1000 times (occupancy)	MAPE in 1000 times (electricity)	Max difference (kWh)	Min difference (kWh)
House1 summer	7.32	0.74%	6.08%	0.23	0.00
House2 summer	8.78	0.29%	6.45%	0.29	0.00
House3 summer	10.67	1.73%	10.33%	0.39	0.00

Table 4.4. Comparison of simulated and original results with each household in summer weekday.

In Table 4.4, historical daily demand is the average consumption of each selected weekday. It can be noticed that although MAPE is increasing in the electricity simulation, the differences of daily demand (kWh) between simulation and history are quite small, which are 0.23, 0.29 and 0.39 for each household during summer weekday, respectively.

Also, as previously discussed, there are some missing original data in house3 weekdays, which can cause the error increasing, but insignificantly. The aggregate validation results show that the stochastic model used in this study is reliable to predict daily domestic electricity demand accurately.

Meantime, as the verification outputs are based on all known historical data, it should be identified that this model can forecast electricity consumption in advance, which need compare aggregated simulation results to unknown (data are not added in the simulation) original load data. It is aimed to find out the degree of accuracy this stochastic model can achieve.

Because the synthetic results are randomly generated, they are, of course, not expected to be same with measure data. Therefore, peak period and hourly validation, which aggregate simulated results from selected time periods, are presented in the following sections.

4.7.2 Peak period aggregate validation

Peak period is highly depended on related occupancy pattern. For the occupancy who have full-time jobs, the peak periods are mainly focused on morning from 6am to 9am and evening from 5pm to 11pm during weekday usually. For household with complex occupancy pattern, like house2, one occupancy has part-time job, and another one is retired, the peak periods are selected with three peak periods, morning from 6.00 to 9.00, afternoon 12.00 to 17.00, and evening from 17.00 to 22.00.

In peak period validation, simulation results of electricity consumption are randomly generated by stochastic model. Then compare with instantaneous load which is not added into the stochastic model. For each selected peak period, electricity load for both simulated and original are aggregated to calculate the difference, example results are shown at table 4.5. It is still selected summer season for each household as an example.

Because simulation outputs contain both existed load curves and predicted load patterns, so it is important to find out if the predicted demand can cover original consumption which is aggregated by instantaneous load. Therefore, as the switch-on events of electricity appliances are mostly stochastic, the 1000 times simulation results are aggregated during each peak period, then compare with measured demand at same peak period.

The results in table 4.5 reveal that during morning and evening selected peak period, the Maximum simulated demand always exceeds original/measure with difference, which has limited the boundary of electricity consumption in the selected period. Meantime, the minimum difference shows that one or many of simulated results are entirely identical with measured demand, which means this stochastic model can predict peak period in accuracy. However, as the occupancy behaviours are unpredictable, it is not possible to randomly select one of simulated results as predicted result to utilize in demand side management. It may cause a huge difference when comparing with the original demand. Demand side management requires fixed demand which can be used in control strategy in advance. The maximum simulated demand is a possible solution which can cover the original demand with some minor overflows.

Summer weekday peak period	1000 times simulated average demand (kWh)	Original instantaneous demand (kWh)	Max simulated demand (kWh)	Max difference (kWh)	Min difference (kWh)
House1 morning	1.2375	0.8392	1.7615	0.9223	0.0055
House1 evening	3.5984	3.1707	4.9548	1.7841	0.0016
House2 morning	1.8343	2.7032	2.7664	1.6564	0.0065
House2 afternoon	1.4137	1.8975	1.8113	0.8160	0.0862
House2 evening	2.2717	2.3377	3.4699	1.1322	0
House3 morning	3.4803	4.1019	6.4121	2.7453	0.0027
House3 evening	5.0442	5.7855	7.8317	2.9263	0.0008

Table 4.5. Aggregate summer weekday peak period electricity demand validation results.

On the other hand, it is noticed that the maximum simulated demand in house2 afternoon peak period is less than original, one possible reason is the time period is too long, as 5 hours in this case. So, it is important to break down the peak period into small time interval to reduce the difference and find out how accurate results the model can achieve.

4.7.3 Sub-hourly aggregate validation

Accurately predict electricity demand is a very tough task. The occupancy behaviours are regularly changed with many related or unknown factors. Previous simulations have set the maximum electricity demand during selected peak period for each household. However, the difference is huge and not be able to use in demand side management.

Therefore, it is divided the period from one hour to 10 minutes based on every 10 minutes. For each picked period, the simulation is running 1000 times to identify if the aggregate simulated results can cover the corresponding measured demand. Each simulation contains a whole day result with 30s time resolution basis.

In the first, it is selected hourly period as test sample, each hour simulated results are aggregated to calculate hourly demand. Therefore, in 1000 times simulation results for each household, the maximum hourly demand for each hour can be generated to constitute max synthetic electricity demand daily profile.

Then it is used to compare with measured electricity consumption to find out if the synthetic hourly demand can still fit with measured demand. It should be noticed that the measured data has not been used in the simulation, which is entirely unknown for the stochastic model. An example validation is shown in Fig. 4.37.

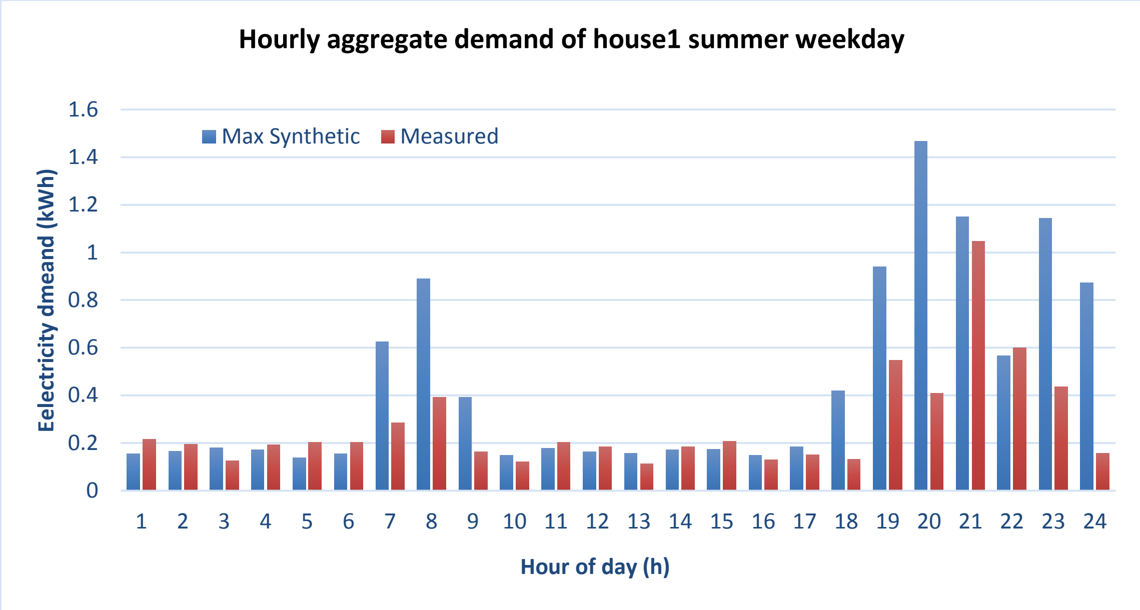


Fig. 4.37. Comparison of hourly max estimated electricity demand and measured data in hourly verification (house1 summer weekday).

Fig. 4.37 presents the stochastic model is suitable for predicting hourly electricity demand in advance. There are some differences between synthetic and measured. Then, cut-and-trail is employed to test sub-hourly and 10-minute time intervals during the peak period. It is aimed to identify if these time intervals are still reliable to satisfy the measured demand. An example of sub-hourly validation is presented in Fig. 4.38.

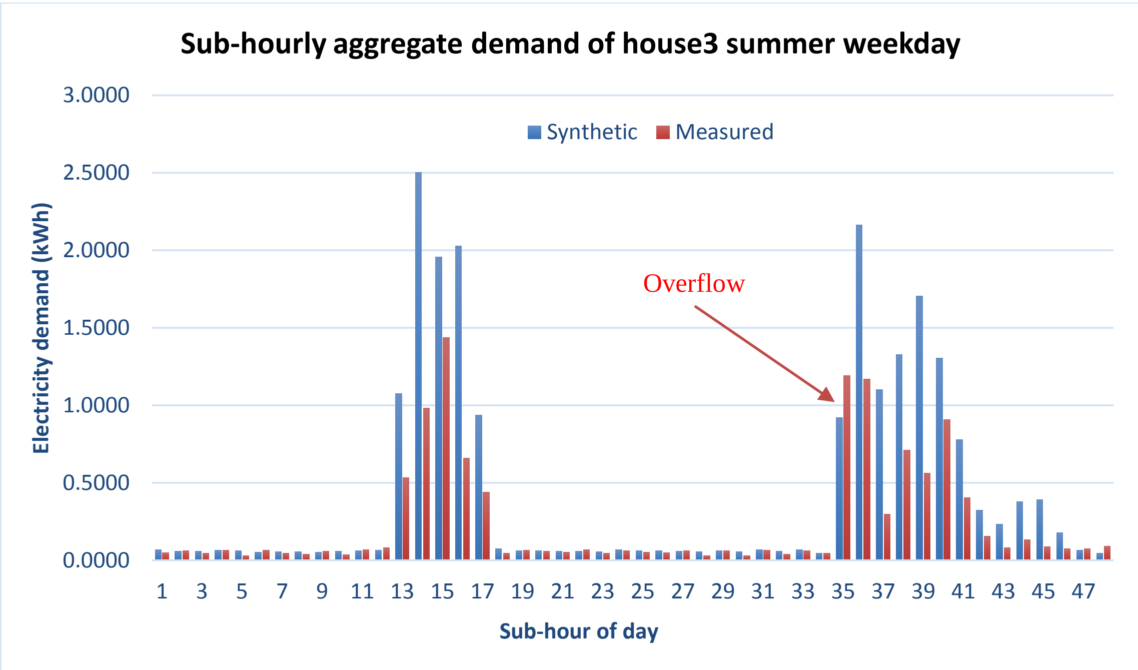


Fig. 4.38. Comparison of sub-hourly max estimated electricity demand and measured data (house3 summer weekday).

It can be seen there is only one overflow, where the measured data is 1.19 kWh, and synthetic demand is 0.92 kWh. The difference is around 0.27 kWh, which is acceptable in the demand side prediction. Meantime, it is presented that off-peak demands are nearly same or with minor differences (below 0.1 kWh), which can be neglected in order to focus the investigation in peak demand.

In the previous of peak period demand, it is noticed that during afternoon peak period of house2, maximum simulated peak demand is lower than measured. Therefore, this type of peak period is used as an example to identify if sub-hourly time interval is available for predicting electricity demand. The results are shown in Fig. 4.39.

From Fig. 4.39, it can be seen that the differences between synthetic demand and measured data are remarkably reduced in sub-hourly time interval. It is from 0.816 kWh (total in 5 hours) to around 0.07 kWh (30 minutes). The difference can be reduced by break period to a shorter interval. On the other hand, it should be proved which minimum time interval this model can achieve. Therefore, it is simulated in 20-minutes, 10-minutes and 5-minutes to identify if the model can still hold accurate results by comparing measured data. An example of 10-minute validation result is presented in Fig. 4.40.

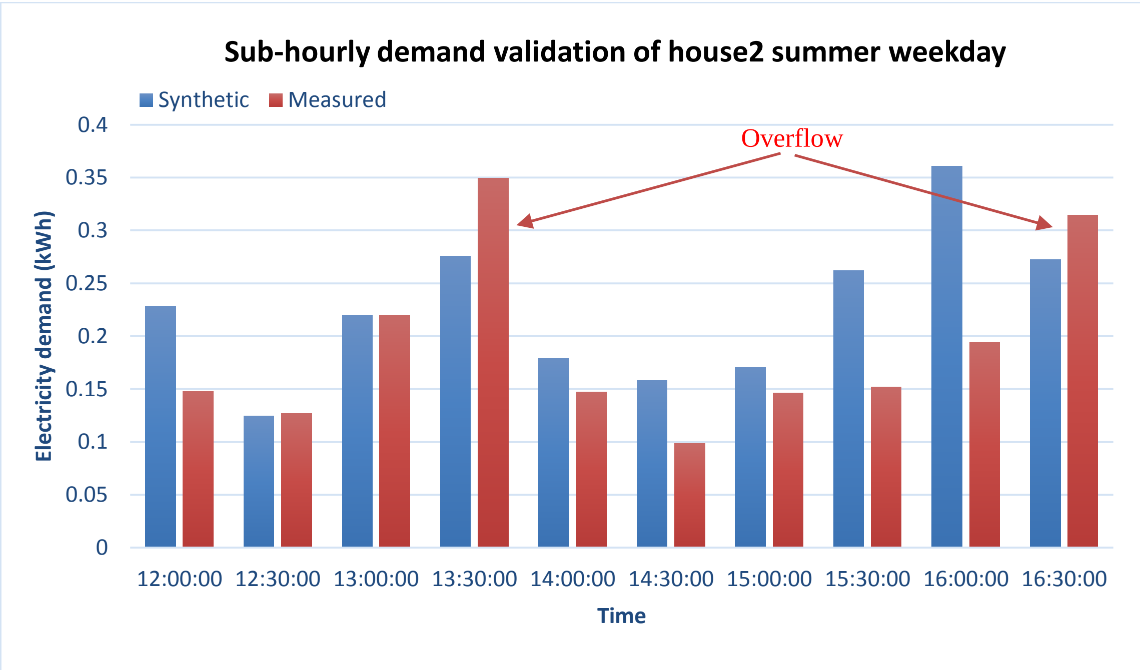


Fig. 4.39. Comparison of sub-hourly synthetic electricity demand and measured data during house2 summer weekday afternoon peak period (30s resolution basis aggregation).

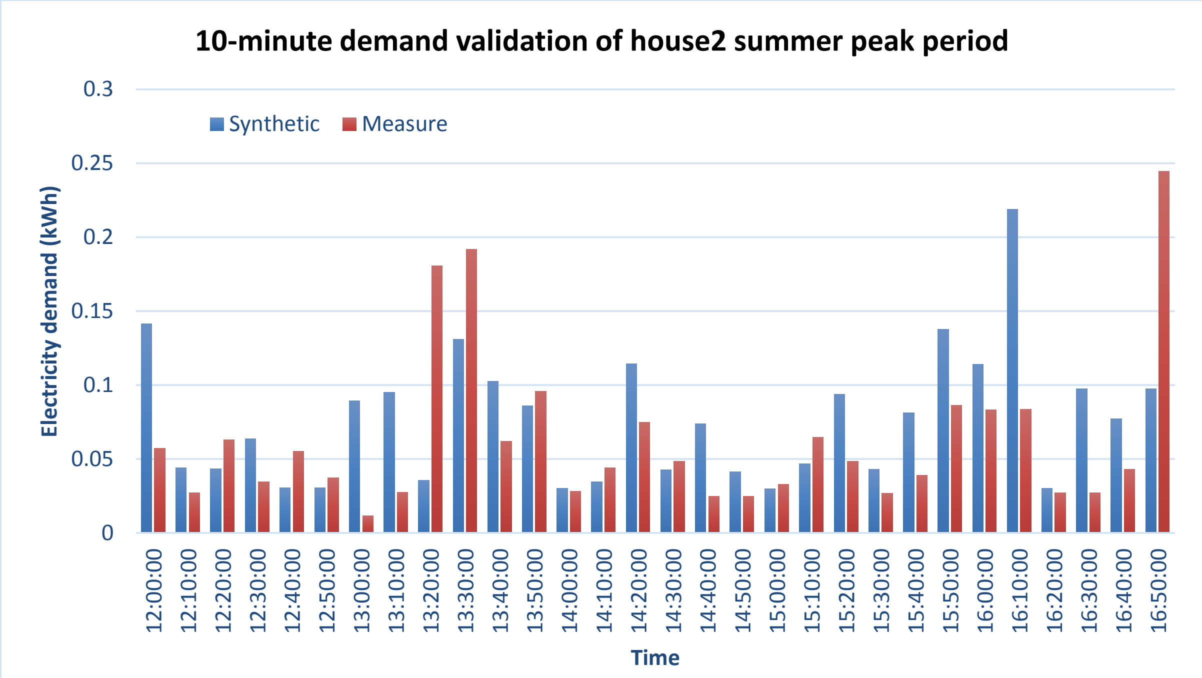


Fig. 4.40. Comparison of 10-minute synthetic electricity demand and measured data during house2 summer weekday afternoon peak period (30s resolution basis aggregation).

It can be seen when breaking down time interval into a shorter period like 10-minute time interval, differences are hugely increased. The synthetic demand cannot satisfy measured data. Meantime, it is also tested other weekday of house2 and load of profiles of house1 and house3 from daily to 5-minute time interval. The results show that while breaking down process, the errors between synthetic and measured are decreasing and then increasing.

The minimum reliable time interval for the stochastic model in this study is identified as 30-minute. It means the stochastic model can accurately predict maximum electricity demand 30 minutes ahead, which is a significant advantage for demand side management.

Another important aspect of this model is the dynamic feature, it should be proved that when adding fresh measured data, the model can still forecast electricity demand accurately in advance within 30-minute time interval. Thus, load profiles of house3 in summer weekday are selected as examples. In the first sub-hourly verification, it is used six weekday load profiles to predict the seventh weekday load data by simulating in 1000 times. The aggregated result is shown in Fig. 4.41.

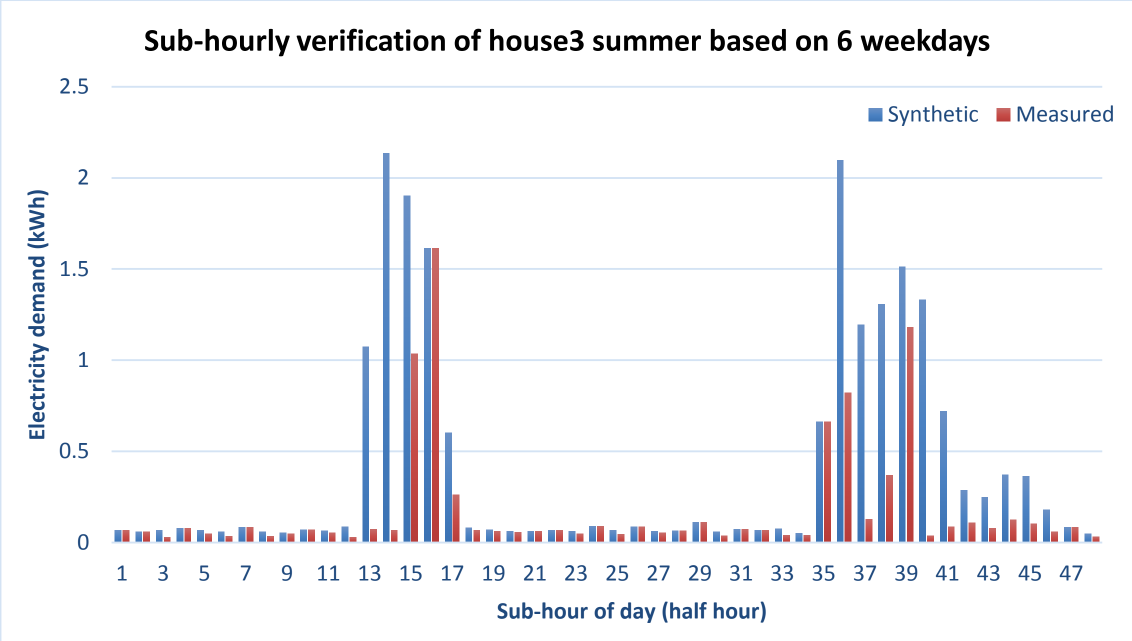


Fig. 4.41. Comparison of predicted electricity demand and measured demand of house3 summer weekday based on six weekday load profiles.

Secondly, it is added the seventh weekday load data into the stochastic model to update the transition probability matrix and related AECO of each number of occupancy. Then the updated model is used to generate updated results by simulating 1000 times, which are employed to be validated with the eighth weekday load pattern. The output is presented in Fig. 4.42.

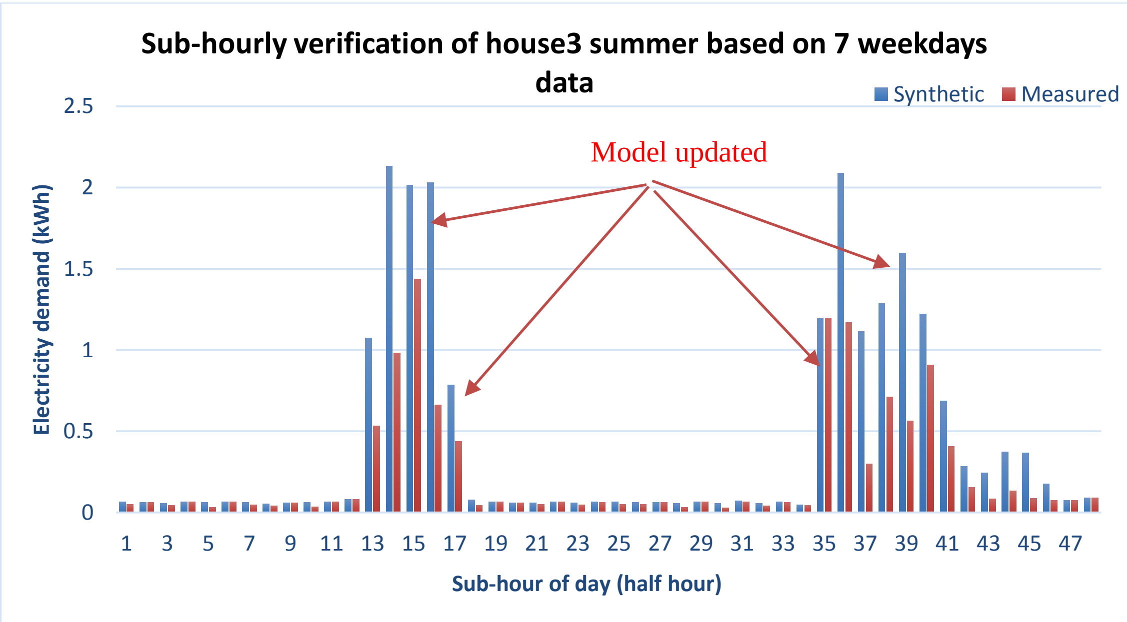


Fig. 4.42. Comparison of predicted electricity demand and measured demand of house3 summer weekday based on seven weekday load profiles.

Fig. 4.42 reveals that the model is dynamically updated by adding fresh data, and also system variations can be captured. It is a crucial factor of dynamic prediction methods. Meantime, the predicted results can also satisfy the measured demand, which can prove the stochastic is reliable to be used in sub-hourly dynamic prediction in demand side management. In addition, it is noticed the synthetic demand during the peak period is increasing when adding fresh original weekday data into the model for simulation. The reason is the randomness of occupancy pattern, because occupancy profile of every weekday is unique.

4.7.4 Summary of electricity demand validation

According to the validation of prediction results in different time interval which from daily to 10-minute, specific analysis outputs are shown above. The prediction results not only review existed load patterns which are already happened in the past, also contain unknown demand which may occur in the future.

By simulating in 1000 times with 30s resolution, maximum, minimum and average synthetic demand in aggregation are generated, respectively. With the comparison between different type of synthetic demand and measured data, it can be found that the stochastic model in this study is reliable to dynamically predict sub-hourly maximum electricity demand in advance with minor overrating. Also, the model can capture the system variation in dynamic, which is a crucial aspect when applying model into related demand side management.

4.8 Comparison with other stochastic model.

As the previous discussed, occupancy pattern is a significant factor of domestic electricity demand. With the lack of high-resolution occupancy profiles for domestic households, many researchers employ Time-Use (TU) occupancy patterns to randomly generate related electricity demand, some models are widely used and cited by many other researchers, like Richardson`s model, which is the one of most popular bottom-up combined with Markov-Chain models [13]. Richardson`s model is verified by 22 measured dwellings, which shows a good comparison of synthetic data and measured data, like time-coincidence, diversity of demand, and annual mean daily demand [13].

However, occupancy pattern for each household is unique, it cannot use universal or national investigated occupancy profile to replace real one for particular household. In order to validate this feature, it is used Richardson`s model to randomly simulate 100 times for generating a number of electricity demand in summer. Then comparing with our stochastic model results, and real measured data which from one of our participated households in this study.

In the first, as the simulation results from Richardson`s model is stochastic, it is calculated average load of each selected time interval (1-min in his model), then comparing with our model average and real historical average. It is select house1 summer as an example, daily load profile comparison is presented in Fig. 4.43.

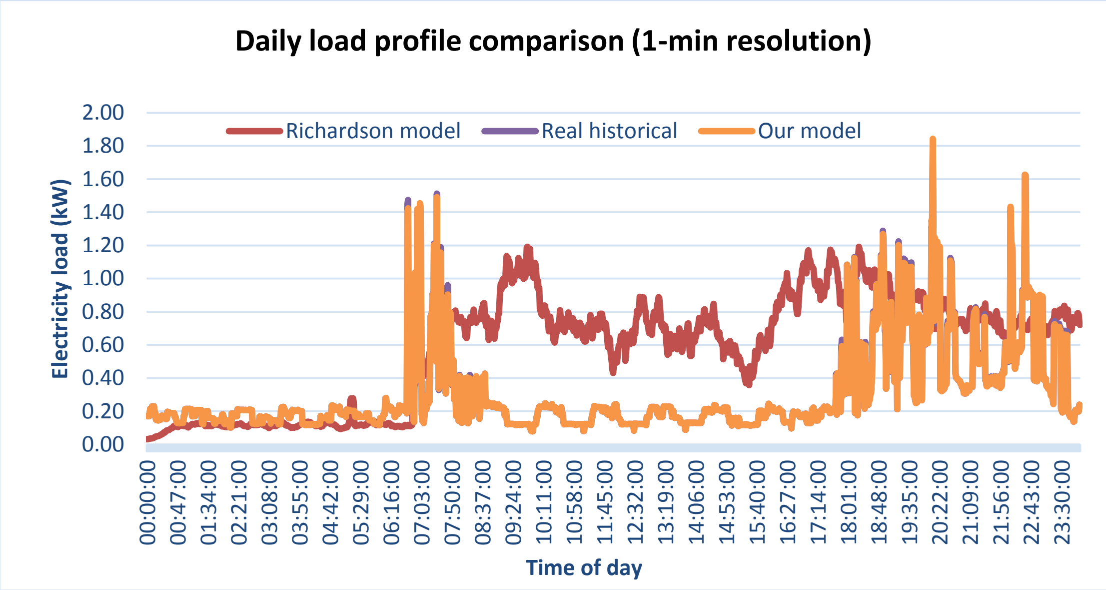


Fig. 4.43. Comparison of Richardson model and our model with real historical load in a day.

