TOTAL UTILITY DEMAND PREDICTION FOR MULTI-DWELLING SITES CONSIDERING VARIATION OF OCCUPANT BEHAVIOR SCHEDULES

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ABSTRACT
Based on the authors' previous works, this paper describes a new methodology that uses a bottom-up approach for accurately calculating the time series utility loads (e.g., energy, power, city water, hot water, etc.) for multi-dwelling systems, including residential buildings, residential block areas, and even the entire city. This calculation considers the behavioral variations of the inhabitants of the dwellings. The proposed method constitutes a procedure for calculating cooling/ heating loads based on a series of Monte Carlo simulations where the HVAC on/off state and the indoor heat generation schedules are varied at a time interval. A data set of time-varying inhabitant behavior schedules with a 15-minute time resolution was integrated into the model. The established model, which is called the Total Utility Demand Prediction System (TUD-PS), was integrated to estimate a multi-dwelling system, where we can accurately predict various peak demands and seasonal or annual demands. By applying this method to a typical residential building, we highlighted several advantages of TUD-PS.

KEYWORDS
Total utility demand prediction, High time resolution, Probabilistic inhabitants' behavior schedule, Probabilistic HVAC turning on/off events, Multi-dwelling residential building

1. INTRODUCTION

The cogeneration system (CGS) is widely accepted as one of the most effective provisions in achieving high efficiency in building energy conservation, leading to reduced CO_2 emissions. Recent developments in compact CGSs such as fuel cell and gas engine systems have encouraged rapid dissemination in the residential building market. We call such compact CGSs as home cogeneration systems. To achieve a greater prevalence, a high time resolution prediction is required for both power and thermal demands to derive the most efficient operation and the most effective designs because CGSs provide power and hot water simultaneously.

The authors have developed Total Utility Demand Prediction System (TUD-PS) as a novel framework for predicting high time resolution utility demands in a dwelling, considering various stochastic processes such as the inhabitants' behavior schedule and meteorology. As reported in previous BS** (Tanimoto et al. (20081,b,c), Tanimoto & Hagishima (2005, 2010, 2011)), TUD-PS can examine the building thermal system model and the stochastic inhabitant behavior schedule model simultaneously in the form of a dynamic numerical prediction system for utility loads such as thermal load, power, gas, water, and hot water demand with a 15-minute time resolution. By comparing field measurement data sets obtained from a couple of residential buildings, we have already validated how appropriately TUD-PS can reproduce the bottom-up demands. (Tanimoto et al. (20081,b,c)).

In general, a residential space has a greater hot water demand than an office space. But actual demand varies substantially among different dwellings because it is affected by the daily schedules of its inhabitants, showing typical stochastic features. Hence, simply multiplying the predictions for a set of dwellings such as a residential building, a residential block, or even a city area by assuming a "standard dwelling" and a "standard schedule" seems inappropriate. Such a procedure leads to unrealistic and over estimated peak values. Using TUD-PS, one can predict the utility demands of any residential building or area accurately with a high time resolution by superposing the respective dwellings through Monte Carlo simulation.

There have been several precursors on the point of the bottom-up approach. Capasso et al. (1994) and Patero & Lund (2006) established bottom-up methods for predicting the daily electric power demand profile for a given dwelling, both of which were validated by field data measurement. Armstrong et al. (2009) demonstrated another bottom-up approach to correctly predict Canadian household electric power demand profiles. Unlike TUD-PS, those works does not consider the stochastic likelihood of whether HVAC in each room is turning on or off according to the indoor and outdoor environment, which might in turn affect how frequently the occupants want to use HVAC.

This paper reports the effectiveness of TUD-PS when applied to an entire residential building consisting of 100 independent dwellings and where only the HVAC heat pump system is presumed to function for space heating and cooling; specifically, it focused on the maximum demands of the entire building. The study shows that the central supplying system for electric power and hot water can remarkably reduce the maximum demands as a whole and that stochastic prediction is necessary and important when considering varying occupants' behavior schedules.

2. TUD-PS

Since most of the framework of TUD-PS was summarized in our previous paper (Tanimoto & Hagishima (2010)), we will begin by simply providing an overview of the features and newly updated functions of TUD-PS. First, TUD-PS reproduces a raw daily behavior schedule of each inhabitant classified by his/her attributes (e.g., age, sex, profession) with a 15-minute time resolution. The daily personal schedule, which is different from a day-to-day schedule because of its stochastic substance, determines when an individual stays in the dwelling, in which room she/he is, and how much electric power and city water she/he uses, because the individual's activity every 15 minutes can be assumed to consume unit power of the utilities used. By accumulating data for all family members in each room and dwelling, daily time series of power demands for lighting, electric household appliances other than HVAC, domestic hot water, and city water are predicted. Concerning electric power demand for HVAC, TUD-PS predicts thermal cooling or heating load for each room based on the dynamic calculation with a 15-minute time resolution. For example, in a calculation procedure for a typical dwelling having 3LDK (two bedrooms, one Japanese Tatami room, and a living and dining room with kitchen (LDK)), TUD-PS solves a set of simultaneous heat balance equations with 159 unknown variables. In the process, indoor anthropogenic heat gain derived from both electric appliances and human bodies is considered. Regarding how the HVAC turns on and off, a stochastic model with Markov chain (Tanimoto & Haghisma (2005)) is applied to both heating and cooling, where two transition states, HVAC off-to-on and on-to-off, function depending on the indoor global temperature and outdoor air temperature to determine whether the next state is on or off, although we have a newly developed and more

