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COOLING LOAD SIMULATION CONSIDERING ACTUAL VARIATION OF INHABITANTS' BEHAVIOR FOR ACCURATE ESTIMATION OF URBAN MAXIMUM ENERGY REQUIREMENT

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Abstract

A brand-new methodology for considerably accurate time-series cooling load calculation in a dwelling is established, motivated by the fact that dwelling energy requirements so significantly affect the so-called urban heat island. Calculation that takes variation among dwelling-inhabitants' behaviors into consideration appears to be important. The proposed method contains two crucial features. The first is a procedure for cooling load calculation based on a series of Monte Carlo simulations where HVAC *on*/ *off* state and indoor heat generation schedule are variable time-step by time-step. The second feature is an algorithm to generate myriad schedule data of each inhabitant's behavior that must be provided with fine time resolution.

Introduction

A firm growth of energy consumption in non-industrial sectors works as a drag force to reduce fossil energy waste in support of the COP3 perspective. From not only this but also the so-called urban heat island point of view, energy requirements for dwelling-related elements in urban areas have drawn a great deal of attention. Particularly, considering the capacity of urban utilities such as electricity and the gas and water supply, we have to pay more attention to predict an accurate maximum energy requirement accelerated by the dwelling-related sectors.

In a practical calculation on an individual building scale, the result from a deterministic dynamic calculation procedure inputting statistically arranged weather data such as TAC (statistically disposed outdoor temperature for a design calculation proposed by the Technical Advisory Committee of ASHVE, (Takeda, 1990)) and so forth is regarded as a maximum load. However, experience has taught us that the integrated load for a holistic apartment building or a certain urban block area obtained by summing up these individual dwelling loads is greatly overestimated. Several early studies (e.g. Hokoi et al., 1990, Andersen et al., 2000) dealt with the so-called stochastic thermal load, although they were all concerned solely with idealistic thermal systems and its calculation procedure, which is not nearly sufficient for discussion of the above-mentioned impediment. The biggest reason for this overestimation is undoubtedly the time consistency, assuming that we all behave in entirely the same manner not only in terms of HVAC operation schedule but also all those of daily life-style resulting in the same energy consumption.

Incidentally, for a roughly estimated maximum requirement, there is an alternative method such as the Demand Sensitivity Factor (DSF), indicating how much electricity is required to compensate for a rise in outdoor air temperature. In fact, Kishimoto et al. estimated a reliable DSF during peak summer season for Osaka (Kishimoto et al., 2003). Although theirs is a brilliant approach, its lack of robustness is controversial. Because, we cannot analyze the detailed causes of increase in the maximum load and determine whether it is due to HVAC or other elements. It is also impossible to predict whether differences in lifestyle lead to differences in energy consumption and so forth.

To clarify and resolve these problems in order to predict a realistic maximum load, it is necessary to establish a brand-new methodology for considerably accurate time-series energy load calculation, which will be introduced in this paper.

Holistic strategy for the new methodology

Our proposed methodology consists of two parts.

One is to build an algorithm to generate myriad schedule data of each inhabitant's behavior provided by fine time resolution (15-minute intervals). With this kind of schedule data, we can obtain a set of individually different time-series of utility demand by assuming functional electric household appliances and other utilities for each behavior (e.g. "preparation for supper" indicates a combination of "a 500W microwave, an 8000kcal/h gas-range and 5L hot water"). Because one of the individual dwellings' daily schedules is different from another, the aggregated peak maximum load obtained promises to be much more realistic than that obtained by the conventional method. Both gas and water supply loads are directly predicted by space-integration of the respective schedule data within a dwelling building or a certain building block area and so on. Electricity usage is not so easily predicted, because most of the air conditioning load is electricity. Hence, a dynamic thermal load calculation must be performed in order to obtain the cooling load, which is subsequently converted into electricity. The sum of this HVAC load plus the loads of other electric household appliances represents the total electricity supply load. Having a presence or absence flag in the schedule data for each behavior (e.g., "schooling" is unequivocally one of the behaviors conducted outside the dwelling), we can obtain a realistic dynamic cooling load only if certain additional information concerning HVAC operation is given. This is actually the second point of the methodology.

