Synthetic Domestic Electricity Demand in Thailand Using a Modified High-Resolution Modeling Tool by CREST

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ABSTRACT

A residential electricity demand profile is one of the key means of investigating the impact of high penetration in low carbon technologies (such as photovoltaic systems and electric vehicles) on distribution networks. However, it is difficult to identify the true daily electricity consumption of Thai households, due to the lack of routine monitoring on real-time demand. Furthermore, residential electricity consumption is normally recorded on a monthly, low time resolution basis. In this paper, the CREST demand model is employed to simulate high-resolution domestic electricity demand in Thailand, without installing new monitoring devices and avoiding customer interruption. This is achieved through a stochastic process which is a combination of patterns of active occupancy, outdoor ambient lighting characteristics, and daily activity profiles. Since the model is based on time use survey data from the UK, outdoor irradiance and appliance configuration are adapted to fit the Thailand case study. In order to verify the model, the synthetic load profiles of the CREST demand model are compared against the measured data from the actual monitoring of a real low voltage network in Thailand. The application of the high-resolution CREST model shows promising results for the simulation of domestic electricity demand profiles in Thailand.

Keywords: CREST Demand Model, Electricity Demand Model, Residential Load Profile, Time Use Data, Thai Households

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1. INTRODUCTION

In order to assess the performance of low voltage (LV) distribution networks with increasing low carbon technologies such as solar photovoltaic (PV) systems and electric vehicles, the timing of residential electricity demand has a significant impact on power quality such as voltage variations, when the penetration level of low carbon technologies is high. For example, the impact on voltage rise from PV generation usually occurs at noon, during light load conditions. On the other hand, under-voltage problems can occur in the evening during heavy load conditions, when many electric vehicles are charging at the same time. However, there is a lack of routine real-time monitoring for LV networks in Thailand and electricity metering at the residential level is conducted at a low resolution, normally on a monthly basis. Therefore, it is difficult to know the exact daily electricity consumption of domestic residents.

Domestic load profiles can be drawn by the actual measurement of electricity consumption in relation to specific customers and locations. The real daily electricity demand profiles of residential and business customers in urban areas of Thailand have been monitored and collected by the Metropolitan Electricity Authority (MEA) since 2007 [1]. The MEA aims to use the monitored dataset to provide more precise load forecasting and updating electricity tariffs. Recordable meters were installed in 1,002 selected dwellings in three big cities, namely Bangkok, Nonthaburi, and Samut Prakan, to monitor electricity consumption at a resolution of 15 minutes. However, only 171 of the monitored dwellings were residential houses, consisting of 52 small energy consumption customers (using less than 150 kWh per month) and 119 medium energy users (consuming more than 150 kWh per month).

The modeling of residential electricity demand based on time use data is an alternative solution, which aims to simulate the daily electricity use profiles of domestic households in LV networks, without installing new monitoring equipment (i.e., smart meters) and avoiding customer interruption. Time use data informs activities carried out by participants over 24 hours, along with weather, building characteristics, lifestyle and habits of occupants, appliance design, and appliance control [2]. Many studies have found that the pattern of electricity use in each domestic dwelling is highly dependent upon the number of occupants. The individual profiles of electricity consumption in the household are determined according to the time residential end users switch on lights, heating systems, and appliances, how long for, and the time they are switched off [3]. Moreover, residential electricity demand profiles are highly correlated with the timing of active occupancy such as when people are at home and awake. Time use data can be obtained by the survey method or simulated using probability, stochastic modeling, or the Markov chain technique [2].

Examples of time use data methods for modeling residential electricity demand in some countries are reviewed in [2]. Stoke *et al.* modeled domestic lighting using a stochastic approach, and 30-minute resolutions of monitored data in 100 households in the UK to measure lighting demand with a resolution of one minute [3]. Wilke *et al.* employed French time use survey data from 1998 to 1999, to model household activities based on three types of time-dependent probabilities: the probability of being at home, the conditional probability of starting an activity while being at home, and the probability of the distribution function for the duration of that activity [4]. Widen *et al.* simulated a high-resolution series of household activities and electricity demand based on time use data in Sweden, using surveyed data for the years 1996 and 2007. The domestic electricity demand profile was stochastically generated from occupancy behavior along with appliance holdings, ratings, and daylight distribution [5]. Furthermore, by using a similar technique, Widen and his colleagues also developed models to meet residential lighting [6] and hot water heating demand [7].

A high-resolution residential electricity demand model for UK households was developed by the Centre for Renewable Energy System Technology (CREST), Loughborough University, UK. The bottom-up occupancy model to meet electricity demand in the UK used survey data and active occupancy data for UK households [6]. Furthermore, this model for domestic electricity use is based on a combination of active occupancy and daily activity profile patterns to analyze how much time people spend performing certain activities. A one-minute resolution stochastic model of electricity demand was created through the simulation of appliance use [7], based on the Markov chain technique. Additionally, the Markov chain technique in this model is validated by actual data from electricity users in the UK.