It can be seen clearly by using universal occupancy pattern, the load profile generated from Richardson model is completely different with our model and real historical load data. As the results from Richardson model are random, therefore, it is calculated the daily aggregated demand then compare with historical daily demand, result is shown in Fig. 4.44.

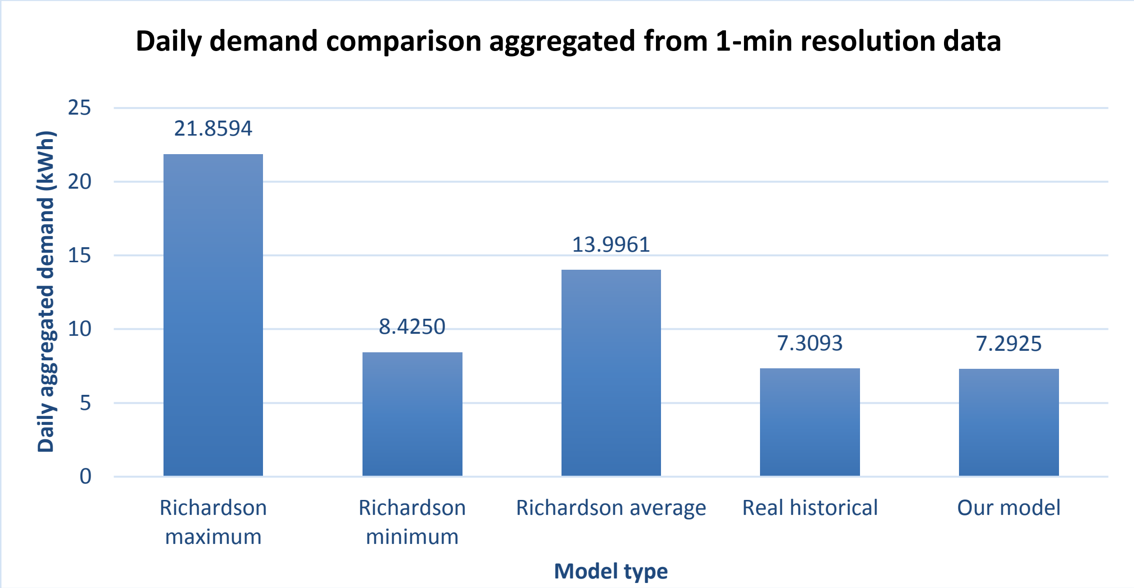


Fig. 4.44. Daily demand aggregate result comparison of Richardson model, our model and the historical model.

From Fig. 4.44, the output simply reveals that without concerning particular occupancy pattern in the electricity demand simulation, the results may vary from original demand, which is not acceptable and cannot be used in the demand side management for individual household.

4.9 Summary

By introducing two different types of prediction methods for domestic electricity demand, the specific stochastic model is chosen to predict electricity demand in dynamic. For each participated household, the stochastic model employ its independent occupancy profile to randomly generate 1000 occupancy patterns, which contain existing profile and unknown activities. Then AECO method is using to mapping the number of active occupancy to related electricity load. Therefore, daily, peak period, hourly, sub-hourly, minutely electricity demand are produced. By comparing with measured data, sub-hourly is identified the minimum time interval to generate maximum synthetic electricity demand by aggregating simulated results. The results show the model can entirely predict electricity demand sub-hourly in advance.

Chapter 5. Dynamic heat demand prediction for UK households

5.1 Introduction

It is known that heat consumption in domestic dwelling is partial “fixed”. It is related with house type, weather conditions, house structure, and dwelling location. These physical factors mainly determine not only space heating and domestic hot water consumption, and also with heat loss and gain. When the dwelling is built up, these factors are settled until the house is retrofitted.

Meantime, weather condition is another important factor for heat demand analysis. UK households during the summer typically require very little heat consumption like domestic hot water. However, in other country, like Russia, the domestic dwellings still need much heat for space heating.

On the other hand, unlike electricity load with meter to record, total heat consumption of a domestic dwelling has not been measured in accuracy. Also, the fluctuation of domestic heating load is not frequently changed. This type of variation is highly related on occupancy profiles, especially in winter. Typically, domestic heat consumption for majority households in UK is estimated by gas meter to roughly calculate heat demand in total. It cannot clearly represent influence of occupancy behaviour. For example, in winter occupants usually switch-on gas boiler to keep warming dwelling whenever they are asleep or go to outside.

Domestic heat demand can be divided into two domains: static and dynamic. The former is fixed consumption, which is require from dwelling. The later one is dynamic demand, which is related from occupancy, as depended on thermal comfort of residents. In order to measure domestic heat demand for particular household in accuracy, many researchers in recent years select scientific software for building energy simulation. It can consider many crucial influent factors as shown above, to model and simulate heat consumption for target dwelling. Meantime, thermal comfort of residents in the building energy simulation software are static when related models are built up.

Occupancy profiles randomly vary from day to day and house to house. Related thermal comfort are also frequently varied. Therefore, how thermal comfort of occupancy can change the domestic heat demand is an important research topic but seldom study have focused it. In order to identify this research gap and generate heat demand dynamically, in this study it is chosen three different domestic house stocks. Each household is presented to build related visual models independently in EnergyPlus, which is a widely used software in building energy simulation area. By adjusting the heat parameters like thermal comfort and occupancy profiles, dynamic heat consumption simulation are provided in this chapter. Section 5.2 introduces the heat demand conditions in the simulation; Section 5.3 presents heating parameters setting and visual house model implementation; Section 5.4 shows the simulation results in annual, month and day. Section 5.5 depicts two different validation methods and provides a feasible solution to efficiently generate heat consumption in dynamic; Section 5.6 concludes the main finding of domestic heat demand prediction.

5.2 Domestic heat demand simulation requirements

5.2.1 Standard Assessment Procedure (SAP)

Fixed heat demand requires specific detail parameters of particular dwellings, such as architectural information, materials use, efficiency of heating system, ventilation, and solar gain. These factors are directly concluded by Governments by using Standard Assessment Procedure (SAP) to evaluate the energy rating on a scale of 1 to 100. Dwelling with a higher number means the heat consumption and heat loss are less than others with a lower assessments. Unfortunately, SAP calculation is not free online, and most assessments are charged from different service. Meantime, when building visual dwelling model in EnergyPlus for a number of houses, the models require specific factors of all elements. These elements can influent SAP assessment, but it is not ideally possible to get all of them naturally.

5.2.2 House type and related thermal comfort

Information of occupancy patterns and house types which involved in this research are detailed in Table 5.1, as same in Robert`s project [54]. The density of each household is calculated by total number of occupancy dividing with total floor area. Higher density with more heat demand requirement during a peak period but less in an off-peak time, comparing with a lower one, especially in winter.

Thermal comfort is a crucial aspect for building energy simulation. The analysis and calculation of particular thermal comfort in selected buildings are very complicated. Because it is required a large amount of data. In order to directly apply thermal comfort into our building model, it is selected thermal comfort temperature of occupancy to replace the total elements of thermal comfort.

	House1	House2	House3
House type	Mid-Terraced	Mid-Terraced (large)	Semi-Detached
Number of occupants	2	2	5
Age groups (elder >65)		2	
Adults (30-40)	2		2
Children (2-10)			2
Infant (0-2)			1
Total Floor Area (m^2)	118.2	171.43	73.78
Density of occupancy	0.017	0.012	0.068
Energy system	Grid and central gas supply	Grid and central gas supply	Full electricity

Table 5.1. Information of occupancy and house for participated houses in this study [54].

The comfort temperature is settled by external physical environments of dwelling and internal emotional factors of occupancy. The former one includes the related factors like weather condition, energy system installed in the house, and SAP. The later one was related to individual temperature that different age group of residents feel comfortable. The UK Government adopts 21 ℃ as an adequate level for living rooms and 18 ℃ for all other areas of a dwelling [54]. Meantime, because the elder occupancy and children require higher temperature to feel comfort, the comfort temperature for each participated household is presented in Table 5.2. The comfort temperature is various in different living rooms. For example in house3, it is 19 ℃ for the adult room, 22 ℃ for young children room and 25 ℃ for the infant room. However, these differences cannot be clearly presented in EnergyPlus model. Therefore, a unified setting is selected which aims to make the infant feel comfort, as set with 23 ℃ in the Table 5.2.

Room type	House1	House2	House3
Living rooms	21 ℃	22 ℃	23 ℃
Other rooms	18 ℃	19 ℃	20 ℃

Table 5.2. Thermal comfort temperature initial setting for each investigated household.

5.2.3 Occupancy profiles

As occupancy profiles are randomly changed every season, the models are simulated seasonally for each participated house.

Occupancy profiles of each household in a whole year are chosen from chapter3 results then updated with occupancy patterns. For example, the occupancy in house1 both have a full-time job, which mean after 9.00 in the morning until 17.00, there should be no one active during weekday.

Meantime, because the occupancy status in EnergyPlus only have on and off indicators, and do not provide the precise number of active occupants. Therefore, occupancy patterns are aggregated from each peak period. Then Occupancy pattern is calculated daily from first-time occupancy wake up in the morning, and last time occupancy go to bed in the evening for each season with sub-hourly time interval. The details are shown in Table 5.3.

Occupancy	House1	House2	House3
Spring (3,4,5) weekday	6.30 – 9.00 ; 18.00 – 23.30.	6.30 – 13.00; 17.00 – 23.00.	6.00 – 9.00; 17.00 – 23.00.
Summer (6,7,8) weekday	6.00 – 9.00 ; 17.30 – 23.30.	6.00 – 22.00.	6.00 – 8.30; 17.00 – 23.00;
Autumn (9,10,11) weekday	6.30 – 8.30 ; 17.00 – 22.30.	6.00 – 23.00.	6.00 – 8.30; 17.00 – 22.00.
Winter (12,1,2) weekday*	6.00 – 9.00 ; 17.00 – 23.00.	7.00 – 23.00.	4.00 – 10.30; 14.30 – 22.30

Table 5.3. Synthetic occupancy profiles of each household in every season.

Original winter data of house3 (27th Dec and 28th Dec) are during Christmas holiday, which can be identified as weekend profiles.

The other original occupancy patterns during weekend are unknown in this study. It is known if there is nobody at home, the heat consumption of the whole dwelling will be very little. Therefore, in order to classify the heat demand consumption between weekday and weekend in this study, it is assumed that each dwelling is not occupied at every weekend.

5.3 Visual house model implementation

5.3.1 Model initialization

All the visual house model are built in DesignBuilder with EnergyPlus. EnergyPlus is a popular architectural simulation software, which can model various energy flow such as heating, electricity, cooling, and ventilating. [102].

The aim of this study in heating demand prediction is to identify how occupancy profiles can dynamically alter related heat consumption in domestic dwellings. Therefore, in order to maximum eliminate the influence of these fixed factors which are discussed above. It is naturally built a semi-detached visual house then add solid wall with proper insulation between the two sides with neighbour to generate small terraced house and all one floor to provide large terrace house, respectively. Thus, it is assumed that these three type of households have similar energy rating.

5.3.2 Related heat parameters setting

Related factors of thermal comfort temperature in EnergyPlus simulation excluding physical elements are density, occupancy profiles and energy system. These factors are settled particularly in EnergyPlus model, and an example is presented in Fig. 5.1.

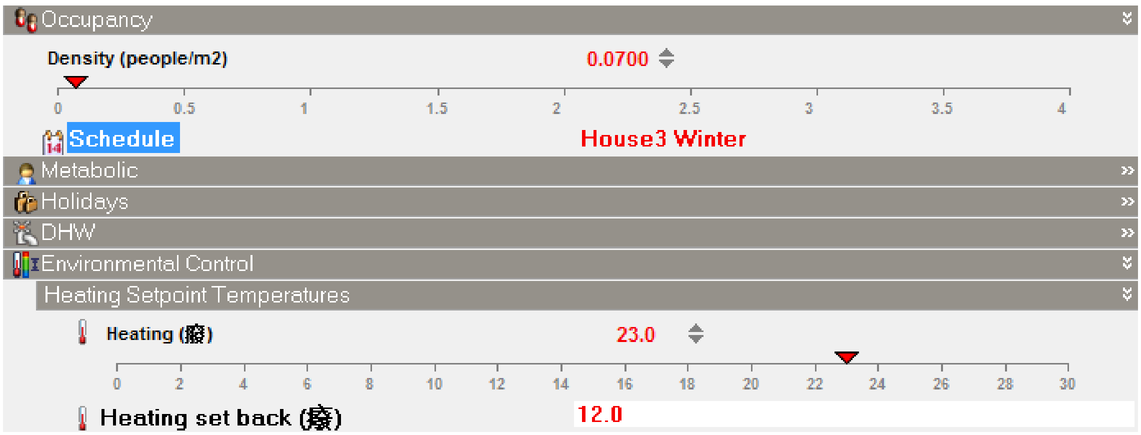


Fig. 5.1. Example of comfort temperature parameters setting with semi-detached house.

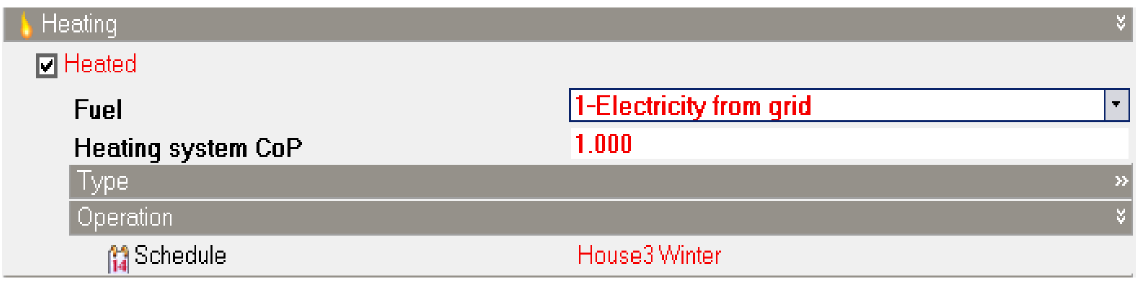


Fig. 5.2 Example of energy system parameters setting with semi-detached house.

The heating set back temperature is set as 12 degree C to keep dwelling warm in order to prevent damage from cold weather. Energy system parameter are shown in Fig. 5.2. It is set same elements with original, and because it is full electricity supply from the grid, and the Coefficient of Performance (CoP) of heating system is chosen as 1. Operation schedule is same with the occupancy schedule above. For other household with central gas supply, the CoP is settled as default as 0.68.

5.3.3 Model implementation

The visual model of each house is implemented in DesignBuilder (version 3.4.0.039) with EnergyPlus (version 8.1). An example of semi-detached house is presented in Fig. 5.3, other models of house are given in appendix.

Fig. 5.3. The visual semi-detached house with three bedrooms (house3)

The minimum time interval in DesignBuilder is sub-hourly, which is selected as simulation time interval.

From the previous discussion, occupancy patterns differ from day to day, even aggregated from season to season. Using fixed occupancy profiles for a whole year simulation can cause miscellaneous results, which are commonly in inaccuracy. Thus, for each house model visual located in London in this study, every season is simulated independently by using individual occupancy profiles.

On the other hand, heat consumption may be increasing when the indoor temperature is lower than comfort temperature. Space heating and DWH obtain majority heating load in domestic dwellings. Therefore, it is aggregated the summation of space heating and DHW consumption to represent the total heat load by excluding the consideration of physical factors.

5.4 Heat demand simulation.

In the first, annual heating consumption are simulated in daily for each visual dwelling to typically generate an overview of annual load map. Secondly, hourly heating demand are presented in week to provide clear seasonal consumption in detail. In the last, sub-hourly heat consumption are shown to depict the influence of occupancy behaviours.

5.4.1 Daily heating load in annual

An example of annual heat demand profile of house3, which consume fully in electricity, is presented in Fig. 5.4 with daily consumption. It is shown the maximum heat load is held in December, and minimum one is occurred in the summer. During summer, heat demand is mainly manipulated by domestic hot water. In term of weather conditions in UK, it is rare household using air conditions for recovery indoor temperature in summer, which is not considered in this study.

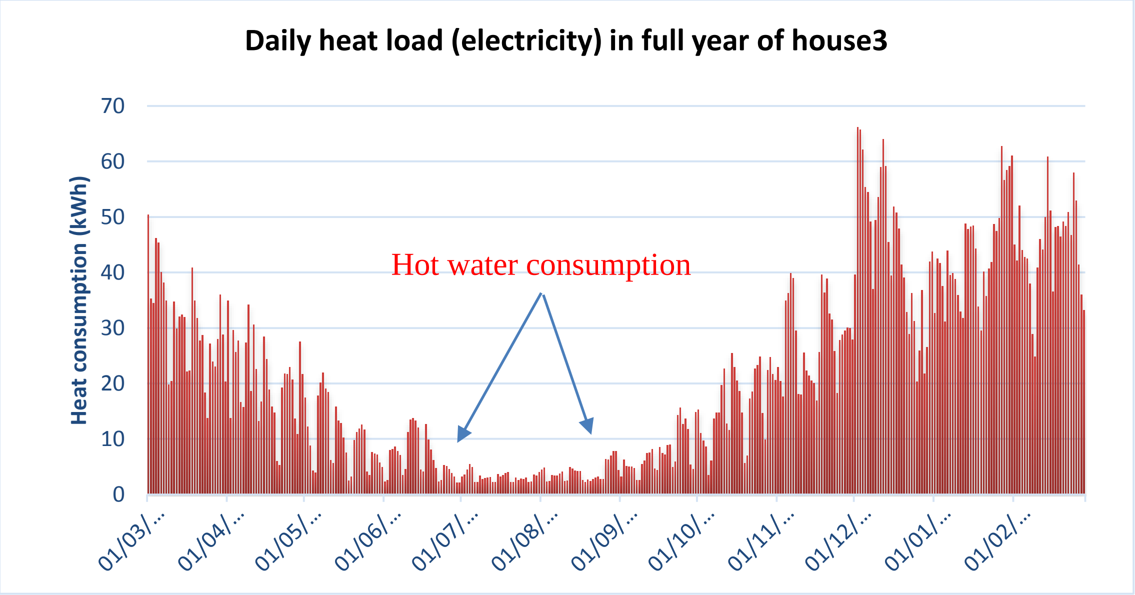


Fig. 5.4. An example simulation result of daily heat demand (Electricity) in the year of semi-detached house.

5.4.2 Mean hourly heating demand by month

Another example of month demand composed by mean hourly by day is shown in Fig. 5.5, which present the monthly heat consumption in February of house2.

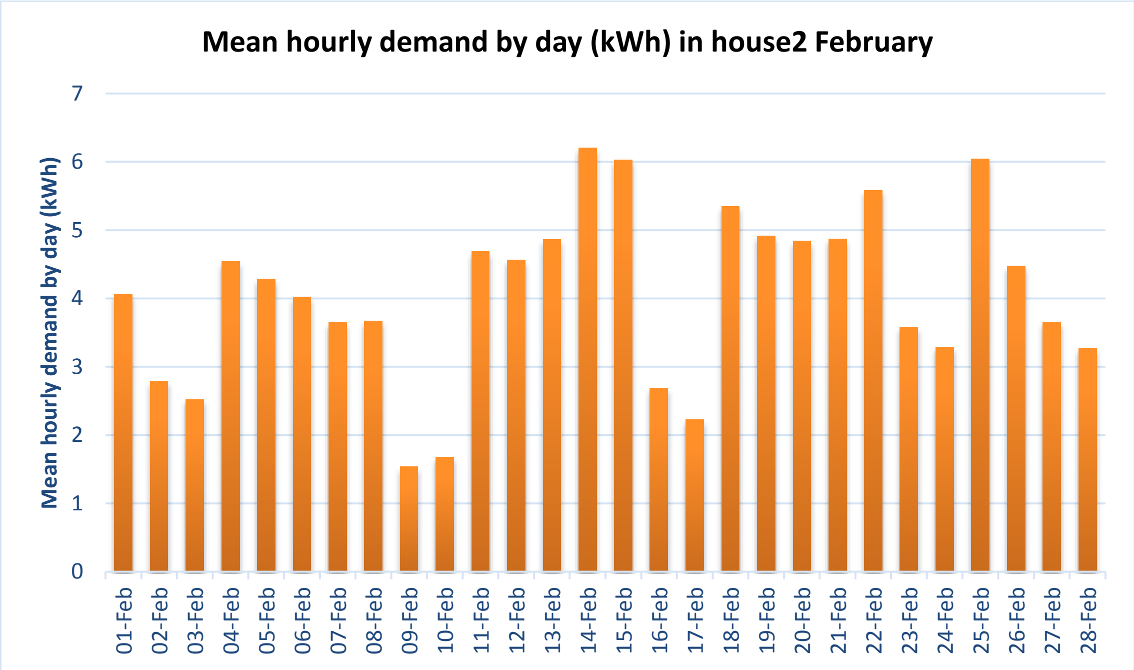


Fig. 5.5. An example simulation result of mean hourly demand in February (winter), by month of house2.

The year in the simulation is set by default as 2002, and it is assumed the occupants are not at home during every weekend from the previous discussion. Therefore, it can be seen the mean hourly heat consumption during weekend is extremely lower than weekdays, as shown in Fig. 5.5. Meantime, as the weather data which are applied in DesignBuilder is using past fifty years average climate data, the simulation results are fixed no matter how much times in the simulation. Therefore, the variation of hourly heat consumption between weekday and weekend are mainly manipulated by occupancy profiles.

5.4.3 Sub-hourly heating consumption by day

So it is important to find out accurate difference heat consumption between occupancy and non-occupancy. The minimum time interval, which is set as sub-hourly in DesignBuilder, is selected in this study.

It is simulated each house both with original occupancy profiles and non-occupancy profile for the whole month in each season. House1 during winter is picked as an example. Then calculate the mean sub-hourly heat consumption by a day, and an example of comparison between occupancy and non-occupancy result of house1 weekday in January is shown in Fig. 5.6.

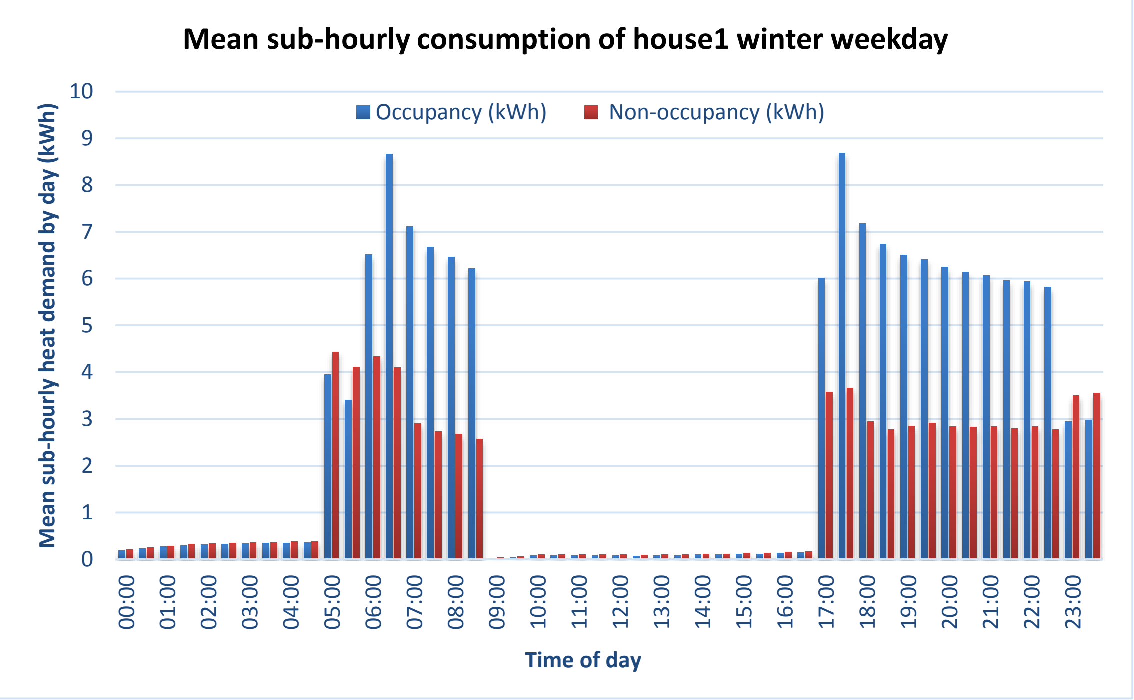


Fig. 5.6. Mean sub-hourly heat demand comparison between occupancy and non-occupancy of house1 during winter weekday.

Fig. 5.6 reveals the difference between occupancy and non-occupancy heat load in winter. Occupancy part is simulated by using original occupancy patterns, and non-occupancy heat consumption is modelled by assuming occupancy not at home. Examples in other seasons with different house are presented in appendix. It can be found that the difference is mainly focused on the peak period when occupancy is active. Also, there are some minor differences at 5am, as occupancy may wake up early or need pre-heat house, the occupancy schedule simulated in EnergyPlus start at 5am each morning.