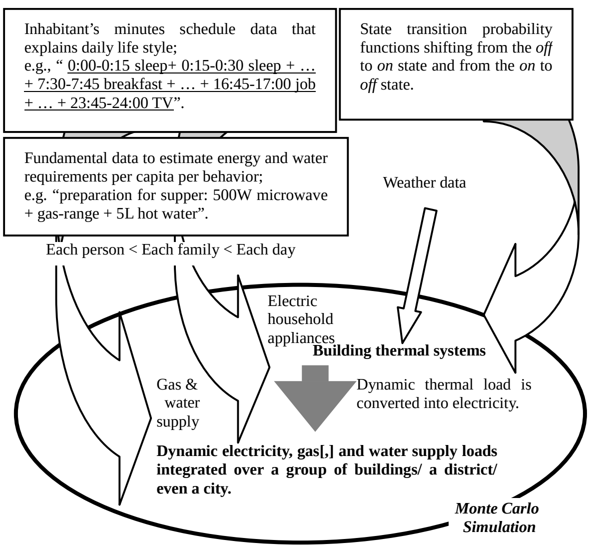


Fig.1 Schematic flow of new methodology.

An important question is how to generate the individual schedule data. To that end, we utilize several public shared databases that provide only restricted statistical data such as averaged probabilities of respective behaviors at every 15 minutes; averaged ongoing minutes and standard deviation of respective behaviors on weekdays, Saturday, and Sunday. All these data are statistically separated into several classes, such as working male, working female, housewife, high-school student, senior male, and senior female, which we call "people attributes". What is needed at this point is an algorithm to generate raw schedule data from these statistical data, an algorithm universally applicable to every data attribute. This will be explained in Chapter 4 in detail.

The second point of the methodology is a stochastic model of HVAC operation. Inspired by Fritsch et al., 1990, we are trying to see a sequence of HVAC operation as a *Markov Chain* (Tanimoto et al., 2005). In short, if he/ she feels uncomfortably hot when passing through his/her home (which can be assumed by a presence or absence flag in the schedule data), he/ she would change the HVAC state from *off* to *on*. Herein we report state transition probability functions derived from field measurement data of an air conditioner being shifted from the *off* to *on* state and from the *on* to *off* state, which will be explained in the next Chapter.

Based on the package we mentioned above, we can finally conduct a series of *Monte Carlo Simulation* experiments to obtain remarkably accurate maximum energy requirements for respective dwellings in which the inhabitants have different schedules and HVAC operations can vary every 15 minutes. Fig.1 shows a schematic flow of our proposed methodology.

State transition probability for the *Markov Model* dealing with *on*/ *off* cooling schedule

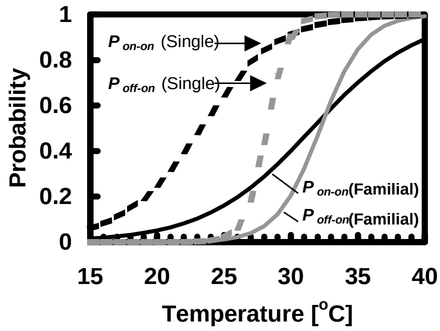
Considering the air conditioning schedule in a

Table 1 Result of identified parameters.

	$P_{on\text{-}on}$ vs. outdoor air temperature			$P_{off\text{-}on}$ vs. indoor glob[al] temperature		
			Averaged error	Parameters		Averaged error
	a [-]	θ [°C]		a [-]	θ [°C]	
Familial_#1	1.306	29.6	1.02E-2 (n=36)	2.209	31.0	4.78E-3 (n=10)
Familial_#3	1.263	33.5	1.94E-2 (n=26)	1.491	33.3	2.52E-3 (n=6)
Average	1.285	31.6	-	1.850	32.2	-
Single_#1	1.341	23.9	2.28E-2 (n=36)	3.796	28.0	7.04E-3 (n=6)
Single_#2	1.402	25.5	1.52E-2 (n=41)	1.850	28.1	2.32E-3 (n=11)
Single_#3	1.471	20.3	8.71E-3 (n=27)	4.629	28.6	2.24E-3 (n=8)
Average	1.405	23.2	-	3.425	28.2	-

Averaged error $= \frac{1}{n}\sum_{i=1}^{n}\left(P_i - \frac{1}{1+a^{-(\theta_i-\theta)}}\right)$

n: Number of data, P_i : Measured probability, θ_i : Measured temperature.