In this current study, the electricity demand for Thai households is modeled using the CREST demand model. This tool includes the representation of electrical demand and generation, resident occupancy, solar thermal collection, and thermal models with a resolution of one minute [8]. This is an open-source development model in Excel VBA (Visual Basic for Applications) and available to download free of charge in [9]. In addition, this high-resolution stochastic model for electricity demand by CREST requests information on the number of occupants, type of day (weekend or weekday), month, and appliances. Moreover, the bottom-up development of the model allows the change in appliances and their usage patterns to be adapted to the case study in Thailand.

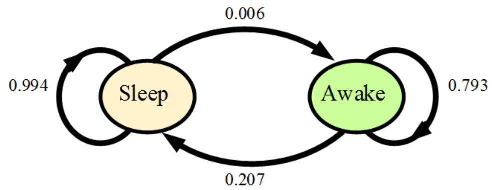
To adapt the CREST demand model to make it suitable for residents in Thailand, information such as location, type of day, and month will be changed to align with specific cities and seasons in Thailand such as the level of natural daylight used in the lighting activity profile simulation. Information on the proportion of dwellings with appliances is adapted with the aid of censuses from the Energy Policy and Planning Office (EPPO) and National Statistical Office of Thailand (NSO). Storage heaters have been changed to air-conditioning for the modified daily activity profile. The number of occupants in each dwelling is randomized between one to five, based on the proportion of the population living in private households, and type of living quarters, according to the data collected from the NSO. The synthetic residential load profiles provided by the modified CREST demand model will be verified using the actual load profiles monitored in a real Thailand LV network.

2. MARKOV CHAIN TECHNIQUE

The Markov chain technique is a well-established stochastic approach to data generation [10], involving mathematical systems that hop from one "state" (a situation or set of values) to another. It is useful for creating stochastic occupancy and domestic demand data and has the same characteristics as the time use survey. The Markov change technique is based on the concept that each state is dependent only on the previous state and the probability of the state changing, held in "transition probability matrices" [7].

When applying the Markov chain model to the residents' behavior in a house, occupancy behavior includes the states of "sleep", and "awake", which together with other behaviors could form a "state space" (a list of all possible states). In addition, as well as the state space, the Markov chain provides the probability of "transitioning" from one state to another state. If the time use data is in a ten-minute period, it will contain 144 transition probability matrices for a given house with one resident in one day.

The example in [7] demonstrates the Markov chain diagram and transition probability matrix of a one-



Active occupants	Next state (at 00:10)	
	Sleep	Awake
Current state (at 00:00)		
Sleep	0.994	0.006
Awake	0.207	0.793

Fig. 1: *Example of the Markov chain technique.*

Table 1: *Example calculation of the transition probability matrix at 00:00–00:10 for a one-person household on weekdays.*

Number of active occupants		Number of occurrences in the TUS data		Transition probability
at 00:00	at 00:10			
Sleep	Sleep	1428	1428+8=1436	1428/1436=0.994
Sleep	Awake	8		8/1436=0.006
Awake	Sleep	55	55+211=266	55/266=0.207
Awake	Awake	211		211/266=0.793

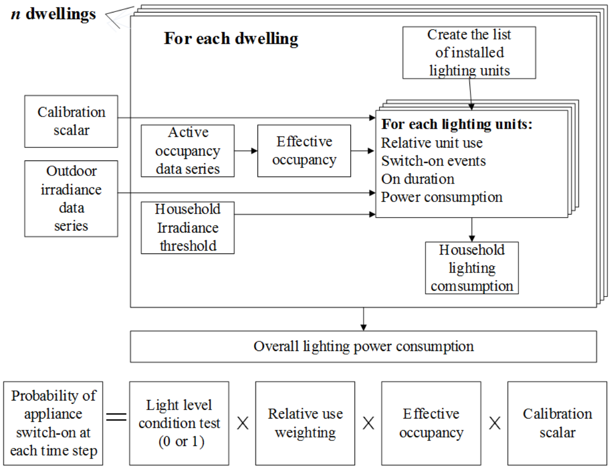


Fig. 2: *Outline structure of the lighting energy use model.*

person household, starting at midnight, as shown in Fig. 1. If a person is asleep at 00:00, they are very likely to continue sleeping at 00:10, according to a probability of 0.994. On the other hand, if a person is awake at 00:00, then the probability of them going to bed at 00:10 is 0.207. Consequently, the concept is similar, whereas the transition matrix probability is slightly different for ten minutes later (i.e., 00:10 to 00:20). For one day, in the case of one resident, the size of the transition probability matrix is $2 \times 2 \times 144$. Moreover, a two-person household is represented similarly but with a 3×3 transition probability matrix for each time step.

