Load Profiling of Singapore Buildings for Peak Shaving

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***Abstract*—This paper carries out load profiling of Singapore housing units and office buildings using bottom-up method for peak load reduction through optimization. Housing units in Singapore are classified according to the number of rooms, ranging from one to five. Average daily, monthly and yearly electrical usage of all these units is obtained. To explore the strategies for peak load reduction, a mathematical model based on bottom-up method is created. Statistical data - hourly probability factors, frequency of daily operations, saturation levels and nominal wattage of appliances - are gathered for typical Singapore households, and load profiles are generated. The accuracy of the bottom-up model is verified by comparing the load data of a typical three-rooms housing unit in Nanyang Technological University. Then, the problem of peak load reduction is formulated into an optimization problem with peak load as cost function and hourly probability factors of certain appliances as decision vaiables. Solution to the optimal hourly probability factors is obtained using genetic algorithm and it is demonstrated through numerical simulations that about 40% reduction in peak load can be achieved. Finally, some statistical information on load estimation for office buildings is presented.**

I. INTRODUCTION

Energy is one of the critical factors for the development of Singapore's economy in the immediate and long-term future. With increasing population and energy demand, researches are focusing on technologies like smart grid [1] to improve the energy utilization. One of the primary goals of smart technology is to achieve peak load reduction to minimize overall electricity consumption and use of expensive peaking plants [2]. For peak load reduction, a good understanding and estimation of customer load profiles is required. Load data is also crucial for planning electricity distribution networks and optimal production capacity. Since more than 90% of the energy is consumed by households and office buildings, load profiling of housing units is crucial to achieve peak load reduction.

Optimal load scheduling and autonomous control of appliances are some of the promising solutions to achieve peak load reduction [3]. To design algorithms for these, it is important to know the contribution of individual appliances to the overall load. Measurement of total energy consumption in a building can be easily obtained through meter readings and it is not at all difficult. However, the load consumption of individual appliances is difficult to know and is also costly to be measured [4]. Bottom-up method provides a statistics based mathematical model to carry out load profiling and analyze the contribution of individual appliances [5], [6].

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In this paper, bottom-up method is used to carry out the load profiling of Singapore housing units. Statistical information of appliances like saturation levels, frequency and time cycles of operations, etc., are gathered and a load profiles are generated for an average Singapore household. The accuracy of the bottom-up model is verified by comparing the computed loads with the available load measurements. The contribution of individual appliances to the peak load is identified. The problem of peak load reduction is formulated into an optimization problem with peak load determined by bottom-up method as objective to be minimized and hourly starting probability factors of certain appaliances as decision variables. Using a derivative-free optimization solver - genetic algorithm - the optimal hourly probability factors are computed. Through numerical simulations, the load profiles with optimal hourly probabilities and nominal hourly probabilities are computed and compared. It is shown that around 40% reduction in peak load can be achieved.

The following paper is organized as follows. In Sec. II, observed load profile of Singapore households, overview of bottom-up method for simulating load profiles and its application to Singapore housing units are presented. Sec. III presents an optimization approach and its solution procedure for achieving peak load reduction. Sec. IV presents the mathematical model of load estimation for Singapore's office buildings. Finally, the paper ends with some concluding remarks in Sec. V.

II. LOAD PROFILING OF HOUSING UNITS

A. *Observed Load Profile*

The average daily, monthly and yearly data of Singapore's residential electricity usage can be obtained from Energy Market Authority's (EMA) official website [7]. Based on the statistics published by EMA, the public housing can be distinguished into 1 or 2 rooms type, 3 rooms type, 4 rooms type and 5 rooms type, with an average monthly electricity consumption of 148.6 kWh, 277.8 kWh, 387 kWh and 472 kWh, respectively. Hourly data of average electricity usage is usually not available for whole Singapore. Small-scale data could be obtained from the prototype monitoring facility at Nanyang Technological University, developed during a research project. The facility has electricity usage data of 320 housing units, recorded every 30 mins. since June 2012. Average load profile of a random day, 26-FEB-2012, is shown in Fig. 1.

