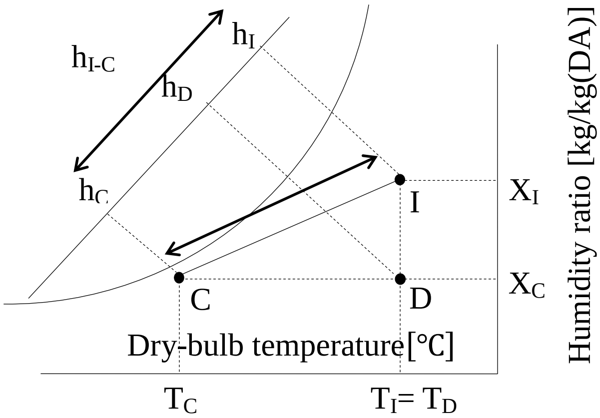
point), inlet port (I point), and air diffuser (C point). The measurement interval of the air conditioner was five min. The average of the data measured in 1 h was required to calculate the SHF. The SHF was calculated at each time point and for each indoor unit. Then, the 1 h average SHF was calculated by the weighted average of the enthalpy difference between the air outlet and the suction port over 1 h for each indoor unit. The SHF of the entire system was calculated with the weighted average of the enthalpy difference of each of the indoor unit of SHF each time (Equation 2). The sensible heat load per hour could be calculated by multiplying the SHF (Equation 2) with the total heat load.



$$\mathrm{SHF} = (h_D - h_C)/(h_I - h_C) \qquad (1)$$

Figure 2. Each state point

$$\text{SHF of the entire system} = \sum_{j=1}^{m} \sum_{\substack{t=1 \\ \mathrm{S=On}}}^{n} \left(\mathrm{SHF_{jt}} \times \varDelta \mathrm{h}_{\mathrm{jt,I\sim}C}\right) \Bigg/ \sum_{j=1}^{m} \sum_{\substack{t=1 \\ \mathrm{S=On}}}^{n} \left(\varDelta \mathrm{h}_{\mathrm{jt,I\sim}C}\right) \qquad (2)$$

j: Index of indoor unit m: Number of indoor unit

t: Time s: Status of air conditioner (on/off)

ANNUAL HEAT LOAD ESTIMATION METHOD

The results of the simulations that were carried out using short-term measurement data and preliminary survey items diverged from the actual load data. Therefore, a parameter estimation method was proposed that used Bayesian estimation to estimate multiple parameters simultaneously. The input parameters and internal heat data were updated by Bayesian estimations, with the aim to improve the annual load estimation accuracy. The unknown parameters were assumed to be five. It was difficult to estimate these parameters simultaneously. These parameters were then grouped into two categories and set as the representative parameter for each group. The representative parameters were varied from -2 to +2 at 0.1 increments. Group 1 depended on the temperature difference between the inside and outside. Group 2 influenced the internal heat. The parameter values were calculated using equation (3). Representative parameter 0 represented the mean value of each parameter. Representative parameter 1 representedthat the standard deviation was added to the mean of the parameter. Table 2 shows the prior information (mean and standard deviation) for each parameter.

$$\text{Parameter} = \text{mean} + (\text{standard deviation} \times \text{representative parameter}) \qquad (3)$$

Table 2. Prior distribution (mean and standard deviation) for each parameter

	Parameters	Prior distribution	
		mean	standard deviation
Group 1	Infiltration [ACH]	0.2	0.08
	Heat insulation thickness [mm]	30	12
Group 2	Personnel density [people/m^2]	*1	*2
	Electricity for lighting [W/m^2]	*1	*2
	Electricity for indoor equipment [W/m^2]	*1	*2

*1 Actual measurement value at each time

*2 (Actual measurement value at the time)×0.5

Bayesian estimation

The probability density was updated with Bayesian estimation when new information was obtained. The Bayesian estimation is represented in equation (4).

$$\text{Posterior probability} \propto \text{Likelihood} \times \text{Prior probability} \qquad (4)$$

The procedures to combine the representative parameters of group 1 and 2 are described below.