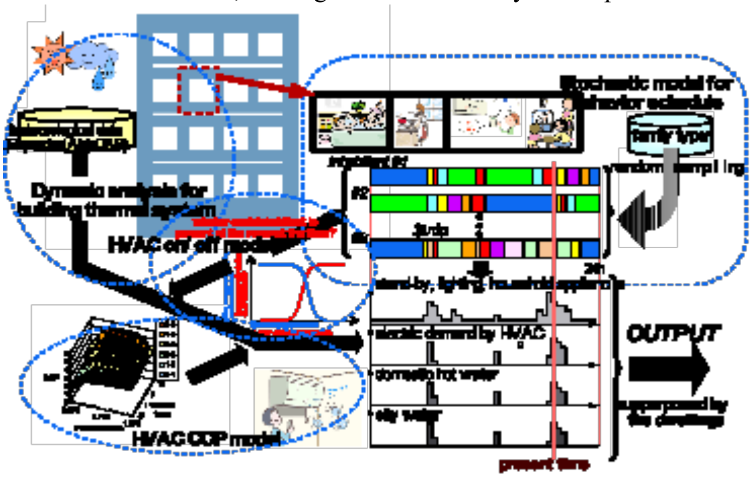

***Figure 1**. Holistic framework of*

Table 1. *COP characteristics assumed for the present study.*

$$COP = COP_{rat} \times f_{part} \times f_{temp}$$

i) Partial load factor

$$f_{part} = \begin{cases} \mathrm{Max}\left(L / L_{med}, 0.1\right) & \text{if } L < L_{med} \\ 1 & \text{if } L_{med} \le L \le L_{rat} \\ \mathrm{Max}\left(1 - 0.2 \cdot \dfrac{L - L_{rat}}{L_{\max} - L_{rat}}, 0.8\right) & \text{if } L_{rat} < L \end{cases}$$

ii) Outdoor temperature factor

f_{temp} when heating

	$T_{out} \le 2$	$2 < T_{out} \le 7$	$7 < T_{out} \le 12$	$12 < T_{out}$
$L \le L_{med}$	0.65	0.82	1.00	1.18
$L_{med} < L < L_{rat}$	$0.65 + 0.05 \cdot \frac{L - L_{med}}{L_{rat} - L_{med}}$	0.82	1.00	1.18
$L = L_{rat}$	0.70	0.82	1.00	1.18
$L_{rat} < L < L_{\max}$	$0.79 + 0.19 \cdot \frac{L - L_{rat}}{L_{\max} - L_{rat}}$	$0.82 + 0.14 \cdot \frac{L - L_{rat}}{L_{\max} - L_{rat}}$	1.00	$1.18 - 0.14 \cdot \frac{L - L_{r}}{L_{\max} - l}$
$L_{\max} \le L$	0.89	0.96	1.00	1.04

f_{temp} when cooling

	$T_{out} < 25$	$25 \le T_{out} < 35$	$35 \le T_{out}$
$L \le L_{med}$	1.00	1.16	1.30
$L_{med} < L < L_{rat}$	1.00	1.16	1.30
$L = L_{rat}$	1.00	1.16	1.30
$L_{rat} < L < L_{\max}$	1.00	$1.16 + 0.12 \cdot \frac{L - L_{rat}}{L_{\max} - L_{rat}}$	$1.30 - 0.23 \cdot \frac{L - L_{rat}}{L_{\max} - L_{rat}}$
$L_{\max} \le L$	1.00	1.04	1.07

$L_{\max}$: Maximum capability [kW], L_{rat}: Rating capability [kW], L_{med}: Medial capability [kW], L: Demanded load [kW], COP_{rat}: Rating COP, f_{part}: Partial load factor, f_{temp}: Outdoor temperature factor, T_{out}: Outdoor temperature [°C]