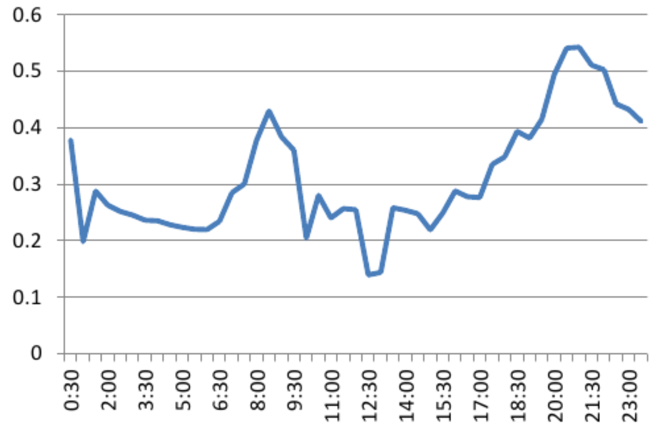

Fig. 1. Average load profile in NTU on February 26, 2012.

According to the NTU monitored data, the average daily load per unit is 220kWh/Day. Comparing with the EMA statistics, this amount is close to the average of three-room public housing load which is 255.4kWh/Day. It is also a fact that majority of the monitored units in NTU are three rooms type. This observation implies that the load profile of households in NTU complies with the average statistics of Singapore. From Fig. 1, it can be observed that there are two electricity load peaks, one between 07:30 and 08:30, and another between 20:30 and 21:30. The load is relatively low in the early morning between 09:30 and 17:30 in a day. This is fairly reasonable as activities involving electricity are more when people are at home in the morning and evening.

B. Influence of Ambient Temperature

The average load consumption in a day depends on various factors like ambient temperature, weather, humidity, season, etc. Among all, temperature is considered to have significant effect on load consumption. To observe the relation between these two, average monthly electricity usage of public and private housing and ambient temperature are plotted in Fig. 2.

From Fig. 2, it can be seen that the average electricity consumption and temperature follow the same trend. Peak electricity usage is observed during the month of June when the temperature is also at its peak. Similarly, low electricity usage is observed during the month of January when the temperature is low. However, the fluctuation of the energy consumption between peak and bottom is only around 50 kWh which is not considered as a very significant change. This is because of the characteristic of Singapore's climate, which is tropical marine climate with a relatively stable temperature throughout the year. Therefore, it can be considered that the effect of temperature on electricity usage is insignificant in Singapore.

C. Bottom-up Method

The data obtained from NTU monitoring facility provides information only regarding average electricity usage. There

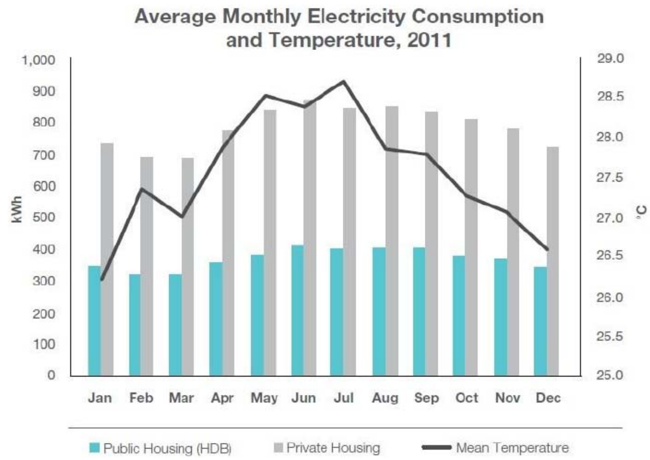

Fig. 2. Average monthly electricity consumption and temperature.

is no information on how the domestic electricity load is composed by different electricity appliances in an individual household. To generate a hourly load profile, bottom-up method is used [5], [6]. Bottom-up approach uses statistical data for simulating households' electricity consumption. In this approach, the total load in the building is built up from the elementary load components, which can be a single household or even a single piece of appliance. The advantage of bottom-up approach is that it can analyze every individual appliance' effect on the total load, which could be quite helpful in the future study of smart grid. The logic of this approach is shown in Fig. 3. The point of entry to the procedure is marked with a large triangle pointing towards the next block. The exit point is marked with a large triangle pointing out. The parts including computational loops have two exit arrows, one with solid line and one with dashed line. The solid line points into the repeating loop itself and the dashed line points into the following step as the loop exits.