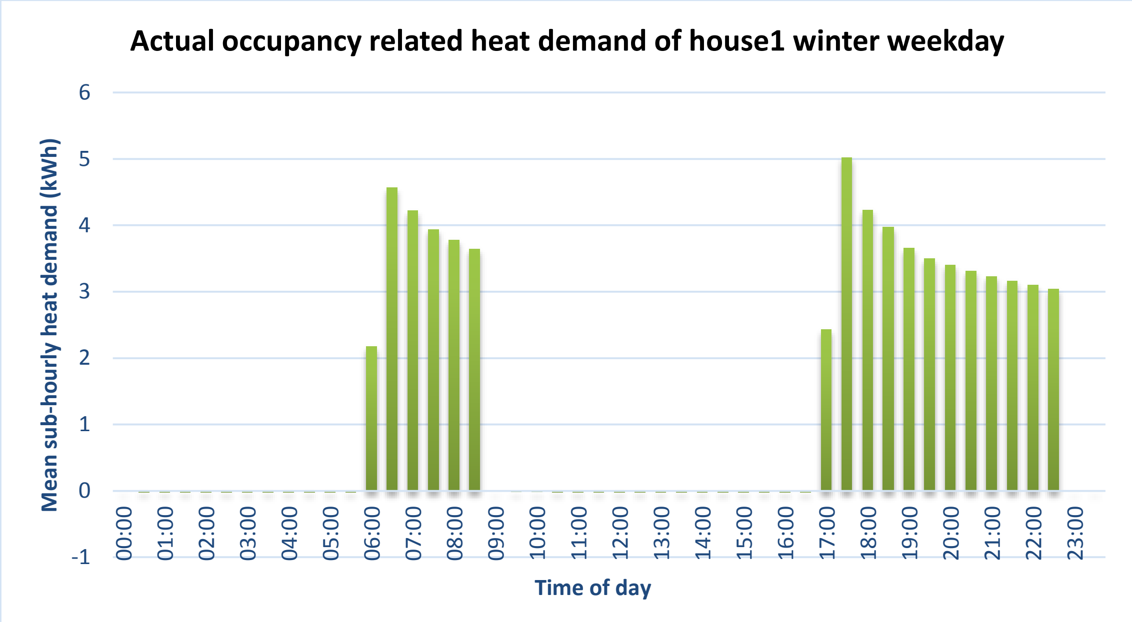


Fig. 5.7. Mean sub-hourly actual heat demand of occupancy related during winter weekday of house1.

With calculating the difference, actual occupancy heat demand which excluding fixed demand (non-occupancy related heat consumption) can be identified, as shown in Fig. 5.7. The maximum difference of heat demand in Fig 5.7 is 5 kWh.

The occupancy profiles of house1 in winter is from 6.00 to 9.00 in the morning and 17.00 to 23.00 in the evening from Table 5.3. It can also be found the actual occupancy related heat demand has adequately covered these two peak periods in Fig. 5.7.

5.5 Results validation and discussion

Measure heat consumption in accuracy is not ideally possible currently. In order to validate the simulation results, it is selected house3 winter profile as an example. Because it is entirely supplied by electricity, winter electricity load can be used to minus summer load, and then corresponding heat consumption is generated roughly.

Meantime, it is important to prove the visual model in this study can dynamic predict heat demand for each household. Therefore, random occupancy profiles in each season are generated by using the stochastic model which provided in chapter 4. Then these synthetic occupancy patterns are applied into particular related house to validate if the model can dynamically capture the heat demand in advance.

5.5.1 Heat consumption validation

It is very difficult to validate heat consumption as the original data is not possible to be fully measured, and normally it is only gas consumption. Thus, considered house3 is electricity supply only, it is possible to use winter load to minus summer consumption to briefly generate heat demand in winter. In order to eliminate the influence of randomness, loads at each thirty seconds in winter and summer weekday of house3 are calculated in average. Then these simulation results are aggregated into sub-hourly time interval to compare with simulated data as shown in Fig. 5.8, where the measured data is the difference value between winter and summer average load.

Although it is not expected that simulated results will fully match with measured data, there are much difference as presented in Fig. 5.8. One possible reason is the measured load is not accurate, which cannot mainly represent realistic heat consumption. In addition, as the DesignBuilder cannot present the number of active occupancies, but the heat consumption vary from one active occupancy to two active occupants. Therefore, it is very crucial to address the relationship between the number of active occupancies and related heat consumption in dynamic heat demand prediction.

On the other hand, using winter load to minus summer load is not a feasible solution to validate the heat demand. This type of measured data is generated from the average result, and simulated data is from single day profile because the full month data is not available.

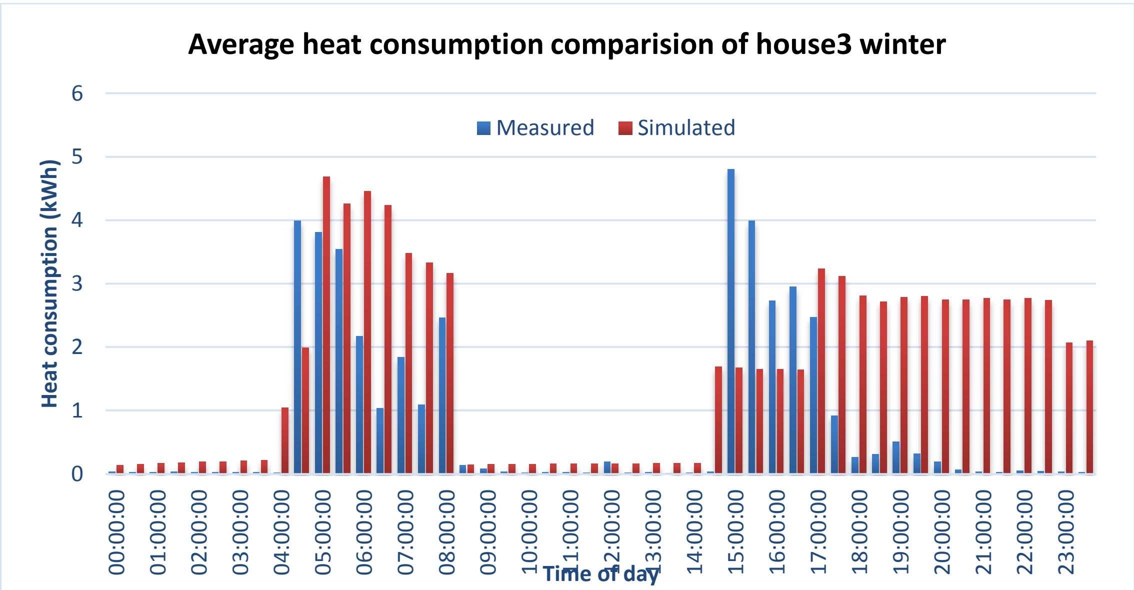


Fig. 5.8. Roughly comparing measured data with simulated load during winter of house3.

5.5.2 Dynamic heat demand prediction and verification

From previous discussed, domestic heat demand for a particular house contains two aspects, static and dynamic. The former one can be generated by applying non-occupancy related profiles, and this type of heat consumption is only related with physical factors of individual domestic dwelling. The later aspect is depended on occupancy profiles. Meantime, because the number of minimum simulation days in DesignBuilder is 14 (at least two weeks), and also occupancy patterns vary from day to day. So it is not efficient to simulate 365 times because individual occupancy profile for each day should be updated in the model for a whole year.

Therefore, in order to efficiently generate domestic heat demand for individual dwelling in dynamic, the simulation and validation procedures are shown in following steps:

Step 1. Non-occupancy related heat demand generation for a whole year.

For particular domestic dwelling, non-occupancy related heat consumption is only dominated by weather conditions. The weather data of each single day used in the simulation is the average results of past fifty-year records at same time. Thus, it is very simple to generate whole year profile of this type of heat consumption in DesignBuilder with sub-hourly resolution.

The heating system is only switched-on when the dwelling is too cold like indoor temperature is below 12 degree C in order to protect dwelling avoid damage. It is assumed that the targeted dwelling is nobody staying inside in this type of simulation, so the occupancy schedule is set to off, and the density is changed to zero.

With identical physical factors initialization, the simulated heat demand is reliable to replace realistic relative heat consumption.

An example of a single day heat consumption is presented in Fig. 5.9. In addition, mean sub-hourly non-occupancy related heat demand is generated for every month.

The two peak periods in Fig. 5.9 show how heating system warming dwelling in terms of keeping indoor temperature above 12 degree C to protect dwelling.

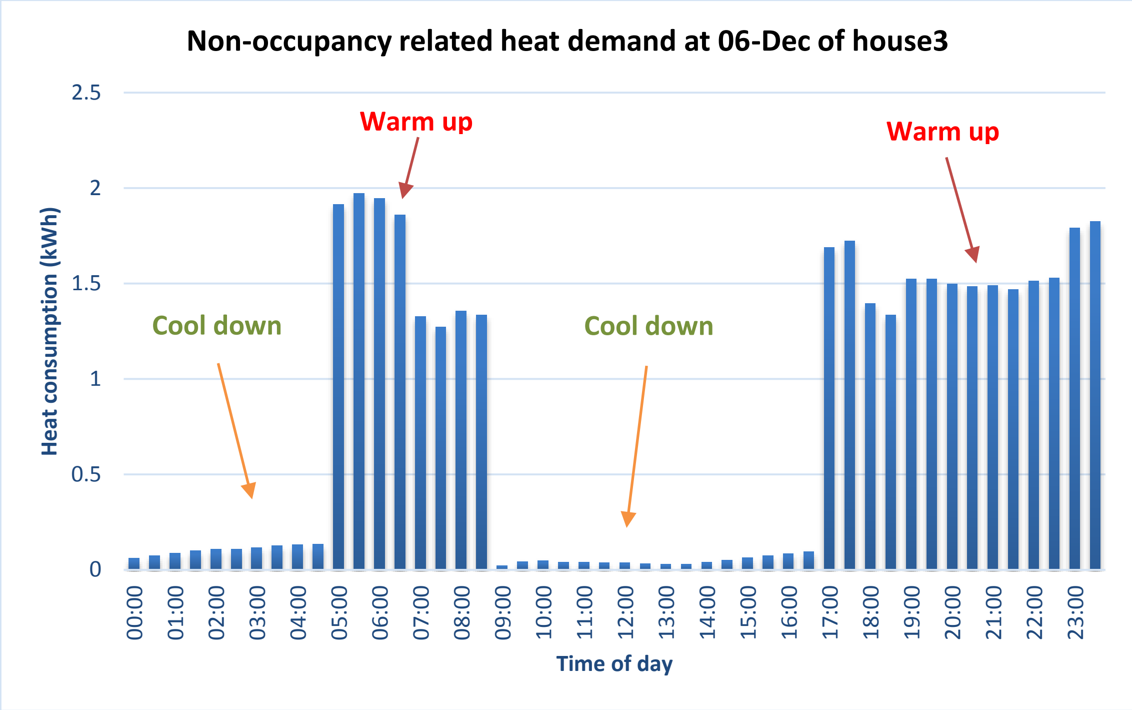


Fig. 5.9. An example of single day non-occupancy related heat demand simulation of house3 winter.

Step 2. Occupancy related heat demand generation for a whole year

When the domestic dwelling is occupied by at least one occupancy, the internal temperature will be heated to reach the thermal comfort level. The related temperature has been shown in Table 5.2, which will lead heat consumption increasing when occupancy is active.

It is important to adequately generate occupancy related heat consumption. Thus, occupancy related heat consumption in sub-hourly resolution can be provided by applying related occupancy profiles in each season from Table 5.3 in the visual model, to generate heat consumption for every month independently.

An example is provided in Fig. 5.10.

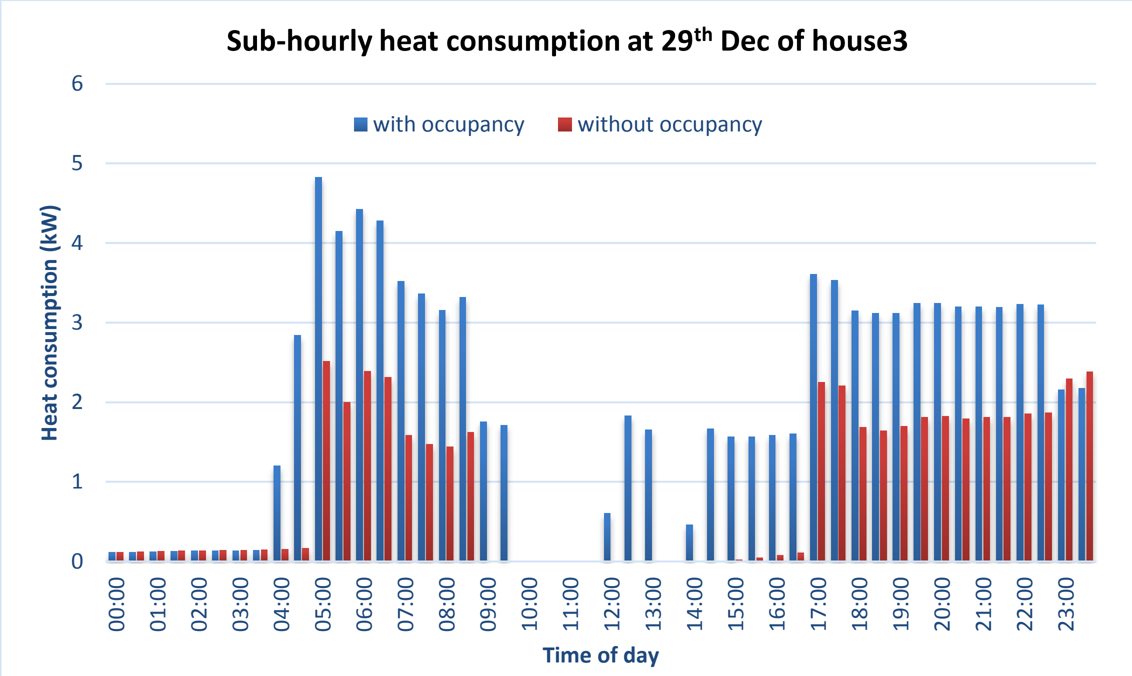


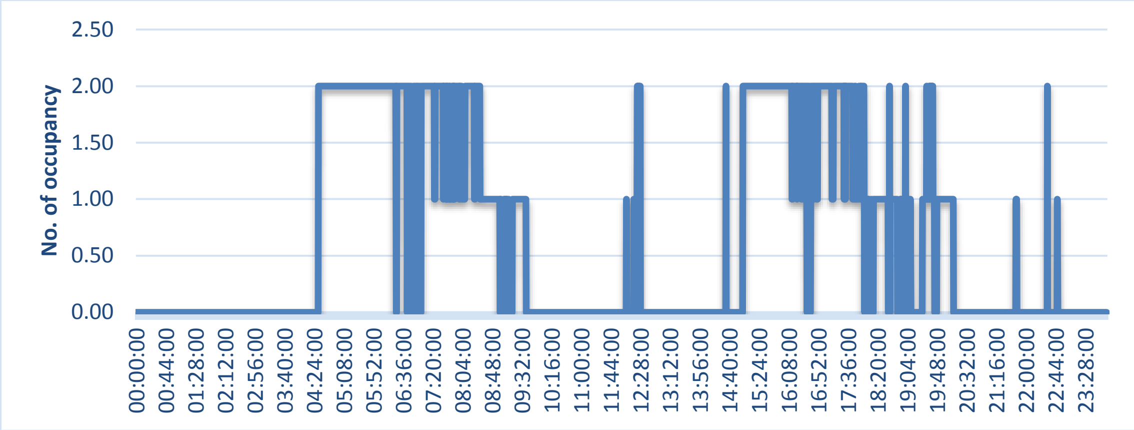
Fig. 5.10. An example of comparison between heat consumption with occupancy and without occupancy at 29th Dec of house3.

The occupancy profile in Table 5.3 is a collection set which contains all historical profiles, which means the simulation for each month is using identical occupancy profiles. It should be noticed that the example shown in Fig. 5.10 is using historical aggregate profile not realistic profile.

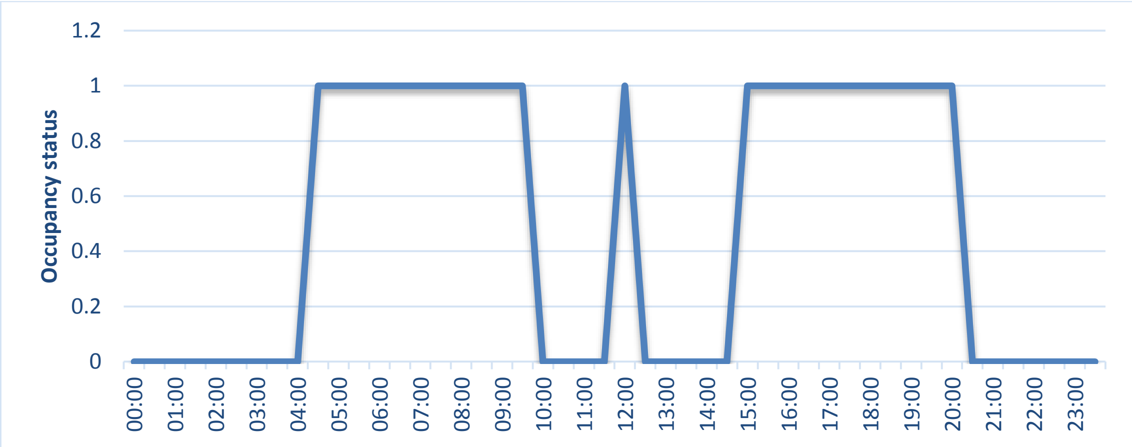
Step 3. Transition from original occupancy profiles to occupancy status

At each half hour during weekday in selected month, when there is at least one active occupancy, occupancy status can be determined as 1, and others are set to 0. Thus, corresponding occupancy status can be provided. We still select 29th Dec of house3 as example. Original occupancy profile (30s resolution) transfers to related occupancy status (aggregated in 30min resolution) are presented in Fig. 5.11

It has been noticed there are some single peak value in the evening are missing in the transition, because these data are not consecutive, they can be identified as pseudo peak period which can be neglected.



(a)



(b)

Fig. 5.11. Transition from occupancy profile (a) to occupancy status (b) at 29th Dec of house3.

Step 4. Synthetic heat consumption generation and validation

With the results in step2 and step3, for each selected half hour time interval, when the occupancy status is 1, then map to occupancy related heat consumption. Otherwise, map to without occupancy heat consumption.

Because occupancy status can be generated dynamically by stochastic model, as shown in the previous chapter. Therefore, synthetic heat consumption generation can be provided dynamically.

In order to validate this type of synthetic results, original occupancy profile are used in the same model to generate simulated results. An example of comparison at 29th Dec of house3 is presented in Fig. 5.12

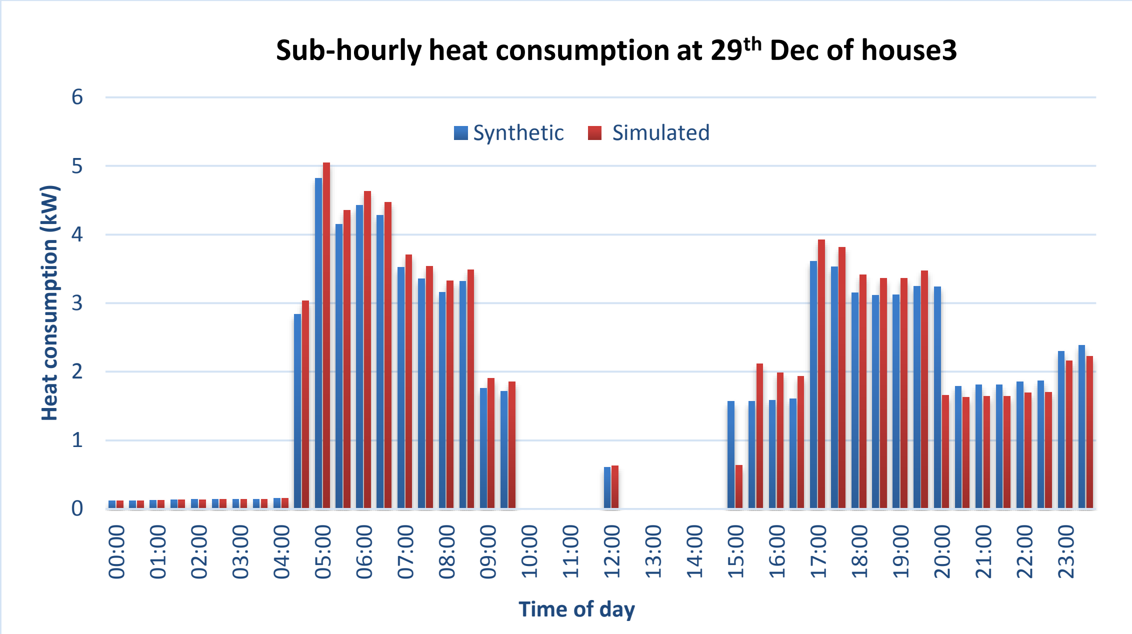


Fig. 5.12 Comparison between synthetic and simulated heat consumption of house3

Result in Fig 5.12 shows a good match between synthetic and simulated data, which means synthetic data can be used to replace simulated one.

Therefore, with the step from 1 to 4, every weekday can be simulated at least one month in advance. Then dynamic occupancy profile provided from the stochastic model can be used to efficiently generate related heat consumption within sub-hourly resolution.

5.6 Summary

DesignBuilder is a powerful, but static scientific software which using fixed parameters for every heat consumption simulation, and also it limits the minimum simulation interval as 14 days. In terms of occupancy profiles vary from day to day it is not efficient to simulate in 365 times with total different parameters in order to generate whole year heat demand profiles. Therefore, a feasible and effective method is presented in this chapter, which can provide accurate simulation result with sub-hourly resolution in dynamic.

Chapter 6. Control system design and improvement of BMT-HEES

6.1 Introduction

Bio-fuels micro-tri-generation with hybrid electrical energy storage (BMT-HEES) is a novel energy system which contains off-grid electricity supply, heat and cooling generation by using renewable energy. Unlike the traditional energy supply, such as central gas with grid, this type of "all-in-one" energy production not only can provide energy generation generally by domestic users, and also supply energy beforehand by pre-established control system. Consider with the off-grid feature, frequently operating engine, like switch-on and off, can extremely depress the efficiency of energy generation. Therefore, pre-set control system, which in order to improve system efficiency, is an important prerequisite for effective energy supply.

In this chapter, sub-systems in BMT-HEES are introduced throughout, which includes the engine, hybrid electrical energy storage, heat recovery and storage, and refrigeration. In the first, control system requirements including system overviews, system size determines, feasibility and flexibility is discussed in section 6.2. Then, general control strategies for each sub-system, which setting fundamental control requirements, are presented in section 6.3, as it is helpful to confirm the energy demand can be satisfied with preliminary control. Hardware implementation of fundamental control strategy is provided in section 6.4, which is using STEP7 S300 for programming PLC with WinCC. Intelligent control system is discussed in section 6.5 and by calculating the whole system efficiency, comparison between general control strategy and intelligent control strategy is given.

6.2 Control system requirements

It is clear that an off-grid energy production must be able to satisfy energy demand instantaneously without doubt. However, with the diversity of households, including appliances, house structure/type, and occupancy components, system size is the primary consideration when installing this type of energy production into particular domestic dwelling. The system size not only contains engine size and also with the capacity of energy storage, which including thermal storage and electrical storage. Meantime, this system should be able to satisfy reasonable energy demand and capable of system variations, like appliances and occupancy changes.

6.2.1 System overview

Control system including system design and control strategy is a very tough task when applying BMT-HEES into particular domestic dwellings. The schematic diagram of BMT-HEES [17, 18] is presented in Fig. 6.1.

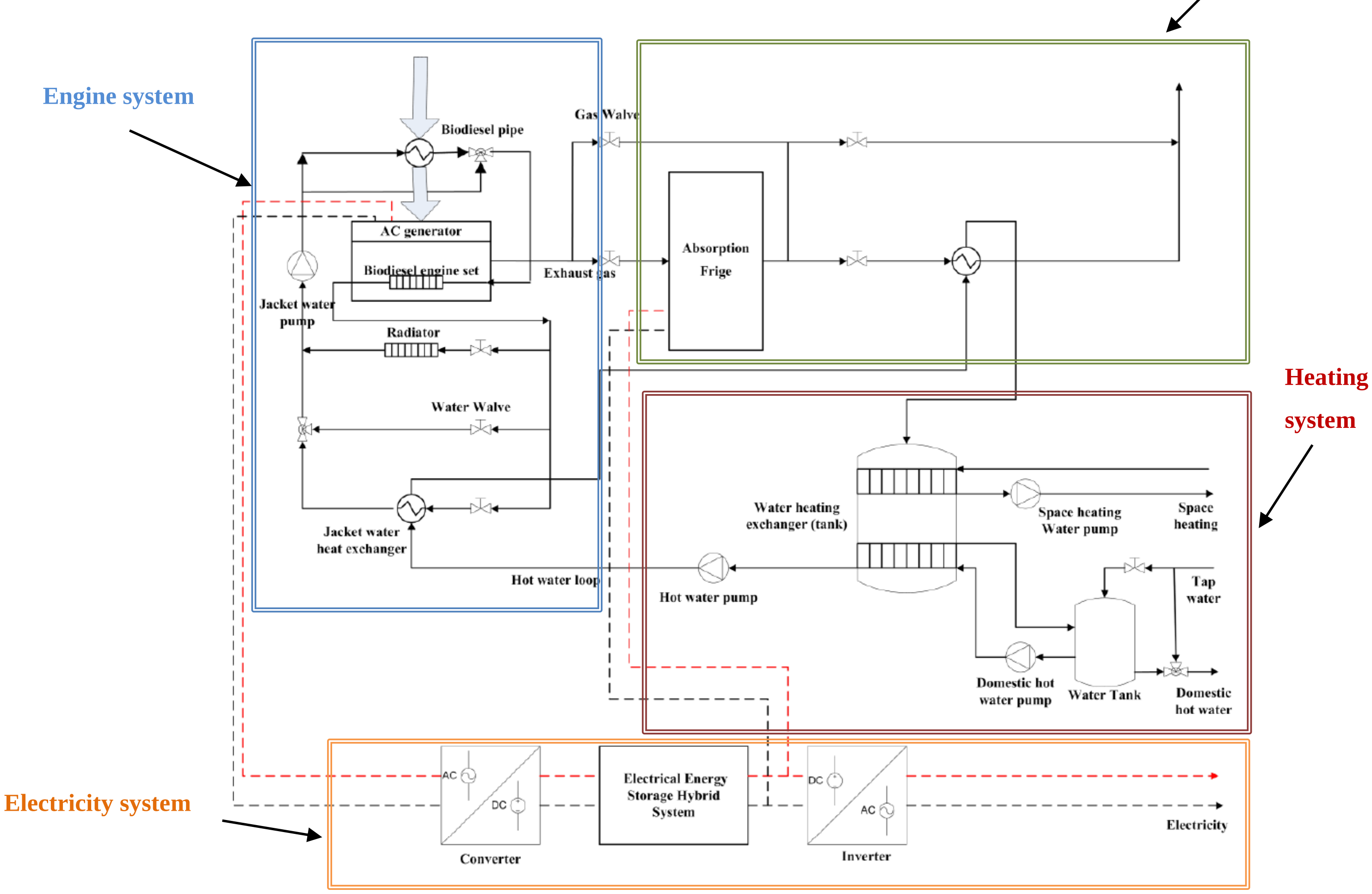


Fig. 6.1. Schematic diagram of BMT-HEES including engine system (blue rectangle), electricity system (orange rectangle), heating system (red rectangle), and exhaust system (green rectangle) [17, 18, 19].

