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Bayesian inference of structural error in inverse models of thermal response tests

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HIGHLIGHTS

- Model inadequacy in TRT interpretation is examined using a Bayesian framework.
- Random measurement errors and structural model inadequacy are explicitly quantified.
- Bayesian framework is applied to two TRTs affected by aboveground disturbances and groundwater flow.
- Bias function quantifies inadequacy of physical model selected to interpret TRTs.
- GSHP design parameters are inferred with full quantification of associated uncertainties.

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ABSTRACT

For the design of ground-source heat pumps (GSHPs), two design parameters, namely the ground thermal conductivity and borehole thermal resistance are estimated by interpreting thermal response test (TRT) data using a physical model. In most cases, the parameters are fitted to the measured data assuming that the chosen model can fully reproduce the actual physical response. However, two significant sources of error make the estimation uncertain: random error from experiments and structural bias error that describes the discrepancy between the model and actual physical phenomena. Generally, these two error sources are not evaluated separately. As a result, the suitability of selected models to correctly infer parameters from TRTs are not well understood. In this study, the Bayesian calibration framework proposed by Kennedy and O'Hagan is employed to estimate the GSHP design parameters and quantify the random and structural errors in the inference. The calibration framework enables us to examine structural errors in the commonly used infinite line source model arising due to the conditions in which the TRT takes place. Two in situ TRT datasets were used: TRT1, influenced by contextual disturbances from the outdoor environment, and TRT2, influenced by a strong groundwater flow caused by heavy rainfall. We show that the Bayesian calibration framework is able to quantify the structural errors in the TRT interpretation and therefore can yield more accurate estimates of design parameters with full quantification of uncertainties.

Nomenclature

C	volumetric heat capacity (J/(m^3·K))
E	expectation
Ei	exponential integral
I_{sol}	global solar irradiance (W/m^2)
n_x	number of scenario parameters
n_θ	number of calibration parameters
p	probability distribution
q	heat rate per unit length of BHE (W/m)
$\bar{q}$	averaged heat rate per unit length of BHE (W/m)
r_b	radius of borehole (m)
R_b	borehole thermal resistance (m·K/W)
t	time or elapsed time after heat injection (s)

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T	temperature (°C)
$\overline{T}$	mean fluid temperature (°C)
T_{DB}	dry-bulb temperature (°C)
ν	precision parameter of covariance function
$\dot{V}$	volumetric flow rate (m^3/s)
x	scenario variable
y_c	simulation output
y_f	field measurement data
y	augmented observation vector, $y = (y_f^T, y_c^T)^T$

Subscripts

b	model inadequacy (bias) function
c	computer data
f	field data
in	inlet
n	time step
N	total number of data (time steps)
out	outlet
s	soil or ground
0	initial
δ	bias (model inadequacy) function
η	computation model, GP emulator

Superscript

T	transpose of vector or matrix

Greek letters

α	thermal diffusivity (m^2/s)
β	correlation parameter of covariance function
δ	model bias
ε	observation (random) error
ε_n	numerical (random) error
ζ	real (unobservable) physical process
η	model emulator term
θ	calibration parameters
θ^*	randomly generated parameters by LHS method
σ	standard deviation
λ_{eff}	effective thermal conductivity (W/(m·K))
Σ	covariance function of Gaussian process
ψ	hyperparameter vector

Acronyms, abbreviations

BC	Bayesian calibration
BI	Bayesian inference
CI	credible interval
GP	Gaussian process
LHS	Latin hypercube sampling
MAP	maximum a posteriori
MCMC	Markov chain Monte Carlo
PM	posterior mean
PPDF	posterior probability density function

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

1. Introduction

Ground-source heat pump (GSHP) systems that utilize the shallow part of the ground as a heat source or sink have witnessed widespread use in recent years. The ground is not only a spatially inhomogeneous composite medium but also a porous medium. Therefore, subsurface heat transfer involves conduction and advection (e.g., forced convection by groundwater flow and natural convection). Identifying and measuring dominant heat transfer processes in the subsurface, where the ground heat exchangers (GHEs) are installed, is difficult and expensive compared to quantifying them for the load side of the GSHP, where the energy is supplied. This intrinsic nature of geothermal applications leads to significant uncertainties in the design and operation of GSHPs.

Research on uncertainty quantification of GSHP system performance follows the framework of the ISO's Guide to the Expression of Uncertainty in Measurement (GUM) [1]. The GUM framework emphasizes uncertainties associated with sensor data. GUM has been used to quantify uncertainties for various GSHP configurations and operation strategies. Notable studies include uncertainty analysis of the thermodynamic performance of a GSHP [2,3], uncertainty in performance of a hybrid GSHP combined with a solar thermal collector [4], and uncertainty in evaluating the energy balance of a GSHP's load and source sides [5].

In GSHP systems, the uncertainty associated with ground-related parameters is particularly important. These include the ground thermal conductivity and borehole thermal resistance. Both parameters have a significant impact on the design length of the GHE: Incorrect estimation can lead to a large increase in initial costs due to oversizing, or system failure during operation due to undersizing [6]. The GUM framework has also been used to quantify the uncertainties in these GSHP design parameters [7,8]. However, current work only considers sensor error as the main source of uncertainty and not the estimation process as a whole. The design parameters of a GSHP system are typically estimated via an inverse model using measured temperatures and heat rates from thermal response tests (TRTs).

In inverse problems, such as in the inference of GSHP design parameters, the first task is to match the experimental conditions to the assumptions and boundary conditions made in the physical model (e.g., analytical or numerical). It involves selecting or developing a physical model that best represents the experiment and thus enables accurate inference of relevant parameters. However, often the physical model only partially represents the actual physical phenomena being measured. This may be due to a lack of information on the system of interest or simplifications necessary in the modelling process.

A closer examination of the commonly used forward model for interpreting TRTs further highlights instances where experimental conditions do not match the physical model; in the uncertainty quantification literature, this is termed "model inadequacy." For instance, the commonly used infinite line source (ILS) model [9,10] and infinite cylindrical source (ICS) model [9] for interpreting TRTs assume that a TRT is conducted under the following conditions: the ground surface is adiabatic and the heat flux from the source is constant. However, at an actual TRT site where the TRT setup is fully exposed to the outdoor environment, such assumptions are usually violated by the fluctuation of the supply voltage [11,12], the heat exchange between the above-ground TRT setup and the outdoor environment [13,14], and heat transfer in the ground surface [15].

This mismatch between the model assumptions and the experimental conditions are well acknowledged and many studies have investigated this issue. For example, related to the unstable power rate issue, Shonder and Beck [11] developed a parameter estimation method that includes a one-dimensional numerical model as a forward model to consider the fluctuating power input. Hu et al. [12] proposed a data processing method that uses the Gaussian kernel regression method to eliminate the high frequency noise in the heat rate. Witte et al. [16] tried to solve the unstable power issue by using a special TRT apparatus equipped with a water-to-air heat pump, buffer tank, regulating valves, and control components. Because the apparatus could maintain a constant heat rate by mechanical control, very stable estimation behavior was achieved. Additionally, efforts have been made to study the effect