When the type of the household is given, the appliance load curve loop is activated. The set of appliances used are defined statistically. The hourly power consumed by the individual appliance is estimated and fed back into the overall household load curve to generate a total household load by accumulating all individual appliance load curve. The "Appliance load curve generation loop" generates the load curve for one day period for one particular appliance. The "Household Load Curve Generation Loop" repeats the process until all appliances in the house are counted.

The list of appliances varies in different households. Therefore, a coefficient called saturation level is introduced. Mathematically, saturation level is the probability of finding an appliance in a household. For example, if an appliance can be found in 50 households among a total of 100 households, the appliance' saturation level is 0.5. When an appliance is activated, the rated load of the appliance will be added into the household's electricity consumption at the corresponding time until it completes a full cycle of a single activation.

When every piece of appliance in the unit is considered, a daily load profile can be drawn by summing up the individual appliance' consumption. An appliance can be activated at any time and multiple times in a day. A starting probability func-

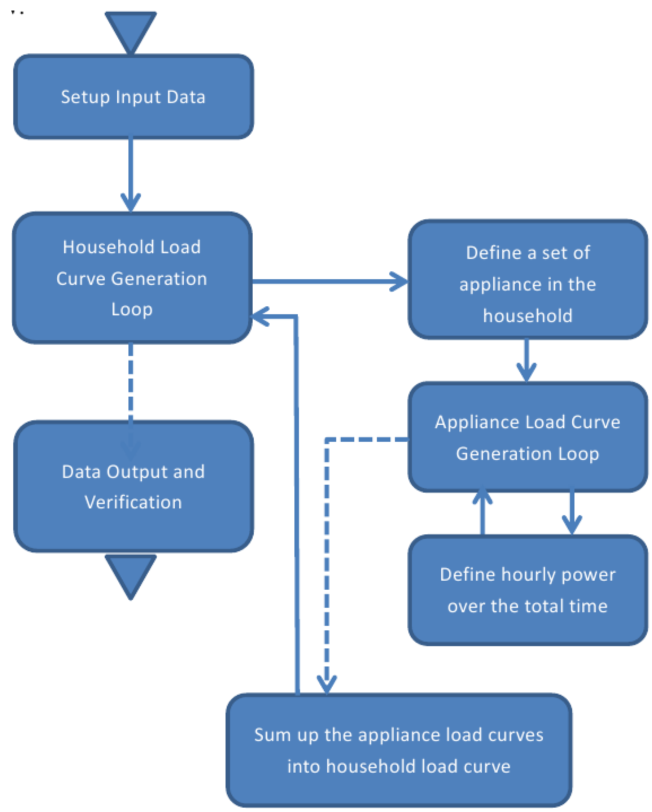

Fig. 3. Flowchart for the Bottom-up Method.

tion P_{start} is introduced to help determine when an appliance will be activated. P_{start} is defined for each time step and it receives a value between 0 and 1. The value of P_{start} various through a serious of calculation. When the appliance is off, the turning on is checked using P_{start}. Activation occurs when P_{start} is larger than a randomly generated number between 0 and 1 by computer. Then, the consumption cycle of the appliance will be added to the household's total load curve. When the end of one consumption cycle is met, the appliance is turned off and the checking for starting the appliance will carry on again. Starting Probability function P_{start} is calculated by the following equation [8]:

$$P_{start} = P_{hour}(A,h)f(A,d)P_{step}(\Delta t_{comp})P_{sat}(A) \quad (1)$$

where A is the appliance, Δt_{comp} is the computational time step, h is the hour of the day, P_{sat} is the appliance saturation level, P_{hour} is the hourly probability factor which models the activity levels of the appliance during a day, f is the mean daily starting frequency, d is the time-cycle of appliance A and P_{step} is the step size scaling factor which scales the probabilities according to Δt_{comp}.

