Bayesian Calibration for Transient Energy Simulation Model

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ABSTRACT
Building simulation has become increasingly important because of its capability to assess potential energy efficiency savings in buildings. In the simulation modellingprocess, many assumptions and simplifications are required and many uncertain inputs are also involved. The aforementioned issues may cause a significant discrepancy between a reality and prediction. With this in mind, this paper investigatesapplicability of a Bayesian calibration technique to a transient simulation model. This will improve prediction accuracy and reduce uncertainty. The Bayesian calibration is a way to estimate the posterior distribution based on the quantified prior distribution.For sampling uncertain inputs, MCMC(Markov Chain Monte Carlo) method was applied in our study. One of the MCMC methods, DRAM(Delayed Rejection Adaptive Metropolis) was employed. This paper addresses Bayesian calibration, uncertainty analysis, and risk analysis for whole-building building energy simulation modelling(EnergyPlus). For this study, an office building was selected and 28 unknown inputs were identified. The Bayesian calibration was conducted in three steps: (1) determination of prior probability distributions for uncertain inputs, (2) formulation of likelihood functions,and (3)MCMC method for posterior distributions. Lastly, Coefficient of Variation of the Root Mean Squared Error (CVRMSE, ASHRAE Guide line14) was used for the validation of the approach. In the paper, the following is discussed: (1) posterior distributions of inputs against their prior distributions, (2)results of Bayesiancalibration for the model, and (3) advantages of Bayesian calibration for dynamic simulation model.

KEYWORDS
Bayesian,Markov Chain Monte Carlo,dynamic simulation,model calibration

INTRODUCTION
Building simulation has been attributed to reduction of building energy use.The simulation tools can present predicted results such as energy use, thermal comfort, indoor air quality, etc.However, modellingassumptions and simplifications as well as

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uncertainty inputs, which are involved in the process of performance simulation, are believed to cause a gap between simulation prediction and measurement. Many studies presenteddiscerniblediscrepancies between the building simulation results and the real measurements (IBPSA, 1987-2011).In the light of this perspective, the calibration technique is a necessity to estimate uncertaininputs and to cancel out knowingly or unknowingly unmodeledor simplifieddynamics.

This paper addressesapplicability of the Bayesian calibration technique to a transient energy simulation model (EnergyPlus v.6.0) and describesits impacts and advantages. For this study, the Bayesian calibration method was conducted in three steps: (1) determination of prior probability distributions for uncertain inputs based on the literature, (2) formulation of likelihood functions,and (3)Markov Chain Monte Carlo(MCMC) for posterior distributions.

SIMULATION MODEL

A 5-storeysample office building located in Seoul, Korea was selected for this study. Figure 1 shows the energy simulation model consisting of five thermal zones (four perimeter zones and one interior zone) in each floor. A total floor area is 6,125 m^2, and a ratio of window area to wall area is 35.7%. As for the HVAC system, “IdealLoadAirSystem (or purchased air)” was applied. The IdealLoadAirSystem is used to calculate heating and cooling loads without taking into account equipment efficiency or performance (Ellis &Torcellini, 2005). For a building energy performance tool, EnergyPlus 6.0 developed by Department of Energy (DOE) was utilized.The 28unknowninputs (Macdonald, 2002; ASHRAE, 2009; Hopfe, 2009; Doe, 2010) in the EnergyPlus modelwere selected in this study (c.f.Table2 Prior distributions).The selected unknown inputs were composed of normal distribution with mean (μ) and standard deviation (σ). The unknown inputs were assumed independent of each other.