Fig,2 Total averaged shapes of $P_{off\text{-}on}$ and $P_{on\text{-}on}$ for familial and single dwellings.

dwelling, cooling is difficult to describe in a modeling than heating on the ground of its frequent intermittence in operation. In Japan, people are sensitive to the use of cooling air conditioners because it is generally considered that an air conditioning system consumes a great deal of electricity (in this sense, people are inclined toward energy conservation, especially concerning cooling). While the heating is, in general, operated continuously, which is enough by a simple modeling such as the *Degree Day*. Hence, when attempting to model a cooling operation schedule, we inevitably seek another novel method. To regard the cooling schedule as a *Markov Process* is one novel approach. When you apply the Markov approach, the state transition probabilities either from the *off* to *on* state or from the *on* to o*ff* state should be determined (Tanimoto et al., 2005).

We gathered field measurement data on 4 familial and 3 single dwellings during the summer season by deploying numerous handy hygrothermal meters with self-recording functions to measure room air, room globe and outdoor air temperatures. These measurements led to conclusions on the probability of turning on an air conditioning system vs. indoor globe temperature and the ongoing probability of air conditioning vs. outdoor temperature. This analysis was transformed into state transition probability functions; i.e., shifting from the *off* to *on* state ($P_{off\text{-}on}$) and from the *on* to *on* state ($P_{on\text{-}on}$). Next, we can draw the state transition probability functions from *on* to *off* ($P_{on\text{-}off}$) by subtracting the *on* to *on* state probability ($P_{on\text{-}on}$) from 1. Those two probabilities, $P_{off\text{-}on}$ and $P_{on\text{-}on}$, of all cases except for two familial dwellings that seem to be singular cases, are approximately expressed in the form of a Sigmoid Function.

$$P(t) = \frac{1}{1+a^{-(t-\theta)}} \qquad \cdots(1)$$

where a expresses thermal sensitivity and θ is a threshold for turning an air conditioner *on* or *off*. $P(t)$ represents a predicted state transition probability at characteristic temperature t. Identified parameters of each case are shown in Table 1, the shapes of $P_{off\text{-}on}$ and $P_{on\text{-}on}$ in Fig. 2.

<u>Universal algorithm to generate a set of raw schedule data for individual inhabitants</u>

We have developed a universal algorithm to generate a schedule data set at a time-resolution interval of 15 minutes from published statistical data. The published data sources we use are two. The primary statistic database is the "National Survey on Living Time Schedule" provided by NHK (Nippon Hoso Kyokai) Laboratory, 2000. The secondary one is "Survey on Time Use and Leisure Activities" that comes from the governmental statistical database of the Statistics Bureau of the Ministry of Internal Affairs and Communication, 2001. Both are only able to provide several pieces of fundamental information such as averaged probabilities of respective behaviors at every 15 minutes (AP), percentage of people who adopt that behavior over a day (PB), averaged ongoing minutes (AOM) and its standard deviation (SDOM) of respective behaviors in a day. Those statistical data are presented by three classifications of days and by eight classifications of people attributes as shown in Table 2. This means that there are a total of 24 different data sets. The original statistical data has three layers or categories of classification for behaviors; large, middle, and small. The small category includes 42 classifications. We use both small and middle categories, rebuilding the data into

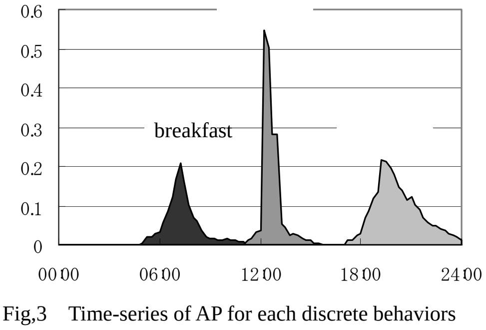
Table 2 Classifications of behaviors, characteristics of days and people attributes.