3. CREST DEMAND MODE

The CREST demand model used for domestic energy demand simulations consists of three one-minute high-resolution models: Domestic occupancy model [6], domestic lighting energy use model [11], and domestic appliance use model [7].

3.1 Domestic Occupancy Model

The domestic energy load profile is highly dependent on the timing of the occupants' activities. An active occupant is defined as someone who is in the house and awake. The occupancy model aims to generate stochastic occupancy data with the same characteristics as the UK time use data survey of 2000 [12]. The time use data contains detailed 24-hour diaries, completed at ten-minute resolutions by thousands of participants.

To create the occupancy profile, the transition probability matrices in the Markov chain technique are derived from the time use data, categorized by: (1) the number of household residents and (2) type of day (weekend or weekday). An example of the transition probability matrices developed using the UK time use survey data is demonstrated in Table 1 [7]. Moreover, the 144 calculations are repeated for each category to complete the 24-hour occupancy profile. After verification, this model simulation outputs for stochastic active occupancy patterns in UK households which correlate very closely with the statistical characteristics of the original time use survey data.

3.2 Domestic Lighting Energy Use Model

The use of electric lighting in a domestic dwelling depends on the level of natural light coming in from outdoors, coupled with the activity of the household residents. The structure of the lighting energy use model is outlined in Fig. 2 [11]. The outdoor irradiance data series is a global variable which means all houses in the same area experience the same irradiance and it feeds directly into any individual lighting unit that may possibly be turned on. In addition, a lighting unit represents one or more bulbs connected to a single switch. The model uses a full year of irradiance data from 2007 recorded on-site at Loughborough University. Another global variable is the calibration scalar which allows the model to be adjusted such that the overall mean annual lighting energy demand equals any required value.

Each house is assigned an active occupancy data series created by the domestic occupancy model. This active occupancy level is then adjusted to provide an "effective occupancy" value, taking account of the shared lighting. Furthermore, a household irradiance threshold is randomly assigned to each dwelling to define the natural light level below which the occupants will consider using lighting. Therefore, the probability of switching on a lighting unit at any point in time is determined by the effective occupancy, outdoor irradiance level, weighting of the relative lighting unit use, and calibration scalar. Once switched on, the duration that a lighting unit remains on is then considered through a stochastic calculation whereby the probability distribution of light event duration is based on a survey of 100 dwellings [2]. Finally, the on/off status of the units is combined with their individual rating, and then aggregated to give a lighting energy consumption profile for each household.

In the simulation, the individual dwelling is allocated a set of characteristic installed lighting units based on industry statistics, including data on the mean number of installed bulbs and relative proportions of different bulb technologies. Firstly, the total number of units in each property is picked at random. Secondly, the lighting technology category of each unit is selected as either incandescent, compact fluorescent, fluorescent tube, halogen, or other types such as a light-emitting diode.

In [11], the switch-on event of a particular lighting unit is assessed by combining the following factors:

- The current irradiance level is compared to the allocated dwelling irradiance threshold to determine if the natural light level is low enough to require artificial lighting. The probability distribution of the irradiance threshold is considered using two factors: (1) the complex nature of daylight coming into the house and the high variability in the resulting indoor luminance, and (2) the high variability in the human response to low light levels.
- Each lighting unit is randomly allocated a fixed weight at the start of the simulation to indicate how much it is used in comparison to other units since some units will be turned on more often than others. The relative usage weight of each lighting unit is selected randomly based on the distribution of weight formed from a natural logarithmic curve.
- The effective occupancy considers the sharing of lights. If there are two or more active occupants in a house, they may be in the same room and will naturally share the lighting. On the other hand, if there are no active occupants, then the effective occupancy will be zero, with no switch-on events occurring. This value is derived from the survey data on annual lighting usage in the dwelling, according to the number of total occupants.
- The calibration scalar value is employed to calibrate the mean energy demand output in order to provide the overall average lighting energy use, per dwelling, per year.

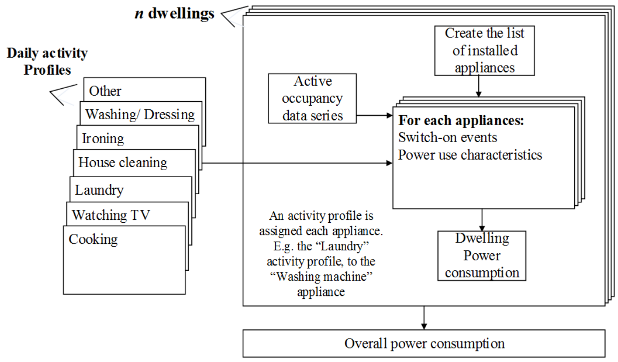


Fig. 3: *Outline structure of the appliance use model.*

3.3 Domestic Appliance Use Model

The pattern of electricity demand in an individual house is highly dependent upon the activities of the occupants and their associated use of electrical appliances, where appliance refers to any individual domestic electricity load. The appliance use model is a combination of active occupancy patterns and daily activity profiles, illustrating how people spend their time performing certain activities. Hence, synthetic electricity demand is created through the simulation of appliance use. The model covers all major appliances commonly found in the domestic environment [7].

