Interpretation of Thermal Response Test (TRT) in energy piles using Bayesian Inference

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An efficient design of energy geo-structure systems requires an accurate characterization of the structure and ground thermal parameters (e.g., thermal resistance of the ground heat exchanger \( R_b \), and the thermal conductivity of the surrounding ground \( \lambda \)). The Thermal Response Test (TRT) is the international standard method for these parameter determinations. Traditionally, TRTs have been performed only in boreholes and piles of small diameter, i.e., 300 mm maximum. However, in recent years, TRTs in large-diameter piles are becoming more common. Although these types of TRTs can provide acceptable results if adequate interpretation methods are selected, some concerns about the added uncertainty of the estimations due to the increased logistic challenges prevail [4, 7].

In this context, Bayesian Inference represents an invaluable resource for analyzing TRTs in energy piles. Bayesian approaches allow accounting for structural model errors and provide credible intervals, giving uncertainty metrics that are difficult to obtain by classic deterministic methods. Additionally, since Bayesian techniques combine prior knowledge with observations (experimental data), they have a significant potential for uncertainty assessment in short-duration tests, as demonstrated by recent studies in traditional TRTs [1, 2, 8].

In the present study, a stochastic method based on Bayes’ Theorem [1] has been adapted to interpret the results of a short-duration TRT carried out in an energy pile in Mexico [5]. The aim is to infer Posterior Probability Density Functions (PPDFs) for the parameters of interest (ground thermal conductivity \( \lambda \) and concrete thermal resistance \( R_c \)), taking into account our previous knowledge (prior distributions) and the given measurements of the TRT (likelihood). For this case study, prior distributions were assigned based on the site stratigraphy and international ground thermal properties databases [3]. The [7] method was employed to calculate the likelihood. This method uses G-functions developed specifically for the ground \( (G_g) \) and the pile \( (G_p) \), which described their transient response. Finally, a Markov Chain Monte Carlo (MCMC) method (Gibbs sampling) was used to obtain the PPDFs. From the PPDFs, the point estimates of the parameters and their 95% credible intervals were extracted. The above procedure is described in detail in Figure 1. The results are consistent with those obtained using a deterministic analysis (see Table 1). However, the PPDF provides more information about the uncertainties of the parameters. The above is crucial to perform more realistic designs and to evaluate accurately the financial viability of a project based on energy geo-structures.

Table 1: Results comparison between deterministic analysis and Bayesian Approach of a TRT executed in Mexico

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Deterministic analysis</th>
<th>Bayesian Approach Posterior Mean</th>
<th>95 % Credible Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground thermal conductivity</td>
<td>( \lambda ) Wm(^{-1})K(^{-1})</td>
<td>1.630</td>
<td>1.607</td>
<td>1.566 – 1.649</td>
</tr>
<tr>
<td>Concrete thermal resistivity</td>
<td>( R_c ) mKW(^{-1})</td>
<td>0.078</td>
<td>0.0775</td>
<td>0.0773 – 0.0778</td>
</tr>
</tbody>
</table>
Figure 2: TRT Interpretation using Bayesian Inference: a) Input data, b) Bayesian Inference, c) Markov Chain Monte Carlo – Gibbs sampling, and d) Results and analysis. Note: \( \lambda \) = Ground thermal conductivity, \( R_c \) = Concrete thermal resistance, \( T_f \) = Fluid Temperature, \( q \) = Heat transfer rate, \( R_p \) = Pipe thermal resistance, \( G_g \) = Loveridge G-function for ground, \( G_c \) = Loveridge G-function for concrete, PPDF = Posterior Probability Density Function, CI = Credible Intervals, \( \text{q}_{2.5\%} \) = 2.5 % quantile, \( \text{q}_{97.5\%} \) = 97.5% quantile.

**Contributor statement**

Conceptualization: Norma Patricia López-Acosta, David Francisco Barba-Galdámez; Formal Analysis: David Francisco Barba-Galdámez; Project Administration: Norma Patricia López-Acosta; Software: David Francisco Barba-Galdámez; Visualization: David Francisco Barba-Galdámez; Writing – Original Draft: David Francisco Barba-Galdámez; Writing- Review & Editing: Norma Patricia López-Acosta.

**References**