From Fig. 6.1, it can be seen there are four sub-systems in BMT-HEES, which are bio-fuel with diesel engine system [17], heating system [18], electricity storage system [19] and exhaust including cooling system. These sub-systems can also be identified as energy generation system and energy consumption systems, which can allow three different types of energy (electricity, heat and cooling) cycling in the whole system. Each sub-system contains several PLC controllers which are working with different type of valves. The control can capture the signals from each control unit such as valves, thermometers, and energy storage. Then it can calculate the estimated energy demand in next select time period and send the feedback to each control unit to meet related demands.

Biodiesel engine set with AC generator in engine system can simultaneously generate heat and electricity by injecting biodiesel. Domestic electricity demand can be selectively satisfied by electrical energy storage or from AC generator directly. Meantime, heat demand including domestic hot water (DHW) and space heating is satisfied by water tank that can restore redundant heat from water circuit. Moreover, there is an additional heating wire (3 kW) in the main water tank (water heating exchanger tank). It can generate heat for space heating or DHW alternatively by consuming electricity. This heating wire can only be supplied by AC generator, which is not shown in the Fig. 6.1.

A Bio-fuel with diesel engine

In terms of energy challenges in UK, and due to the renewable and low carbon emissions of vegetable oil, the applications of variable vegetable oils applied in diesel engines have great attraction to energy researchers in recent years. In addition, vegetable oils have advanced impacts in higher viscosity and oxygen component, lower cetane number, lower volatility and less heat energy when comparing with diesel [130, 131].

Yu in [17] compares the performances in same environments of four vegetable oils such as croton, jatropha, rapeseed and sunflower with gas oil. He reports that preheated croton oil has great advantage in replacement of gas oil in the operation of diesel engine, which has high efficiency, energy-saving and lower carbon emissions. Therefore, croton oil is selected as a prime fuel in Yanmar diesel engine with 6.5 kW power generations [17] as shown in Fig. 6.2

Fig. 6.2. Yanmar YTG6.5S diesel generator [17].

B Micro-trigeneration system

Trigeneration as a novel technique has been promoted rapidly by the increasing energy demand, negative environment and finite resources. To achieve the high efficiency, cost effectiveness and minimum emissions, trigeneration has been employed successfully instead of cogeneration as the main power generation system in large plants such as food industry, hospitals and office buildings [132].

Wu in [18] has developed a sophisticated micro trigeneration system as shown in Fig 6.3. With the biodiesel engine set, heat and electricity can be generated concurrently, and the coolant water can transfer heat from internal engine to external environment by heating exchangers and restore heat in water tank for DHW use and space heating. Meantime, exhaust gas can preheat the bio-fuel and also re-heat water tank. The genset in biodiesel engine can supply electricity off-grid to meet related domestic demand and also drive cooling appliances such as fridge and refrigerator. Therefore, the domestic energy demands including heating, electricity and cooling can be satisfied by this micro-trigeneration system. The redundant heat can be restored in water tank or emit with exhaust gas.

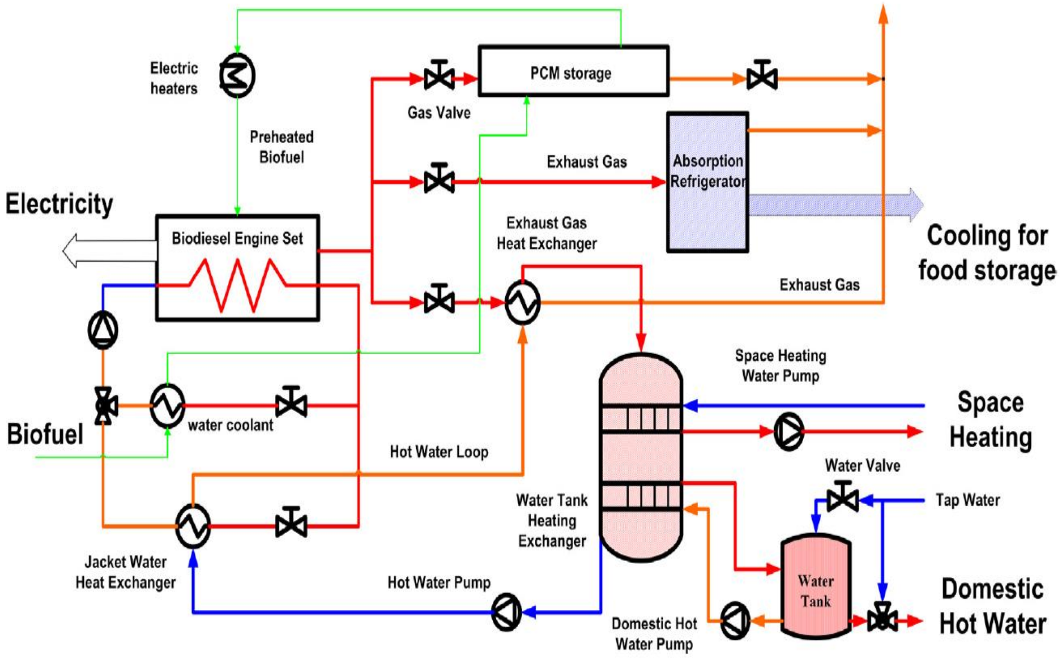


Fig. 6.3. Schematic diagram of the micro trigeneration system [18].

C Hybrid electrical energy storage

The problem of BMT system in Fig. 6.3 is how to deal with redundant electricity in winter in terms of its off-grid. In order to satisfy the heating demand of domestic end-users, like DHW and space heating, the duration of engine operation is much longer in winter than other seasons, for example, in winter, the engine should be pre-operated before occupant wake up to warm the house in terms of external temperature, but all of the appliances are switched-off at same time excluding cooling appliances and appliances with standby model, therefore, electrical storage is necessary to be installed in order to save energy. The another advantage of electrical storage is to improve the efficiency of biodiesel engine set, such as in summer, in terms of low heating demand, the duration of engine generation is controlled decreasingly, but appliances require electricity concurrently. Therefore, electrical energy storage can provide balance between demand and generation, and also offer high efficiency of energy generation, energy saving and low carbon emissions.

Therefore, Chen in [19] has provided a novel hybrid electrical energy storage system, as shown in Fig 6.4, which combined batteries and super-capacitor to meet the diversity of domestic electrical demand. The specification of super capacitor and batteries are shown in Table 6.1.

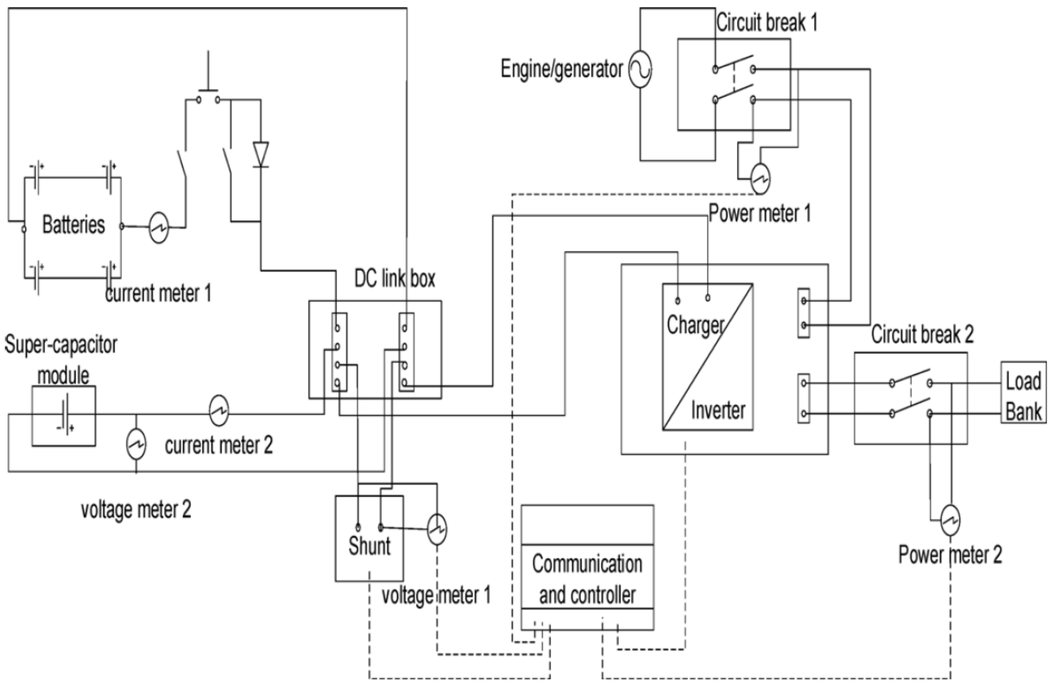


Fig 6.4. The layout of hybrid electrical energy storage system [19].

Unit name	Unit description	Unit power output
Batteries	Valve Regulated Lead Acid (VRLA), six units, 12 V/220 Ah (total)	2.8 kWh
Super capacitor	30 V/160 F HCC	4.4kJ (1.2 kWh)

Table 6.1. Specifications of electricity energy storage units in BMT-HEES.

D Exhaust system including absorption fridge

Cooling demand in this system is represented by fridge, which can be driven by heat from exhaust gas or electricity from electrical storage alternatively. In addition, heat exchange is another important factor in the whole system, which contains internal water loop (from the engine system) and external water loop (the heating system and exhaust system). In order to maximum recover redundant heat which generated by biodiesel engine, these water circuits have been linked by individual heat exchangers.

Heat recovery in exhaust system is another important feature in BMT-HEES, as it may massively improve system efficiency. The exhaust gas emission has five options; it can be used to reheat the water tank or drive fridge, even for both, and also can be directly passed by pipe.

6.2.2 Feasibility of control system

Feasibility of control system means the control system should be suitable for handling a wide range of operation conditions, such as demand side management from minimum demand to maximum potential consumption for various households. Meantime, feasibility can ensure the control system operating safely, which means instantaneous demand can be responded by control system immediately without any initiative control strategy. Another concern of feasibility in control system is the control system should has ability to satisfy the undesirable demand and operate smoothly, which can prevent the system lose efficiency. In addition, control system should be feasible to handle unanticipated future changes like appliance or occupancy variations.

6.3 General control system design

6.3.1 General control logic

The aim of general control system is using the Yanmar engine to mainly fulfil the peak demand and the energy storage to satisfy off-peak consumption with set-point criteria. The general control strategy of Yanmar diesel generator during weekday is designed to set expectation of operation schedule. The engine will start in the morning at around 6am, and then shut down for a few hours during the daytime from 10am to 5pm. Then restart around 5pm then stop working roughly at about 10pm to 0am (depends on if Battery/Super capacitor can sustain for the whole night). The load percentage of Yanmar engine in operation is depended on instantaneous electricity demand. The detail of engine performance is shown in Table 6.2.

Load (%)	Engine power (kW)	Fuel energy(kWh)	Total heat recovered (kWh)	Heat Efficiency (%)	Electricity efficiency (%)
10	0.64	8.19	3.15	38.45	7.81
25	1.61	9.86	3.4	34.49	16.30
50	3.28	13.53	4.93	36.44	24.23
75	4.81	17.66	7.25	41.05	27.25
100	6.35	22.62	9.28	41.03	28.09

Table 6.2. Details of Yanmar engine performance [17].

Battery/ Super capacitor will provide electricity during the time when the AC generator is shut down. In addition, during the peak period when the engine is operating by demand, battery/ Super capacitor storage is acting as an electricity consumer to be charged by the engine generator. State of Charge (SOC) is an indicator of how much percentage of electricity stored in battery/ Super capacitor in terms of their full storage capacity.

When demand is increasing, engine needs few seconds to response to working in higher load model, which probably leads failure of the system (without battery). Therefore, battery is essential to improving system stability. On the other hand, if an undesirable demand is occurring, which is higher than battery and engine power, then super capacitor can be rapidly operated, it is aiming to ensure system can operate normally without fault.

The investigation of national domestic households for how people spent their time at home shows that the activities of occupancy are mainly happened at two periods: morning period and evening period. These two periods are typically related cooking appliances operating for breakfast and dinner, also conjunct with other appliances, like cleaning, entertainment. Therefore, the period for the engine management is set between 6am to 9 am in the morning and 5pm to 10pm in the evening. In addition, it is determined when the batteries and super capacitor are commonly worked above with 60% of SOC, the life of cycle will be extremely extended.

Also, it is very important to maintain the hot water temperature for domestic use, so the temperature boundary of water storage is set as 60 degree C. The heating wire in big water tank is commonly switched-off. It is only used when there is little electricity demand but high heating demand, like in winter with very cold weather condition.

Therefore, the control logic for the engine operation can be determined, and the judgements of the engine start and shutdown are presented in the following:

A Judgement of the engine start

The Yanmar engine is expected to start between 6am to 9am, or between 5pm to 10pm, if it meets the following criteria which with OR logic relationship:

- User`s electricity demand has been predicted more than 2kWh and last for more than 30 minutes.
- User`s heat demand has been predicted more than 2kWh and last for more than 30 minutes.
- The SOC is less than 60%.
- The temperature of hot water storage is lower than 60 degree C.

B Judgement of the engine shutdown

The engine is expected to shut down between 11pm to 6 am, and 9am to 5pm, if it meets the following preconditions which with AND logic relationship:

- User`s electricity demand has been predicted lower than 2kWh and last for more than 30 minutes.
- The SOC is higher than 60%.
- The temperature of hot water storage is higher than 60 degree C.

It should be noticed that the logic relationship between these criteria or preconditions judgement excluding time. For the engine start is OR, and for the engine shutdown is AND, which means the engine may be operating longer period than expectation.

Thus, the total running time of the engine in general control system is around 8 hours per day.

6.3.2 Initial valve setting

Specification of gas valve (as shown GV) and water valve (WV) are presented in Fig. 6.5 and Fig 6.6, respectively.

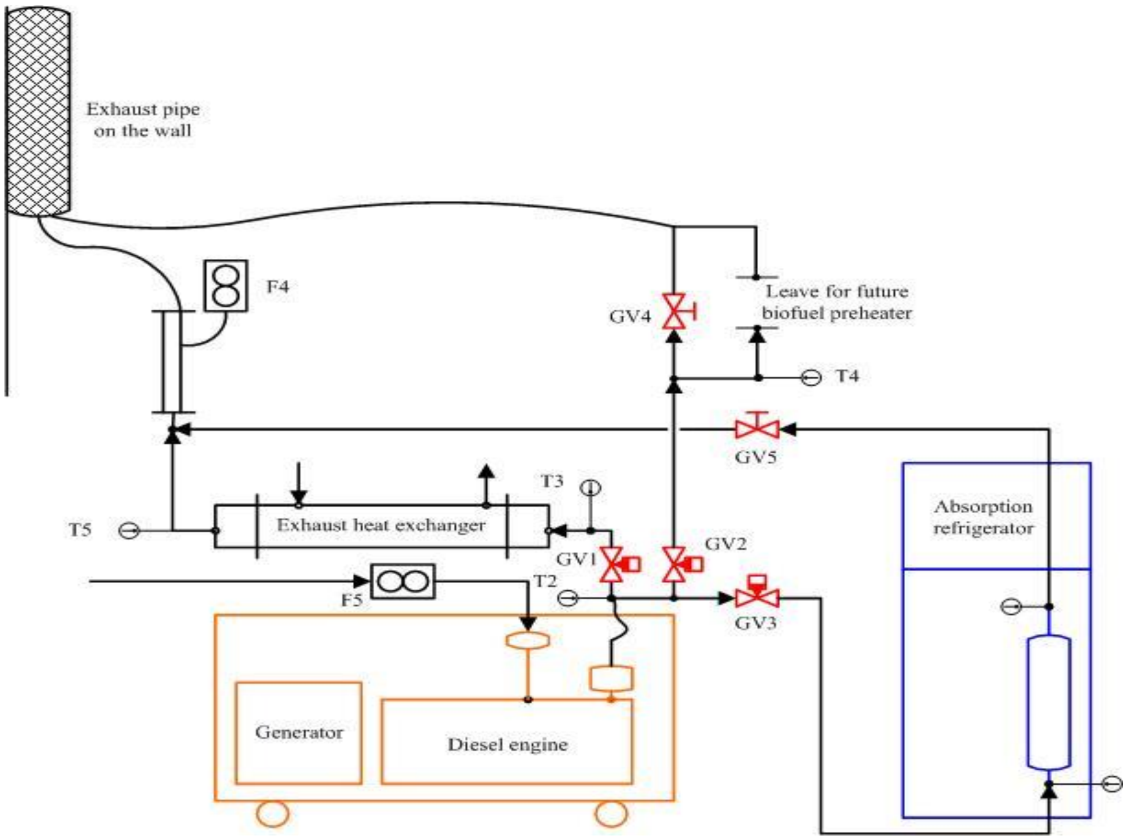


Fig. 6.5. General control strategy of the gas valve (GV).

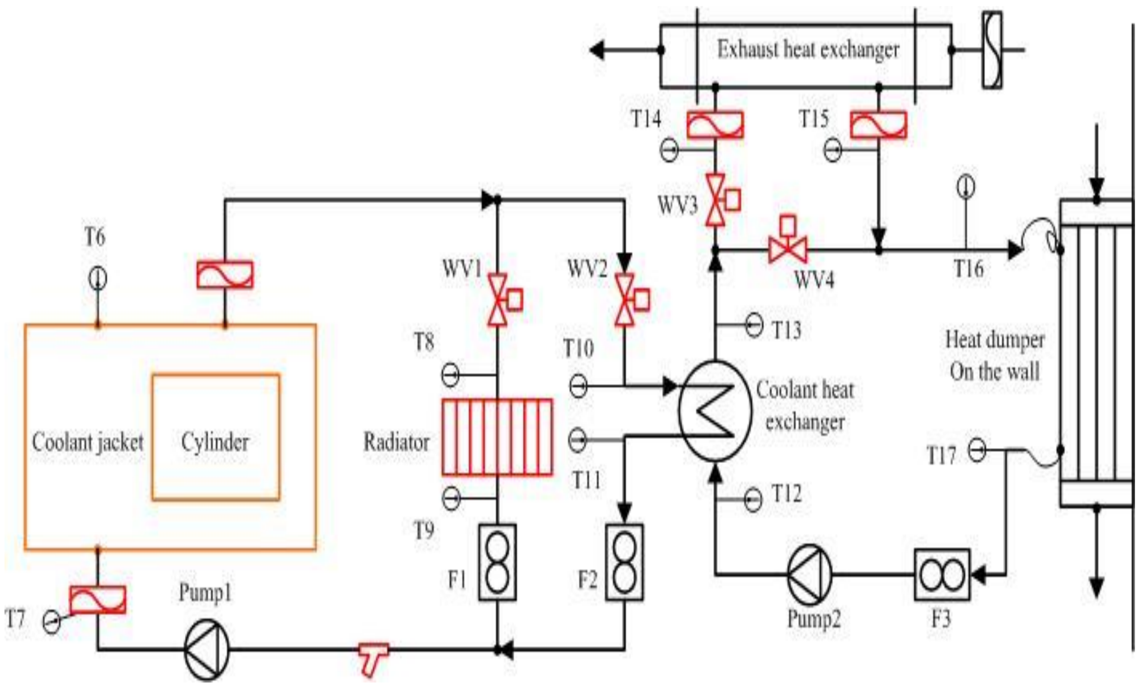


Fig. 6.6. General control strategy of the water valve (WV).

From Fig. 6.5 to Fig. 6.6, it can be found there are a series of thermometers in the engine, heating and exhaust system, which are from T2 to T17. These thermometers are the important indicators which can provide feedback of current system conditions during engine operation. As T1 is used to measure the temperature of preheated biofuel, it is not shown in these figures. Thermometers T2 to T5 are aim to control the exhaust gas flow in five options by different conditions, as through exhaust heat exchanger, absorption refrigerator, directly pass or conjunction of them. Meantime, T6 to T 11 are used to control internal water loop within three different cases, and T12 to T17 are employed to indicate if there is a requirement to control the external water loop.

Flowmeters identified from F1 to F5 can be seen in Fig. 6.5 and Fig. 6.6, as they are used to measure the flow rate for water and exhaust gas.

In order to effective use energy including heat and electricity, energy storage is utilized to sustain the minimum power consumption when occupancy is asleep during the night. Thus, when the engine is starting at the first time in the morning, the whole system should be heated by redundant heat which generated by the engine. The temperature of the coolant jacket is not higher enough to use a radiator to cool down.

Therefore, the default setting of valves for water loop is directly passing heat through coolant heat exchanger to exhaust heat exchanger without radiator in the internal water loop, and the heat dumper (water tank) installed in the external water circuit. Thus, initial settings of water valve and exhaust gas valve are shown in Table 6.3.

Valve name and description	*Valve initial setting*
Water valve 1 (before radiator)	*DC 0V (totally close)*
Water valve 2 (before water HX)	*DC 10V (totally open)*
Water valve 3 (before exhaust HX)	*DC 10V (totally open)*
Water valve 4 (bypass exhaust)	*DC 0V (totally close)*
Gas valve 1 (before exhaust HX)	*DC 10V (totally open)*
Gas valve 2 (before biofuel preheater)	*DC 0V (totally close)*
Gas valve 3 (before fridge)	*DC 5V (half open)*
Gas valve 4 (bypass biofuel preheater)	*Off*
Gas valve 5 (after fridge)	*On*

Table 6.3. Initial setting of water valve and exhaust gas valve in general control system.

6.3.3 Preliminary check procedure before engine start

For the safety purpose, general check should be done before starting the engine which aim to confirm all of the valves and pump are ready for operating, as shown the initial setting in Table 6.3.

All temperatures sensors should be checked firstly, which is the aim to make sure they are within a reasonable range, like (10-25 degree C). Otherwise, a warning is given and pointed out which sensor is not in the range. In the second, gas valves status should be tested, to confirm they are in the pre-setting conditions, which provide the safety of exhaust emission system. After that, water valves like WV1 and WV2 are checked to identified they are initial position before turning on the inner water circuit pump, and same with WV3 and WV4, to confirm at least one is open before turning on the external water circuit pump.

When valve check are finished, pumps are open and then flow rates are determined in these two water circuits. If the flow rates of F2 and F3 are more than 2L/min for 30s, then start the engine.

6.3.4 Engine load control procedure

The Yanmar engine needs to run on idle speed to warm up the engine before any load can be added onto it.

In terms of engine protection and life cycle extension, the engine load is controlled by employing the following procedure:

a) Start the engine and run it on idle speed (about 10% load) to warm up for around 5 minutes.
b) Then, if T6 is higher than 45 degree C, engine load can be added.
c) Engine load needs to be added gradually instead of immediately shift from idle to a very high load.

6.3.5 Internal water circuit control

In order to effective use engine and AC generator, it is very important to sustain the temperature of coolant water in a reasonable range, like 75 degree C to 85 degree C from Yanmar engine in this study. If the coolant water temperature is too high, like over 85 degree C, it can cause significant engine wear, waste of engine oil, depression of the engine power, or even damage to the engine. Meantime, if the temperature of coolant water is too low, such as lower than 70 degree C, a series of undesirable results can be produced. Not only will the bio-fuel usage be increased, and also the engine efficiency will be extremely depressed. Therefore, 78 degree C is the expected and suitable temperature boundary of coolant water in the control of internal water circuit.

In terms of maintaining this reasonable temperature in daily engine operation, water valves are used to control the coolant flow in the internal water circuit. Coolant heat exchanger and radiator are aims to cool down the coolant by applying different control strategies for various situations.

The T7 is the most important thermometer for monitoring the temperature of coolant water. The initial setting of the water valve in internal water circuit is WV1 entirely close and WV2 entirely open, because the temperature of the whole system is quite low when the engine has been shut down for a long period. Meantime, the thermometer T7 normally indicates that the temperature is lower than 70 degree C.

Thus, at that moment, in order to increase the temperature of coolant water, the water flow through heat exchanger is reduced by changing the valve status of WV2 from totally open (100% percentage) to half open (50% percentage). Then wait for two minutes to observe if there is any tendency of temperature increasing. If nothing happens, manipulate WV2 from half open to slightly open (20% percentage), which can keep reducing the water flow through coolant exchanger and increase temperature to a suitable level.

As the engine can continuously produce a lot of redundant heat during operating, therefore, in order to avoid the undesirable results, the WV2 is gradually operated from slightly open to totally open, or even using radiator to cool down the coolant water.

Consider with all possible situations of coolant water during engine running, the general control strategy of internal water circuit is present in Table 6.4.