The structure of the model is illustrated in Fig. 3. A set of daily activity profiles characterize the chances of people performing various activities at different times of the day. The same daily activity profiles are applied to all houses. In addition, the time use survey data is used to construct the daily activity profiles with each quantifying the probability of the specific activity being undertaken as time-of-day function. The time use data is grouped according to the number of active occupants and then further subdivided into weekends and weekdays. Hence, the proportion of dwellings used in the daily activity profile is calculated from the number of dwellings where the activity of interest is taking place.

Each dwelling is assigned an active occupancy data series and a set of installed appliances. A dataset of installed appliances is selected on a random basis using statistical ownership data from the UK at the beginning of simulation. Moreover, the individual appliance is mapped to one of the daily activity profiles, whereas multiple appliances may be assigned to a single activity. For example, ovens, microwaves, and electric hobs are assigned to the cooking activity. In the case that appliances are not associated with a particular activity or depend on active occupancy such as telephones, fridges or freezers, and electric space heaters, they will be assigned to the "other" activity profile.

The switch-on event of each appliance, occurring at each time step of a simulation, can be determined by the following procedure.

- **Step 1:** The activity profile is selected according to the appliance activity, the number of active occupants, and type of day.
- **Step 2:** Activity probability is determined according to the activity profile at the time any of the active occupants are engaged in the activity.
- **Step 3:** The activity probability is multiplied by the calibration scalar in order to ensure the mean annual consumption in kWh/year of the appliance is correct. Each appliance has a calibration scalar factored into the probability of switch on, thus determining the average number of times the appliance is used in a year.
- **Step 4:** The step 3 results are compared to a random number between 0 and 1. If the probability is more than the random number, then a switch-on event occurs.

After an appliance switch-on occurs, the power use is calculated to create the electricity consumption profile of each appliance. The power usage of each appliance may be configured in either the on or off state, the latter representing standby. Many types of appliances are assumed to have a constant power demand when switched on, such as televisions. Moreover, some appliances such as washing machines demonstrate time-varying demands, which differ considerably throughout a cycle. Finally, the whole electricity demand of each dwelling is generated by adding together the power generated by all appliances and lighting units within the same house.

3.4 Modification of the CREST Demand Model

The original CREST demand model is configured to include up to 33 appliances per household, based on the UK figures. However, some appliances such as dishwashers and tumble dryers are rarely found in Thailand, and therefore excluded from the demand model. Consequently, the number of appliances is reduced to 18, as seen in Table 2, with the proportion of dwellings with appliances adapted using the information from EPPO and NPO censuses for 2008 and 2010, respectively.

Air-conditioning replaces storage heaters in the modified daily activity profile. If the switch is in the on position, the electricity use of each 12,000 BTU air-conditioning unit is defined as 1 kW constant power demand. In addition, the times when the air-conditioning starts and stops are stochastically defined. During the summer season, two 12,000 BTU air-conditioning units are employed in this modified model. The first unit has the proportion of the dwelling set to 1.0 and can start any time between 6 p.m. and 11 p.m., stopping at a random time between 5 a.m. and 7 a.m. (10-minute resolution). Another unit expects to be turned on during the afternoon with the proportion of the dwelling set to 0.3. This unit can start at a random time between 11 a.m. and 4 p.m., and stop at 6 p.m. Moreover, the electric shower is excluded from this test, since it is rarely used during the summer in Thailand.

4. TEST SYSTEM

The test system is a three-phase, 400 V, 50 Hz, low voltage feeder chosen from a real low voltage network in an urban area of Thailand, as can be seen in Fig. 4(a). This LV feeder has two main circuit branches consisting of 20 customers in total. The phase connection of each house is identified in Fig. 4(b) with 8, 10, and 2 customers in phases A, B, and C, respectively. Each house is fed by a 3-phase, 4-wire over-head distribution system measuring approximately 326 m in length. The parameters of the main feeder and branch lines are taken from [13], as shown in Table 3. After the walk-through survey, all customers were observed to have at least one air-conditioning unit.