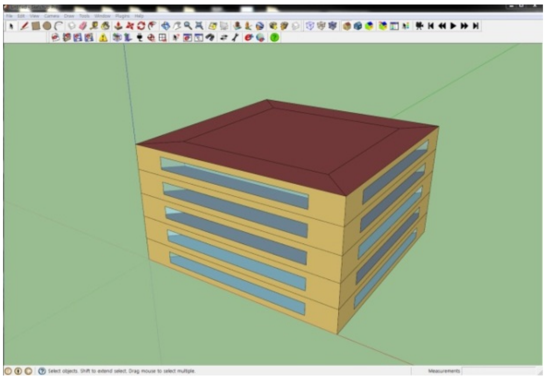


Figure 1*.Targetbuilding (Display: OpenStudio)*

BAYESIAN CALIBRATION

There are typically three ways for calibrating the simulation model: (1) manual calibration (‘trial and error’ or ‘rule of thumb’ approach: selection of any input based on expertise or intuition → change the value of it → see the result and repeat until it is satisfactory), (2) deterministic optimization (use of an optimization function that minimizesa difference betweenthe prediction and the measurement), and (3) Bayesian calibration (stochastic optimization).In this study, the authors selected the Bayesian calibration for reducing uncertainty of theunknown inputs inherited inthe simulation model, rather than a best-fit one.The Bayesian calibration, which is based on the Bayes'theorem as shown in equation (1), is an effective stochasticapproach for finding a distribution of solutions in each unknowninput (θ)in the simulation model (m) given observed data (y).To calculate on posterior distribution ($P(\theta|y, m)$), prior distribution ($\pi(\theta, m)$) and likelihood function $P(y,m|\theta)$must be taken into account. The likelihood function is the probability of the data for thegiven unknowninputs (θ).Observation ($y(x)$) formulated by model outputs $\eta(x,\theta)$ at known inputs (x), unknown inputs (θ), and observation error ($\varepsilon(x)$) as the Gaussian process model defined by Kennedy and O'Hagan (2002) (equation (2)).

$$P(\theta|y,m) \propto P(y,m|\theta) \times \pi(\theta, m) \tag{1}$$

$$y(x) = \eta(x,\theta) + \varepsilon(x) \tag{2}$$

Due to lack of real observed data (e.g. electric or gas consumption), we used simulation outputs (monthly total energy load), which were generated based randomly selected inputs and climate file (*.epw) in 2009-2011 years, as observed data.The observed data in 2009-2010 years were used for Bayesian calibration. On the other hand, the observed data in 2011 year was used for validation of the calibrated simulation model data.Table 1 shows observation results for the sample office building (Figure 1).

Table 1.*Observed data(kWh/m^2)*

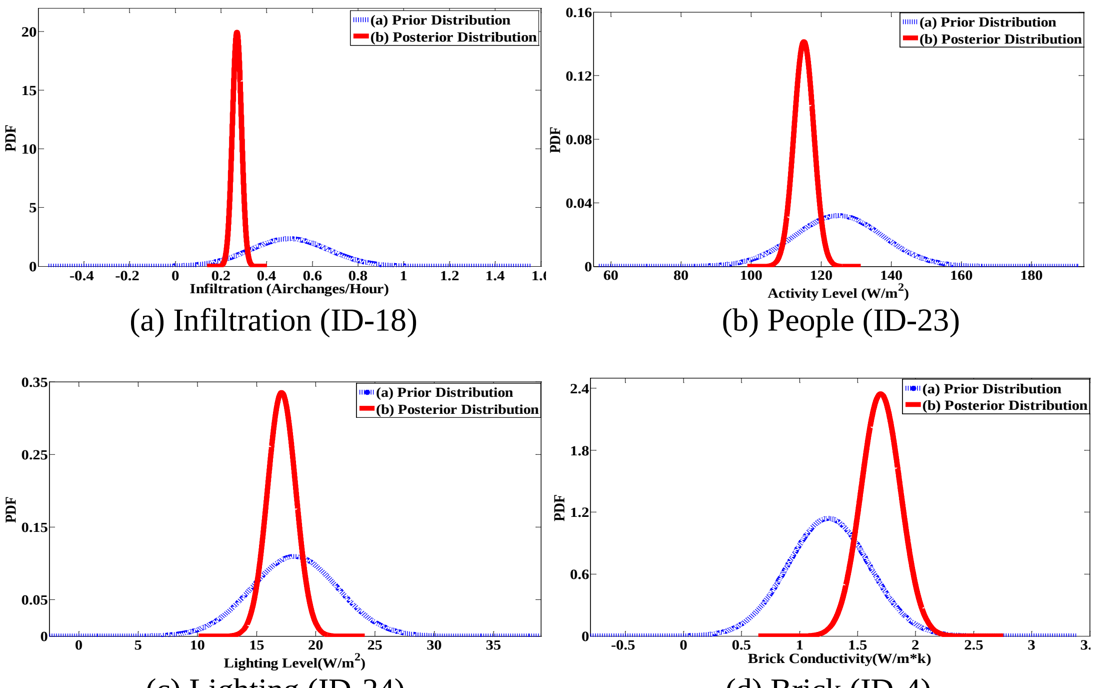
Month	For calibration		For validation
	Year2009	Year2010	Year2011
1	5.85	6.57	7.50
2	3.70	4.58	3.88
3	3.92	4.01	3.70
4	4.64	3.27	3.81
5	8.35	5.87	7.38
6	10.18	8.98	9.21
7	9.71	9.13	8.95
8	12.04	10.71	10.04
9	9.07	8.13	8.96
10	6.33	5.53	5.57
11	4.23	3.92	4.42
12	5.19	5.16	4.95

The authors adopted Metropolis-Hastings MCMC chain using multivariate Gaussian proposal distribution. The Metropolis-Hastings algorithm is a convenient sampling technique in MCMC method. The MCMCis Monte Carlo integration using Markov

Chains (Gilks et al, 1995).To runs MCMC chain, the time period wasselected as 4,000 iterations, and the time period for burn-in phase was selected as the first 10%of a chain(Van Oijen et al, 2005). The burn-in phase will discard a portion of the initial iterations for drawing right searches in input space.