	WV1	WV2	2mins	WV1	WV2	2mins	WV1	WV2
T7 >85	0	10	-------	5	10	-------	10	10
	5	5	-------	10	5	-------	Warning	
	10	0	-------	Warning				
T7<70	0	10	-------	0	5	-------	0	2
	5	5	-------	0	5	-------	0	2
	10	0	-------	2	0	-------	Warning	
T7=78	Remember the status of valves in the first column (in red), set back the that status							

Table 6.4. General control strategy of internal water circuit.

6.3.6 External water circuit control

Refer to Fig. 6.6, external water circuit is mainly depended on the internal water loop. If the temperature of input coolant water is lower than expectation, the WV2 will be gradually close to recovery the temperature, which can significantly reduce the heat transfer in coolant heat exchanger.

The thermometers T13, T16 and T17 are used to monitor and control the external water circuit, where T13 is aim to indicate the temperature of external water from coolant heat exchanger, T16 and T17 are employed to measure the input flow temperature and output water temperature of water tank as shown as heat dumper on the wall in Fig. 6.6. The water flow is from T13 – T16 – T17 – T13, like a loop.

The initial setting and temperature boundary of external water valve is presented in Table 6.5.

	WV1	WV2	WV3	WV4	
Initial	0	10	10	0	
T13>75	5	5	10	0	
T13>80	10	0	10	0	
T16>85	10	0	5	5	GV move needed (Situation 1)
T16>90	10	0	0	10	GV move needed (Situation 2)
T17<65	0	10	0	10	
T17<60	0	10	10	0	GV move needed (Situation 3)

Table 6.5. General control strategy of external water circuit.

6.3.7 Exhaust emission control

Using exhaust gas to recover heat or drive fridge can significantly improve the overall system efficiency. But sometimes, when the heat demand of end user is quite small and the temperature of outflow from water tank is quite high, like during summer, then the exhaust gas is passed through pipe directly without any heat exchange, as it may damage to engine and whole system. For safety and environment protection concerns, control system should be able to avoid this situation happen.

Initial setting of gas valve is aim to use redundant heat from exhaust gas to heat external water and driven cooling appliance. Thus, it is set as GV1 totally open, GV2 close, GV3 half open, GV4 close, and GV5 open.

GV1 and GV2 are related to water circuits, GV3, and GV5 are employed in refrigeration control. GV4 is always open currently; it may be used for control the gas flow to preheat biofuel in the future.

For the gas valve related to water circuits, there are three situations as from previous external water circuit control which needs GV1 and GV2 to be involved to associate, the details are presented in Table 6.6.

	GV1 (initial)	*GV2 (initial)*		*GV1*	*GV2*
Situation 1	10	0	--------	8	2
Situation 2	10	0	--------	0	10
Situation 3	10	0	--------	10	0

Table 6.6. Three conditions of gas valve (GV1 and GV2) control.

6.3.8 Refrigeration control

Refrigerator can be driven by electricity or exhaust gas alternatively. The refrigerator is supplied by electricity only when the engine is shutdown. When the engine is starting, exhaust gas can provide the required energy to operate the refrigerator.

It is noticed the refrigerator has a cycle working mode. Usually, it runs around 15 minutes on every operating cycle and requires zero power on standby. After operating cycle, it works on a standby mode and has a very litter energy consumption. When the engine is running on ideal speed for warming up, and the refrigerator is operating as well, the exhaust gas may not be able to entirely supply the refrigerator. Therefore, the judgement of electricity storage supply refrigerator is when engine is shutdown or engine is running on low load, like warm up stage.

When engine is operating on 50% load, the refrigerator is entirely driven by exhaust gas by totally open GV3 and GV5. When the thermometer in the refrigerator output indicates the temperature is higher than 240 degree C, then half open GV3 and keep GV5 totally open.

When the engine is shutdown, after 2 minutes close GV3 and keep GV5 open.

6.3.9 Emergency control

A crucial feature of the control system is fault tolerance. The general control system can typically satisfy the energy demand mostly. However, there may be an unexpected demand added into the system, usually is electricity demand. If this load is higher than 6.5 kW that is the maximum capacity of the engine, and meantime the SOC is lower than 60%. Therefore, it can cause the system lose stability and efficiency, which can be identified as an emergency situation.

Emergency situation is typically happened with system variations, like appliances or occupancy changes. For example, the occupancy installed and operated an electrical shower for bath because the pipe of water tank is broken or blocked. Or, there are some visitors in the dwelling and each of them need electricity demand simultaneously.

Therefore, a time-shifting control strategy is operating for this type of case. The appliances are primarily divided into two different parts, uninterrupted or interrupted. The interrupted appliances, such as kettle, washing machine, iron, vacuum, electrical heater, and microwave, are able to shit to use in another period, which can release load to supply the unexpected electricity demand.

6.4 Hardware implementation of general control system

General control system is implemented in a Siemens SCADA (Supervisory Control and Data Acquisition) system, the system structure is shown in Fig. 6.7.

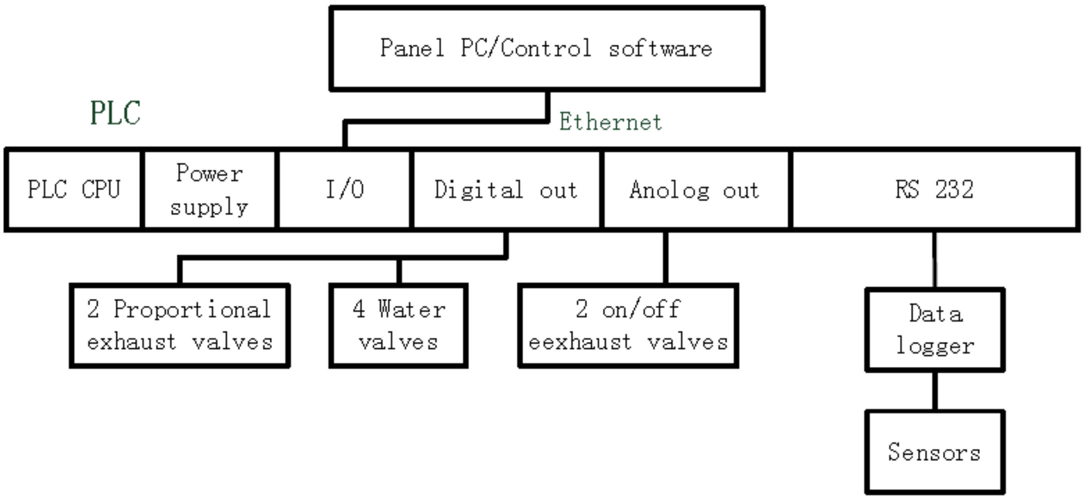


Fig. 6.7. SCADA system diagram with PLC.

From Fig.6.7, it can be seen there are mainly three layers in SCADA system in this study. The first layer is Panel PC, and the second layer is control model that contains various different parts, the last one are consisted of by valves, data logger and sensors. In the last layer, two proportional exhaust valves (GV1 and GV2) and four water valves are communicating with PLC controllers; GV3 and GV5 are modelled with only on and off status. All data are collected from a total number of 42 sensors, then recorded in data logger; Panel PC can invoke these data via RS 232 model, also same as PLC controllers.

All valves are worked with individual PLC controller, and also all thermometers and flowmeters in the BMT system. In order to visually monitor and control whole system, WinCC software is used to generate visual interface of SCADA system, which is shown as Panel PC in Fig. 6.8.

A Siemens STEP-7 S300 software is employed to implement PLC control in the second layer of SCADA system. The initial setting of all parameters in BMT system, also real-time system monitoring, and data logging are manipulated in the control box as shown in Fig. 6.9.

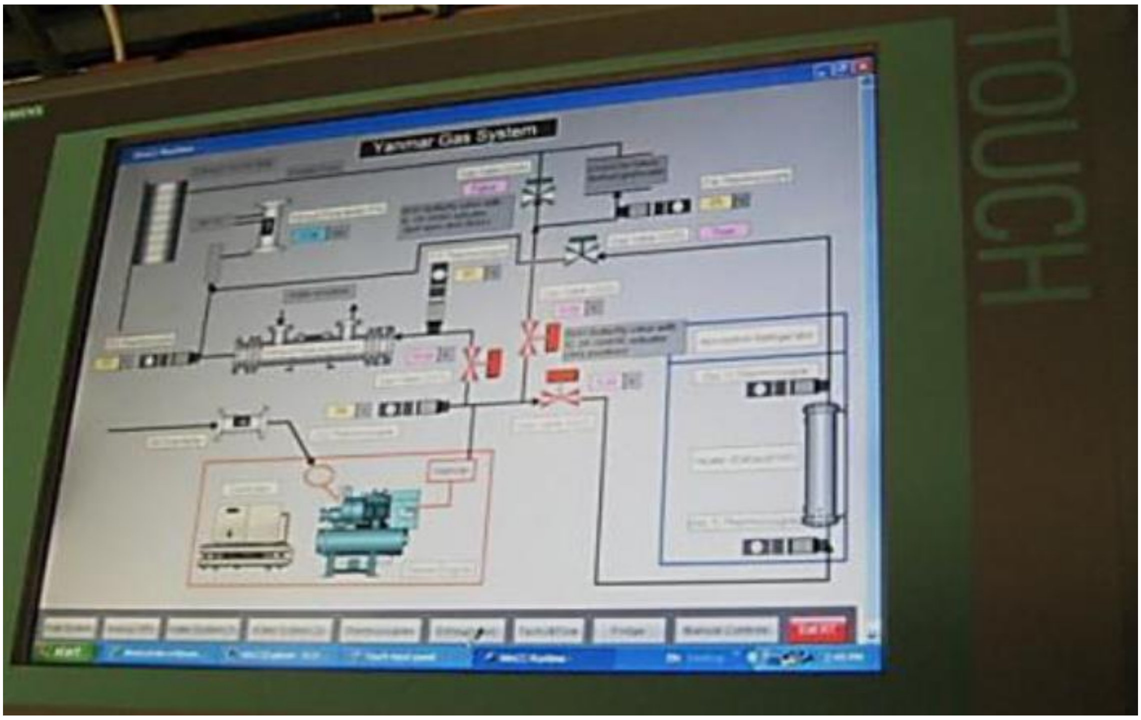


Fig. 6.8. The visual interface of SCADA system.

The first layer and second layer in SCADA system is linked an Ethernet protocol, which allow users can visually monitor and control all units expediently.

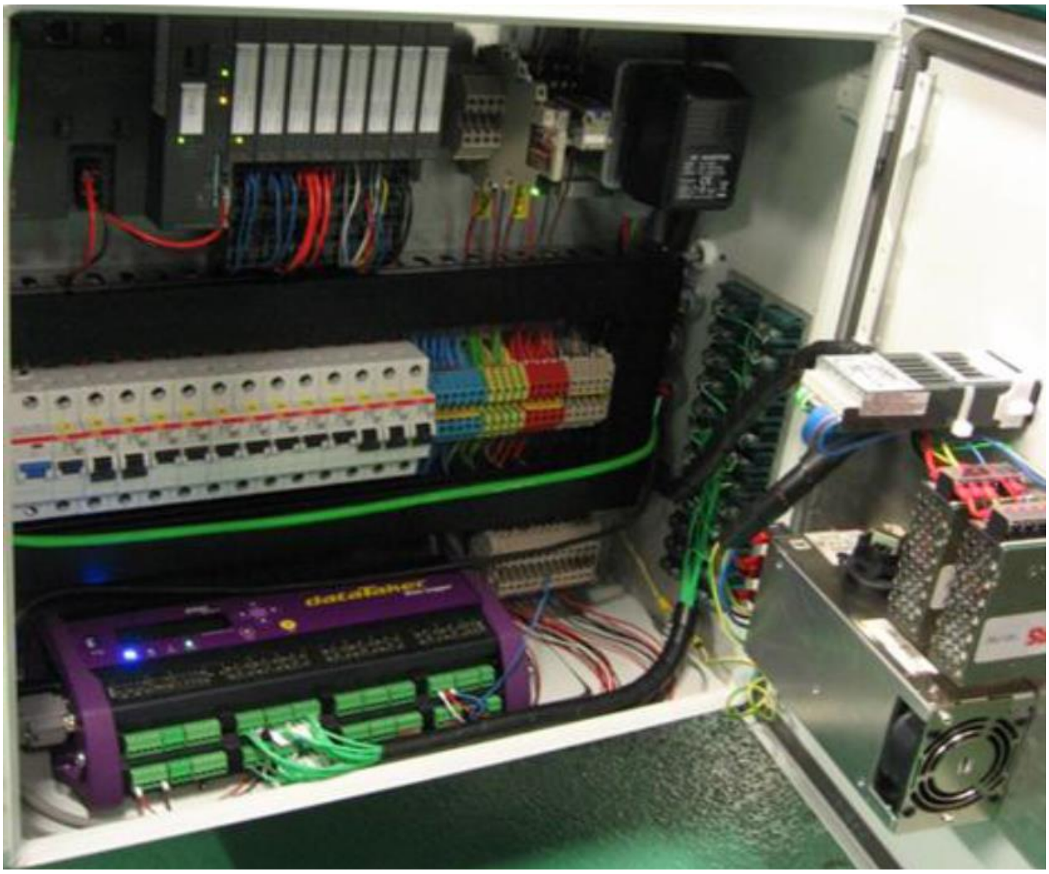


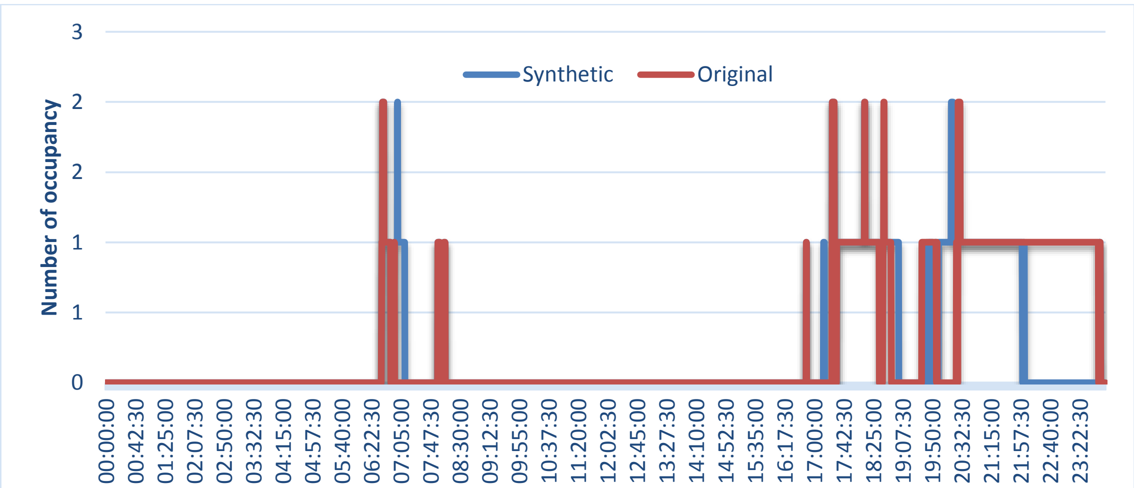
Fig. 6.9. Control box connected with Panel PC.

6.5 Intelligent control strategy of BMT-HEES

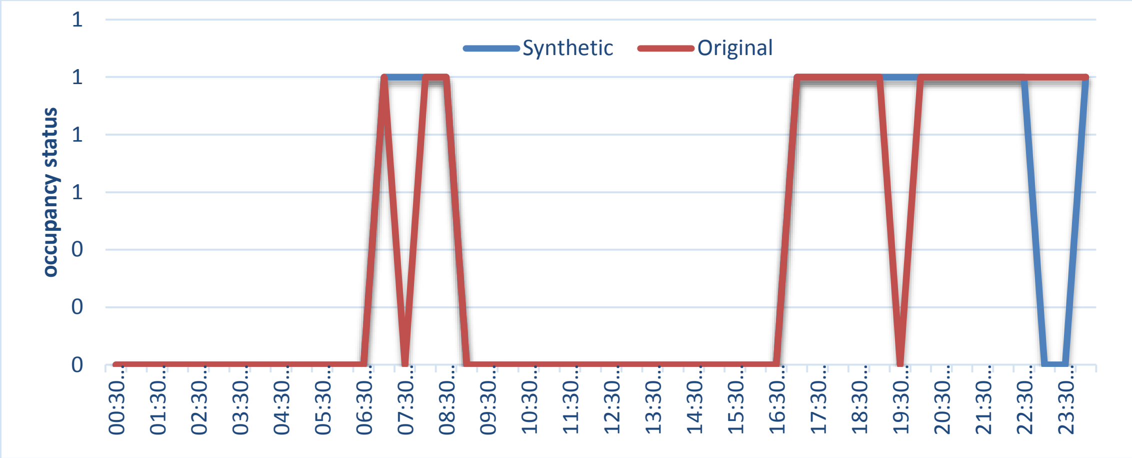
The aim of intelligent control system is to improve system stability and efficiency, and also pre-operate appliance to meet the energy demand of occupancy. The general control which is provided previously can passively satisfy the domestic energy demand. However, when the engine is operating on a lower load and batteries are under charging procedure, there is an expected load occurring, it can cause the system unstable. In addition, engine is operating on lower load level for a long period can reduce the whole system efficiency.

Therefore, intelligent control strategy is a very important supplement for the safety and energy saving for existed control system. However, this type of strategy requires detailed energy demand in high-resolution to control engine and energy storage in advance.

In addition, occupancy pattern is a crucial factor in energy demand prediction of domestic household. In chapter 5, it is transferred occupancy pattern from 30s resolution to occupancy status in sub-hourly resolution. Because it is useful for determining the primary occupancy active period. In the first, for selected household in a particular season, the occupancy model is simulated in 1000 times to randomly generate occupancy patterns. Then one of them is stochastically selected to compare with original one. An example comparison of house1 autumn weekday is shown in Fig. 6.10.



(a)



(b)

Fig. 6.10. Occupancy pattern comparison of house1 autumn weekday, (a) 30s resolution, (b) aggregate in 30 minute.

Although the diversity of predicted occupancy profile is various in 30s resolution, when aggregate in the occupancy status which shows the occupancy active period, the synthetic pattern is nearly identical with original, as shown in Fig.6.10. The main daily occupancy active period is divided into two parts, from 07.00 to 08.30 and 17.00 to 22.30. Therefore, the predicted occupancy status aggregated from the simulated output can be used to replace the real-time one in heat demand forecasting with sub-hourly resolution.

Unlike electricity demand, heat demand does not have a dynamic feature. Heating demand always covers a period with a stable level of consumption. The synthetic occupancy status can primarily indicate the main occupancy active period. Thus, sub-hourly energy consumption can be produced by the predicted maximum electricity consumption and heat demand. These results are utilized into control system to optimize the control strategy.

6.5.1 Electricity dominative strategy

The efficiency of energy storage in various level of temperate is diverse. For example, batteries normally have higher efficiency in summer rather than lower in winter. Also, there is a potential damage for batteries and super capacitor working long period in low-temperature environment. In order to maintain energy storage properly, the heat back temperature is set to 12 degree C, as same with whole dwelling in Chapter 5.

The Yanmar engine can generate electricity and heat simultaneously when it is started. Consider with the feature of heat demand, the intelligent control strategy is presented as electricity dominative.

In the first, the energy output of Yanmar engine during half an hour is presented in Table. 6.7. The max power is shown as the max system power which includes engine and electrical storage.

Load (%)	Engine output (kWh)	Max power with storage (kW)	Fuel energy(kWh)	Total heat recovered (kWh)	Heat Efficiency (%)	Electricity efficiency (%)
10	**0.32**	4.64	4.10	**1.58**	38.45	7.81
25	**0.81**	5.61	4.93	**1.7**	34.49	16.30
50	**1.64**	7.28	6.77	**2.47**	36.44	24.23
75	**2.41**	8.81	8.83	**3.63**	41.05	27.25
100	**3.18**	10.35	11.31	**4.64**	41.03	28.09

Table 6.7. The details of Yanmar engine output in sub-hour [17].

The warming up stage of engine is only expected to operate around 10 minutes per day (morning and afternoon), and it is aimed to preheat the whole system with very low engine power and energy efficiency. Therefore, the influence of this stage is neglected in intelligent. There is a linear relation between engine load and engine out [17]. The load points given in Table 6.7 are chosen to simply present the engine performance. The other load modes which have not been shown in Table 6.7 are hidden.

In order to calculate system efficiency without complicated, it is assumed that the engine will be only operated in these four modes as shown in Table 6.6. Each level has individual engine power output, heat recovery, heat efficiency and electricity efficiency. Engine has supplied the whole energy consumption including charging electrical storage and heating storage, and also for driving refrigerator.

If the predicted energy demand is higher than the energy provided, the engine load is increasing gradually into higher load mode, until 100%. It also should be noticed the heating wire in water tank can transfer electricity to heat with around 95% efficiency. When the heat demand is high, but electricity demand is low, the engine can use heating wire to primarily supply heat demand. The engine control logic for start and shutdown in intelligent control strategy are same criteria with general control strategy.

The refrigerator in this study is 120 W, the heat consumption of the refrigerator is quite little comparing with the water tank. Thus, the total heat recovered in Table 6.7 is assumed as the heat recovery in water tank for space heating and DHW.

For each particular engine load mode, the amount of electricity and heat supplied by engine can be presented. Thus, it is compared with the predicted energy demand to determine which load mode the engine will be operated in sub-hourly interval.

The whole day is divided into 48 time points (sub-hourly), and these time points are categorized into two parts, peak period and off-peak period from prediction.

The weekday procedure of engine load mode identification for every household in a particular season is shown below:

Step 1. Get the predicted electricity demand profiles $E_{pre}\ (i)$ and maximum instantaneous electricity consumption each time point i

Step 2. Provide predicted heat demand results of each time point.

Step 3. Calculate the off-peak summary predicted electricity consumption E_{off} as:

$$E_{off} = \sum_0^n E_{pre}\,(i), i \in [o, n] \qquad (6\text{-}1)$$

Where *n* is the number of off-peak time points.

If $E_{off} > 1.6\ kW$; it means the SOC at the end of the off-peak period is lower than 60% (Total electricity storage size is 4 kW). Then re-calculate the E_{off} and get the time point when it is achieving the 60% level of SOC. Then start the engine at that time point to charge electricity storage, and go to step 5; otherwise, go to step 4.

Step 4. Compare the predicted energy demand of time point in the first peak period with engine energy output in 25% load mode. If the predicted demand is lower than 25% mode, then compare max system power with the maximum predict instantaneous consumption. If the predicted one is lower than the system, keep engine shutdown and move to next time point in the peak period. Otherwise, start the engine and go to step 5.

Step 5. When engine is starting, it is compared the max power in current mode with the maximum predicted instantaneous consumption. If the max power is lower than the predicted one, the engine load should be increased suitable level. Otherwise, compare the predicted energy peak demand with engine energy output in 25% load mode, to determine if the engine should be kept at 25% level.

Step 6. Then, if the engine in step 5 cannot satisfy the energy demand, gradually switch to higher load mode, then compare again, until 100%.

Step 7. Compare the energy output in step 5 with next sub-hourly predicted demand to determine which mode the engine will choose, until the end of peak period.

Step 8. Repeat step 3 to step 7.

The engine operation in intelligent control strategy is active different with the passive working in general control system. The redundant electricity can be transferred to heat by using heating wire, and waste heat can be used to drive refrigerator or exhaust directly.

Meantime, it is crucial to find out the volume of water can be heated during engine running in different modes.

$$m_{water} = \frac{Q_{HC}}{C_w \Delta T} \qquad (6\text{-}2)$$

Where C_w = 4.2 kJ/kg°C, m_{water} (the amount of water heated by heat recovered), Q_{HC} is the heat recovered amount.

So the volume of heating water at different initial temperature for half an hour is calculated and shown in Table 6.8.

Engine load mode	Heat recovered (kWh)	12°C – 60 °C, water (L)	15°C – 60 °C, water (L)	18°C - 60 °C, water (L)
25%	1.7	30.35	32.38	34.69
50%	2.47	44.11	47.05	50.41
75%	3.63	64.82	69.14	74.08
100%	4.64	82.86	88.38	94.69

Table 6.8. Volume of water heated by recovered heat from the engine in different load modes.

The volume of heated water in Table 6.8 only contains the water heated be recovered heat. The water heated by heating wire during some circumstances will be considered similarly. The size of water tank in this study is twenty litres for the big one and ten litres for the small one. Thus, it can be found the heat recovered is sufficient for heating water.

In addition, because the intelligent control strategy is a type of pre-setting procedure, the SOC will be checked passively by general control strategy. Usually, the engine will continuously work half an hour with the particular mode to entirely charge batteries and heat system at the end of last peak period during the day. It also should be noticed the intelligent control strategy is for peak period only, and the engine is controlled by general control logic during the off-peak period. Moreover, the predicted heat demands (space heating and DHW) in this study are not realistic, as the parameters of realistic dwellings are unknown. In order to identify how intelligent control strategy can influence system efficiency, it is assumed that the synthetic heat demand is realistic.

Therefore, the intelligent control strategy implementation for different household in every season is applied by using engine mode identification procedure. Consider with the heat demand in different season, the implementation is primarily focused on three domains: spring/autumn, summer and winter. House1 is selected as an example to present the intelligent control strategy in different seasons.

6.5.2 Spring/Autumn intelligent control

The sub-hourly energy demand of house3 winter weekday (5^{th} Nov) is presented in Fig. 6.11 and Fig. 6.12, respectively.

