Thermal response test performance evaluation with drifting heat rate and noisy measurements

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ABSTRACT

Thermal Response Test (TRT) is the state-of-the-art in-situ test to assess the effective ground thermal conductivity (k_g) and effective borehole thermal resistance (R_b^*) of a borehole installation. The test consists in measuring the temperature variation of the fluid circulated in a borehole heat exchanger when a step load is applied to the system. Knowing the heat rate and borehole geometry, it is possible to use a parameterized model to recreate the temperature response analytically or numerically through inverse modelling, thereby finding the most suitable values of k_g and R_b^* . The parametric model most commonly used for TRT analysis is the Infinite Line Source (ILS) model. TRTs are usually performed in a test borehole and the estimated parameters are then utilized for the design of medium to large size borehole fields. The accuracy of the results that the test can provide is therefore crucial to optimize the borehole field configuration and obtain a cost-effective, reliable ground source heat pump installation (GSHP). In this paper, a study on the influence of the input signals (loads) on estimated parameters is presented. To achieve this goal, a reference model representing the "true system" is used to generate synthetic TRT data with "imperfect" input load. The utilized reference model takes into consideration the effect of the fluid and grout thermal capacities, which are not considered in the ILS model. The setup is tailored to investigate how the error introduced by the interpretation model varies as the "imperfection" in the input load increases. Results show that measurable disturbances (i.e. not noise) may strongly influence the TRT results with differences as high as 25% compared to the true thermal conductivity, even for tests respecting the ASHRAE criterion of ±1.5% standard deviation in the heat rate.

1. INTRODUCTION

Ground source heat pumps (GSHP) are among the most efficient systems for heating and cooling of buildings and have the potential to contribute to the overall reduction of energy use and Green House Gases emissions. A key element for optimal design and operation of these systems is the accurate estimation of the effective ground thermal conductivity (k_g) and the effective borehole thermal resistance (R_b^*). The former indeed strongly influences the thermal response of the ground while the latter is an indication of the thermal performance of the Borehole Heat Exchanger (BHE). Both the thermal response of the ground and the thermal performance of the BHE influence the performance of the Ground-Source Heat Pump (GSHP) system. It is thus decisive to accurately estimate these parameters.

The state-of-the-art method used to estimate k_g and R_b^* is Thermal Response Testing (TRT). The TRT method was introduced by Mogensen (1983) and it consists in injecting heat in the ground via a BHE while recording the temperature response of the fluid circulating inside the BHE. The parameters k_g and R_b^* can then be estimated by minimizing the Root Mean Square Error (RMSE) or MSE between the experimental response and the response obtained from a parametrized model. This is also referred to as inverse modelling because parameters are estimated from data through a model. The parametrized model being used in 90% of TRTs (IEA ECES Annex 21, 2013) is the Infinite Line Source (ILS) model (Carslaw & Jaeger, 1959; Ingersoll & Plass, 1948)

$$\Delta T(t) = q'\left(R_b^* + \frac{1}{4\pi k_g} E_1\left(\frac{r_b^2}{4\alpha t}\right)\right) \qquad [1]$$

where $\Delta T(t) = T(t) - T_0$ is the temperature change since the start of the test, r_b is the borehole radius, α is the thermal diffusivity and E_1 refers to the exponential integral. For large x, $E_1(x)$ can be approximated by the first term of a series expansion, which leads to

$$\Delta T(t) = q'\left(R_b^* + \frac{1}{4\pi k_g}\left(\ln\left(\frac{4\alpha t}{r_b^2}\right) - \gamma\right)\right) \qquad [2]$$

In this way, k_g and R_b^* can be estimated through a linear regression, given the ground volumetric heat capacity, C_g, r_b and T_0. The first hours of the test are usually disregarded in the linear regression since both the ILS and its approximation are not valid then. Linear regression is a convenient estimation method that is most likely the reason for which the ILS model approximation is so broadly used. The ILS model [1] and its approximation [2] are, however, only valid for a step heat rate (per meter), q'. This is challenging to achieve in reality as noted in the literature (IEA ECES Annex 21, 2013; Rolando, 2015; Spitler & Gehlin, 2015; C. Zhang, Guo, Liu, Cong, & Peng, 2014).