A random number between 0 and 1 is generated and compared with P_{start} at the beginning of each computational time step. If P_{start} wins the comparison, the appliance is turned on. When the time of the on-cycle is reached, i.e., $t = t_{start} + t_{cycle}$, the appliance is turned off and starts to check for the next turn on using the same method. If an appliance has standby electricity use, it will be added to the whole load curve continuously, for example, refrigerator and TV. t_{cycle} is the average on-cycle for an appliance. The daily average energy consumption by a household can be calculated by active and standby consumption parameters using the following formula [8]:

$$E = \frac{\left[3600 P_{standby} + f \sum_{n=1}^{n_{cycle}} P_{cycle,n} t_{cycle,n}\right] 30}{3600000} kWh/month \quad (2)$$

D. Load Profiling

To generate load profiles for a household, the list of appliances and their saturation levels is considered as given in the Table I. Details of the power consumption data is given in Table II. The appliances average daily starting frequency and time per cycle is presented in Table III. Hourly probability factors are obtained from Ref. [8] and are presented in Table IV.

TABLE I. APPLIANCE' LIST AND THEIR SATURATION LEVELS.

Appliance	Saturation Level
Microwave oven	0.93
Refrigerator	1
2nd Refrigerator	0.15
Coffee Maker	0.34
Range Oven	0.42
Clothes-washer	0.97
TV	1
2nd TV	0.21
Play station	0.26
Computer	0.92
Air Conditioning	0.88
Hair dryer	0.93
Lighting	1

TABLE II. APPLIANCE' LIST AND THEIR POWER CONSUMPTION.

Appliance	Nominal Wattage (W)	Standby Wattage (W)
Microwave oven	1500	N.A.
Refrigerator	110	8.1
2nd Refrigerator	110	8.1
Coffee Maker	1000	N.A.
Range Oven	1050	8
Clothes-washer	1200	N.A.
TV	105	4
2nd TV	83	4
Play station	96	4
Computer	110	2.5
Air Conditioning	1300	N.A.
Hair dryer	1600	N.A.
Lighting	120	N.A.

TABLE III. APPLIANCE' LIST AND THEIR AVERAGE DAILY STARTING FREQUENCY AND TIME PER CYCLE.

Appliance	Mean daily frequency (f)	Time per cycle (min)
Microwave oven	5	5
Refrigerator	40.5	12
2nd Refrigerator	40.5	12
Coffee Maker	0.76	6
Range Oven	0.46	12
Clothes-washer	0.36	54
TV	1.62	90
2nd TV	0.28	60
Play station	0.3	60
Computer	2.5	60
Air Conditioning	1.36	120
Hair dryer	1.46	7
Lighting	10	30

Using the data presented in Tables I, II, III and IV, and simulating the bottom-up method presented in the previous subsection, average load profile of households is obtained as shown in Fig. 4.

TABLE IV. APPLIANCE' LIST AND THEIR HOURLY PROBABILITIES.

Appliance	Hourly Probability Percentage Factor P_{start}							
	1	2	3	4	5	6	7	8
Microwave oven	0.37	0.05	0	0	0	0.17	1.72	2.55
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Coffee Maker	0.37	0.05	0	0	0	0.17	1.72	2.55
Range Oven	0.37	0.05	0	0	0	0.17	1.72	2.55
Clothes-washer	0.5	0	0	0	0	0	0	0.7
TV	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46
2nd TV	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46
Play station	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46
Computer	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46
Air Conditioning	2.55	1.33	1.23	1.23	1.33	1.73	2.13	3.55
Hair dryer	3.4	1.94	0.87	0.77	0.87	0.97	11	9.46
Lighting	2.55	1.33	1.23	1.23	1.33	1.53	2.13	4.05

Appliance	Hourly Probability Factor P_{start}							
	9	10	11	12	13	14	15	16
Microwave oven	4.14	5.94	6.97	7.66	7.92	7.15	6.39	5.89
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Coffee Maker	4.14	5.94	6.97	7.66	7.92	7.15	6.39	5.89
Range Oven	4.14	5.94	6.97	7.66	7.92	7.15	6.39	5.89
Clothes-washer	2	4.61	7.02	7.23	7.23	7.34	7.34	7.34
TV	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8
2nd TV	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8
Play station	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8
Computer	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8
Air Conditioning	4.07	3.99	3.77	3.97	4.07	4.47	4.97	6.03
Hair dryer	2.43	3.4	1.88	1.85	2.85	1.93	1.13	1.8
Lighting	3.07	3.99	3.27	2.82	2.57	3.27	3.97	3.5