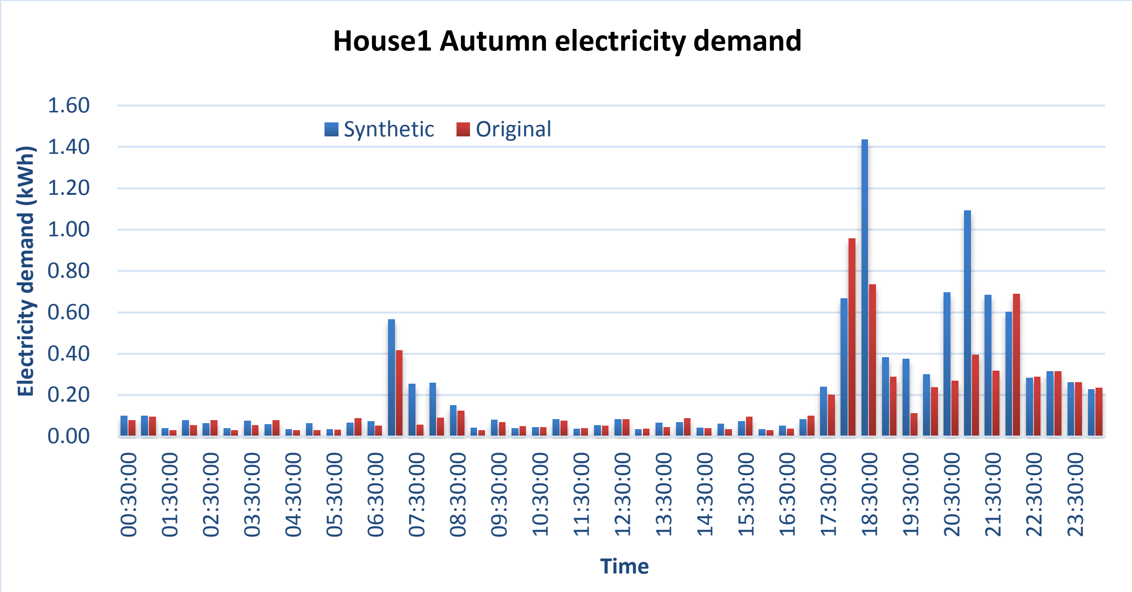


Fig. 6.11. Sub-hourly electricity demand of house1 autumn weekday.

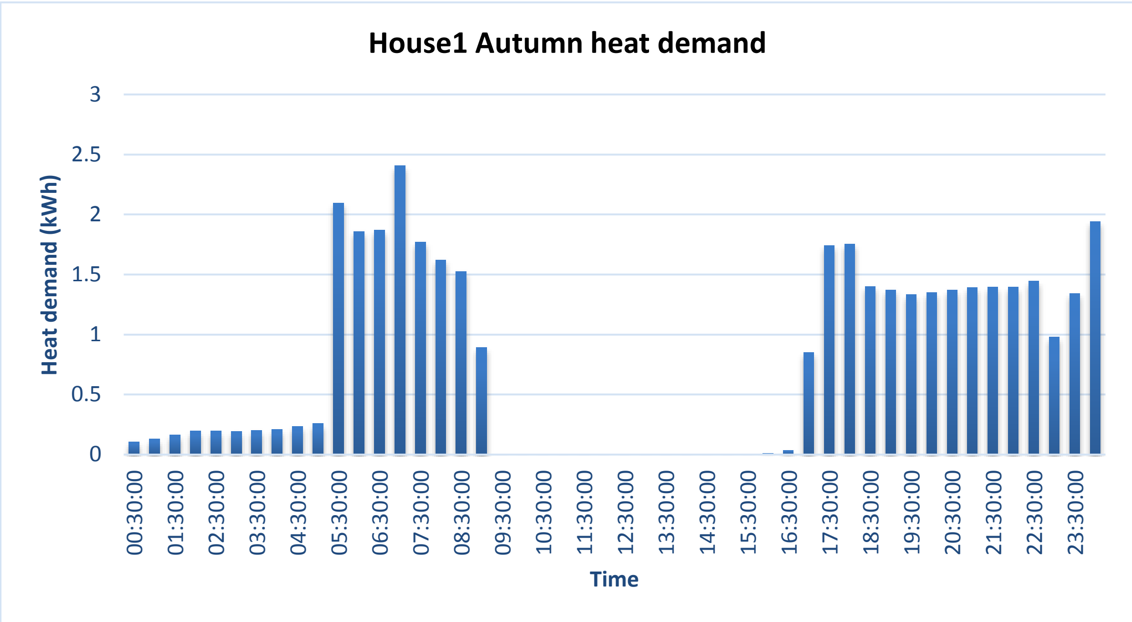


Fig. 6.12. Sub-hourly heat demand of house 1 autumn weekday.

Fig. 6.11 shows the summation of electricity consumption from 00.00 to 06.30 for predicted and potential are 0.8186 kWh and 0.7264 kWh, and SOC are 79.5% and 81.84%, respectively.

From Fig. 6.12, it can be seen the first heat peak demand from 05.00 to 05:30 is 2.1 kWh, which is higher than the 50% load mode of the engine. Thus, the engine will start 05:00 with 50% load mode to supply electricity to the heating wire and the electrical storage. Because of the high efficiency of heating wire, the temperature of water tank is quite high. Thus, the engine will be shut down at 05.30.

The maximum instantaneous simulated electricity load in 30s resolution for a weekday of house1 autumn is presented in Fig. 6.13. The simulation is based on all historical load patterns.

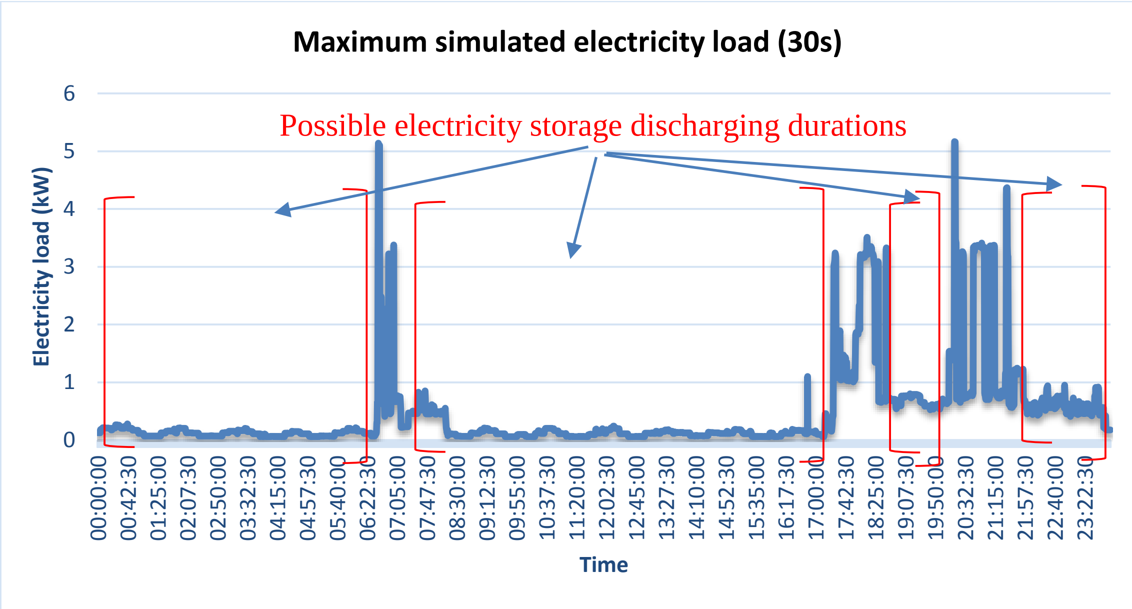


Fig. 6.13. The maximum instantaneous electricity load at each 30s from in 1000 times simulation.

Fig. 6.13 reveals four potential periods for electricity storage discharging operation. It can be found the engine may be operated during other peak periods. There are two single peak loads which are over 5 kW, at 06:40:00 and 20:18:30. It means the engine should be operated at 50% load mode at 06.30 to 07.00 and 20.00 to 20.30 for safety purpose. For other time points, 25% load can satisfy the electricity demand.

Fig. 6.13 also shows the potential maximum electricity load over 4 kW (energy storage capacity) only have few seconds,

The first predicted electricity peak demand in Fig. 6.11 is from 6.30 to 7.00 is around 0.56 kWh, and the maximum predicted instantaneous load is 5.14 kW. Therefore, the engine should be started at 6.30 at 50% load mode for half an hour.

The summation of predicted electricity consumption in Fig. 6.11 from 7.00 to 17.00 is 1.63 kWh, which is 59.25% of SOC. The maximum instantaneous during this period is

1.06 kW. Because the predicted result mostly higher than realistic, the engine is shutdown during this period.

The engine will start at 17.30 with 25% load mode with half an hour. Then it is gradually switched to 50% mode at 18.00 and kept until 18.30, then change to 25% mode until 19.00. The engine will be shut down from 19.00 to 20.00. Although the maximum instantaneous load point out that the potential maximum is 5.09 kW, the maximum period electricity demands only 0.7 kWh from 20.00 to 20.30. Thus, the engine will be restarted at 20.00 with 25% load mode. Then it is operated at 50% mode for one hour, and switched to 25% model at 21.30 until 22.30 shutdowns.

The general control strategy is passively responded by original load as shown in Fig. 6.14. Fig. 6.14 shows the original electricity consumption with 30s resolution in a single weekday. It can be found that the main peak period is evening after 17.30, and the maximum load during evening is less than 4 kW.

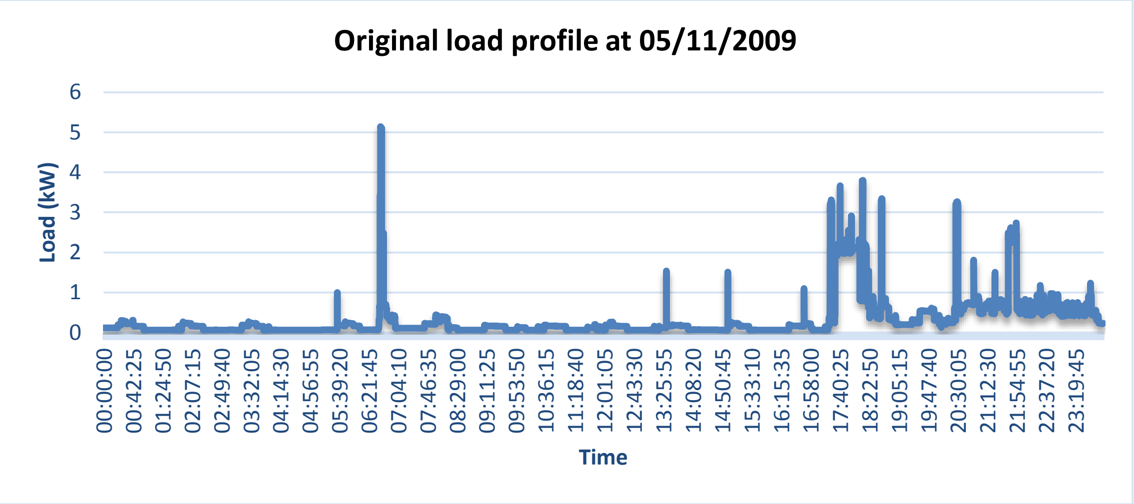


Fig. 6.14. Realistic electricity consumption of house1 autumn weekday.

Then it is considered with the aggregate sub-hourly energy demand. Thus, it can be seen the engine will run at 25% mode in the morning and evening peak period, except at 05.00 to supply heating wire at 50% mode.

Therefore, the engine operation scheme within intelligent control and general control is presented Fig. 6.15.

Because intelligent is an active control strategy, the engine in intelligent control is always operated forwardly as shown in Fig. 6.15.

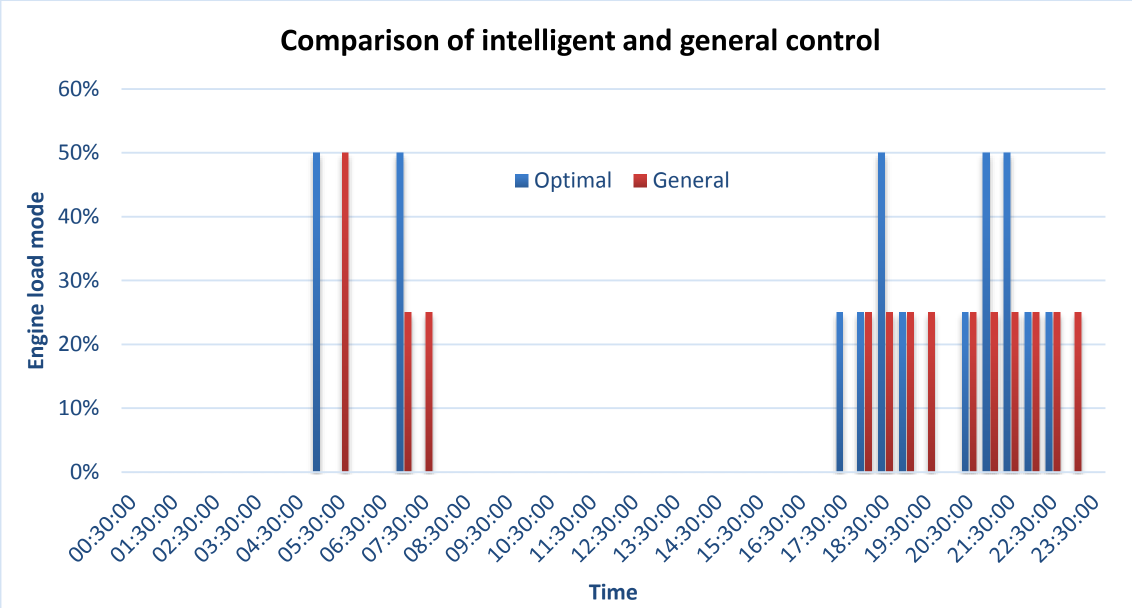


Fig. 6.15. Comparison between intelligent control and general control.

The system performance is presented by applying the results from Fig. 6.15. In the first, the summation of time point is identified independently; secondly, the engine performance listed in Table 6.7 is utilized to calculate the engine performance at each time point. The system performances within general control and intelligent control are shown in Table. 6.9.

	General control	Intelligent control
Engine duration (h)	6.5	5.5
Fuel consumption (kWh)	64.09	63.43
Heat efficiency (%)	34.49	35.38
Electricity efficiency (%)	16.3	19.90
System efficiency (%)	50.79	55.28
Total electricity generation (kWh)	10.44	12.62
Total electricity demand (kWh)	7.65	10.58
Total heat recovered (kWh)	22.1	22.55

Table. 6.9. The system performance comparison between general control and intelligent control of house1 autumn weekday.

The intelligent control during autumn shows that the system efficiency excluding energy storage is improved from 50.79% to 55.28%, and electricity efficiency is from 16.3% to 19.90%, respectively. Meantime, it is noticed that the total electricity generation is higher than total electricity demand. The reason is the engine is used to supply electricity to the heating wire in water tank to satisfy the heat demand, especially in the morning with 50% load mode.

In addition, the intelligent control strategy has improved system efficiency but with less fuel consumption comparing with general control strategy. With the predicted energy demand, intelligent control strategy can be an ideal solution with energy saving, high efficiency and low emissions.

6.5.3 Summer intelligent control

Summer case is presented in this section; an example is selected from house1 summer weekday. In the first, sub-hourly electricity demand and heat demand are presented in Fig. 6.16 and Fig. 6.17, respectively.

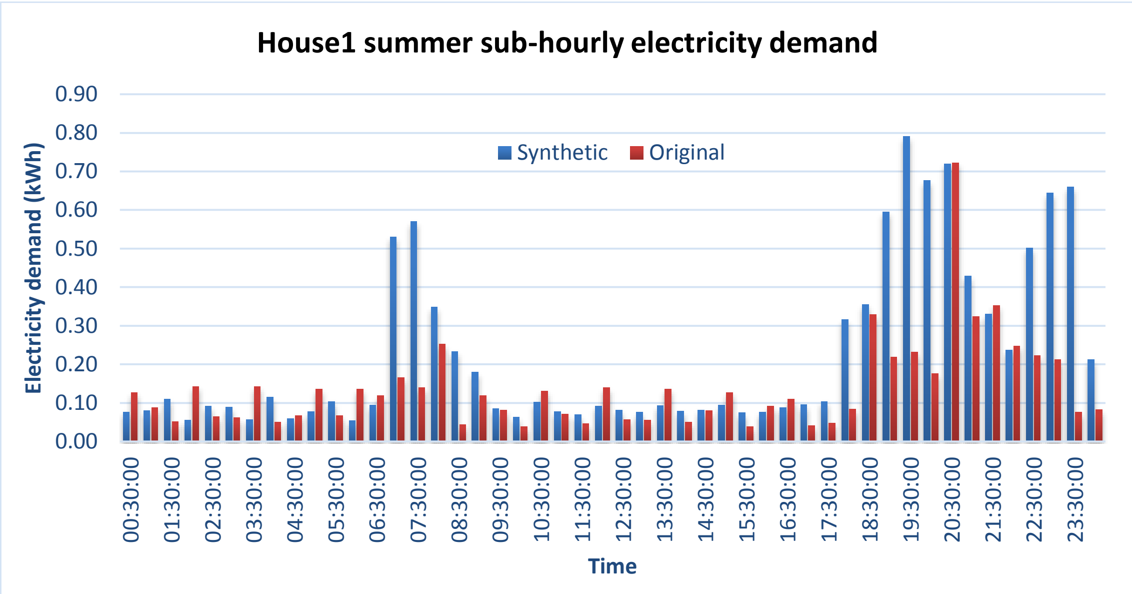


Fig. 6.16. Sub-hourly electricity demand with predicted and original of house1 summer weekday.

Fig. 6.16 reveals there are two peak periods within synthetic demand, and one peak period within original demand. The maximum demand for both synthetic and original is less than 1 kWh, which can be satisfied by 25% load mode or 50% load mode.

The predicted occupancy status shows the morning peak period is from 07.00 to 09.00, and evening peak period is from 18.00 to 23.00. The related heat demand is shown in Fig. 6.17.

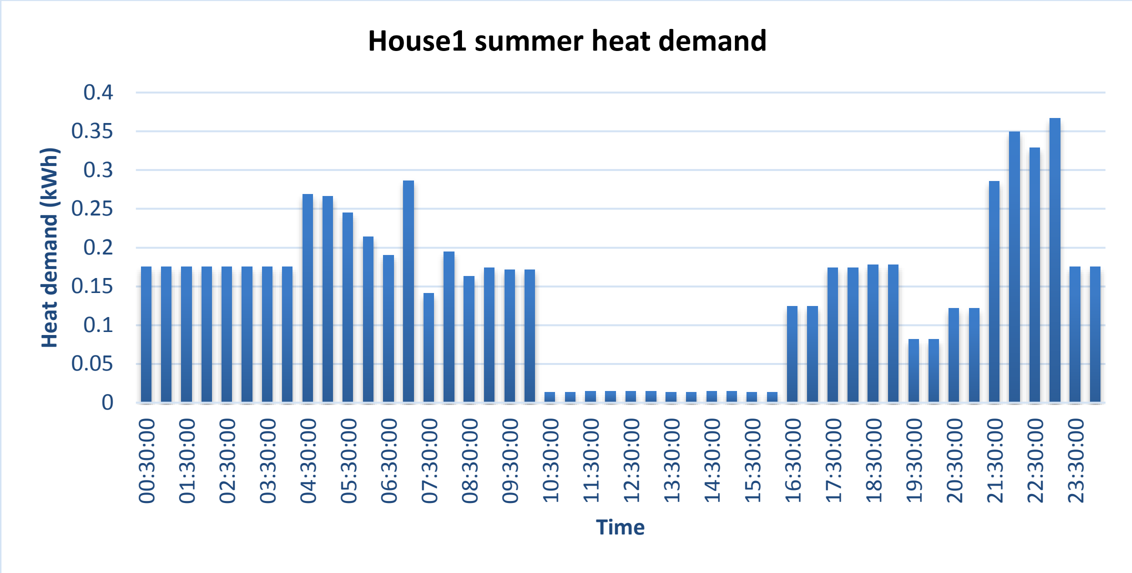


Fig. 6.17. Sub-hourly heat demand of house1 summer.

From Fig. 6.17, it can be found the heat demand in summer is quite low, the primary heat consumption is DHW only.

In order to address potential period for operating energy storage, the load model is simulated in 1000 times, and the maximum instantaneous at each thirty seconds is picked. Then the whole day profile is presented in Fig. 6.18.

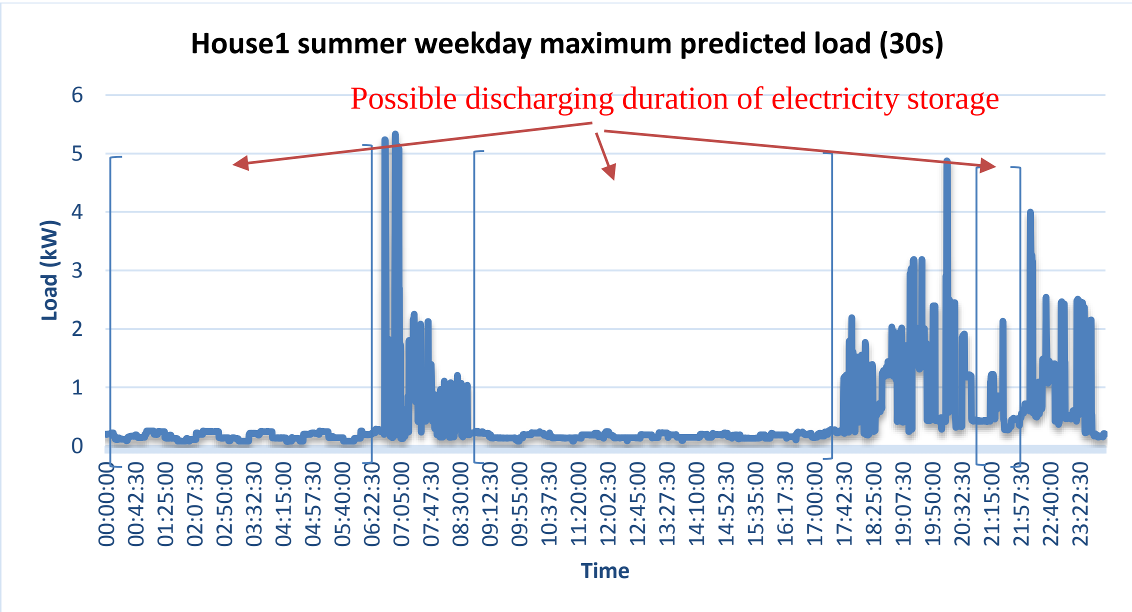


Fig. 6.18. Maximum predicted load in thirty-second resolution of house1 summer.

Fig. 6.18 shows there are three potential periods that battery/super capacitor may be operated.

The electricity demands of predicted and original during 0.00 to 06.30 are calculated as 1.06 kWh and 1.25 kWh, related SOC levels are 73.5% and 68.75% respectively. Then the related demands during second off-peak period from 09.00 to 17.30 are presented as 1.43 kWh and 1.34 kWh, corresponding SOC levels are 64.25% and 66.5%, respectively. Thus, the electricity storage can entirely support these two off-peak period if it is fully charged before 09.00.

From Fig. 6.16 to Fig. 6.18, it can be found the potential maximum electricity consumption is 5.1 kW, which can be satisfied by 25% load mode of the engine AC generator. So the engine will be operated at 06.30 at 25% mode because the SOC is lower than 60%, and then last one and half hour until 08.00. At the 08.00, the SOC will indicate that the energy storage is full, and then the engine shutdown until 17.30. From 08.00 to 09.00, the electricity demand is 0.52 kWh and 0.26 kWh for predicted and measured, respectively. It means the engine may be operated before 17.30, which is depended on when occupancy is active in the evening.

In the evening peak period, the engine may be operated at 17.00 or 17.30, so the engine is controlled by SOC state at this period. When engine starts, it works on 25% load mode to charge the batteries and supply electricity for domestic end-users until 21.00. Then it is restarted at 22.00 for one hour and shut down at 23.00.

The general control strategy is based on the original load pattern, as shown in Fig. 6.19.

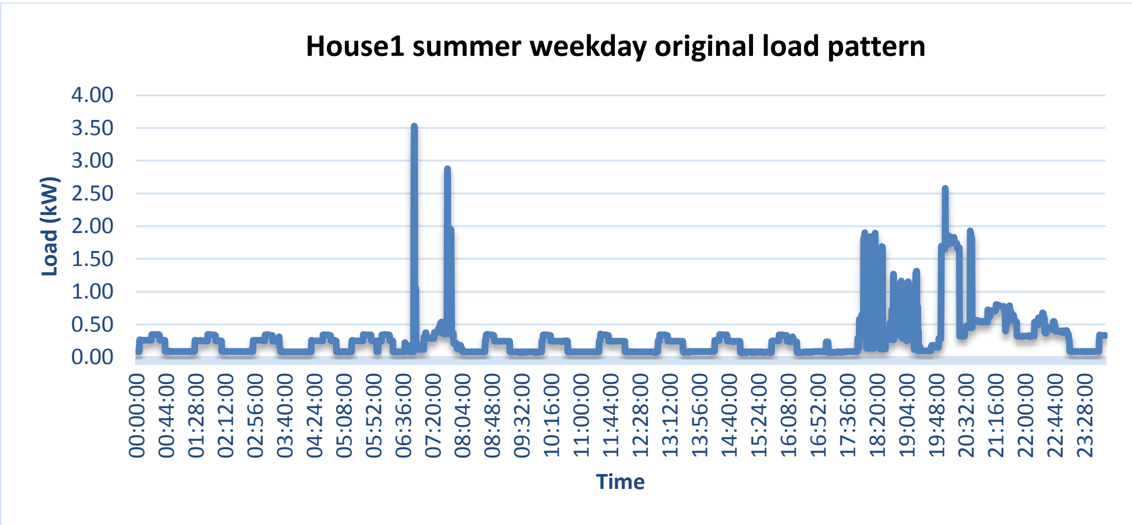


Fig. 6.19. Original load profile of house1 summer weekday.

From Fig. 6.19, it can be noticed there are only few peak load in the morning. Therefore, the engine only need be operated for half an hour to supply these pseudo peak demand and charge batteries. Then the engine will be restarted at 18.00, until 22.00 shutdowns.

Therefore, the control schemes of intelligent and general are presented in Fig. 6.20.