Classifications of behaviors
(1) Sleeping (2) Dining (3) Fundamental acts to fulfill daily needs (4) Resting and hospitalizing (5) Working (6) Social relationships bringing with working affairs (7) Class and lecture (8) Extracurricular activities (9) Cooking, cleaning and laundering (10) Shopping (11) Childcare (12) Household chores (13) Commuting (14) Schooling (15) Social activities (16) Conversation and personal relationships (17) Sports (18) Leisure and exercise (19) Hobby and cultural activities (20) Television (21) Radio (22) Reading newspaper (23) Reading magazines and comics (24) Reading books (25) Listening to music (26) Watching videos (27) Resting (28) Other activities
Characteristic of days
<1>Weekdays <2>Saturday <3>Sunday
People attributes
1) Working male 2) Working female 3) Housewife 4) Elementary school child 5) Junior high school student 6) High school or college student 7) Senior male (older than 70) 8) Senior female (older than 70)

28 classifications, which are summarized in Table 2. The key idea to generate a set of raw schedule data from these restricted statistical information is the concept of "generate & kill" that is commonly shared among the field of artificial intelligence or multi-agent simulation.

Dividing "behavior" into "discrete behaviors"

The biggest impediment is the fact that the package of published statistics data does not include crucially important information on how many times each behavior takes place in a day. Therefore, we divide a time-series into several single-peaks of AP from a time series, having multi peaks. For example, suppose an averaged probability time-series of "dining", which usually has three peaks as shown in Fig.3. This means that dining takes place three times in a day. As a consequence, the "dining" has to be divided into three independent time-series implying "breakfast", "lunch", and "dinner". Hereafter, we call these newly divided time-series "discrete behavior" ("dining" is called as "behavior"). "Dining" is one of the easiest examples, whereas it is difficult to divide for a behavior bringing with a broken multi peaks. We went thorough a trial & error process to estimate whether we should divide the time series for the respective 28 behaviors into several discrete behaviors. Resolving the time series of a certain behavior into several discrete behaviors requires another elaborate step. Namely, AOM, SDOM, and PB are requisite for each discrete behavior, which information is necessary in the following generating process. AP, AOM, SDOM, and PB for the discrete behavior are analytically deducted from those for the original behavior provided by the statistical data and also some stochastic relations.



Fig,3 Time-series of AP for each discrete behaviors

Generating process

There are two stages; selecting a set of discrete behaviors in a day and displacing these discrete behaviors on the scale of that day, which are schematically shown in both Fig.4 and Fig.5. One important assumption is that any discrete behaviors except "television" cannot be happening simultaneously. This might be unrealistic, given that people may listen to the radio and cook or eat at the same time, etc. Also, the original statistical data imply that simultaneous events do occur. However, we have concluded that such simultaneity is not so significant that it affects the holistic accuracy of the generated raw data.

Picking up a set of discrete behaviors over a day

Due to a series of roulette selections based on PB, a set of discrete behaviors is picked up. The duration of each discrete behavior is determined according to the Logarithmic Gauss Distribution defined by AOM and SDOM. If the total time length of the day is not within a range of 24 hours $\pm\varepsilon$, the set is discarded and tried again from the beginning. At this moment, ε is assumed to be 1 hour. The surviving daily set is also put through some screenings from a common sense point of view. For example, commuting #1 (one of the discrete behaviors of commuting that means "traveling to the office") and commuting #2 (which means "traveling home from the office") must be included at the same time in a daily set, which indicates that commuting #1 and commuting #2 are statistically dependent. Total time length of the finally surviving set that is a possible $24\pm\varepsilon$ hours is adjusted to exactly 24 hours.