The ASHRAE TRT guidelines specifies that the standard deviation of the power should be within ±1.5% of the average power with power peaks no larger than 10% of the average power (ASHRAE, 2015). However, as stated in Mazzotti et al. (2018), standard deviation is not the best metrics for power variation since information about potential time-correlation in the signal or the noise is lost. One of the objective of this paper is providing an estimate of such effect through examples of regression analysis with time-correlated power variation matching the ASHRAE criterion.

The problem of imperfections in the loading condition supplied during TRT tests is popular in literature and several contribution have been made to deal with this issue. Some authors have proposed methods to bypass the power variation issue by experimentally keeping the power constant (Rolando, 2015; Rolando, Acuna, & Fossa, 2017; H. J. Witte, Van Gelder, & Spitler, 2002). This is an interesting solution although most of the TRT rigs do not have the specifications required to achieve such tolerances. Moreover, the measured power will still be subject to measurement noise and it should be determined how this noise affects the calculated temperature response. These TRT rigs are also not immune to power outage or accidental shut-offs.

Another solution is to use a model that can account for power variations, such as the Zero-Order Hold (ZOH) time-superposed ILS

$$\Delta T(t_n) = q'(t_n)R_b^* + \sum_{i=0}^{n-1} \frac{\Delta q'(t_i)}{4\pi k_g} E_1\left(\frac{r_b^2}{4\alpha(t_n - t_i)}\right) \quad [3]$$

Here, ZOH simply means that the power is considered constant between two sampling points. Using the time-superposed ILS requires using an optimization algorithm to minimize the RMSE, which is a disadvantage compared to the straightforward linear regression. This holds in general for other complex models and a number of optimization methods have been used to solve the parameter estimation problem such as Nelder-Mead (Austin, 1998), Levenberg-Marquardt (Li & Lai, 2012), conjugate gradient (Pasquier, 2015), Gauss-Newton (Bozzoli, Pagliarini, Rainieri, & Schiavi, 2011), quasi-Newton (Choi & Ooka, 2015) and Newton-Raphson methods (Mazzotti et al., 2018). Jain (1999) provides a comparison of several optimization algorithms used in combination with a numerical model to analyze TRTs.

Other authors suggested more advanced methods proposed to analyze TRTs. Beier and Smith (2003) suggest using deconvolution via the Laplace domain to deal with imperfection of the supplied load and obtain the system step response. Pasquier (2015) developed a tool allowing the stochastic interpretation of TRTs using either the Finite Line Source (FLS) model (Claesson & Javed, 2011) or a Thermal Resistance and Capacitance Model (TRCM) (Pasquier & Marcotte, 2014). Choi et al (2018) propose a Bayesian approach to infer posterior probability density functions of k_g and R_b^*, which, in turn, are used to produce uncertainty intervals for those parameters. Beier (2018) and Pasquier (2018) use the temperature time-derivative to estimate k_g. More recently, Pasquier et al (2019) have suggested the use of a multi-objective optimization strategy to reduce correlation between the estimated parameters.

Parameter estimation has also been performed using numerical models (Aranzabal et al., 2016; Austin, 1998; Bozzoli et al., 2011; Shonder & Beck, 1999; Signorelli, Bassetti, Pahud, & Kohl, 2007; R. Wagner & Clauser, 2005, 2005; V. Wagner, Bayer, Kübert, & Blum, 2012).

Besides improvements in the parameter estimation techniques, thermal response testing also has seen other developments, notably: Distributed TRT (e.g. Acuña, 2013; Fujii et al., 2009), alternative testing techniques using a heating cable (e.g. Raymond, Lamarche, & Malo, 2015) or a constant inlet temperature (e.g. Choi & Ooka, 2017), and determination of a criterion for the test duration (e.g. Poulsen & Alberdi-Pagola, 2015).