Step (1): The prior probability, $f(x)_w$, was calculated with equation (5). Prior distribution of the representative parameters of group 1 and 2 was calculated with equation (6).

$$f(x)_w = f(x)_1 \times f(x)_2 \qquad (5)$$

$f(x)_1$:Prior distribution of representative parameter of group 1

$f(x)_2$: Prior distribution of representative parameter of group 2

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (6)$$

σ^2: Variance (=1) x: Representative parameter value

μ: Mean of representative parameter (=0)

Step (2):The parameter value was calculated with equation (3). The zone air temperature and sensible heat load during the measurement period were calculated using the heat load calculation program.
Step (3): The likelihood, $L(x)_w$, was calculated with equation (7).$L(x)_1$and $L(x)_2$ were calculated with equation (8).

$$L(x)_w = \prod_i L(x)_1 \times \prod_i L(x)_2 \quad (7)$$

$L(x)_1$: Likelihood of representative parameters, x for average zone air temperature during unconditioned period for each day

$L(x)_2$: Likelihood of representative parameters, x for daily sensible heat load

i: Day index

$$L(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp^{-\frac{(g(x)-\mu)^2}{2\sigma^2}} \quad (8)$$

σ^2: Variance

μ: Average room temperature during unconditioned period and integrated daily heat load (Actual measurement)

g(x): Average room temperature during unconditioned period and integrated daily heat load (Simulation)

Step (4):The posterior probability was calculated by multiplying the likelihood with the prior probability.

RESULTS

Figures 3-6 show the posterior probability density for the combination of the representative parameters of group 1 and 2 for the 20 days measurement period. Here, "without prior information" shows the likelihood, i.e., the probability of the occurrence of an actual measurement value without considering prior information. The peak probability density could be estimated by the peak position in group 2, regardless of the presence or absence of prior information (Figures 3-4). For group 1, the peak appeared only when prior information was considered. In the absence of prior information, the probability density was uniform, and no peak value could be identified. The difference between the inside and outside temperature was considered to be low in summer. The parameters of group 1 therefore did not affect the load much. The posterior distribution could be determined from an estimated peak position in group 2, regardless of the presence or absence of prior information (Figures 5-6). The posterior probability exhibited a narrower distribution by considering the prior information and the uncertainty of the parameter was reduced for group 2. However, the representative parameter fluctuated greatly from the measured value when it approached -2. In group 1, the peak appeared when the prior information was considered.

Figures 7-8 show a comparison of the annual sensible heat load with or without prior information. The annual heat load was calculated by NewHASP/ACLD using the peak value of Figures 3-6. Figure 7 shows the results using the measurement data of summer. Because the cumulative cooling load without prior information was fitted to the measurements, the error for the measurement period was smaller than for the cases with prior information. The heating load error between the simulations and actual measurements was large. Figure 8 shows the results using the measurement data in winter. The accuracy of results for the measurement period was better when prior information was ignored (Figure 7). The cumulative cooling load error between the simulations and actual measurements was large.

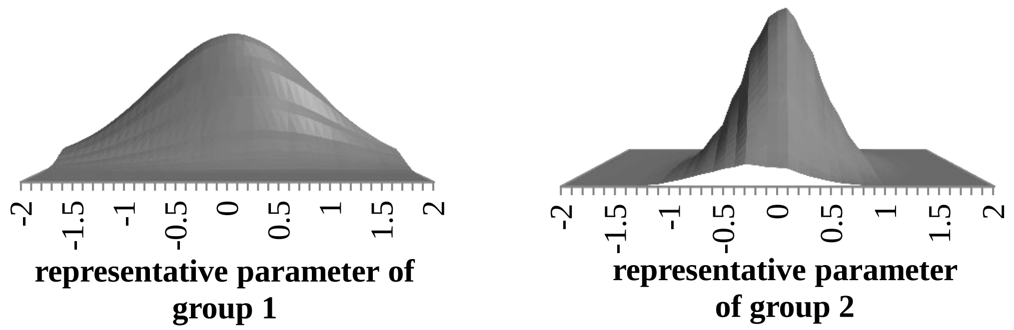


Figure 3.Probability density function (Summer, With prior information)