Displacing a set of discrete behaviors in a day

A day consists of 96 units of 15 minutes to be filled by a set of the above described discrete behaviors. Each discrete behavior has a specific time length that can span several intervals of 15 minutes. This process is regarded as a typical example of fitting pieces into holes as one does to complete a puzzle, and is a well developed field of mathematical science. Assuming that i is a time flag ($1 \le i \le 96$), b_j is one of the discrete behaviors ($1 \le j \le r$; r is a number of discrete behaviors), $t(b_j)$is the time length of the discrete behaviors, and $P(i,b_j)$ is the averaged probability of discrete behavior b_j at i (this is actually the AP of discrete behavior b_j at i), we can express the process by the following items.

#1. The place to start, IT ($1 \le IT \le 96$), is determined according to the Uniform Random Distribution.

#2. Due to a roulette selection based on $P(IT,b_j)$, one of the discrete behaviors is determined as b_m.

#3. To mark flags of b_m before and after IT, $t(b_m)$ is divided into two parts by the following equations.

$$DT(i,b_j) = \frac{\sum_{k=i+1}^{i+1+4\times 12} P(k,b_j)}{\sum_{k=i-4\times 12}^{i+1+4\times 12} P(k,b_j)} \qquad \cdots(2)$$

$$t_{fore}(IT,b_m) = DT(IT,b_m) \times t(b_m) \qquad \cdots(3)$$

$$t_{back}(IT,b_m) = (1 - DT(IT,b_m)) \times t(b_m) \qquad \cdots(4)$$

#4. During $t_{fore}(IT,b_m)$ after IT and $t_{back}(IT,b_m)$ before IT, mark flags of b_m. Remove b_m from a set of discrete behaviors to a white-elephant-box.

#5. The next time, place KT (the next place to $IT+t_{fore}(IT,b_m)$) is assumed before placing.

#6. Due to roulette selections based on $P(KT,b_j)$, one of the discrete behaviors (excepting any of those put in the white-elephant-box) is determined as b_n.

#7. During $t(b_n)$ after KT, mark flags of b_n. Remove b_n from a set of discrete behaviors to the white-elephant-box.

#8. If there are remnant discrete behaviors in a set, go back to #5, otherwise go to the next step.

#9. Go through some screenings from a common sense point of view. For example, commuting #1 must be placed before commuting #2, and so forth. If the set is okay, keep it, otherwise discard it.

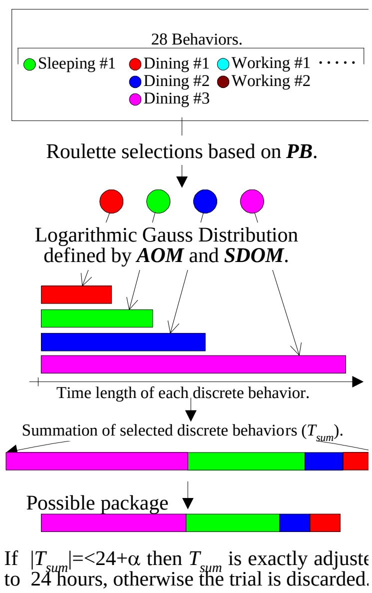


Fig.4 Flowchart of "picking up a set of discrete behaviors among a day".