Fundamental capabilities of air conditioners assumed in the study

Recommended upper floor area	Cooling Rating output [kW]	Cooling Maximum output [kW]	Cooling Rating COP	Heating Rating output [kW]	Heating Maximum output [kW]	Heating Rating COP
6-jou (9.9 m^2)	2.2	3.3	5.5	2.5	6.1	6.25
8-jou (13.2 m^2)	2.5	3.5	5.1	3.5	6.2	5.95
12-jou (26.4 m^2)	5.5	5.8	3.52	6.0	9.5	4.76

accurate stochastic model for cooling, which is based on multi-layer neural network (Tanimoto & Hagishima (2011)). In this study, we assume a series of heat pump systems powered by electricity, where three sizes of capacity, 6-, 8-, and 10-Jou classes, are available (a Jou is a unit of area in a Japanese Tatami room; 1 Jou = 1.65 m^2). The COP characteristic of the heat pumps for both cooling and heating is defined in Table 1, which is a modified version of Tanaka & Hosoi (2006)'s model. Here partial load factor and outdoor air temperature affect COPs of cooling and heating.

HVAC temperatures for cooling and heating are 26°C and 20°C, respectively. Irrespective of the inhabitants' activities, HVAC is compulsorily terminated immediately after over-heating/cooling, which implies that more heating/cooling load is required when reaching a temperature higher/lower than 20°C/26°C.

Figure 1 shows a schematic concept of TUD-PS for a multi-dwelling.

Table 2. *Fourteen family types considered for the study.*

Family type #	Number of family members	Members
1	3	Working male, Housewife, Child#1
2	3	Housewife, Child#1, Child#2
3	3	Working male, Housewife, Child#2
4	4	Working male, Housewife, Child#1, Child#1
5	3	Working male, Working female, Child#1
6	4	Working male, Housewife, Child#1, Child#2
7	5	Working male, Housewife, Child#1, Child#1, Child#1
8	6	Working male, Housewife, Child#1, Child#1, Child#1, Senior female
9	2	Working male, Working female
10	2	Senior male, Senior female
11	3	Working male, Working female, Child#3
12	3	Working male, Housewife, Child#3
13	1	Working male
14	1	Working female

Child#1: elementary school age, Child#2: secondary school age, Child#3: high school age.

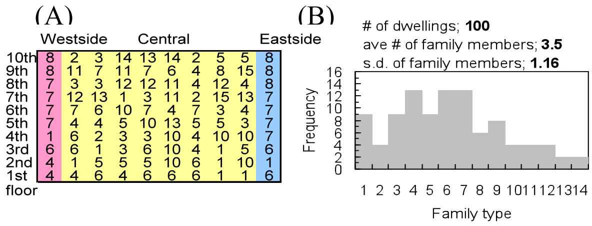

Figure 2. *Assignment of family type in each dwelling in the building (A), and frequency (B).*