Uncertainty in the estimation of parameters has also been investigated in recent years (Choi et al., 2018; H. J. L. Witte, 2013; X. Zhang, Huang, Jiang, & Zhang, 2015) although this aspect is unfortunately too often disregarded in TRT analyses. It seems nevertheless crucial to include such considerations for design of GSHP systems given the high-impact of both k_g and R_b^* on the borehole field geometry. For instance, can imperfections in the heat rate and/or measurement noise on both temperature and heat rate lead to inaccurate, or even biased, parameter estimation? As of today, as far as the authors there is no clear answer to that question and this study intends to make a contribution in that direction.

In this paper, the sensitivity of commonly used inverse modelling techniques based on ILS is investigated for different testing conditions. Advanced methods for TRT analysis should be encouraged but as mentioned previously, more approachable analysis are normally used in practice. In particular we are interested in the ILS inverse modelling techniques sensitivity to noise and load “imperfections”. The study is done through simulations using synthetic data. This approach enables knowing a priori the true value of the parameters to be estimated and evaluate the error introduced in the inverse modelling step.

2. METHODOLOGY

2.1. General description of the procedure

As discussed in the introduction, the goal of this paper is testing the robustness of inverse modelling strategies used for the analysis of TRT data. The test proposed is performed through simulations and the procedure used is based on the following ideas.

1. Utilizing a detailed borehole simulation model to generate reference TRT dataset given all the necessary parameters to define the system.
2. The TRT dataset produced should resemble tests performed in reality with their own imperfections.
3. There is the possibility to include measurement noise.
4. The chosen inverse modelling technique should be applied without previous knowledge on any of the parameters used to produce the model.

2.2. The reference model

In this work, the model by Javed and Claesson (2011) is selected for the generation of synthetic TRT data. This model (Figure 1b), similarly to the ILS, treats the ground as a one dimensional axial symmetric solid, but in addition considers also the grout and the capacity of the fluid circulating within the borehole. Therefore, it offers a better description of the short-time behavior of a BHE as compared to the ILS. The simplification of the model introduced by Javed and Claesson compared to a realistic configuration (such as the U-pipe of Figure 1c) enabled providing an analytical expression for the solution of the dynamic heat transfer problem. Figure 2 shows the difference in dynamics of the two models in the beginning of the transient. The grey boxes in the figure represent the time range between 20 and 70 hours when assuming a α of $1.6{\cdot}10^{-6}$ m^2/s and a r_b of 0.07 m. It can be observed that for this particular case the difference between the two models in this time range is between 0.1 and 0.001.

Although the model does have some limitations, namely it lacks description of the heat transport of the fluid along the vertical direction and for the thermal shunt effect occurring between the downward and upward pipes, it is a good trade-off between details and simplicity. For the purpose of this paper the Javed-Claesson model will be the reference model and will represent the "true" response of the ground. Since the reference model is 1D-axial symmetric we cannot talk about effective borehole thermal resistance R_b^*. For this reason, the notation R_b, i.e. borehole resistance on a section, will be used instead of R_b^*.

2.3. Synthetic data

Table 1 shows the parameters used in the tests presented in this article. Note that the fluid considered in the simulations is water The specific choice of parameters have been made to have significant differences in the properties of the ground and the grout in order to investigate the effect of the model error when using ILS in the inverse modelling procedure. TRT datasets, consisting of a heat rate $q'(t)$ and the relative mean fluid temperature changes ($\Delta T(t_i)$), have been obtained by selecting loading conditions $q'(t)$ and generating the relative temperature $\Delta T(t_i)$ by means of convolution of the temperature response to a heat step $g(t_i)$ given by the Javed-Claesson model, and the heat rate variation $\Delta q'(t)$ between uniformly spaced time steps with sampling intervals of 5 minutes.