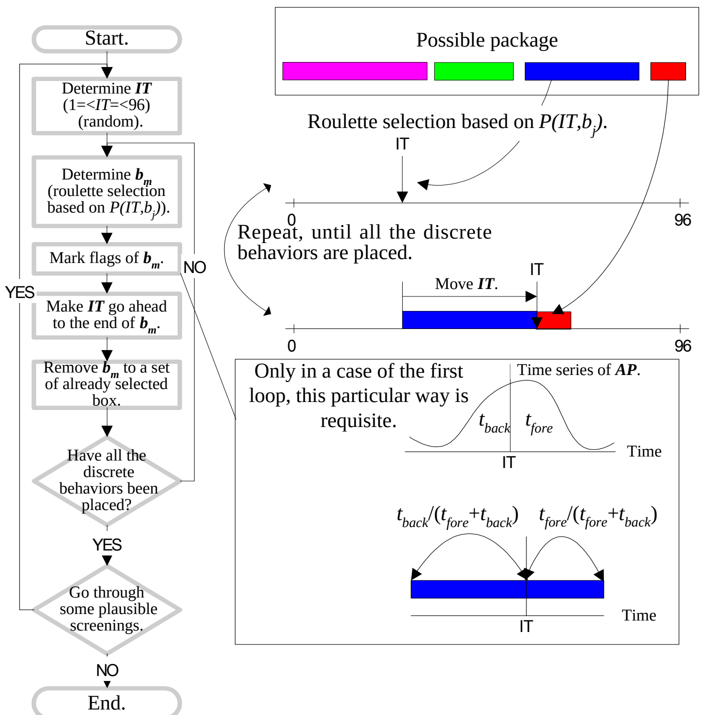


Fig.5 Flowchart of "displacing a set of discrete behaviors on a day".

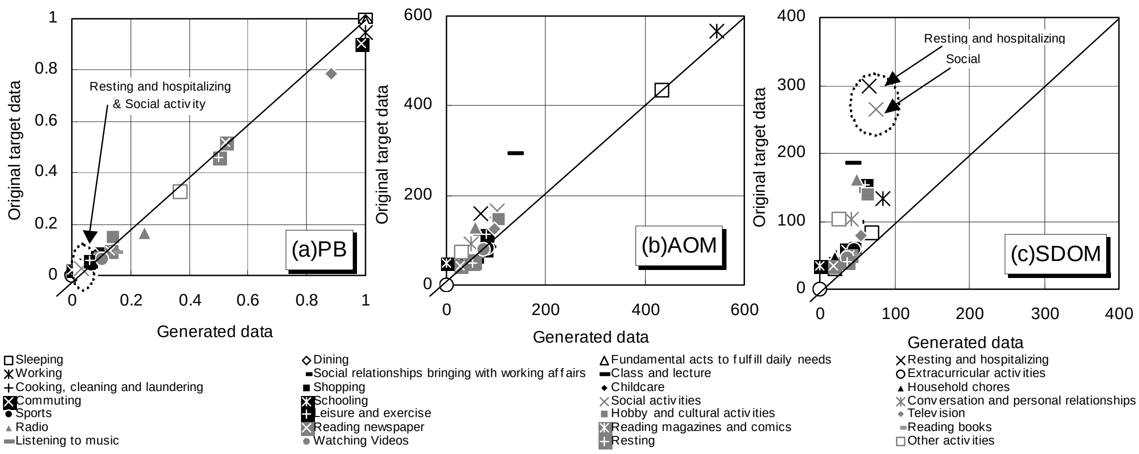


Fig.6 Comparisons of PB, AOM and SDOM between the original target data and calculated data from the generated raw samples in case of "Working, male/ Weekday".

Table 3 Calculation result of EST.

People attributes	Characteristic of days	EST x10^{-4}	People attributes	Characteristic of days	EST x10^{-4}
Working male	Weekdays	**142**	Junior high school student	Weekdays	**221**
	Saturday	**174**		Saturday	**143**
	Sunday	**172**		Sunday	**88**
Working female	Weekdays	**96**	High school or college student	Weekdays	**186**
	Saturday	**103**		Saturday	**154**
	Sunday	**111**		Sunday	**102**
Housewife	Weekdays	**166**	Senior male	Weekdays	**163**
	Saturday	**154**		Saturday	**131**
	Sunday	**169**		Sunday	**111**
Elementary school child	Weekdays	**181**	Senior female	Weekdays	**204**
	Saturday	**113**		Saturday	**184**
	Sunday	**191**		Sunday	**192**

Results and accuracy

According to the procedure described above, 10^4 raw samples were generated for 24 respective data sets in terms of the characteristic of days and the people attributes.