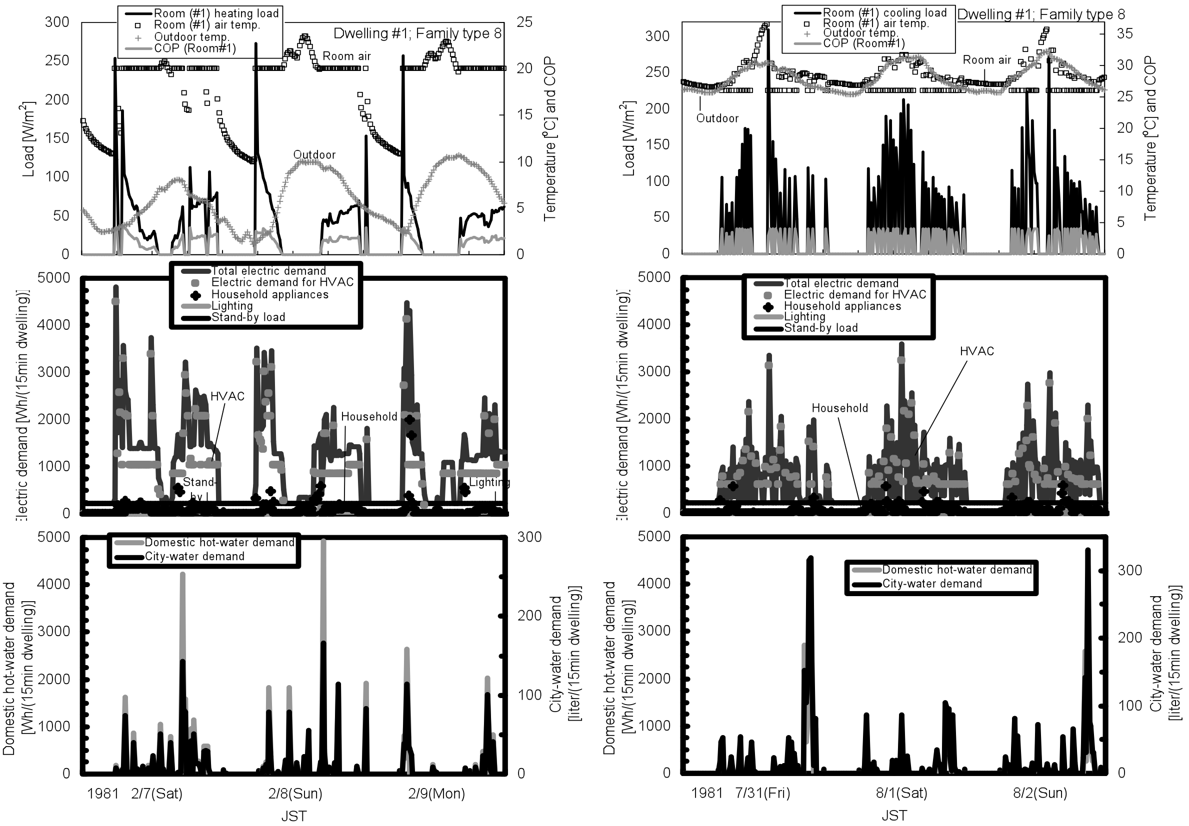

Figure 3. *Detailed time series output of three consecutive days of winter and summer at the west-side dwelling of the top floor occupied by family type #8. See the text for details about each panel.*

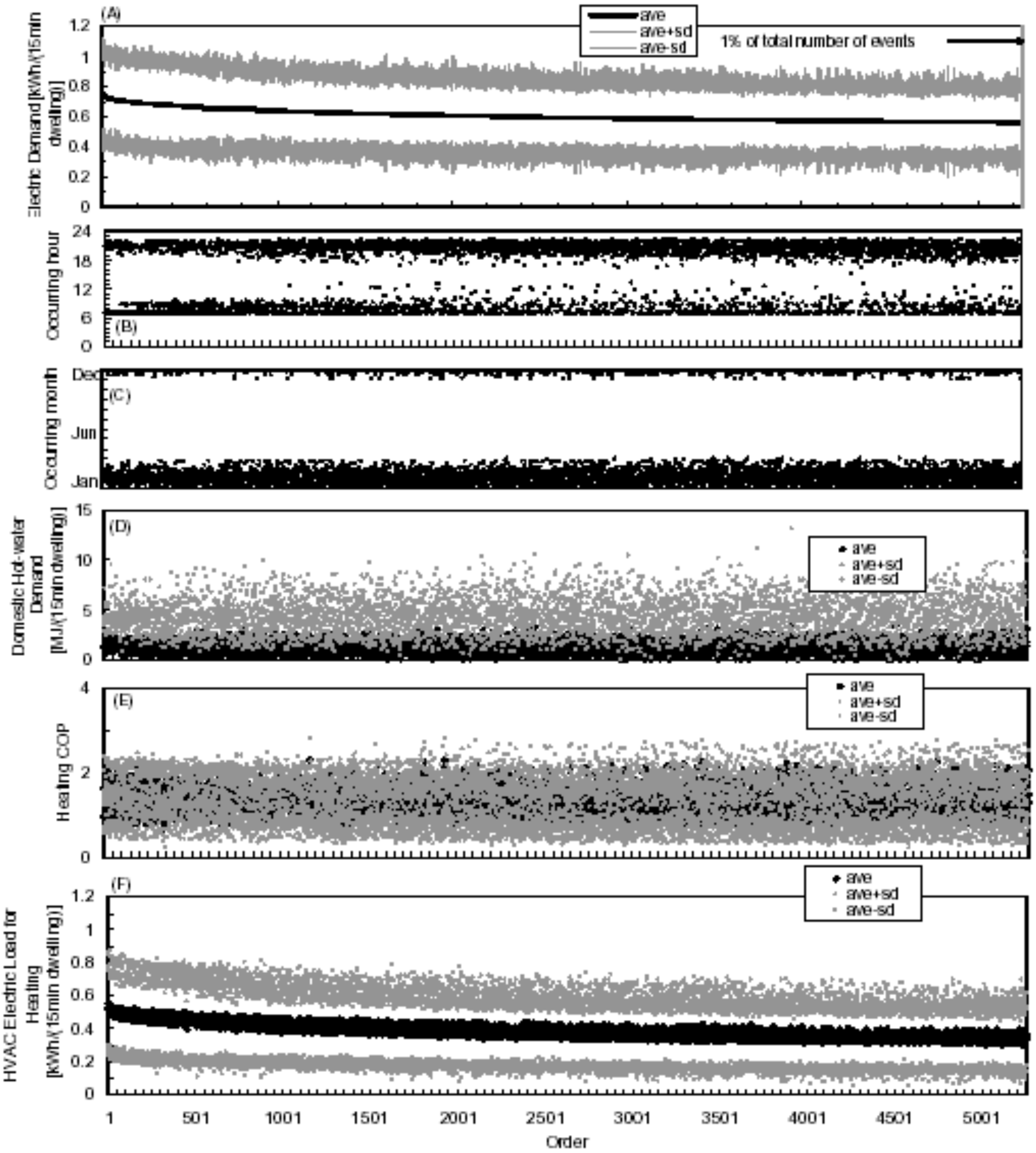

Figure 4. *Sorted total electric power demand of the entire building (A) with occurring time (B) and date (C), hot water demand (D), heating COP (E), and heating electric power (F).*