Appliance	Hourly Probability Factor P_{start}							
	17	18	19	20	21	22	23	24
Microwave oven	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Coffee Maker	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Range Oven	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Clothes-washer	7.43	7.43	7.74	7.74	7.43	6.12	3.9	0.9
TV	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.87
2nd TV	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.87
Play station	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.87
Computer	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.87
Air Conditioning	6.32	6.84	7.34	7.56	6.79	6.67	4.84	3.22
Hair dryer	3.8	4.8	7.77	8.25	6.8	5.34	4.85	3.87
Lighting	6.02	7.69	8.34	8.56	8.64	8.17	6.49	4.25

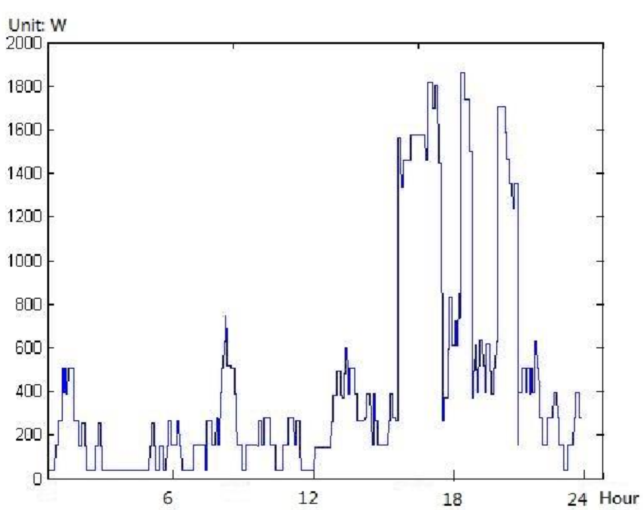

Fig. 4. Load profile of a one room unit computed using bottom-up method.

A total monthly power consumption of 347.7 kWh is simulated, which is around the average monthly public housing electricity sales as given in Ref. [9]. From Fig. 4, it can be seen that there is a small peak in the morning at around 8:00 am, followed by low load until around 4:00 pm in the afternoon. A much higher load occurs between 4:00 pm and 10:00 pm.

III. PEAK SHAVING

The peak load determined by bottom-up method is a function of hourly probability factors, frequency of daily operations, saturation levels and nominal wattage of all appliances. To solve the peak shaving problem as an optimization problem, parameters that can be varied, needs to be identified. Factors like frequency of daily operations, saturation levels and nominal wattage of appliances are fixed, and therefore, cannot be altered. The only available factors, which can be modified are the hourly probability factors. By changing the hourly probabilities, the times at which loads can be scheduled get modified and the resulting load history gets affected. If the hourly probabilities can be modified in a way such that the peak load can be reduced, it can result in peak shaving. To achieve maximum reduction in peak load, the peak shaving problem is formulated into an optimization problem.

Among the appliances listed in Table III, units like refrigerators, which operate continuously throughout the day, have fixed hourly probabilities, and cannot be varied. Air conditioning unit, which has high load consumption and operates for a sufficiently long amount of time, is critical for thermal comfort, and therefore cannot have its probability factors changed. The remaining appliances can be scheduled at different times in a day and therefore have their probabilities changed. Even though requirements may arise for some of these appliances to be operated during peak load times, their low power consumption and short operational times make their loads get compensated either from an energy storage device like battery or by temporarily suspending the air conditioning unit.

The peak shaving problem is solved as an optimization problem, with peak load as cost function and probability hour factors as parameters. The cost function can be expressed mathematically as

$$J = \min_{p_{h,A}} P_{\max} \tag{3}$$

where $p_{h,A}$ is the hourly probability factors' vector, h and A denote time and appliance, respectively, and $P_{\max}$ is the peak load.

