Annual Thermal Load Estimation Using Prior Information and Short-term Measurement Data

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ABSTRACT
To determine the energy savings by the renewal of air conditioning equipment, a building’s cooling and heating annual load needs to be known. However, the required field measurements over a year are difficult to obtain when the building is in use. Therefore, methods need to be developed that can estimate the annual load based on short-term measurement data. To achieve this aim, we proposed a method that used a heat load calculation program. We created input from prior information and updated the input data with short-term measurement data, with the aim to improve the accuracy of the annual load estimation. This reduced parameter uncertainty by considering a priori information. The results of these thermal load calculations showed a good thermal load estimation accuracy for the same season as the measurement period and worse accuracy for a reverse season.

KEYWORDS
Parameter estimation, Bayesian estimate

INTRODUCTION
To determine the energy savings obtained by the renewal of air conditioning equipment, a building’s annual cooling and heating load needs to be known. However, the required field measurements over a year are difficult to obtain when the building is in use. Therefore, methods need to be developed that can estimate annual load based on short-term measurement data. We previously developed a heat load model with a small number of uncertain parameters and defined the parameters to best fit the measured short-term load (Morita et al., 2011). However, the error between the estimated and actual heat load increased in winter when fitting to measured data of summer only. The uncertain parameters were, for example, the heat capacity and thermal insulation. Heat capacity and thermal insulation could not be identified when using this method. The range of each parameter could however be estimated if there
was a drawing of the target room. Dong-HyunLee et al. (2012) calibrated the uncertain parameters using Bayesian estimation. However, actual measurement data have not been used in this paper. We therefore proposed a method for parameter estimation using Bayesian estimation to estimate multiple parameters, and examined its applicability using field measurement data. We created input data from prior information and updated the input data with short-term measurement data, with the aim to improve the accuracy of the annual load estimation. To achieve reliable estimation, many parameters were grouped into two representative parameters in the parameter estimation procedure. We estimated the annual cooling and heating load and compared it with the heat load of the actual measurements.

SIMULATION MODEL
This study focused on a university building (Figure 1). A simulation that used the actual measurement data and preliminary survey results (Table 1) calculated the zone air temperature and heat load. The measurement period was about one year (2011/8/15-2012/7/31). From these data 20 days of summer and winter were selected and the remainder of the data was used to validate the estimation accuracy. The simulations were performed using NewHASP/ACLD.

Table 1. Preliminary survey items and actual measurement data

<table>
<thead>
<tr>
<th>Design drawings</th>
<th>Specifications of the outer wall, inner wall, floor, inner ceiling, and window(materials and thickness)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual measurement data</td>
<td>Unit</td>
</tr>
<tr>
<td>Room temperature and humidity, adjacent room temperature and humidity</td>
<td>°C · %</td>
</tr>
<tr>
<td>Temperature and humidity inlet and outlet of the air conditioner</td>
<td>°C · %</td>
</tr>
<tr>
<td>Capacity of the outdoor unit</td>
<td>W</td>
</tr>
<tr>
<td>Indoor unit (on-off)</td>
<td></td>
</tr>
<tr>
<td>Electricity (illumination)</td>
<td>W</td>
</tr>
<tr>
<td>Number of people</td>
<td>people</td>
</tr>
</tbody>
</table>

SENSIBLE AND LATENT HEAT SEPARATION TECHNIQUE
The compressor method was applied to measure the total heat load of packaged-air conditioner that is installed in the target room. It was therefore necessary to separate the total heat load into latent and sensible heat load. The sensible heating fraction (SHF) was calculated with equation (1) using the enthalpy of the separation point (D...
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.

\[
\text{SHF} = \frac{h_{I} - h_{C}}{h_{I} - h_{C}}
\]

(1)

**Figure 2.** Each state point

\[
\text{SHF of the entire system} = \sum_{j=1}^{m} \sum_{t=1}^{n} \left( \text{SHF}_{jt} \times \Delta h_{jt,1-C} \right) / \sum_{j=1}^{m} \sum_{t=1}^{n} \left( \Delta h_{jt,1-C} \right)
\]

(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 represented that the standard deviation was added to the mean of the parameter. Table 2 shows the prior information (mean and standard deviation) for each parameter.

\[
\text{Parameter} = \text{mean} + (\text{standard deviation} \times \text{representative parameter}) \quad (3)
\]

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

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Prior distribution</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>standard deviation</td>
<td></td>
</tr>
<tr>
<td>Group 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infiltration [ACH]</td>
<td>0.2</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Heat insulation thickness [mm]</td>
<td>30</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>Group 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personnel density [people/m²]</td>
<td>*1</td>
<td>*2</td>
<td></td>
</tr>
<tr>
<td>Electricity for lighting [W/m²]</td>
<td>*1</td>
<td>*2</td>
<td></td>
</tr>
<tr>
<td>Electricity for indoor equipment [W/m²]</td>
<td>*1</td>
<td>*2</td>
<td></td>
</tr>
</tbody>
</table>

*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).

\[
\text{Posterior probability} \propto \text{Likelihood} \times \text{Prior probability} \quad (4)
\]

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).

\[
f(x)_w = f(x)_1 \times f(x)_2 \quad (5)
\]
\[
f(x)_1: \text{Prior distribution of representative parameter of group 1}
\]
\[
f(x)_2: \text{Prior distribution of representative parameter of group 2}
\]

\[
f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp \left( -\frac{(x-\mu)^2}{2\sigma^2} \right) \quad (6)
\]
\[
\sigma^2: \text{Variance (=1)} \quad x: \text{Representative parameter value}
\]
\[
\mu: \text{Mean of representative parameter (=0)}
\]
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).

$$L(x)_w = \prod_{i} L(x)_1 \times \prod_{i} L(x)_2$$  \hspace{1cm} (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

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

$\sigma^2$: Variance

$\mu$: 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)
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, $\alpha$. The adjacent room’s temperature was calculated as follows: Adjacent room temperature = $\alpha \times$ outdoor temperature + $(1-\alpha) \times$ temperature of target room ($0 \leq \alpha \leq 1$)

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