3. SIMULATION SETTING

As in our previous study (Tanimoto & Hagishima (2010)), the residential building is located in Tokyo and equipped with external insulation of 50 mm, and an LDK faced south. Weather data collected between 1981 and 1995 is provided by Expanded AMeDAS (Akasaka et al. (2000)). There are three types of dwellings in terms of floor size: west side (4LDK, total floor area 95.8 m^2), central (3LDK, 80.4 m^2), and east side (4LDK, 101.0 m^2). The building has 10 stories, which implies that there are 10 dwellings on each floor since we considered 100 independent dwellings. We used 14 family types as shown in Table 2, and assigned one of these types to each dwelling in the building, as illustrated in Figure 2. Average and standard deviation numbers of family members per dwelling are 3.5 and 1.16, respectively.

4. RESULTS AND DISCUSSION

4-1 Insight into a specific dwelling on representative days

Figure 3 shows a detailed time series of the outdoor air temperature, room air temperature, total thermal requirement (sum of sensitive and latent loads), COP of LDK (upper panel), and the accumulated electric power demand of all dwellings (bold line) and its breakdown. It also shows HVAC, electric household appliances, lighting and standby loads (middle panel), and domestic hot water (bold line) and city water demands (lower panel) of the west-side dwelling on the 10th floor where a type #8 family lives. As representative days, consecutive three days of winter (A) and summer (B) are shown.

Interestingly, on/off operation for cooling leads to

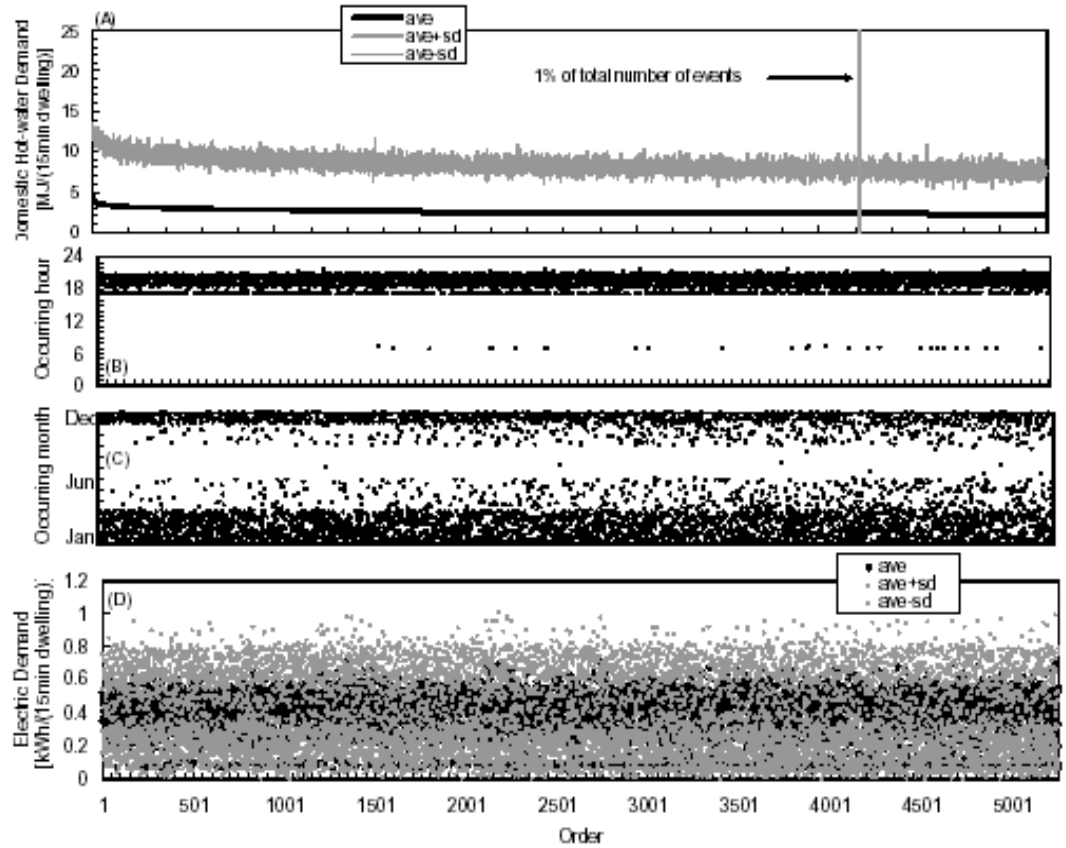

Figure 5. *Sorted hot water demand of the entire building (A) with occurring time (B) and date (C), and total electric power demand (D).*