Since the sum of hourly probability percentage factors must be equal to 100, it can be expressed in the form of following constraint

$$\sum_{h=1}^{24} p_{h,A} = 100 \quad \text{for all } A \tag{4}$$

With the cost function and constraints defined, solution to the probability factors can be computed by any nonlinear programming solver [10]. Due to the stochastic nature of the cost function, the gradient of the cost function with respect to hourly probabilities doesnot remain constant and therefore, derivative-dependent methods like sequential quadratic programming [11] or interior point algorithms [12], [13] cannot be used. Instead, derivative-free and heuristic methods like using genetic algorithm [14] or particle swarm optimization [15] can be used. In this case, the problem is solved using the genetic algorithm solver available in MATLAB software.

The actual cost function given by Eqn. (3) has the problems of solution being trapped in a local minima or have unexpected peaks occasionally. To address these problems, the cost function during numerical optimization is slightly modified. During the evaluation of cost function, around 10 load profiles are computed for the same set of parameters, and then summed and averaged. Peak load of the averaged load profile is treated as the actual cost function. The modified cost function can be mathematically expressed as

$$J = \min_{p_{h,A}} \left[\max \sum_{i=1}^{n} P_i / n \right] \tag{5}$$

Solution to the optimization problem is attempted with a population size of 50. During reproduction, two of the individuals/chromosomes with best fitness are considered elite, and are not changed. 38 of the children are reproduced from crossover and the remaining from mutation. Convergence to the optimal solution is achieved within 10 to 15 iterations. The computed probability factors are presented in Table V. Load profiles of nominal and optimized probability factors, computed using bottom-up method are plotted in Fig. 5. From the two profiles, it can be seen that peak load computed with nominal probability factors is significantly higher than the peak load computed with optimized probability factors. Around 40% reduction in peak load can be observed.

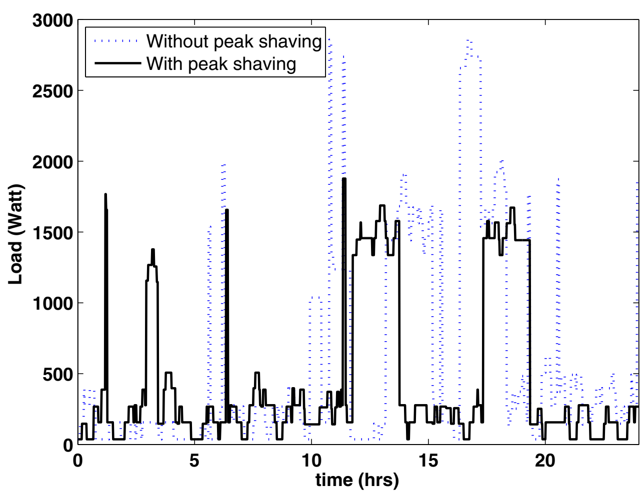

Fig. 5. Load profiles computed using bottom-up method before and after peak shaving.

IV. Load Estimation for Office Buildings

Usually, the space in office buildings is used for rendering services like agency, commission, banking, administrative, legal, architectural, engineering and other professional services. The office building energy consumption consists of two components: landlord's consumption and tenants' consumption.

TABLE V. Appliance' list and their optimized hourly probabilities.