Fig.6 indicates comparisons of PB, AOM, and SDOM between the original statistical data and the data calculated from the generated raw samples in the case of "Working male/ Weekday". Looking at (c) SDOM, you can see several plots deviating from the 45-degree line that indicates a perfect correlation. But all of these plots have very small values in terms of PB, which means such behaviors seem to be very seldom to take place. In short, these plots appear not to significantly affect the holistic accuracy.

To evaluate total errors between the original and the generated data, we define, here, *EST*, which indicates an error of AP integrating data over 24 hours and all the discrete behaviors.

$$EST = Ave\left[Abs\left(P\left(i,b_j\right) - P_{pred}\left(i,b_j\right)\right)\right]_{1\le i\le 96 \quad 1\le j\le r} \cdots(5)$$

$P_{pred}(i,b_j)$ is the averaged probability of discrete behavior b_j at i derived from the generated 10^4 raw samples. Calculated *EST* is shown in Table 3. Most of the data sets have errors less than 2%, which is acceptable.

Summing up, the accuracy of the generating algorithm we propose appears to be sufficient.

Trial calculation to recognize the impact of using raw schedule data

As a trial, a series of numerical experiments are done to clarify the importance of an inhabitant's schedule to an accurate estimation of maximum energy requirement. The point we focus on here is the difference in maximum cooling load between a conventional calculation assuming homogeneous schedules of inhabitants and a novel one considering a heterogeneous schedule of inhabitants as generated by our method. The model residence is a single room apartment where a working male lives alone spending everyday based on entire weekday schedule. The assumed calculation model is summarized in Table 4. The assumed relations between the inhabitant's behavior and electric household appliance usage are described in Table 5. The state transition probability functions for a single residential house reported in Chapter 2 are applied. In short, only when an inhabitant is in the room, which is determined by schedule data (that contains a presence or absence flag as mentioned before), he could change his mind about the state of the air conditioner, turning on/ off or keeping as it is.

Table 4 Basic assumptions for numerical experiments

- Room
  Room size is 4.5m (exterior wall side)*3.6m (interior wall side)*2.4m (height).
  The exterior wall faces south. The interior walls, floor, and ceiling all face the same adjacent rooms.
- Window
  Window size is 3.6m*1.8m (height), 5mm standard glazing.
  Dynamic variation for transmittance of the glazing depending on incidental angle is considered.
- Exterior Wall
  Outside convective heat transfer coefficient (=23.3 W/m^2) + RC200mm + Insulation 50mm + Plaster finishing 10mm + Room-side convective heat transfer coefficient (=9.3 W/m^2).
- Interior Wall
  Convective heat transfer coefficient (=9.3 W/m^2) + Plaster finishing 10mm + RC 150mm + Plaster finishing 10mm + Convective heat transfer coefficient (=9.3 W/m^2).
- Ventilation
  Air change rate; 0.5 /h (air conditioning), 10 /h (ventilating).
- Room Condition
  24 °C, 50 %rh.

Table 5 Assumed relations between behavior and electric household appliance usage

- Heat generation from human body; sensible heat 51W + latent 48g/h (only when the]inhabitant is in a room).
- Lighting is on only when an inhabitant is in a room but not sleeping, and outside is sufficiently dark (both normal direct and global sky solar radiation is less than 58W/m^2).
- A refrigerator is always working, consuming 60W.
- A microwave consumes 200W only during “Dinner”.
- An electric range consumes 300W only during “Breakfast” and “Dinner”.
- A rice steamer consumes 225W during 1 hour before “Breakfast”.
- A television consumes 120W when it is working, but always consumes 2W as a potential load.
- A dryer consumes 225W only during last 15 minutes of “Fundamental acts to fulfill daily needs / morning”.
- A hot water pot consumes 66W only when the inhabitant is in a room but not sleeping.