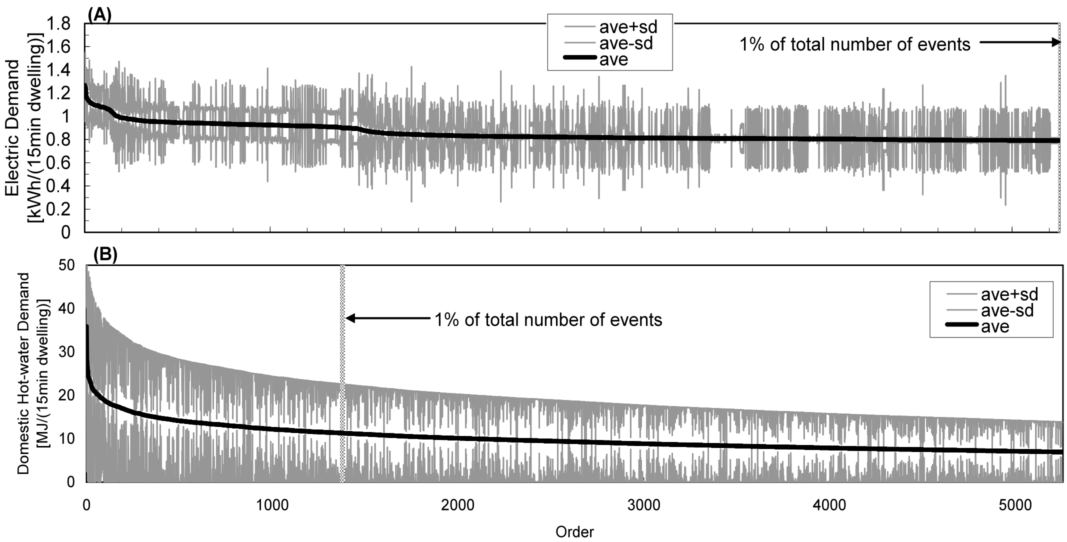

***Figure 6**. Relationship between maximum peak and annual loads for Base Case, LessCapa Case, and Aged and Single Case with its sub-classes (see text). Total electric demand (A), hot water demand (B), cooling (C) and heating (D) electric power demands.*

relatively higher COP compared with heating because, unlike the continuous operation for heating, there is higher partial load factor for cooling. This is because, during lower outdoor temperature, inhabitants barely switch off heating. Heating was found to be turned off at noon on February 8 and February 9 because of a higher outdoor temperature with ample solar energy (not shown) that causes over-heating during the daytime.

<u>4-2 Characteristics of peak demand for the entire building</u>

Figure 4 shows orderly sorted maximum accumulated electric power demands integrated the entire building (nominally shown in the average value per dwelling). The vertical line of 1% indicates the top 1% maximum among 15 years data sets, which means 5285th place (= 0.01 × (365 × (15 − 3) + 366 × 3) × 24 × 4). Panel A shows the total electric power

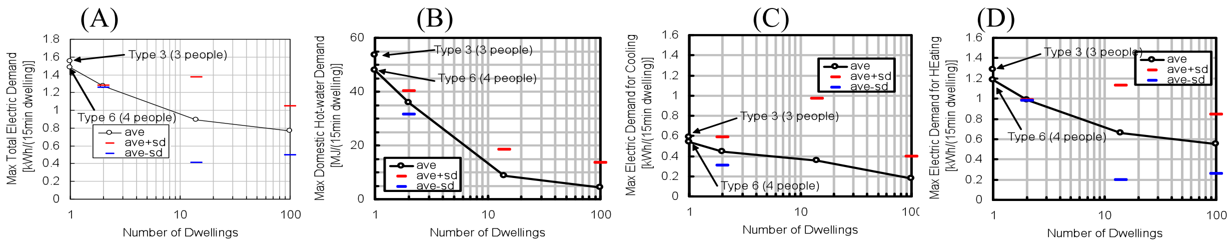

Figure 7. *Influence of sample size on peak loads; total electric demand (A), hot water demand (B), cooling (C) and heating (D) electric power.*