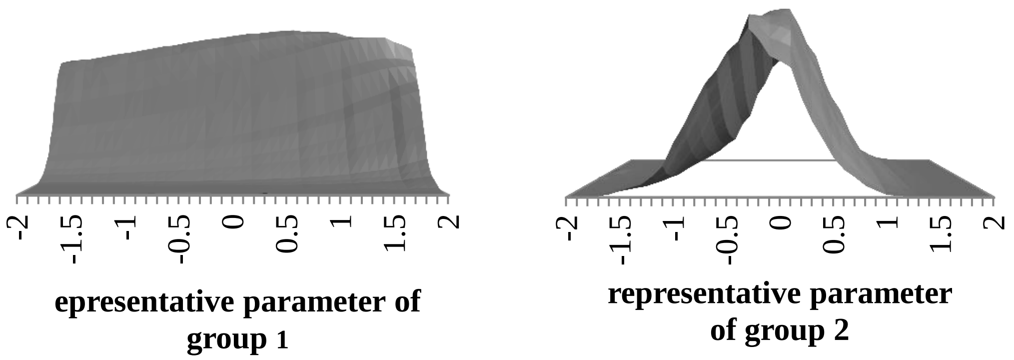


Figure 4.Probability density function (Summer, Without prior information)

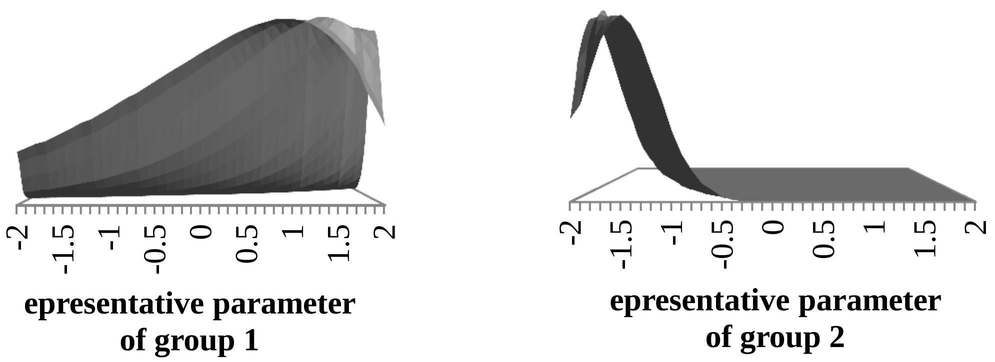


Figure 5.Probability density function (Winter, With prior information)

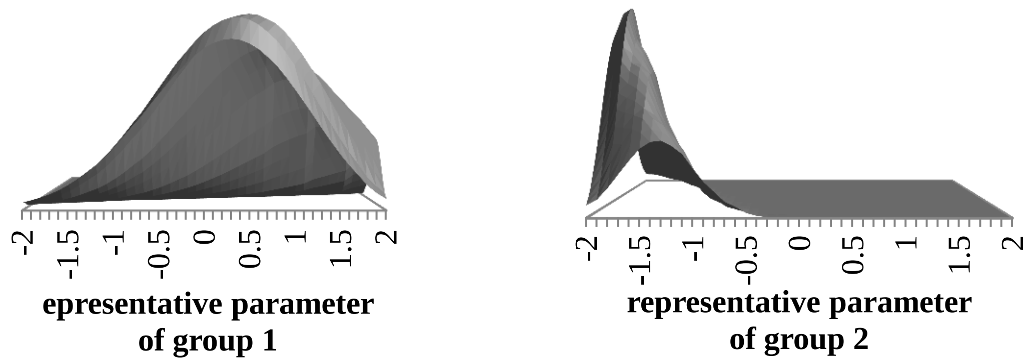


Figure 6.Probability density function (Winter, Without prior information)

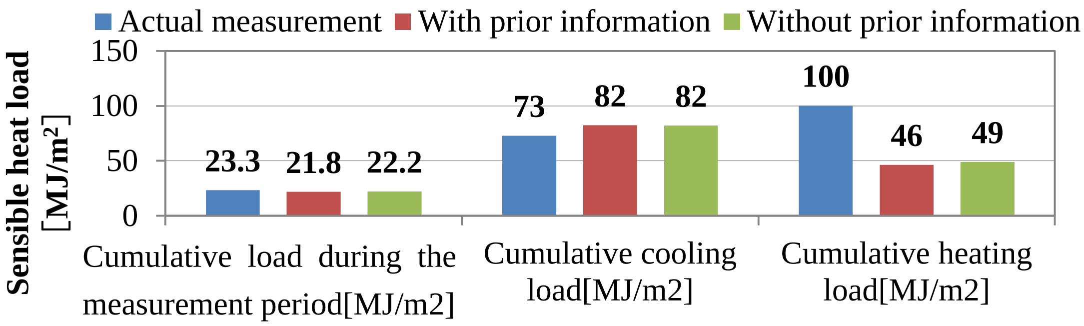


Figure 7.Cumulative sensible heat load (Measurement in summer)

