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Bayesian inference for thermal response test parameter estimation and uncertainty assessment

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HIGHLIGHTS

- Bayesian inference for TRT parameters and uncertainty assessment was proposed.
- Not only point estimates of parameters but also credible intervals can be extracted.
- Numerical TRT and sandbox TRT data were used to verify the proposed method.
- Our method was used to examine the relationship between uncertainty and TRT time.
- Estimation uncertainty decreased exponentially with increasing time: < 10% for 50 h.

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ABSTRACT

The effective ground thermal conductivity and borehole thermal resistance constitute information needed to design a ground-source heat pump (GSHP). In situ thermal response tests (TRTs) are considered reliable to obtain these parameters, but interpreting TRT data by a deterministic approach may result in significant uncertainties in the estimates. In light of the impact of the two parameters on GSHP applications, the quantification of uncertainties is necessary. For this purpose, in this study, we develop a stochastic method based on Bayesian inference to estimate the two parameters and associated uncertainties. Numerically generated noisy TRT data and reference sandbox TRT data were used to verify the proposed method. The posterior probability density functions obtained were used to extract the point estimates of the parameters and their credible intervals. Following its verification, the proposed method was applied to in situ TRT data, and the relationship between test time and estimation accuracy was examined. The minimum TRT time of 36 h recommended by ASHRAE produced an uncertainty of ~ ± 21% for effective thermal conductivity. However, the uncertainty of estimation decreased exponentially with increasing TRT time, and was ± 8.3% after a TRT time of 54 h, lower than the generally acceptable range of uncertainty of ± 10%. Based on the obtained results, a minimum TRT time of 50 h is suggested and that of 72 h is expected to produce sufficiently accurate estimates for most cases.

1. Introduction

The ground has a much higher heat capacity than the air, and maintains a stable temperature. A ground-source heat pump (GSHP) that utilizes the ground as its heat source/sink can therefore be expected to perform better than an air-source heat pump. The ground heat exchanger (GHE) is a key component that affects the performance of a GSHP. Of the various types of GHEs, the most common is the vertical closed-loop GHE, the so-called borehole heat exchanger (BHE). In the design of a BHE, it is necessary to know the thermal conductivity of the ground and the thermal resistance of the borehole. Because the ground is a composite medium with highly site-specific thermal properties, it is difficult to establish the spatial distributions of the thermal properties. Consequently, the spatially averaged nearby thermal properties are estimated by in situ thermal response tests (TRTs) [1]. While a TRT test is expensive, it is recommended for any large installations because the parameters derived from it play a significant role in designing GSHP systems. Bernier [2] conducted an uncertainty analysis using the ASHRAE design method [3,4]. Among related parameters, the ground thermal conductivity had the most significant impact on the design length of the BHE. Assuming that the other parameters are accurately known, an uncertainty of ± 10% in thermal conductivity led to a ± 7.1% uncertainty in the length of the BHE. Robert and Gosselin [5] discussed the impact of ground thermal conductivity on initial and

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Nomenclature

(All bold characters in the manuscript denote a vector or matrix.)

a_r	acceptance ratio
c	specific heat (J/(kg·K))
C	volumetric heat capacity (J/(m^3·K))
CI_L	lower bound of 95% credible interval
CI_U	upper bound of 95% credible interval
e	error
E	expectation
Ei	exponential integral
F	mean temperature determined from forward model (°C)
H	length of BHE (m)
I	indicator function
I_{sol}	global solar irradiance (W/m^2)
k	gradient of semi-log plot
N	number of time steps or measured data
p	probability distribution
P	parameter
$\hat{P}$	estimated parameter
q	heat rate per unit length of BHE (W/m)
$\bar{q}$	averaged heat rate per unit length of BHE (W/m)
Q_n	n-th quartile
Q_T	source term (W/m^3)
r	drawn random number
r_b	radius of borehole (m)
r_σ	error ratio between measurement and forward model value
R_b	borehole thermal resistance (m·K/W)
R_n	random number generator with normally distributed results
t	time or elapsed time after heat injection (s)
T	temperature (°C)
$\bar{T}$	mean of inlet and outlet temperatures (°C)
T_{DB}	dry bulb temperature (°C)
$\bar{T}_{tr}$	unknown true mean temperature (°C)
U	uncertainty (%)
Y	measured temperature used for inference (°C)
v	variance
$\dot{V}$	volumetric flow rate (m^3/s)

Subscripts

c	clean data without error
in	inlet
n	noisy data
out	outlet
s	soil or ground
0	initial

Superscripts

i	iteration step of sampling
n	measured data number
N	total number of data elements (time steps)

Greek letters

α	thermal diffusivity (m^2/s)
λ	thermal conductivity (W/(m·K))
λ_{eff}	effective thermal conductivity (W/(m·K))
ρ	density (kg/m^3)
γ	Euler–Mascheroni constant
σ	standard deviation
$\mathcal{N}$	normal distribution
$\mathfrak{R}$	parameter space
$\mathcal{U}$	uniform distribution

Acronyms, abbreviations

CI	credible interval
MAP	maximum a posteriori
MCMC	Markov chain Monte Carlo
PDF	probability density function
PM	posterior mean
PPDF	posterior probability density function

operation costs. They claimed that determining precise ground thermal conductivity via TRT is economically important, especially when the borefield is large.

To determine the values of ground thermal conductivity and borehole thermal resistance from in situ TRT data, several inverse modeling techniques have been tested since Mogensen [6] first proposed the TRT estimation method. Research on the performance and accuracy of suitable inverse modeling techniques has been prolific because incorrect estimates of ground thermal conductivity and borehole thermal resistance can increase the initial cost of the GSHP system or the probability of system failure. The most well-known and frequently used is linear regression [7,8], which utilizes a simplified infinite line source (ILS) model (exponential integral approximated ILS model) [9,10]. Other parametric estimation techniques have been developed, and involve the combined use of a numerical or an analytical temperature response model and an optimization algorithm. One such method that has been employed in many studies [1,11–15] utilizes the Nelder–Mead simplex algorithm [16]. This is a heuristic optimization method. Gradient-based optimization methods have also been used in some previous studies. For example, Li and Lai [17] used the Levenberg–Marquardt method [18–20], Choi and Ooka [21] used the quasi-Newton method [22–25], and Bozzoli et al. [26] used the Gauss linearization method [27]. All these methods yield deterministic point estimates of ground thermal conductivity and borehole thermal resistance by minimizing the least squares norm. However, such deterministic methods do not consider sources of uncertainty available in the estimation process and also do not quantify the uncertainties included in the estimation results. The uncertainty quantification of parameters is important because it can improve the reliability of GSHP design and, thus, reduce initial cost and operational risks.

The causes of uncertainty in TRTs can be divided into two major categories. The first consists of errors due to contextual disturbances that occur during TRTs, and the second category consists of measurement errors, such as the intrinsic random error and the systematic error of utilized sensors. Considering that TRTs are conducted in outdoor environments, which cannot be completely controlled, the first error is a significant factor. Indeed, TRTs are vulnerable to large contextual uncertainties compared with fully controlled laboratory experiments. The effects of experimental disturbances on TRTs have been investigated by many researchers. For example, the effects of instability in voltage supply from the power grid or the power generator, and the resultant violation of the constant heating rate assumption of the ILS model have been examined [28–32], as well as those of heat exchange between an aboveground TRT setup and the outdoor environment [29,33–38]. If these experimental disturbances are not properly considered in the inverse model used for parameter estimation, the resultant inconsistencies can cause errors in the solution of the inverse problem [21,38]. With regard to measurement error, it is common to all