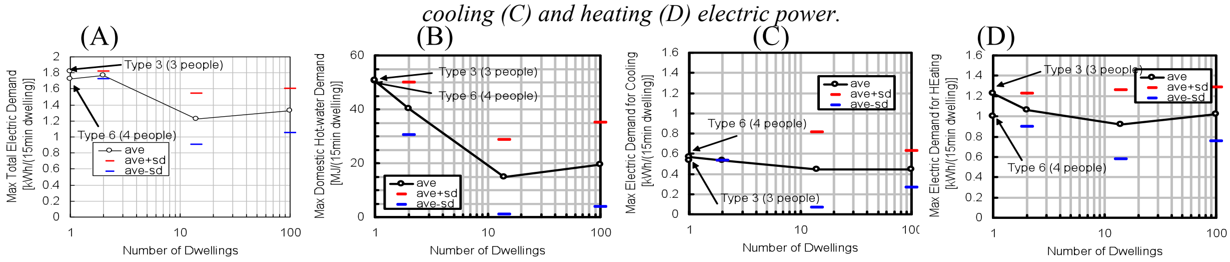

Figure 8. *Influence of sample size on peak loads in case of Const Case; total electric demand (A), hot water demand (B), cooling (C) and heating (D) electric power.*

demand by date (B) and time (C) of the event; panels D–F show hot water demand, heating COP, and power demand from the heating HVAC, respectively. The black line and plot indicate an average value of 100 dwellings, while the gray line and plot indicate the average ± standard deviations. The decreasing tendency of total electric power is certainly consistent with that of heating power demand, which implies that maximum total power demand is dominated by the heating requirement. The top-most maximum demands occur in the early mornings and late nights of winter. Heating COP is approximately 2, which is higher than the annual average (shown in Table 3) because of a larger partial load factor. There is no correlation between total electric demand and hot water demand. Interestingly, the slope of decreasing tendency from the maximum total electric power demand is less steep than that derived from only two specific dwellings (shown in Fig.6, discussed later). This is because the 100 dwelling accumulation compensates for irregular demand at each dwelling, which causes the various peaks of each dwelling to disappear as a whole. Hereafter, we call this the peak shift effect.

Figure 5 shows sorted hot water demand (panel A) with the date and time and total electric power demand (panels B–D) in the same manner as Fig. 4. The hot water peak appears during night in the winter, thus indicating that the peak is dominated by bathing and dishwashing after dinner. Note that the standard deviation of hot water demand is much larger than that of the total electric demand (panel A, Fig. 4), which implies that the peak shift effect for hot water demand is more phenomenal than that observed for electric power demand. This is expected because the use of hot water varies from one family to another.

Instead of accumulating all 100 dwellings, we show in Figure 6 the sorted total electric power (A) and hot water (B) use of two dwellings, dwellings #28

Table 3. *Statistical summary of simulation results; annual summation of total electric power, hot water, city water, standby load, lighting, household appliances, cooling and heating electric power, annual averaged COP for heating and cooling (shown in average ± standard deviation in 15 years). The last two rows are number of events and its event frequency when cooling load overly requires cooling capacity, and its average room temperature when violating the capacity.*

Annual summation/ave	Base	2-Dwelling	LessCapa	Const
Total Electric Demand [kWh/dwelling]	4939 ± 254	5446 ± 293	3907 ± 114	7095 ± 135
Hot Water Demand [MJ/dwelling]	14261 ± 51	13898 ± 259	14261 ± 51	17469 ± 175
City Water Demand [m^3/dwelling]	236 ± 0.8	230 ± 3.7	236 ± 0.8	344 ± 2.4
Average COP for Heating	1.22 ± 0.05	1.05 ± 0.05	3.08 ± 0.09	0.89 ± 0.05
Average COP for Cooling	2.20 ± 0.12	2.42 ± 0.11	3.91 ± 0.14	1.27 ± 0.12
Standby Electric Load [kWh/dwelling]	1744 ± 2	1546 ± 2	1744 ± 2	1740 ± 3
Lighting Load [kWh/dwelling]	87 ± 0.2	99 ± 0.5	87 ± 0.2	97 ± 0.2
Electric Household Appliance Load [kWh/dwelling]	1363 ± 7	1719 ± 13	1363 ± 7	2481 ± 7
HVAC Load Cooling [kWh/dwelling]	183 ± 41	171 ± 47	109 ± 25	882 ± 86
HVAC Load heating [kWh/dwelling]	1562 ± 250	1912 ± 287	603 ± 108	1896 ± 157
Probability of failing to attain set room air temp. due to less capacity (total events during 15 years)	2×10^{-6} (3)	0	3.7×10^{-5} (59)	0
Average room air temp. when failing attain the set temp. [°C]	26.6	-	27.1	-

(family type #3) and #15 (family type #6), with an average number of family member 3.5, matched against that of the entire building's average. Notably, both extreme peak maximum demands of total electric power and hot water based on the two dwellings are much larger than those of the entire building. This is because an aggregation of only two dwellings, especially those featured with analogous family types, shows a negligible peak shift effect.