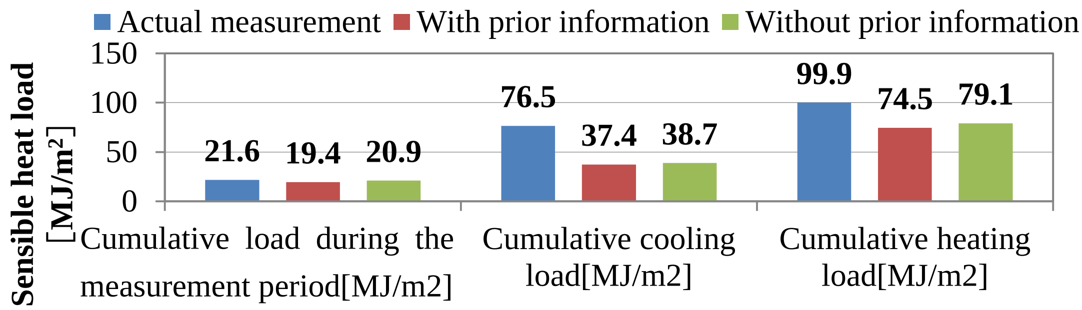


Figure 8.Cumulative sensible heat load (Measurement in winter)

Examination of error factors

Because the target room was on the first floor, the effect of the heat flow through the ground was investigated. In the preceding sections, we assumed in NewHASP that the thickness of the floor was 2 m and that the boundary temperature of the bottom surface was the same as the room temperature. This was however not necessarily so in the measurements. Then, the sensitivity of the influence of boundary temperature was analyzed. The boundary temperature was expressed by the adjacent room's temperature coefficient, α. The adjacent room's temperature was calculated as follows: Adjacent room temperature = α × outdoor temperature + (1-α) × temperature of target room ($0 \leqq \alpha \leqq 1$)

Figure 9 represents the results. The effect of α was large. As a result, it was necessary to consider the influence of the ground. It was necessary to set α as unknown parameter and treat it as a single group or a member of group 1.

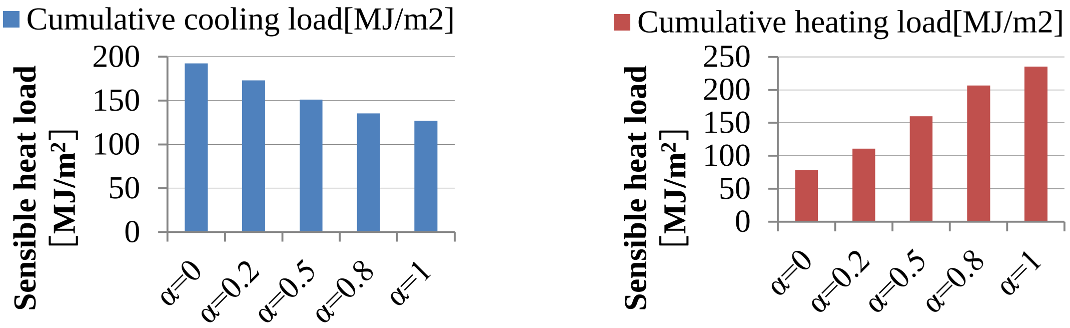


Figure 9.Cumulative sensible heat load (Sensitivity analysis)

CONCLUSION

This study applied a Bayesian estimate for uncertain parameters and proposed a technique to estimate multiple parameters simultaneously. The estimation accuracy of the sensible heat load was verified using the estimated parameters. The peak value for group 1 could be identified by considering priori information. For group 2 the probability of the cause narrowed when considering prior information and the uncertainty of the parameter decreased. Results of the thermal load calculation using the estimated parameters showed that the thermal load estimation accuracy was good for the same season as the measurement period and worse for a reverse season. Because the target room was on the first floor, the influence of the ground was considered as an error factor. The study results showed that its influence on the heat load estimate was big. In addition, many other factors, such as the influence of the ventilation by opening a door, may be reason for error. In this study, it was assumed that five parameters were unknown. The simulation model's uncertainty decreased by expanding the unknown parameters. It aimed to improve the heat load estimate accuracy.

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