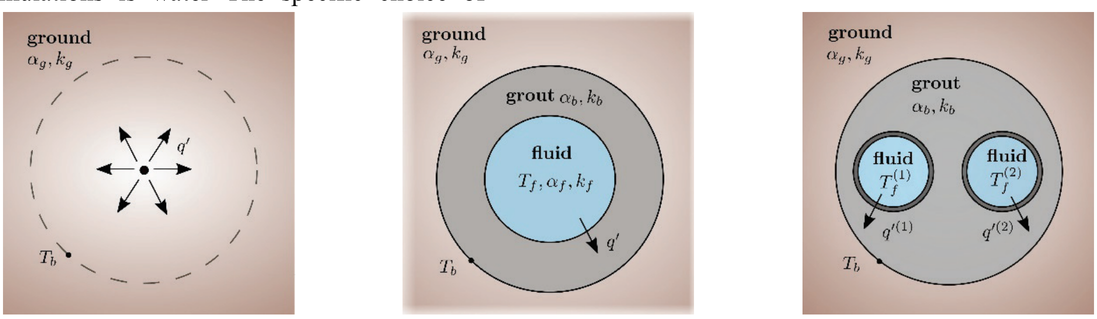
Table 1: Parameters used to compute the "true" response

Properties	Symbol	Value	Units
borehole radius	r_b	0.07	m
ground conductivity	k_g	3.0	W/(m·K)
ground heat capacity	C_b	$3.1{\cdot}10^6$	J/(m^3·K)
grout conductivity	k_b	1.5	W/(m·K)
grout heat capacity	C_b	1.875	J/(m^3·K)
equivalent pipe radius	r_p	$0.02{\cdot}\sqrt{2}$	m
pipe conductivity	k_p	0.42	W/(m·K)
heat transfer coefficient	h_p	725	W/(m^2·K)

As discussed above, one of the requirement of this work is generating data resembling typical dataset from a TRT performed in the field. Such test never comply exactly with the requirement of a perfect heat step and the heat load injected (or extracted) usually slightly deviate from this ideal condition. The method chosen to simulate these deviations consists in modelling the signal content of the heat load q_s via a random walk.

$$q_s'(t+1) = q_s'(t) + R_n \sigma_q \qquad [4]$$

where R_n is a random number generator with a standard normal distribution and σ_q is a scalar number. Each q_s' realization produced with this method is then used to generate the relative mean fluid temperature. The test realizations generated with this method provide the signal content of temperatures ΔT_s but measurement noise is not included. However, measurement noise always occur in a real TRT and it is of interest studying its effect on the parameter estimation. For the purpose of this paper, both the possibility of adding white noise to temperature and heat rate.