RESULTS AND VALIDATION

Figure 2 shows Probability Density Function (PDF) of the four prior and posterior distributions. The four inputs in Figure 2 were randomly selected. The distributions represented in blue are the prior distribution, and the posteriors are shown in red.Table 2 shows mean and standard deviation of 28 unknown inputs before and after Bayesian calibration. As shown in Table 2 and Figure 2, there is a significant difference between prior and posterior distributions. If the prior data are informative, the posterior distributions will be narrower, and more sharply peaked than the prior distribution, indicating that uncertainty is reduced. If initial inputs were completely informative, and have low error, posterior distributions have strong robustness and are sharply peaked. For the infiltration rate (Figure 2(a)), the posterior distribution shifts to the lower bound by 0.23. This update means that air tightness in the calibrated model is less than that in the uncalibrated model. For the activity level (Figure 2(b)), the posterior distribution is toward lower bound while its shape maintains the same as the prior distribution. This shift indicates that the mean of activity level for the calibrated model is smaller than that for the uncalibrated model. Regarding the lighting level (Figure 2(c)), the posterior distribution does not shifted much from the prior distribution. On the contrary, for the conductivity of a brick (Figure 2(d)), the posterior distribution is shifted the most. This inputs increase approximately by 36% from the prior mean value.



(a) Infiltration (ID-18) (b) People (ID-23)

(c) Lighting (ID-24) (d) Brick (ID-4)

Figure 2*.Prior distribution and Posterior distribution (randomly selected 4 out of 28)*

Table 2.Results of Bayesian calibration

Input variables		ID	Prior distribution		Posteriordistribution	
			Mean	St.dev	Mean	St.dev
Plaster Board	Conductivity(W/m·K)	1	0.43	0.15	0.47	0.06
	Density(Kg/m^3)	2	1488	501	1178.79	253
	Specific Heat(J/kg·K)	3	958	109	972.64	70.29
Brick	Conductivity(W/m·K)	4	1.25	0.35	1.70	0.17
	Density(Kg/m^3)	5	2000	33	1980.01	17.24
	Specific Heat(J/kg·K)	6	840	90	892.43	22.14
Medium Weight Concrete	Conductivity(W/m·K)	7	1.68	0.54	0.95	0.19
	Density(Kg/m^3)	8	2310	225	2329.59	72.03
	Specific Heat(J/kg·K)	9	840	90	829.61	9.47
Insulation	Conductivity(W/m·K)	10	0.04	0.01	0.04	0.01
	Density(Kg/m^3)	11	38	27	3.92	4.52
	Specific Heat(J/kg·K)	12	1072	298	969.70	152.07
Acoustic Tile	Conductivity(W/m·K)	13	0.93	0.41	1.20	0.04
	Density(Kg/m^3)	14	1610	436	1830.66	159.32
	Specific Heat(J/kg·K)	15	818	89	803.18	48.43
Window	U-Factor(W/m^2·K)	16	1.72	0.17	1.67	0.095
	SHGC	17	0.17	0.02	0.17	0.00
Infiltration	AirChanges per Hour	18	0.50	0.17	0.27	0.02
Set point temperature	Heating (℃)	19	21.50	2.15	22.64	0.47
	Cooling (℃)	20	27	2.70	28.20	0.88
People	Person/area	21	0.22	0.11	0.17	0.03
	Fraction radiant (%)	22	0.48	0.05	0.50	0.03
	Activity level(W/m^2)	23	125	12.50	115.07	2.82
Lighting	Lighting level(W/m^2)	24	18.22	3.64	17.12	1.19
	Fraction radiant (%)	25	0.42	0.04	0.49	0.01
	Fraction visible (%)	26	0.18	0.02	0.19	0.01
Equipment	Watt/area(W/m^2)	27	16.15	3.23	15.26	1.24
	Fraction radiant (%)	28	0.30	0.03	0.32	0.01

To validate for Bayesian calibration, Coefficient of Variation of the Root Mean Squared Error(CVRMSE) value was used. The simulation model can be consideredvalid, in the case where the CVRMSE values of the calibrated models is equal or less than 15% (ASHRAE,2002).In this study, Latin Hypercube Sampling (LHS) method was applied to obtain 100 samplings, with which calibrated and uncalibrated modelscould be compared.100 CVRMSE valueswere calculated from the simulated results.Energy use from the calibrated and the uncalibratedwere respectively checked by validating the 2011-year-weather data100 times.As shown in Table3, an averageof 100 CVRMSE valuesfor energy use fromthe uncalibrated model was40.21%. On the other hand, an averageof 100 CVRMSE valuesfor prior energy use from the calibrated model was9.94%.An average of 100 CVRMSE valuesforposterior energy use from the calibrated model ranged within the confidence level.It indicates that stochastic calibration enhances the accuracy of model.