A power quality analyzer located at the LV side of the distribution transformer is used to measure and log the electricity consumption along the feeder with 10-minute resolution, as shown in Fig. 5. In addition, the three-phase electrical quantities, such as voltage, active, and reactive powers, are collected and uploaded to the web and database servers via 3G wireless technology. This monitoring data will be used to validate the synthetic aggregated electricity demand of all dwellings in the same LV feeder. The average measured data for daily electricity demand during the weekdays in the summer season, between June 13 and 17, 2016, is demonstrated in Fig. 6. The ambient temperature during that time ranged from 30–40 °C.

The average measured load profiles for one week in Fig. 6 show that all three phases experience high demand during the evening and night periods (7 p.m. to 6 a.m.), for which the air-conditioner is responsible. Furthermore, daily load phase A and B profiles are very close during these time periods. After 8 a.m., phases A and C experience low electricity consumption during the morning and afternoon periods while demand in phase B gradually decreases in the morning, subsequently increasing slowly in the afternoon, possibly due to the use of an air-conditioning system.

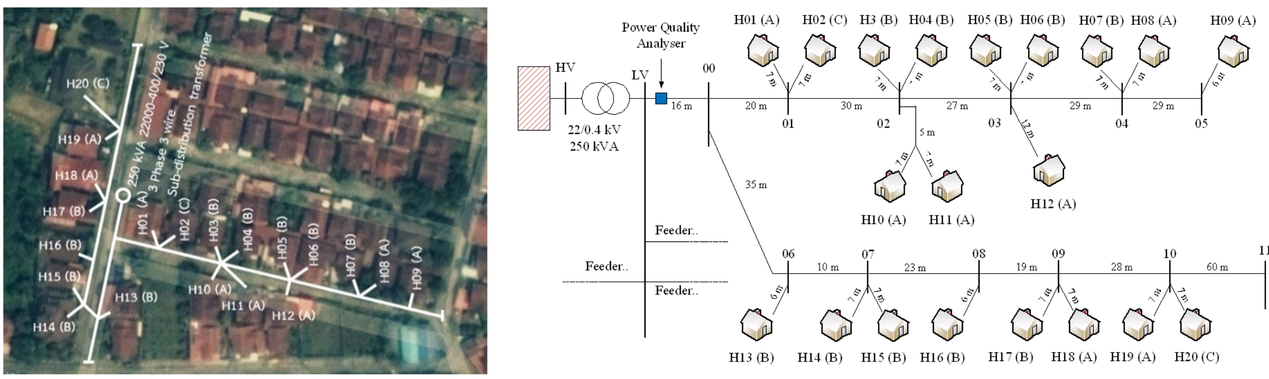
The high-resolution electricity demand model by CREST is employed to simulate the domestic demand of each dwelling. In addition, the appliance configuration in the CREST demand model is modified to make it suitable for Thai households, as explained in Section 3.4. The outdoor irradiance in the UK during September has similar characteristics to June in Thailand. At the start of simulation, the number of occupants in each house is assigned randomly, between 1 and 5, based on the proportion of the population living in detached houses in Thailand

Table 2: *Comparison of appliance configuration between original and modified CREST demand models.*

No.	Appliance type	Proportion of dwellings with appliances		Mean cycle length (min)	Mean cycle power (W)	Stanby power (W)
		For UK (original)	For Thailand (modified)			
1	Chest freezer	0.163	–	14	190	0
2	Fridge freezer	0.651	0.03	22	190	0
3	Refrigerator	0.43	1.00	18	110	0
4	Upright freezer	0.291	0.03	20	155	0
5	Answer machine	0.9	–	0	0	1
6	Cassette/CD player	0.9	0.08	60	15	2
7	Clock	0.9	–	0	0	2
8	Cordless telephone	0.9	–	0	0	1
9	Hi-Fi	0.9	0.22	60	100	9
10	Iron	0.9	1.00	30	1000	0
11	Vacuum cleaner	0.937	–	20	2000	0
12	Fax	0.2	–	31	37	3
13	Personal computer	0.708	0.05	300	141	5
14	Printer	0.665	0.05	4	335	4
15	TV 1	0.977	1.00	73	124	3
16	TV 2	0.58	1.00	73	124	3
17	TV 3	0.18	0.45	73	124	2
18	VCR/DVD	0.896	0.08	73	34	2
19	TV receiver box	0.934	–	73	27	15
20	Hob	0.463	–	16	2400	1
21	Oven	0.616	–	27	2125	3
22	Microwave	0.859	0.13	30	1250	2
23	Kettle	0.975	0.95	3	2000	1
24	Small cooking appliances (group)	1	1.00	3	1000	2
25	Dishwasher	0.335	–	60	1131	0
26	Tumble dryer	0.416	–	60	2500	1
27	Washing machine	0.781	0.88	138	406	1
28	Washer dryer	0.153	0.88	198	792	1
29	DESWH*	0.17	–	20	3000	0
30	E-INST**	0.01	–	5	3000	0
31	Electric shower	0.67	–	3	9000	0
32	Storage heaters	0.028	–	300	10200	0
33	Other electric heating	0.026	–	300	2000	0