Appliance	Hourly Probability Percentage Factor P_{start}							
	1	2	3	4	5	6	7	8
Microwave oven	2.77	4.39	5.98	4.60	2.48	5.07	4.07	2.57
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Coffee Maker	3.51	4.32	3.77	4.25	4.05	3.44	4.53	5.13
Range Oven	3.15	5.33	3.50	2.26	3.72	5.79	4.40	5.95
Clothes-washer	4.12	8.16	3.93	3.67	3.51	3.54	4.64	2.74
TV	5.58	2.10	3.19	2.76	3.49	4.20	3.55	2.95
2nd TV	4.52	3.15	4.84	2.98	2.99	4.41	4.92	4.05
Play station	4.14	6.30	3.78	4.06	3.91	5.17	5.39	2.92
Computer	0.78	3.41	7.35	2.63	2.92	1.47	2.36	3.24
Air Conditioning	2.55	1.33	1.23	1.23	1.33	1.73	2.13	3.55
Hair dryer	3.42	3.06	4.57	2.99	5.25	4.69	3.84	3.04
Lighting	3.39	4.24	5.44	3.58	4.58	5.58	4.49	3.91
Appliance	Hourly Probability Factor P_{start}							
	9	10	11	12	13	14	15	16
Microwave oven	5.34	3.92	2.90	4.92	3.66	6.04	4.13	3.33
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Coffee Maker	3.65	4.03	4.65	3.41	3.68	3.55	6.25	4.42
Range Oven	1.99	5.50	7.77	4.23	4.23	2.53	4.91	3.10
Clothes-washer	3.43	4.14	4.60	4.14	4.01	5.24	4.13	5.16
TV	4.02	3.73	4.98	4.09	4.85	4.35	4.52	5.40
2nd TV	6.64	5.42	4.46	2.25	3.62	4.31	3.92	4.78
Play station	4.80	3.26	4.15	3.69	3.63	4.44	4.47	5.03
Computer	2.97	3.15	2.66	1.32	1.20	1.78	3.38	3.46
Air Conditioning	4.07	3.99	3.77	3.97	4.07	4.47	4.97	6.03
Hair dryer	4.25	3.61	3.20	5.16	3.71	3.74	5.21	3.84
Lighting	3.77	4.29	3.68	4.29	4.61	4.38	3.75	3.93
Appliance	Hourly Probability Factor P_{start}							
	17	18	19	20	21	22	23	24
Microwave oven	3.77	8.64	3.28	2.97	3.42	3.24	4.62	3.90
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Coffee Maker	3.72	4.06	4.87	5.88	3.47	2.92	6.03	2.42
Range Oven	4.35	3.02	4.45	2.40	4.44	4.14	4.55	4.30
Clothes-washer	4.10	3.59	3.31	4.05	3.67	3.58	4.36	4.19
TV	3.07	4.63	5.89	2.63	4.48	6.92	5.26	3.38
2nd TV	5.41	5.05	2.83	4.58	3.60	4.28	3.63	3.39
Play station	3.95	3.13	3.80	3.64	4.96	2.35	5.34	3.72
Computer	1.68	2.51	2.76	2.79	2.52	2.89	38.46	2.32
Air Conditioning	6.32	6.84	7.34	7.56	6.79	6.67	4.84	3.22
Hair dryer	4.58	5.22	5.00	5.90	4.99	5.66	0.75	4.33
Lighting	3.99	3.66	4.17	4.61	3.15	4.74	4.00	3.77

The landlord's consumption includes the following items:

1) Vertical transportation service
2) Central Air conditioning system;
3) Artificial lighting system in common area
4) Ventilation system

The tenants' energy consumption includes the following items:

1) Artificial light system
2) Office equipment
3) Miscellaneous electrical appliances

The main thrust for load profiling of office buildings is to establish a correlation between energy consumption and operational factors in office buildings. The benchmarking studies in Ref. [16], [17] examined all the available independent building parameters like height, age, story height, occupancy rate and building system parameters, such as the chiller's COP and lighting load, etc., for their influence on building energy consumption. The regression analysis showed that no conclusive correlation exists between the building energy and parameters except ground floor area (GFA). It is found that a linear relation exists between these two as given in the following equation

$$y = 195.79x + 154.09 \tag{6}$$

For buildings with less than 10% of the GFA allocated to retail outlets, the relation was obtained as [18]

$$y = 245.52x + 601.1 \tag{7}$$

In both these equations, y is the electricity consumption and x is the GFA. Clearly, it can be seen that with increase in GFA, electricity usage increases.

V. Conclusions

Average daily, monthly and yearly load profiling of one/two, three, four and five rooms type Singapore housing units is carried out. The average daily electrical consumption increases with increase in number of rooms. Variation of average monthly electrical usage and ambient temperatures are insignificant, and they both show the same trend. Hourly load profiling of households is carried out using bottom-up approach. Bottom-up method provided a suitable mathematical framework to monitor different appliances' contribution to the overall load. Using this method, an optimization based framework is designed to determine the hourly starting probability factors of certain appliances to minimize the peak loads. Statistical information on load estimation for office buildings based on GFA is presented.

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