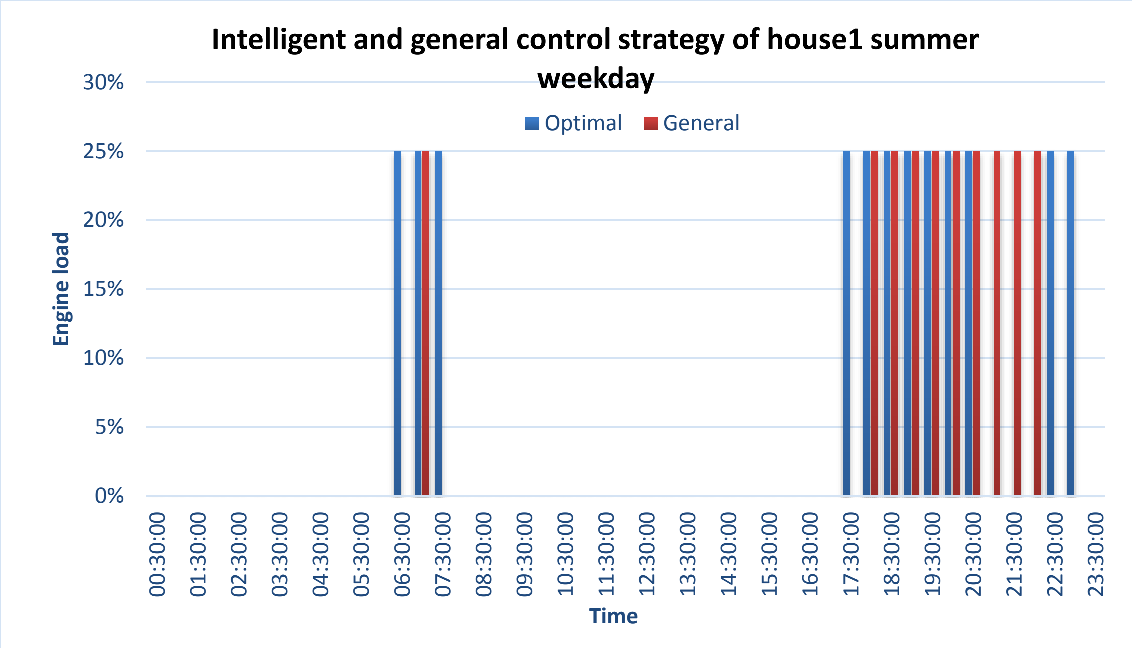


Fig. 6.20. Comparison between intelligent and general control strategy of house1 summer.

By applying Fig. 6.20 into BMT-HEES system, the system performance is shown in Table 6.10.

	General control	Intelligent control
Engine duration (h)	5	6.5
Fuel consumption (kWh)	49.30	64.09
Heat efficiency (%)	34.49	34.49
Electricity efficiency (%)	16.3	16.3
System efficiency (%)	50.79	50.79
Total electricity generation (kWh)	8.04	10.45
Total electricity demand (kWh)	7.65	10.28
Total heat recovered (kWh)	17	22.1

Table. 6.10. The system performance comparison between general control and intelligent control of house1 summer weekday.

From Table. 6.10, the intelligent control strategy is not efficient when comparing with general one. The reason can be analysed from two parts. The first one is SOC level while engine operating is not concerned, because the strategy is one day pre-set. In order to improve the accuracy and efficiency, it is proved that SOC level should be identified every sub-hourly. Another reason is the some predicted demands are much higher than original one; this situation can also use SOC check to avoid.

Thus, deployment of engine and electricity energy storage system should be seriously concerned as another significant issue due to the reliability and stability of control system. For example, the prediction result indicates that there is low demand in next half an hour, and SOC level is over 60% currently, so the engine will be shut down until it meets the criteria. However, after thirty minutes, there is an unexpected peak period occurred and storage system cannot satisfy the demand, thus the engine will be restarted any way. Therefore, sub-hourly SOC level identification need to be involved into intelligent control strategy.

After applied SOC check into control strategy, it is found the intelligent control strategy is same with general control strategy. The reason is the electricity demand in this selected weekday is very low. The engine with 25% load, even only with electricity storage can fulfil all requirements. However, because the instantaneous load pattern is not able to predict accurately. Thus, the intelligent control strategy can replace general one with more stable and safe.

6.5.4 Winter intelligent control

The predicted energy demand of house1 winter are presented in Fig 6.21 and Fig. 6.22, for electricity and heat, respectively.

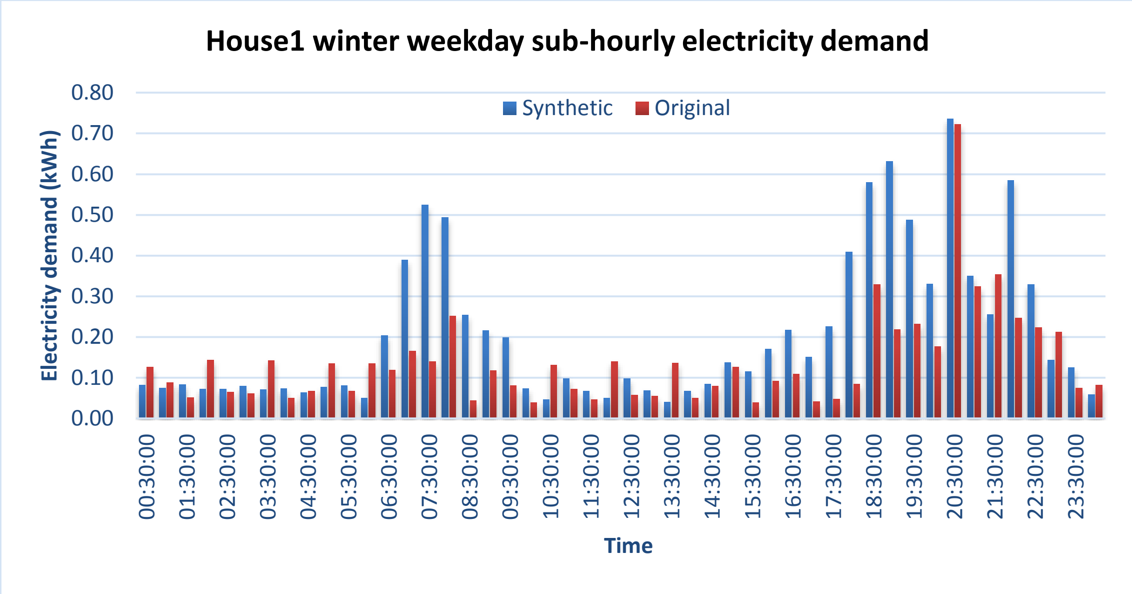


Fig. 6.21. Sub-hourly electricity demand of house1 winter weekday.

From Fig. 6.21, morning peak period and evening peak period can be addressed. The maximum load is less than 0.81 kWh (25% load mode of the engine). Therefore, engine may be operating at 25% load for a whole day.

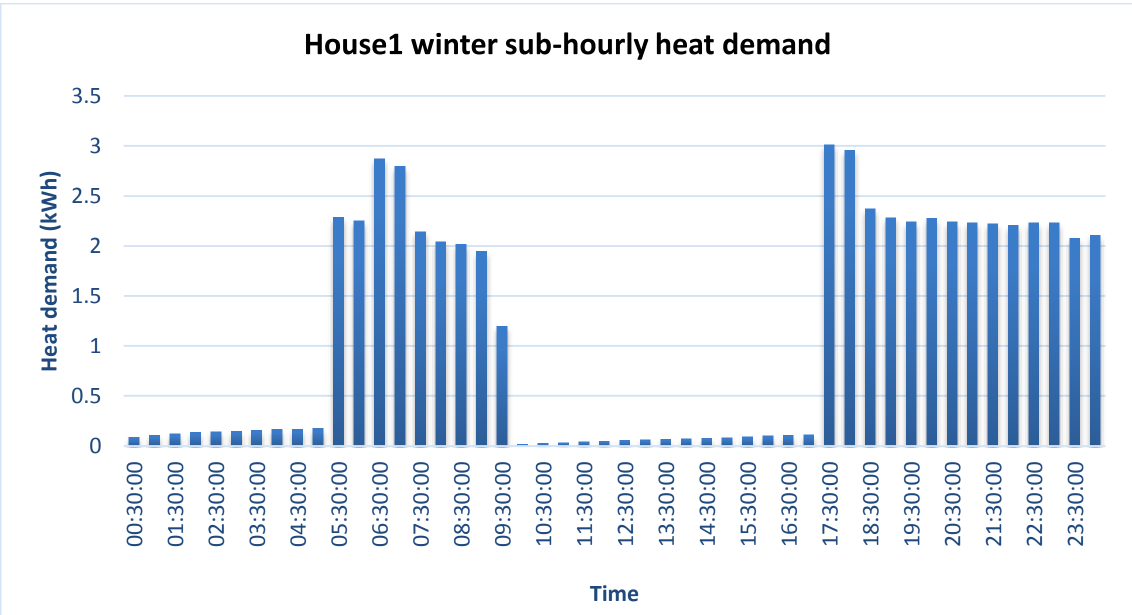


Fig. 6.22. Sub-hourly heat demand of house1 winter weekday.

Fig. 6.22 reveals the feature of heat demand for particular household in winter weekday. It can be found the average sub-hourly heat demand is over 2 kW, which is higher than the engine with 25% load provided, but lower with 75% load supplied. Therefore, the engine may work on 50% load mode during this weekday at some time points.

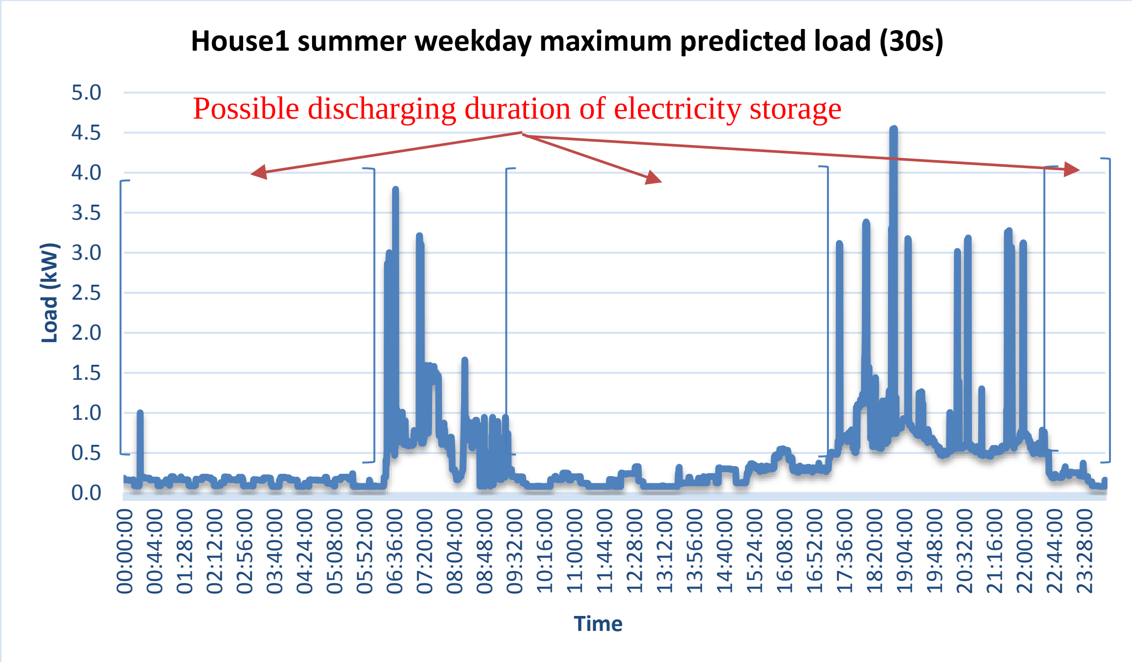


Fig. 6.23. The maximum instantaneous predicted load at each 30s in 1000 times simulation.

Then, the potential working durations of electricity storage is presented in Fig. 6.23. It can be found there are three main periods during this weekday, which are 0.00 - 06.30, 09.30 - 17.00, and 22.30 - 0.00.

In the first, summation of electricity demand during these three periods are calculated as 1.08 kWh, 1.48 kWh, 0.33 kWh for prediction, and 1.25 kWh, 1.29 kWh, 0.37 kWh for measured, respectively. Thus, the off-peak demand during morning and evening can be added into one, as 1.41 kWh and 1.62 kWh, for synthetic and original, respectively.

Therefore, the electricity storage may be operated from 10.30 to 06.30, and from 09.30 to 17.00, respectively.

From Fig. 6.22, the heat demand during 05.00-05.30 require 2.28 kWh, which is higher than the engine with 25% load mode supplied. Therefore, the engine in intelligent control strategy will be started at 05.00 and worked on 50% load mode for half an hour, for providing heat and charge battery and super capacitor.

Because the electricity demand at that time is very little, the engine will supply electricity to the heating wire to transfer electricity to heat. Meantime, the maximum electricity load during morning peak period is lower than 4 kW. Thus, the engine will not be kept on 50% load mode during the morning, even with 25% load mode if the battery is entirely charged.

With the calculation of SOC level during the peak period, the engine will restart at 06.30 with 50% load mode until 07.00, and then gradually switch to 25% model until 08.00. The engine will be shut down at 08.00 because batteries are entirely charged. Meantime, the temperature of water tank is higher than 60 degree C.

The engine may restart before 17.30 if the SOC level is under 60%. However, the predicted demand is usually higher than measured one. Therefore, in the pre-setting intelligent control strategy, the engine will be started at 17.30 with 50% load mode, until 18.00. There is a potential instantaneous load at 18.40 as shown in Fig. 6.23, which is higher than 4 kW. It means at that time engine may be needed to operate to satisfy electricity demand. Thus, the engine will restart at 25% load at 18.30 until 20.30. From 20.30 to 22.30, the energy storage can fulfil all potential electricity demand. The engine will be operated during 22.00 to 22.30 to heat the dwelling and charge energy storage at 50% load mode, and then shutdown at 22.30.

The general control strategy is passively based on the original load profiles as shown in Fig. 6.24.

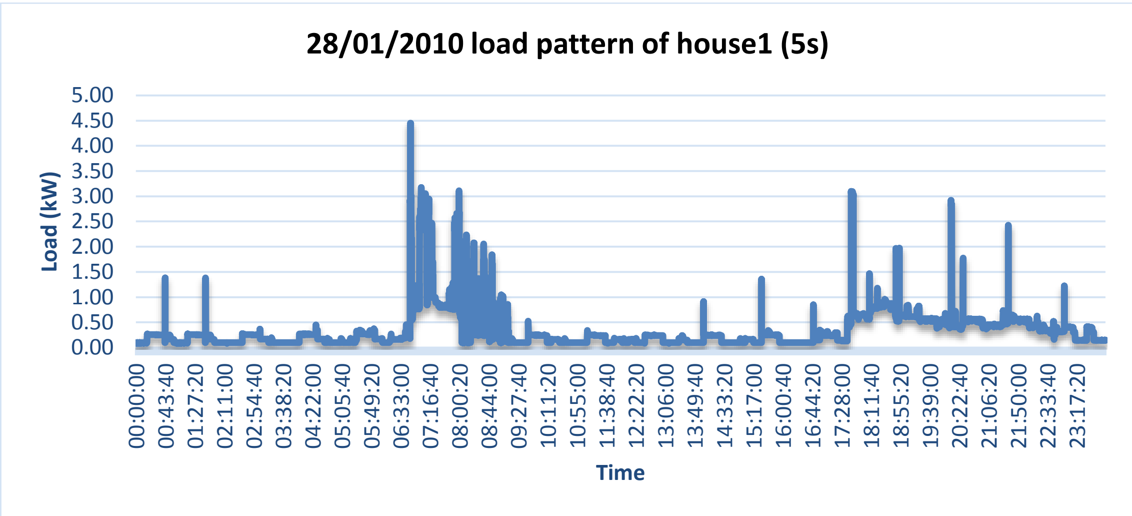


Fig. 6.24. Original electricity load of house1 winter weekday in 5s resolution.

From Fig. 6.24, the general control strategy is primarily focused on the morning peak period from 06.30 to 09.30. There are only few peak loads lower than 4 kW during evening, which can be satisfied by energy storage directly.

The comparison between intelligent control and general control is shown in Fig. 6.25.

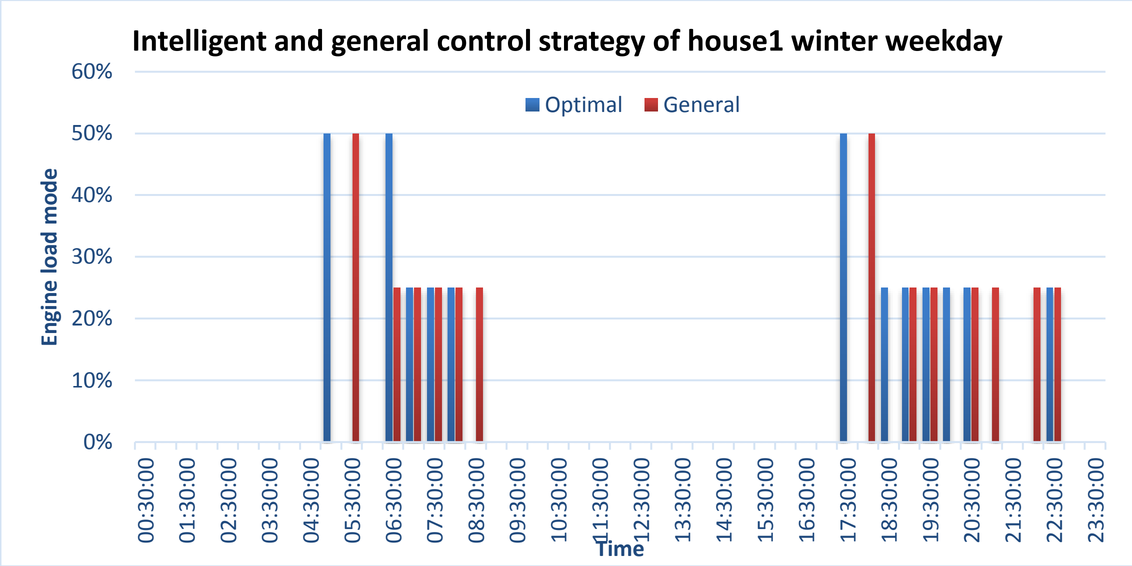


Fig. 6.25. Comparison between intelligent control and general control during winter weekday of house1.

The results of system performance by applying these control strategy into BMT-HEES are shown in Table. 6.11.

	General control	Intelligent control
Engine duration (h)	6.5	6
Fuel consumption (kWh)	67.77	64.68
Heat efficiency (%)	34.79	34.98
Electricity efficiency (%)	17.52	18.28
System efficiency (%)	52.31	53.26
Total electricity generation (kWh)	11.87	11.89
Total electricity demand (kWh)	6.60	9.89
Total heat recovered (kWh)	23.64	22.71

Table 6.11. The system performance comparison between general control and intelligent control of house1 winter weekday.

Because the engine transfers some electricity demand into heat via heating wire in water tank, the total electricity generation is higher than the original demand. In addition, because of the realistic load pattern can be satisfied by electricity storage directly during most of the time in selected weekday example. The intelligent strategy has not shown a remarkable improvement of energy saving and system efficiency.

6.5.5 Summary of intelligent control

By applying the predicted energy demand, the intelligent strategy has some advantages to pre-operate the engine to supply electricity and heat in daily advance. However, the intelligent strategy provided in the previous is static control in this study, as it is not concerned the dynamic feature of SOC. The aim of intelligent control is to find out a suitable solution to improve system reliability, system efficiency and save energy. From the outputs of Section 6.5.2 to section 6.5.4, it is found the intelligent strategy can be a feasible solution to optimize the whole system to achieve the above objectives.

6.6 Summary

The whole control system including general and intelligent for BMT-HEES is discussed throughout in this chapter. The control logic for each sub-system is presented and implemented. An intelligent strategy is shown to provide an alternative solution for satisfying the energy demand for UK domestic end-users.

Chapter 7. Conclusion and future work

7.1 High-resolution occupancy patterns

The nature of high-resolution instantaneous electrical loads in three types of dwellings is deeply analysed in this study. It is assumed the participated households have same appliances with identical loads that are as same with the national average from the literature. Then it is found a number of appliance use for one occupancy is one or two during majority periods when there is at least one occupancy active.

Then the load boundaries are given by calculating any conjunction of two appliances load. The results show the load boundary of one active occupancy is 3 kW in summer. If the particular instantaneous load is above 3 kW, there are two active occupants. For other seasons, the load boundary should be added with average heating appliances independently. Therefore, a defined approach named AECO is given to find out the load boundary for different number of active occupancy in different type of households.

According to AECO analysis, the high-resolution instantaneous electrical load can be converted into related number of active occupants. Thus, the estimated occupancy activity at every time interval is identified. The most remarkable feature of this approach is that it can identify individual occupancy profile for particular household, not by using average occupancy profile like national Time-Use data which has less accuracy to represent related occupancy activity individually.

Meantime, the AECO analysis can be extended into other applications, such as heating or cooling load. Also, daily, weekly, even seasonally high-resolution occupancy profiles can be provided for arbitrary household. Occupancy ordinary life and their daily schedule timetables can be identified by using AECO approach, which is imperative for the energy demand prediction and demand side management.

7.2 Dynamic electricity demand predictions

In order to discover a suitable solution to predict instantaneous electricity consumption in accuracy, a type of ANN named Elman`s network is utilized firstly. Nineteen related factors have been input into the model to generate one instantaneous load at each thirty-second. Because the real-time high-resolution occupancy activity is unpredictable, the results of this ANN model shows it is not an ideal approach to predict high-resolution electricity load in accuracy.

Therefore, an alternative model by using Markov-Chain and Markov-Chain Monte Carlo algorithms is presented. Although the outputs from the models are stochastic, the aggregated results show an excellent match with the original one. Thus, the synthetic high-resolution occupancy profiles are randomly generated based on historical data set. Then, AECO approach is utilized to mapping the number of active occupants to related average electricity consumption.

By simulating in 1000 times with 30s resolution of each household model in every season, the maximum, minimum and average synthetic demand during a selected weekday in aggregation are generated and validated, respectively. With the comparison between these different types of synthetic demand and measured data, it has been found that the stochastic model in this study is reliable to dynamically predict sub-hourly maximum electricity demand in advance with minor overrating.

The model has proved that although the instantaneous electricity load cannot be predicted in accuracy, but the maximum aggregated sub-hourly demand can be given in advance. It means based on historical data collections; the occupancy activities can be predicted in a selected period, like sub-hourly. Meantime, the model can capture the system variation in dynamic, which is a crucial aspect when applying the model into related demand side management.

7.3 Dynamic heat demand predictions

Three types of standard UK dwellings are visually constructed and simulated in this study. The thermal comfort of different age groups occupants is considered seriously in the parameter setting of each model. The heat back temperature is presented to protect the building avoid damage by low temperature.

Then the related seasonal occupancy profiles are used in the heat demand simulation to provide the heat demand in dynamic. The synthetic occupancy patterns of each household are employed as input factors in these visual dwellings.

By mapping with occupancy active heat demand and occupancy inactive heat demand, estimated sub-hourly heat demand is dynamically given of every household. The comparison shows a remarkable match between the estimated demands and simulated one.

7.4 Control system design and improvement

A general control system is designed and implemented for a BMT-HEES system, which including an engine system, electricity storage system, heating recovery system with thermal storage, and exhaust system including cooling appliance. The control logic of the engine and valves operation are given individually. Each control unit is implemented in an SCADA system within a Siemens software STEP7 S300 for programming PLC controllers and WinCC for visualization operation.

An intelligent control strategy is discussed and presented in this study of three types of weather conditions for each participated household. The predicted sub-hourly energy demand outputs are utilized in this intelligent strategy. By comparing with the general control strategy and the intelligent one, it can be found the optimal strategy can improve the system efficiency and reliability. It is proved that this advanced strategy is a reasonable solution to optimize the whole system.

7.5 Recommendation

There are some existed limitations in this study. In the first, it is the data sample. The data set used in this study only have one-week results in each season for all investigated households. It is not enough sufficient to generate comprehensive occupancy feature of particular households. Secondly, the appliances in these selected households are unknown, the AECO analysis can be improved by using more detailed information of appliances. In the third, the architectural parameters of each participated household are not available in this study, which can provide more accurate heat demand prediction.

With these limitations, the future work is aimed to eliminate these shortages firstly. With the sufficient electricity demand record and specific installed appliances, the stochastic model can be enhanced significantly. Precise visual house model can be constructed in DesignBuilder with detailed parameters for particular dwelling. Then the heat demand can be promoted simultaneously.

The current optimal strategy is static and for daily control in advance, because the SOC level is not considered dynamically in this type of strategy. The next step the advanced control strategy will use the particular energy demand if possible to dynamically control the whole system with sub-hourly in advance. Meantime, the SOC status will be a significant factor in optimal control strategy to indicate which load mode the engine should be operated in the next half an hour.