*DESWH: Domestic electric storage water heater

**E-INST: Instantaneous hot water system



(a) (b)

Fig. 4: *A real Thailand LV network used as the test system.*

Table 3: *Parameters of LV distribution lines.*

Parameters	Main feeder lines	Branch lines
Cross-section	$50\,\text{mm}^2$	$25\,\text{mm}^2$
Type	THW	THW
R (Ω/km)	0.4723	0.8698
L (mH/km)	0.8168	0.8906
C (μF/km)	0.0134	0.0124
Installation	Secondary rack	Secondary rack

Fig. 5: *Power quality analyzer.*

according to the housing census conducted by NPO in 2010 [14]. Although the CREST demand model can synthesize electricity demand with a resolution of one minute, the 10-minute resolution is used in this work to align with that of the measured data from the power quality analyzer installed in the field test.

The synthetic daily residential load profile of each house will be different since it mainly depends on the number of active occupants. To simulate the aggregated electricity demand profile of all dwellings in this feeder, the test system and electricity demand profiles of all customers are loaded into the DIgSILENT PowerFactory modeling platform. The time series load flow calculation is applied to simulate the profile of aggregated electricity consumption along the LV feeder, including the energy losses via the distribution line. Moreover, this process is repeated ten times to illustrate the difference in electricity demand profiles created by the high-resolution modeling tool in comparison to the measured data.

In order to validate the model, two indices, namely root mean square error (RMSE) and the coefficient of determination (R^2), are used to examine how close the synthetic profile is to the measured data. The RMSE is commonly used to measure the difference in values. It represents the sample standard deviation of the differences between measured values ($\hat{x}_i$) and simulated values (x_i), which can be written as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{n-1}} \qquad (1)$$

where n is the total number of samples.

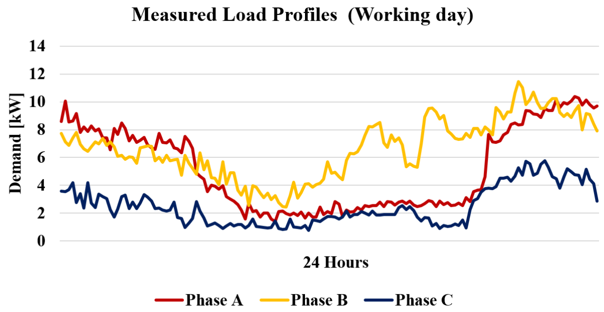


Fig. 6: *Average measured daily load profiles for one week.*

The R^2 is often used to report similarities between two sets of data. This index is determined by a number between 0 and 1, where 0 shows no correlation while 1 exhibits perfect correlation. The value of R^2 is determined from [15]:

$$R^2 = 1 - \frac{\text{SSE}}{\text{SSTO}} \qquad (2)$$

where SSE is the error sum of squares, quantifying how much the data points vary around the estimated regression line, and SSTO is the total sum of squares, quantifying how much the data points vary around their mean.

5. SIMULATIONS AND RESULTS

At the start of each simulation, the number of occupants is assigned to each dwelling randomly, between 1 and 5, as can be seen in Table 4. Figs. 7(a)–7(c) show the group of synthetic aggregated electricity demand profiles of phases A, B, and C after repeating the simulation ten times. In general, the load profiles all follow a similar pattern, where the high demand occurs during the night but quite low during the day. In addition, the high electricity use at night is due to the air-conditioning being switched on. The R^2 is used to verify the similarities between the synthetic aggregated load profiles of each simulation with the average measured data for one week from the field test, as shown in Fig. 7(d). After ten simulations, the difference between measured and synthetic data in phase B is relatively high while the synthetic profile of phase A is very close to the measured data with an average value of R^2 of about 0.70. Furthermore, in phase C, the values of R^2 fluctuate between 0.44 and 0.74. This wide variation may be due to the number of dwellings in this phase being very low, consisting of only two houses.