Let us consider the influence of number of dwellings on the accumulation of the peak shift effects. Figure 7 shows the relationship between respective peak demands and statistical sample size to draw respective peak loads. Data for dwellings #28 (family type #3) and #15 (family type #6) were plotted as representative sample size for a single dwelling. The data where the sample size is two is derived from the accumulation of those two dwellings. The data where the sample size is 14 is based on the accumulation of 14 dwellings selected from each family type as its representative. The data on 100 dwellings is for the accumulation of the entire building. The influence of number of dwellings on accumulation of peak shift effect seems remarkable, especially in case of hot water demand. This is because a residential site consisting of a large number of dwellings, where different demand schedules occur, can de-peak more from the superposing peaks compared to a residential site with small number of dwellings. In short, the peak shift effect can be greater if a larger number of dwellings are accumulated. This tendency is more significant for hot water demand than electric power demand, since the deviation in the time series for the dwellings' demand for hot water is more significant than that for electric power.

The results so far are based on all inhabitants' stochastic schedules, and therefore are deviated from each other even with the same family type. Figure 8 shows the same data as Fig. 7 derived from another setting, the *Const Case*, which implies that the results based on each dwelling from all 100 dwellings shares the same behavior schedule if it has the same family type assigned. For each family type, there are only three schedules: weekday, Saturday, and holiday because, for instance, the same daily schedule is repeated when weekdays are continued. Thus, in the *Const Case*, all inhabitants' default behavior schedules are presumed as deterministic instead of stochastic. Comparing Figs. 7 and 8, we note that the decreasing tendency of peak loads from 10 to 100 dwellings observed in Fig. 7 is not seen in Fig. 8. This fact proves that a peak shift effect depending on the number of accumulated dwellings can be reproduced only by a stochastic methodology like TUD-PS, rather than a deterministic way.

In summary, a prediction methodology such as TUD-PS that considers stochastic deviation in each inhabitant's behavior is necessary for the accurate prediction of a detailed time series for utility demand and peak evaluation.

4-3 Influences on peak brought by HVAC max capacity

As mentioned earlier, it is assumed that each room has the necessary class of heat pump (HP) in terms of its capacity installed, which means that a 10-Jou class HP is assigned to a room that is 9-Jou (1.65 $m^2 \times 9 =$ 14.85 m^2) in size. This setting will be called the *Base Case*. The installation of an HP that is one size smaller than necessary, e.g., an 8-Jou class instead of 10-Jou class in a 9-Jou room, will be called a *LessCapa Case*. The results are summarized in Table 3. Values accumulated only from dwellings #28 and #15 are indicated by *2-Dwelling Case*. Every load shown in Table 3 is an annual accumulation, expressed as an average for 15 years with standard deviation. The last two rows of Table 3 give events frequency with occurring probability when the room temperature cannot be maintained at a set temperature of 26°C (that is the temperature is over 26°C even under cooling operation) for 15 years, and its average room air temperature during the deficiency period.

Remarkably, the *LessCapa Case* shows that the annual accumulated total electric power demand is far less than that of the *Base Case*. This is because the annual accumulated cooling and heating powers reduce due to much higher cooling and heating COP than in *Base Case*. Installing a smaller HP than required increases the deficiency probability for cooling (with no event in which the temperature does not meet the set temperature of 20°C for heating, even if *LessCapa Case* is presumed). The likelihood remains small, because it is less than 25 hours (59 × 15 minutes) during the 15 years. The average temperature during the deficiency period is 27.1°C, which is comfortable temperature. These observed facts suggest that to improve higher COP, there is an alternative energy conservation provision other than research and development activities employed in industrial sectors that produce various types of heat pump systems. That is, installing a smaller HP than recommended is effective and costs less, therefore it is very feasible.

5. CONCLUSIONS

We have established a Total Utility Demand Prediction System (TUD-PS) to predict the utility demands with a high time resolution for a residential sector by superposing respective dwellings using the Monte Carlo simulation. We applied the developed TUD-PS to a residential building with 100 independent dwellings inhabited by various types of families. Using simulation study, we obtained the following results:

(1) It is necessary to consider the diversity of inhabitants' behavior schedule through a properly established stochastic framework such as TUD-PS. One cannot predict utility demands such as electric power and hot water accumulated over the entire building, a particular

residential area, or even a city—especially at a peak time—without such a framework.

(2) The peak shift effect, which can reduce maximum peak load by spatially accumulating dwellings, is confirmed considerable even in a building of 100 dwellings. The peak shift effect tends to be phenomenal for domestic hot water demand, which deviates substantially between dwellings.

(3) As a bottom-up approach to realize significant energy conservation, installment of heat pump or air-conditioner of size smaller than recommended size is quite phenomenal. This is because higher COP than that by usual installment can be realized throughout seasons.

ACKNOWLEGEMENT

This study was supported partially by a Grant-in-Aid for Scientific Research by JSPS, awarded to Dr. Hagishima (#20686040) and by the Asahi Glass Foundation. We would like to express our gratitude to these funding sources.

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