Table 3.*Validation results for uncalibrated and calibrated model (Unit: %)*

CVRMSE	Uncalibrated energy use vs.Observed energy use	Calibrated energy use vs.Observed energy use
Average	40.21	9.94
Within 15% Probability	14.27	82.55

Table 4 represents each average energy use fromthe uncalibrated(b) and the calibrated model(c).The difference (|(a) – (c)|)between the 2011-observed energy use and an average energy use from the calibrated modelis smaller thanthe difference (|(a) – (b)|) between the 2011-observedenergy use and an average energy use from uncalibrated model. It means that uncertainty of the uncalibratedmodelreduced, approaching to2011 observed energy use.

Table 4.*Average energy use for the uncalibratedandthe calibratedmodel (Unit: kWh/m²)*

Month	2011-Observed energy (a)	Uncalibrated Model(b)	|(a) – (b)|	Calibrated Model(c)	|(a) – (c)|
1	7.50	8.97	1.47	7.54	0.04
2	3.88	4.15	0.27	3.96	0.08
3	3.70	3.89	0.19	3.82	0.12
4	3.81	4.15	0.34	3.90	0.09
5	7.38	8.58	1.20	7.43	0.05
6	9.21	10.91	1.70	9.25	0.04
7	8.95	10.92	1.97	8.99	0.04
8	10.04	12.39	2.35	10.17	0.13
9	8.96	10.56	1.60	9.02	0.06
10	5.57	6.19	0.62	5.61	0.04
11	4.42	4.84	0.42	4.53	0.11
12	4.95	5.31	0.36	4.99	0.04
Total	78.37	90.85	12.48	79.21	0.84

In Figure3, monthly average energy uses from the uncalibrated and the calibrated model are shown in a boxplot. As shown in Figure3, the uncalibrated simulation model is distributed in a wide range of energy use. On the other hand, the calibrated simulation model is distributed in a narrower range than the uncalibrated model. It means that the unknown inputs’ uncertainty reduced.It shows advantage of stochastic calibration.

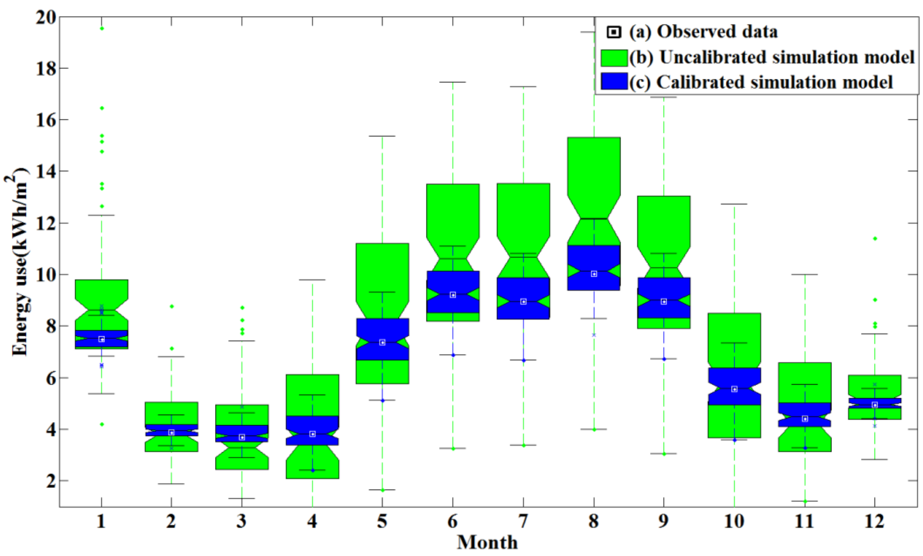


Figure 3*.Energy use(uncalibratedvs.calibratedvs.observed)*

CONCLUSION

This study presents an example of Bayesian calibration for the transient simulation model.In this study, the posterior distribution can be estimated by usingquantification of prior knowledge and reflection on observed data. The main purpose of this study is to increase model accuracy andto validatean energy simulation model.As a result of Bayesian Calibration, the unknown inputs of anenergy simulation modelhave the mean and the Standard deviation for posterior distributions. The calibrated model and the uncalibrated model have difference in the mean and the Standard deviation. The calibrated model was superior to the uncalibrated model in terms of robustness.It was attributed to Bayesian calibration.From the validation results of energy simulation model, it is shown that CVRMSE of the calibrated modelwas better than that of the uncalibrated model.Thus, withcomparing the energy use in after-calibration and before-calibration, the energy useinafter-calibration was stochastically closer to the observed data. Bayesian calibration enhances the reliability and accuracy for a transient energy model.

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