(a) ILS (b) Javed and Claesson (2011) (c) 2D borehole model

Figure 1: 2D models of borehole heat exchangers

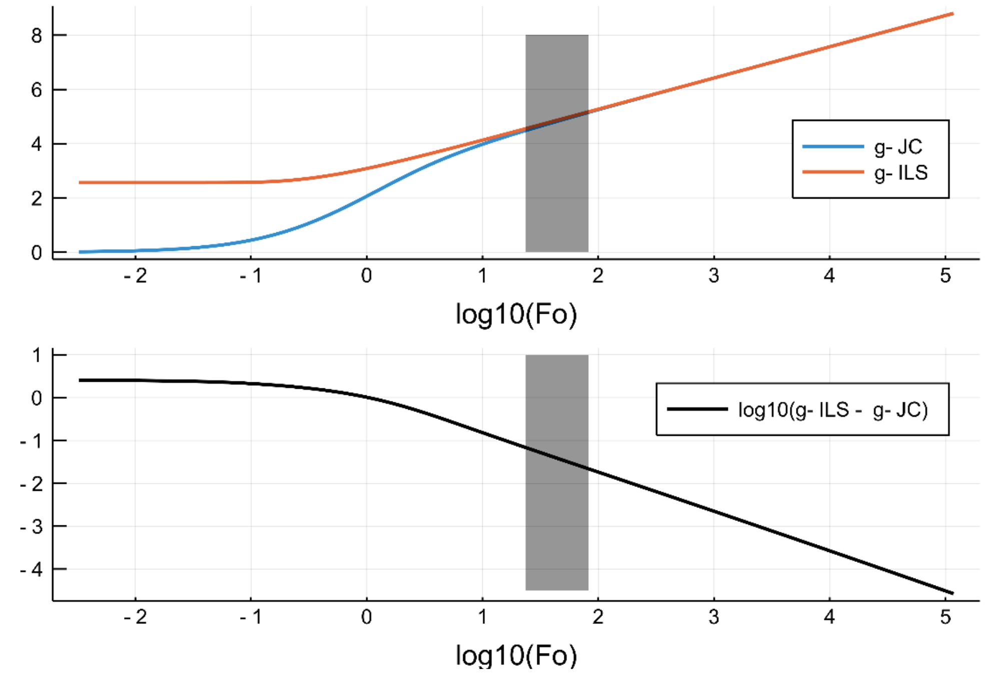


Figure 2: Comparison of the short term response of the the Javed-Claesson model vs. the ILS model

$$q'_N(t+1) = q'_s(t) + R_n \varepsilon_q \quad [5]$$

$$T_N(t+1) = T_s(t) + R_n \varepsilon_T \quad [6]$$

where ε is a scalar. Note that the realizations of R_n are different in eq. [4]–[6].

2.4. Inverse modelling

For the purpose of this article, the performance of the ILS based linear regression approach (eq.[2]) and of the ZOH time-superposed ILS parameter estimation approach (eq.[3]) will be investigated. Both methods are ILS based, but the latter accounts for load variations. For both methods the first hours of the tests are discarded and time range considered for fitting the models to the data is between 20 and 70 hours. The optimization utilized for the parameter estimation approach is "brute-force", i.e. the parameter domain is finely discretized and thermal responses are calculated for each given pair (k_g, R_b). The pair yielding the lowest RMSE is then chosen as best estimate. The discretization patterns used for R_b and k_g are, respectively, between 0.01 and 0.2 with pace 0.001 and between 1.5 and 4.5 with pace 0.005. The total number of simulations required to perform this analysis is 114791. Although brute force is very inefficient, it enables to evaluate the cost function over the whole parameter space providing valuable insights on the optimization problem being studied. Another weakness of "brute force" is that only a discrete number of parameters is considered in the analysis hence it is necessary to cover the parameter space with a fine discretization in order to obtain a solution close to the optimal solution.

2.5. Test sets design and performance evaluation

Choice of tests. A set of tests has been designed to investigate how the dataset characteristics can affect the results of the parameter estimation. A perfect test, i.e. temperature response to a perfect heat rate step is used as reference. Then, the effects of noise and drifting signals is studied separately and, finally, the combination of the two effects is investigated.

Performance. For each test, the results for R_b and k_g from both linear regression and parameter estimation have been evaluated and compared to the relative "true value".

ASHRAE Criterion. The ASHRAE criterion of maximum 1.5% standard deviation of the measured heat rate is used unless otherwise specified. The effect of larger variations is also explored.

Other test parameters. Other parameters that play an important role for the parameter estimation are the choice of the capacity of the ground C_g used in the inverse modeling procedure and in the choice of time-range for the window of data used to estimate parameters. These aspects are treated in other publications (Richard A. Beier, 2018; Choi est al., 2018) and are not directly considered in this paper. Hence, it has been assumed that the guessed value for C_g is equal to the actual value to generate the data and that the time windows of interest is between 20 and 70 hours.