Fig. 8 illustrates the values of RMSE in each phase of all ten simulations divided into four different time periods: (1) midnight to 6 a.m., (2) 6 a.m. to noon, (3) noon to 6 p.m., and (4) 6 p.m. to midnight. As can be observed, in the case of phase B, the errors

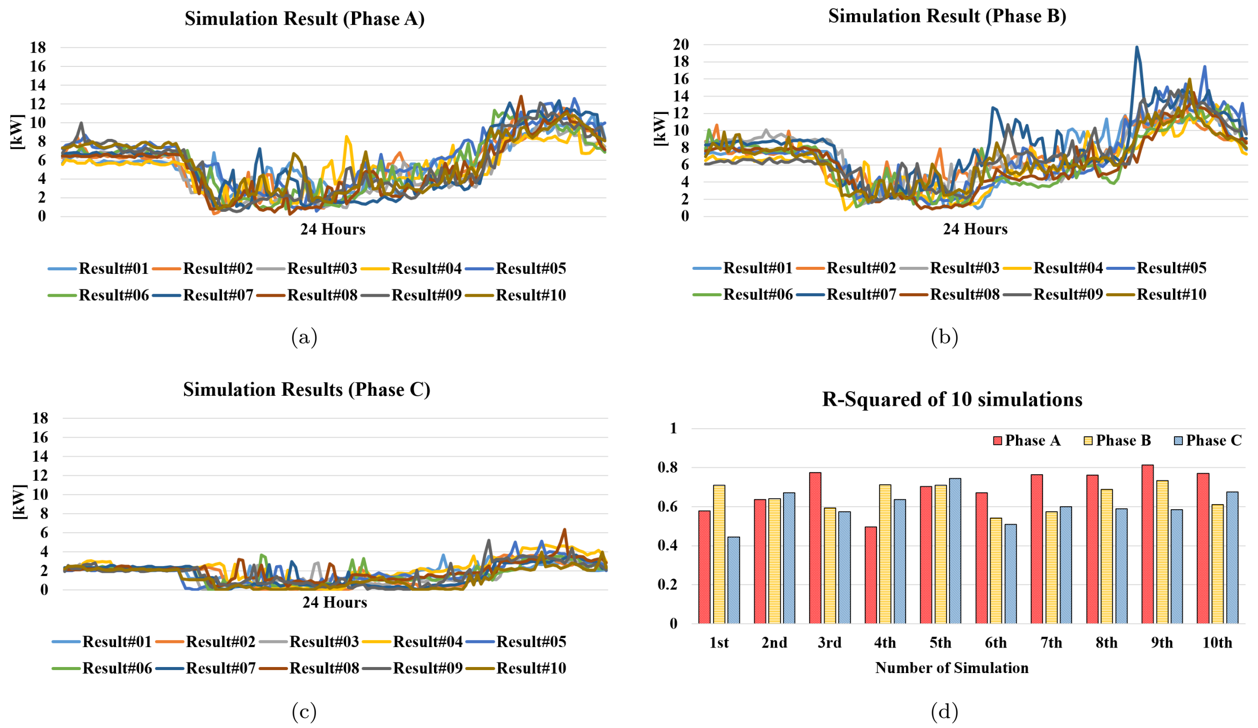


Fig. 7: *Synthetic aggregated domestic electricity demand profiles and value of R^2 for each phase of ten simulations.*

Table 4: *Number of occupants randomly assigned in each of the ten simulated dwellings.*

Phase	House no.	Simulation #1	#2	#3	#4	#5	#6	#7	#8	#9	#10
A	H01	4	5	2	3	3	4	1	3	3	1
	H07	3	5	4	2	2	4	3	3	5	4
	H09	3	4	3	4	4	5	2	4	2	4
	H10	3	2	3	4	5	3	3	5	2	2
	H11	4	1	1	1	4	4	2	1	4	1
	H12	4	4	4	4	4	4	4	5	2	5
	H18	4	3	4	3	1	2	5	4	3	2
	H19	1	4	4	3	4	2	2	4	3	5
B	H03	1	2	2	5	3	5	3	3	1	4
	H04	2	4	3	2	3	2	1	1	2	2
	H05	3	3	3	3	4	1	2	2	2	3
	H06	4	2	3	3	3	5	2	3	4	5
	H08	2	5	1	2	2	4	3	3	2	4
	H13	3	1	2	4	4	1	2	3	4	2
	H14	2	4	2	2	4	4	3	3	4	2
	H15	1	4	5	5	2	1	1	3	2	4
	H16	2	5	1	4	2	2	2	3	2	4
	H17	5	1	5	5	4	5	3	3	5	2
C	H02	4	5	2	4	5	5	2	4	3	3
	H20	4	3	5	3	1	2	1	2	5	2

between simulated and measured data are very high in the afternoon, but low during the evening. On the other hand, phase C has a high degree of errors from 6 p.m. to midnight. Moreover, the errors in phase A are relatively the same throughout the day.