Appendix

A AECO analysis of each household

Synthetic appliance use of House2 winter Thursday evening peak time

Time	Load (kW)	Switched-on appliance	In-use appliance	number of synthetic appliance
16:34:30	2.68	Electrical heater	Electrical heater, lighting	2
16:39:30	5.69	Kettle	Kettle, Electrical heater, lighting	3
16:40:50	3.02	Stereo	Electrical heater, Stereo, Lighting	3
16:41:25	5.62	Toaster	Electrical, Stereo, Toaster, Lighting	4
16:43:25	2.68	Electrical heater	Electrical heater, Lighting	2
16:56:55	3.63	TV	Electrical heater, TV, Lighting	3
17:08:50	1.49	Stereo	TV, Stereo, Lighting	3
17:12:15	2.34	Microwave	Microwave, Stereo, Lighting	3

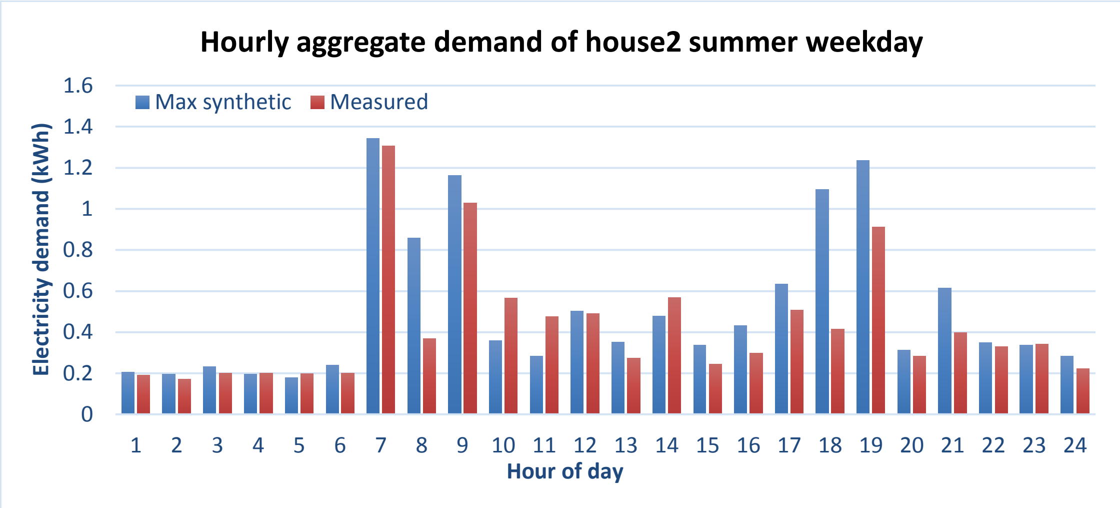
Example of synthetic appliance use of House3 Summer Monday morning peak time

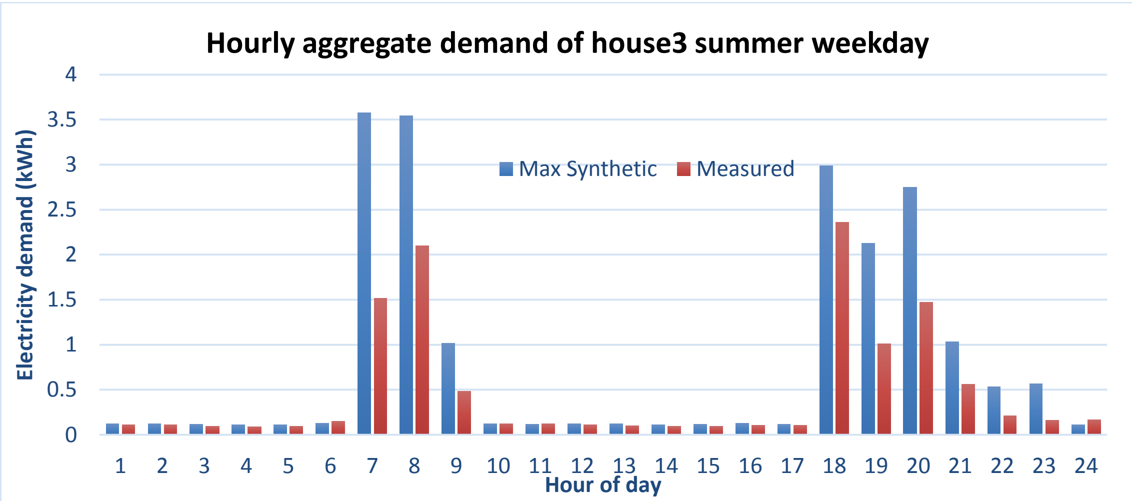
Load (kW)	Switch-on (5s)	In-use (5s)
7.24	Kettle, Toaster, Hob, Microwave	Kettle, Toaster, Hob, Microwave
4.34	Hob, Microwave	Hob, Microwave
7.18	Kettle, Toaster	Kettle, Toaster, Hob, Microwave
7.07	Oven, Toaster, Hob, Microwave	Oven, Toaster, Hob, Microwave
0.97	TV	TV
3.37	Kettle, Toaster	Kettle, Toaster, TV
4.62	Microwave	Microwave, Kettle, Toaster, TV
4.76	Hob, Oven	Hob, Oven,TV
5.52	Toaster	Hob, Oven,TV, Toaster
6.14	Desktop Computer	Hob, Oven,TV, Desktop computer, Toaster
7.01	Iron	Hob, Oven,TV, Desktop computer, Toaster, Iron
0.62	Washing machine	Washing machine
3.64	Kettle, Toaster	Kettle, Toaster, Washing machine
0.93	Stereo	Washing machine, Stereo
2.33	Kettle	Kettle, Washing machine
3.14	Hob	Hob,washing machine
6.15	Microwave, Toaster, Iron	Microwave, Toaster, Iron,Hob,washing machine
3.44	TV	Hob,washing machine,TV
5.95	Microwave,Toaster	Microwave,Toaster,Hob, washing machine
4.40	Microwave	Microwave, Hob, washing machine

Synthetic appliance use of House3 Winter weekday afternoon

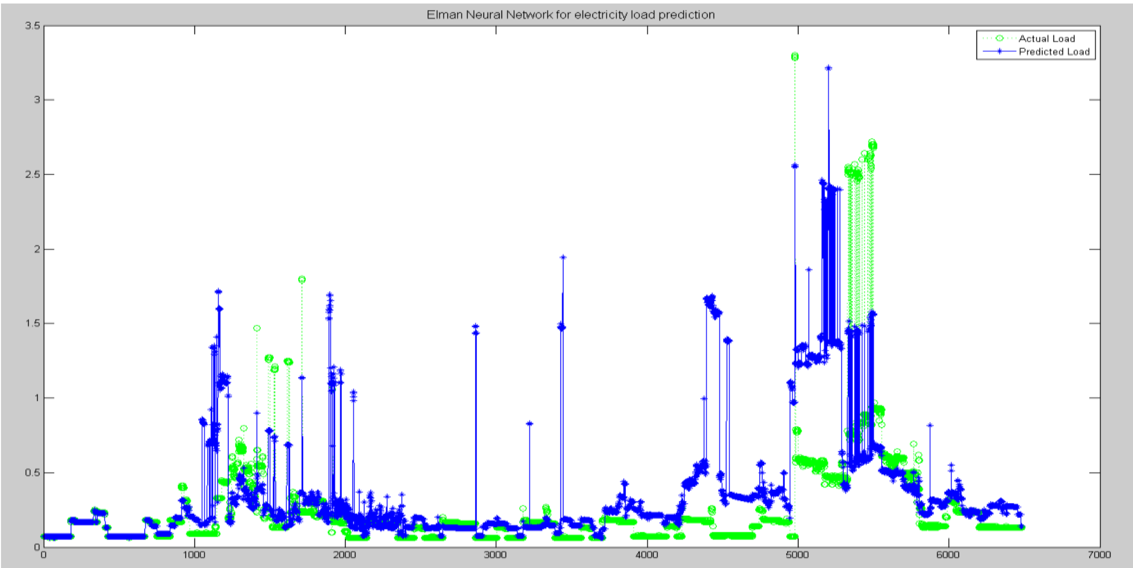
Time	Load (kW)	Switch-on (5s)	In-use (5s)
16:13:25	2.36	Heater (B2)	Heater (B2)
16:13:40	5.22	Kettle	Kettle, Heater(B2)
16:16:15	5.86	TV, Heater (B3)	Kettle,TV, Heater (B3)
16:18:00	5.49	Heater (Re)	TV, Heater (B3), Heater(Re)
16:20:00	8.54	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:05	8.51	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:10	8.53	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:15	8.53	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:20	8.53	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:25	8.45	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:30	8.46	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:35	8.54	Heater (B2)	TV, Heater (B3), Heater(Re),Heater (B2)
16:20:40	6.45	Microwave	Heater (B2), Heater (B3), Microwave
16:22:05	8.59	Toaster, Heater(K)	Toaster, Heater (K), Heater (B2), Heater(B3)
16:25:00	3.42	Heater (Re), TV	Heater (Re), Heater (K), TV
16:26:10	5.91	Heater (B1)	Heater (B1), Heater (Re), Heater (K), TV
16:26:55	8.66	PC, Heater (B2)	PC, Heater (B2),Heater (B1), Heater (Re), Heater (K), TV
16:27:45	10.48	Microwave	Microwave,PC, Heater (B2),Heater (B1), Heater (Re), Heater (K), TV
16:28:10	8.40	Toaster	Toaster, Heater (B2),Heater (B1), Heater (Re), Heater (K), TV
16:29:55	9.76	Heater (B3)	Toaster, Heater (B3), Heater (B2),Heater (Re), Heater (B1)
16:30:00	10.51	Microwave	Microwave, Heater (B2),Heater (B1), Heater (K),Heater (B3)
16:31:20	9.30	Heater (Re), TV	Heater (Re), TV, Heater (B2),Heater (B1), Heater (B3)
16:33:20	8.45	Kettle, Toaster	Kettle, Toaster, TV, Heater (B2), Heater (B3)
16:33:35	8.94	PC	Kettle, Toaster, TV, Heater (B2), Heater (B3), PC
16:33:40	8.91	PC	Kettle, Toaster, TV, Heater (B2), Heater (B3), PC
16:33:45	11.01	Oven	Oven, Kettle, Toaster, TV, Heater (B2), Heater (B3), PC
16:36:05	4.38	Heater(K)	Oven, TV, Heater (K), PC
16:36:35	10.93	Heater(B2), Heater (B3)	Heater(B2), Heater (B3),Oven, TV, Heater (K), PC
16:36:40	10.77	Heater(B2), Heater (B3)	Heater(B2), Heater (B3),Oven, TV, Heater (K), PC
16:36:45	10.82	Heater(B2), Heater (B3)	Heater(B2), Heater (B3),Oven, TV, Heater (K), PC
16:36:50	10.83	Heater(B2), Heater (B3)	Heater(B2), Heater (B3),Oven, TV, Heater (K), PC
16:36:55	10.74	Heater(B2), Heater (B3)	Heater(B2), Heater (B3),Oven, TV, Heater (K), PC
16:37:00	10.77	Heater(B2), Heater (B3)	Heater(B2), Heater (B3),Oven, TV, Heater (K), PC
16:37:20	4.54	Heater (B3)	Heater (B3), Heater (K)
16:37:30	6.67	Heater(B2)	Heater (B3), Heater (K), Heater (B2)
16:39:20	7.52	Heater (B1)	Heater (B3), Heater (K), Heater (B1)
16:41:10	9.52	Kettle	Kettle,Heater (B3), Heater (K), Heater (B1)
16:41:15	12.45	Toaster, Vacuum	Toaster, Vacuum, Kettle,Heater (B3), Heater (K), Heater (B1)
16:41:55	11.23	Heater (Re)	Kettle,Heater (B3), Heater (K), Heater (B1),Heater (Re)
16:43:05	7.38	TV	Heater (B3), Heater (K), Heater (B1),TV
16:44:35	9.34	Kettle	Kettle, Heater (B3), Heater (K), Heater (B1),TV
16:46:35	6.16	Heater (B2)	Heater (B2), Heater (K), Heater (B1),TV
16:49:55	6.18	Heater (B1)	Heater (B1), Heater (B2), Heater (K), TV
16:50:10	9.22	Heater (B3)	Heater (B3),Heater (B1), Heater (B2), Heater (K), TV
16:53:55	6.22	Heater (B1)	Heater (B1), Heater (B2), Heater (K), TV
16:56:15	7.05	Heater(B3)	Heater (B1), Heater (K), TV,Heater(B3)
16:58:00	9.07	Vacuum	Heater (B1), Heater (K), TV,Heater(B3),Vacuum

B Example of hourly electricity demand





An example of ANN output



C Programme code with ANN and Markov-Chain in Matlab and VB.

Elman`s ANN code:

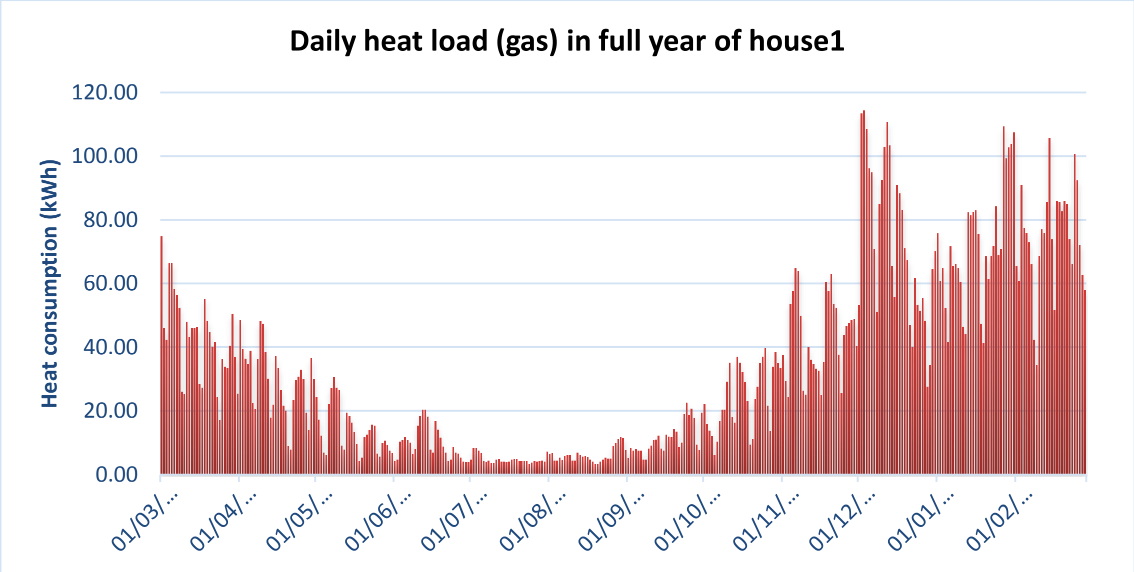
```
clc;
clear all
close all
nntwarn off;

% Load working days normalized data (Autumn working day)

load aunomo;
load aunomo1;

input = a(:,1:19);
output = a(:,20);
p_train = input(1:14396,:);
t_train = output(1:14396,:);
p_test = input(14797:15096,:);
t_test = output(14797:15096,:);

p_train = p_train';
t_train = t_train';
p_test = p_test';
t_test = t_test';

%nn = [22 24 26 28];
%for i = 1:4
threshold = [0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;0 1;];

%setup Elman neural network, the number of hidden neurons are nn(i)

net = newelm(threshold,[18,1],{'logsig','purelin'},'trainlm');

%the parameters of network

net.trainparam.epochs= 50000;
net.trainparam.show = 200;

% initialization of network

net = init(net);

%Elman network training

net = train(net,p_train,t_train);

% predicted output data

y = sim(net, p_test);

% error calculation

error = y - t_test;
%error(i,:) = y - t_test;

%end

%% plot the different result

plot(error,'-ro','linewidth',2)
%plot(1:1:3899, error(1,:),'-ro','linewidth',2);
%hold on;
%plot(1:1:3899, error(2,:),'b:x','linewidth',2);
%hold on;
%plot(1:1:3899, error(3,:),'k-.s','linewidth',2);
%hold on;
%plot(1:1:3899, error(4,:),'c--d','linewidth',2);
hold on;

title('Figure of error in elman network electricity prediction')
set(gca,'Xtick',[1:300])
%legend('22','24','26','28','location','best')
xlabel('time')
ylabel('error')

hold off;
```

Markov-Chain and Markov-Chain Monte Carlo code:

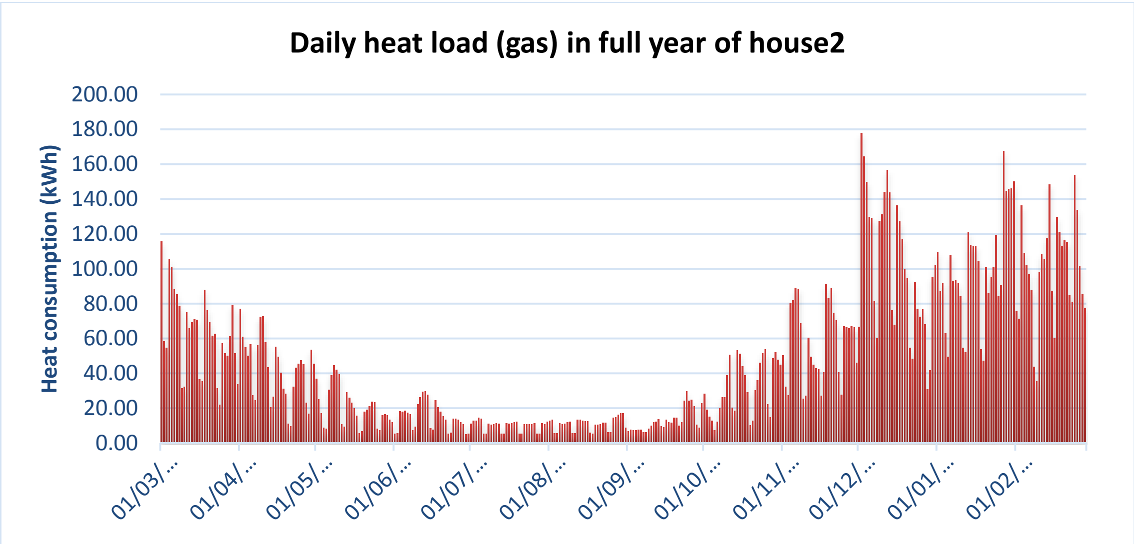
```
Sub Occupancy_Simulation()
'
' Occupancy Simulation Macro - This macro runs 500 times occupancy profile simulation
'
    ' Declare variables
    Dim sRandom As Double ' A variable to store a random number
    Dim nCounter As Integer ' A variable to count loop
    Dim iSimu As Integer ' A loop variablt to count the simulation times
    Dim sAccummulative As Double ' A varible to store a accummulative probability
    Dim nCurrentOccupant As Integer ' The current number of active occupants
    Dim sColumn As String ' A variable to store the column reference
    Dim gCol As String ' A variable to store the column reference
    Dim sRow As Integer ' Variable to store the row reference

    ' ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
    ' Step 1: Initial state idenfitication, which is between 00:00:00 and 00:00:30

    ' Set the number of simulation times
    For iSimu = 0 To 499

    ' Initialise the random number generator
    Randomize

    ' Determine the letter of the column from the Initial_State worksheet
    sColumn = "'Initial_State'!" + Left(Cells(2, 2).Address(True, False, xlA1), 1)

    ' Determine the letter of the column from the Start States worksheet

    gCol = Left(Cells(2, iSimu + 25 + 2).Address(True, False, xlA1), 2)

    ' Generate a random number
    sRandom = Rnd()

    ' Reset the accummulative probability count
    sAccummulative = 0

    ' Determine the start state at time 00:00 by checking the random number against the matrix
    For nCurrentOccupant = 0 To 2

        ' Add the probability for this number of active occupants
        sAccummulative = sAccummulative + Range(sColumn + CStr(nCurrentOccupant + 12)).Value

        If sRandom < sAccummulative Then
            ' This is the start state
            Range("'Simulation_500'!" + gCol + "11").Value = nCurrentOccupant
            Exit For
        End If

    Next nCurrentOccupant


    ' ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
    ' Step 2: Generation of the active occupancy transitions for each thirty second periods of the day

    ' Start Transition, set counter to calculate each transition
    For nCounter = 1 To 2879

        ' Pick a random number
        sRandom = Rnd()

        ' Reset the accummulative probability count
        sAccummulative = 0

        ' Determine the row for this state
        sRow = ((nCounter - 1) * 3) + nCurrentOccupant + 11

       ' Determine the column for this state
       gCol = Left(Cells(2, iSimu + 25 + 2).Address(True, False, xlA1), 2)

        ' Define a loop count variable
        Dim k As Integer

        ' Cycle through the probabilities for this state
        For k = 0 To 3

            ' Get the column reference
            sColumn = Left(Cells(1, k + 3).Address(True, False, xlA1), 1)

            ' Add this probability
            sAccummulative = sAccummulative + Range("'Matrix'!" + sColumn + CStr(sRow)).Value

            ' See if this is a state transition
            If sRandom < sAccummulative Then

                ' Transition to another or same state
                nCurrentOccupant = k
                Exit For

            End If
        Next k

        ' Store the next state
        Range("'Simulation_500'!" + gCol + CStr(nCounter + 11)).Value = nCurrentOccupant

    Next nCounter

    Next iSimu

End Sub
```

D Example of Heat consumption

Appendix- Heat consumption



Daily heat demand (Gas) simulation results in a year of mid-terraced house.

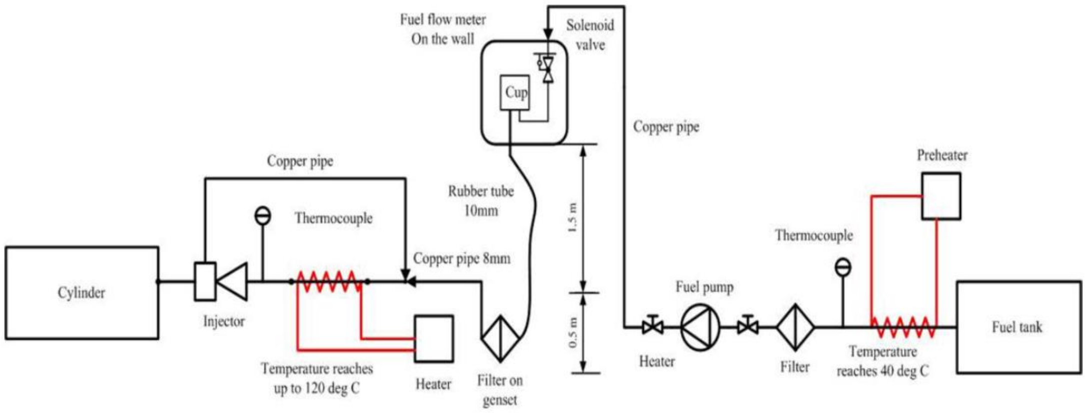


Daily heat demand (Gas) simulation results in a year of large-terraced house.

E Battery performance and fuel control

Performance indicators \ Discharge power level	1kW	2kW	3kW	4kW
Energy released (Wh)	8000.3	7296.26	6887.23	6588.06
Energy consumed (Wh)	6846.71	8257.03	7849.10	7516.11
Discharge duration (hours)	7.83	3.50	2.42	1.63
Charge duration (hours)	3.88	3.48	3.32	3.18
Energy efficiency (%)	92.02	88.36	87.75	87.65
SOC at discharge end (%)	41.1	35.5	30.8	25.5
Discharge Capacity (Ah)	325	299	287	284

Battery performance [19]



Fuel Control [17]

F Internal coolant water loop

There are six situations with T7 conjunct with WV1 and WV2, as shown in Table 6.3.

- If T7 > 85 degree C, and if WV1 is close and WV2 is entirely open, then open WV1 half way. Wait 2 minutes to see if any tendency of temperature is decreasing, otherwise further open WV1 totally.
- If T7 >85 degree C, and if both WV1 and WV2 are half open, then open WV1 totally. Wait 2 minutes. If no decreasing tendency, give a warning.
- If T7 >85 degree C, and if WV1 is fully open and WV2 is close, after two minutes, if the temperature is not decreasing, then give a warning.
- If T7 <70 degree C, and if WV1 is close and WV2 is total open, then operate WV2 to half open, keep WV1 close. Wait 2 minutes to find out if there is any tendency of temperature increasing, otherwise control WV2 to slightly open.
- If T7 <70 degree C, and if both WV1 and WV2 are half open, then close WV1. Wait two minutes to check there is any tendency of temperature increasing, otherwise change WV2 to slightly open.
- If T7 <70 degree C, and if WV1 is open and WV2 is close, then close WV1 and slightly open WV2, after two minutes if the temperature is still stable or low, give a warning.

If the control action works in these six situations, the temperature begins to increase or decrease. Then when the temperature returns to 78 degree C, change the valve setting back to the beginning status (in red). Other thermometers like T8 to T11 are used to monitoring if there is increasing or decreasing tendency after the previous control operation.

G External water circuit

The control strategy of external water valve is designed by considering following situations:

(a) : If T13 > 75 degree C, it means the temperature of coolant water after WV1 is too high, which need to be cool down, therefore, open WV1 half way, and close WV2 to half way, also keep WV3 open and WV4 close.

(b) : If T13 > 80 degree C, the coolant water should be cool down immediately, and normally at this moment, heating in external water loop has been already fully charged, therefore, fully open WV1 to depress the temperature of coolant water and close WV2, also keep WV3 open and WV4 close.

(c) : If T16 > 85 degree C, the temperature of input water for water tank is too high, which can refer to dangerous temperature level of coolant water. Thus, fully open WV1 and close WV2, then control both WV3 and WV4 to half position, as it is not necessary to use exhaust gas for fully heating external water. The external water after coolant heat exchange has been divided into two different branches, one passes through exhaust heat exchanger and another direct inflows to water tank. At this point, gas valve should be controlled simultaneously, and we record this situation as "situation 1" which will be discussed in the followed exhaust emission control. This situation only happens after previous case (b) occurred.

(d) If T16 > 90 degree C, it means the current heating demand is very low, and it is ideally not necessary to keep heating whole external water, which is very dangerous for the engine. Therefore, the heat is partially wasted by radiator in the engine system to protect the engine. Thus, keep WV1 totally open and close WV2, and then close WV3 and open WV4 totally. Because it is not necessary to reheat the external water by exhaust heat exchanger. Meantime, this case is identified as "situation 2", which is used to control gas valve later.

(e) If T17 <65 degree C, the temperature of outflow water from water tank is lower than expected. Therefore, set WV2 and WV4 totally open, and close WV1 and WV3.

(f) If T17 <60 degree C, it is reached the warning level for domestic heat consumption, first the engine will start to recovery heat. If the engine is running and T17 < 60 degree C, all water valves are set back to the initial setting as marked with red. This situation is marked as situation 3 in gas valve control.

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