Table 6 indicates a variation of numerical experiment. There are two focal factors. One shows the effect of an assumed schedule, another indicates the effect of weather data. In Case 1*, daily variable schedule data of an inhabitant is used and the cooling load comes from one sample dwelling. In Case 2*, the averaged cooling load of one hundred dwellings that have same thermal characteristics but different daily variable schedule data was obtained. In Case 3*, determinate schedule data, in which the same daily schedule, defined as an averaged sequence of behaviors, repeats. In Case A*, raw weather data of Tokyo from 1981 to 1995 are applied. In Case B*, the Standard Weather Data (SWD) of Tokyo 1981-1995 that is statistically presumed to express one normal year, being neither too hot nor too cold from mother samples 1981-1995, is inputted. The SWD is commonly used in various practical calculations to meet industrial needs, and it is particularly indispensable for an estimation of annual energy requirement. Whereas, in Case C*, the Weather Data for Design (WDD) of Tokyo TAC 2.5% is used. The WDD is also important for practical application, because it is requisite to determine the capacities of various air conditioning facilities. The WDD is usually a TAC concept (Takeda, 1990).

Table 6 Experimental variations.

Weather data		Raw Tokyo 1981-1995	SWD Tokyo (statistically sampled from 1981-1995)	WDD Tokyo TAC 2.5%
Schedule	A simulation runs;	15 years	1 year	15 days
Daily variable schedule data & a single dwelling cooling load.		Case 1A	Case 1B	
Daily variable schedule data & an averaged cooling load of 100 dwellings.		Case 2A	Case 2B	
Determinate schedule data & a single dwelling cooling load.		Case 3A	Case 3B	Case 3C

The results are summarized in Table 7. Comparing Cases 2A and 3A, or Cases 2B and 3B, indicates that the determinant schedule of the inhabitant repeatedly using the same schedule on a daily basis and also that using all the dwellings in a building or an urban block-area entails huge error vis-à-vis the variable schedule input. If a conventional daily constant schedule is assumed, a large overestimate is inevitable. Also, comparing Cases 1A and 2A, or Cases 1B and 2B, the Monte Carlo Simulation seems to be necessary to obtain a building total or area total maximum load. In addition, if this kind of urban total maximum load is estimated, the conventional calculation for design based on the

Table 7 Results of experiment.

Maximum cooling load [W/m^2]				Seasonal cooling load [MWh/m^2]	Maximum cooling load [W/m^2]				Seasonal cooling load [MWh/m^2]	Maximum cooling load [W/m^2]
The Max	TAC 2.	TAC 5%	TAC 1	Seasonal	The Max	TAC 2.	TAC 5%	TAC 1	Seasonal	AC 2.5%
Case 1A					Case 1B					
	247	218	188	49 ± 16	385	257	219	188	55	
Case 2A					Case 2B					
221	142		99	49 ± 16	194	153		106	55	
Case 3A					Case 3B					CASE 3C
415	259	223	187	46 ± 16	372	261	228	188	52	428

- In terms of Maximum cooling load, “The Max” and “TAC *%” indicate the real maximum load and the maximum load of excessive risk level *%, respectively.
- In terms of Seasonal cooling load, all the integral hourly cooling loads from June to September of one year. Case *A is marked with “ ± ” to indicate that the cases should be expressed not only as an average but also as a standard deviation over 15 years.
- Cooling load includes sensible and latent loads.

WDD does not make any sense. From the stochastic point of view, the methodology to use statistically disposed weather data never obtains a realistic maximum load. Clearly, what is needed is a methodology derived from a stochastic analysis using real raw weather data and real raw inhabitants' schedules. Unequivocally, the Monte Carlo Simulation plus the methodology we have shown here would be appropriate.

Conclusions

To estimate a space integrated maximum requirement such as a building total or an urban area total load accurately, a new methodology, which is based on the Monte Carlo Simulation, is proposed. The key features are two. One, it shows the state transition functions of both HVAC *off ->on* and *on -> off*. Another is a universal algorithm to generate raw inhabitants' schedule data from the statistical database available to the public. Trial numerical experiments imply that the conventional procedure based on determinant calculation and a daily constant inhabitant's schedule results in incredibly huge overestimates compared with those by the novel method we propose.

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