3. RESULTS AND DISCUSSION

All the tests discussed in this section have been produced using the data of Table 1. The "true" values of k_g and R_b for this configuration are respectively 3.0 W/(m·K) and 0.136 m·K/W. The test set selected to investigate the robustness of the parameter estimation problem is described in Table 2. The set includes tests with ideal signal for TRT along with two "imperfect" signals obtained with the random walk process described in eq.[4]–[6]. The coefficients ε_q and ε_T used for obtaining the load and temperature noise are specified for each test. The last column provides the ratio between standard deviation of the load signal and its mean value. All the tests comply with the ASHRAE criterion of 1.5% standard deviation, apart from test 2 and 4. The results of these tests, i.e. the estimated pairs $(k_{g\,reg}, R_{b\,reg})$ for the linear regression and $(k_{g\,opt}, R_{b\,opt})$ for the brute force optimization, are provided in Table 3 and some selected results are shown in Figure 3 and Figure 4. The figures show heat rate and temperatures on the right-end side while the optimization domain and results of the regression (blue square) and of the brute force optimization (red circle) are displayed on the left hand side. Note that the cost function used in the optimization process is $\log_{10}(RMSE)$. The presented temperature curves are the "measured" temperature, the temperature of the ILS generated using the parameters obtained through regression, and the best fitting temperature profile in the brute force optimization process. The grey frame on the right-end side plots represent the time window used in the parameter estimation.

3.1. Ideal signal

The first investigated test is the reference test with step load and no noise (Figure 3a). In this test, since there is no load variation, regression and optimization are equivalent. The contour plot shows a tiny difference between the two optima obtained with the two methods which is explained by the finite resolution of the discretization utilized in the optimization process but ultimately the two results obtained are equivalent, as expected. On the other hand, there is a significant difference between the "true" pair of parameters and the estimated parameters. This bias (around -6% for both conductivity and borehole resistance) is due to the difference between our "true" system (modeled using the Javed-Claesson solution) and the ILS within the time-range used for the parameter estimation. As shown in Figure 2 this difference is quite small and decreases logarithmically with time but the impact is non-negligible.

This particular result is only valid for the setup used in this paper but it showcases how a very good fit between simulated temperature and measurements does not necessarily mean that the parameters identified are accurate.

In test 2 (Figure 3b), white noise is added to the heat rate. This effect has an impact on the optimization procedure which considers this variation of the load as signal. On the other hand it has a minor effect on the regression since in this case the load is assumed to be constant and equal to the mean value. Note that the later statement may not hold for short test durations since enough realizations of the noise should be included for the mean to converge to the real value.

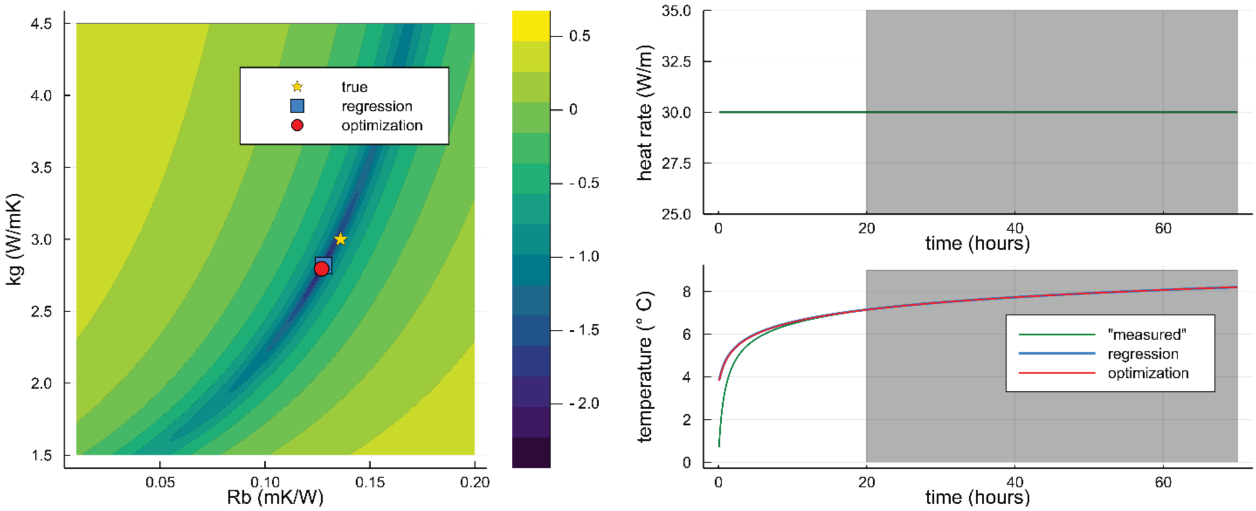
In test 3 (Table 3) noise was added only on the temperature component. As in test 1, optimization and regression yields comparable results for this case. In test 4, both the input and the output are corrupted with white noise; moreover, the noise on the heat rate is increased well above the 1.5 % suggested by ASHRAE. The results show that the optimization procedure further suffers this increase in noise and the error in the thermal conductivity increases to -18.33 %. It is important to keep in mind that tests with noisy data are not deterministic and each test represent a realization meaning that the same input data can provide results that are not equal (e.g. test 6 and 7).