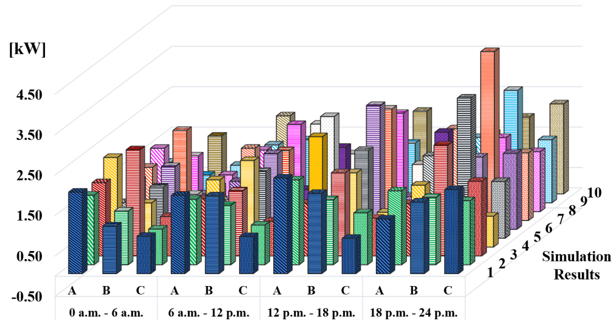


Fig. 8: *RMSE of each phase divided into four time periods with ten simulations.*

The degree of error between synthetic and measured data can be slightly reduced by averaging the electricity demand of each dwelling from the simulated datasets (10 sets per house in this work), as demonstrated in Fig. 9. Four different cases are examined: (1) using three datasets (first to third simulation), (2) using five datasets (first to fifth simulation), (3) using eight datasets (first to eighth simulation), and (4) using ten datasets (first to tenth simulation). When the number of simulated dataset increases, the degree of error in all three phases is reduced, especially for phase A. However, the total RMSE values for all three phases are not much

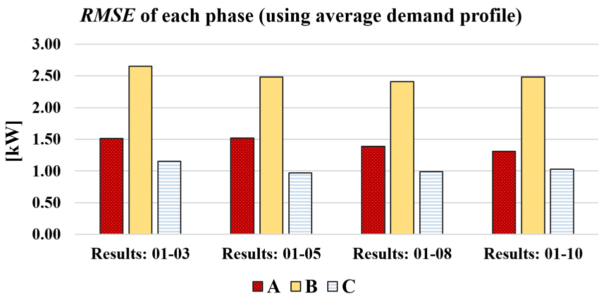


Fig. 9: *RMSE of each phase for each dwelling using the average demand.*

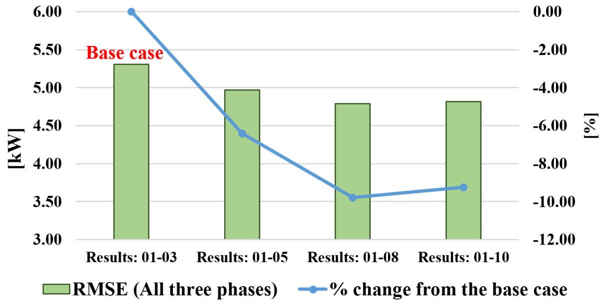


Fig. 10: *Total RMSE of all three phases and each percentage change from the base case.*

different when averaging the simulated data of each dwelling using eight and ten datasets, as can be seen in Fig. 10 .

Since recordable meters are not installed in individual houses for this test, the synthetic electricity demand profile of each dwelling, using the modified CREST demand model, is indirectly compared against the urban residential load profile collected by MEA in June 2016. The average MEA load profile for one month of medium consumption by residential customers on weekdays is chosen for validation. The average simulated data on electricity use for all 20 houses in the ninth simulation with the highest R^2 value (see Fig. 7(d)) is selected for indirect comparison, as illustrated in Fig. 11.

The data patterns of these two demands are quite similar, with high energy consumption in the evening and lower consumption during the day. Although the patterns of simulated and measured demand profiles follow the same trend, the simulated data on electricity consumption is about 50% lower than the average measured data during the day. In contrast, during the night, the simulated data for electricity demand is higher than the average measured data.

6. CONCLUSION

The high-resolution demand model by CREST shows promising simulation results, based on time use data, for the daily electricity demand profiles of Thai households. In this work, the information on

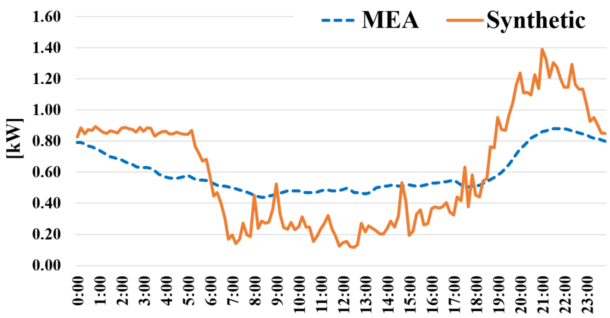


Fig. 11: *Comparison between simulated and MEA demand profiles.*

outdoor daylight characteristics is adapted to fit with Thailand's weather. The appliance configuration is modified using the population and housing census, to suit domestic dwellings in Thailand. Whereas the patterns of active occupancy, daily activities, and domestic lighting demand are still based upon the UK time use survey data. In Thailand, the air-conditioning unit is the key appliance influencing high consumption, especially during the night in the summer season. A daily activity profile of the air-conditioning unit is required to increase the accuracy of the domestic appliance use model. Furthermore, the time use survey data for Thailand should be employed in the CREST demand model, instead of the UK data, to improve the transition possibility matrices of the Markov chain technique, to create more realistic outputs for active occupancy and residential electricity use in Thailand.

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