Table 2: Summary of inputs for the test set

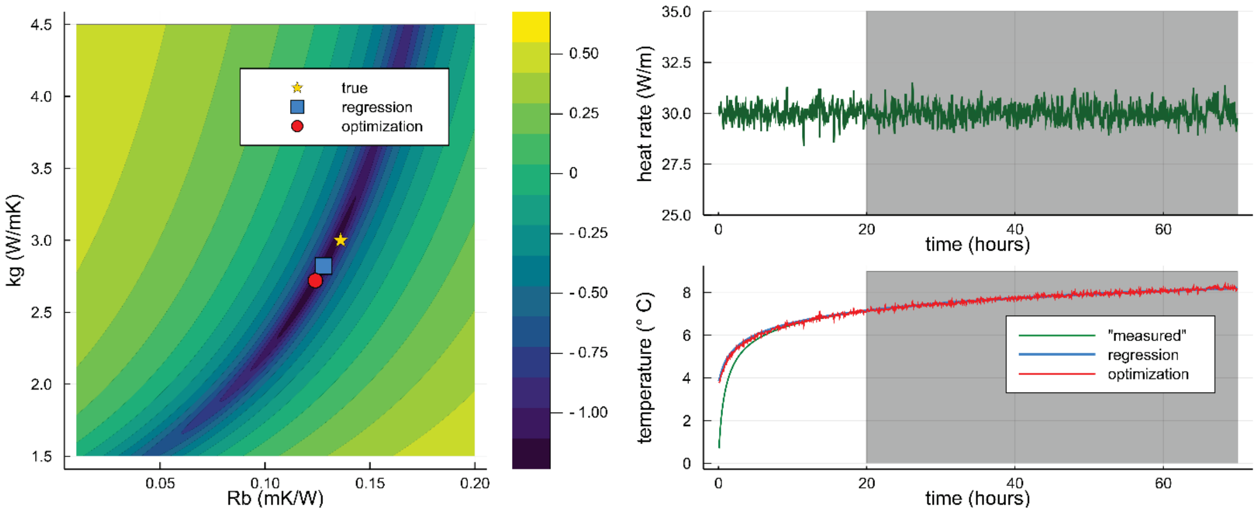
Test	Signal	ε_q [W·m^{-1}]	ε_T [K]	$\frac{\text{std}(q_N)}{\text{mean}(q_N)}$
1	ideal	0.0	0.0	0.00 %
2	ideal	0.46	0.0	1.52 %
3	ideal	0.0	0.1	0.00 %
4	ideal	0.9	0.1	2.98 %
5	non-ideal 1	0.0	0.0	1.13 %
6	non-ideal 1	0.2	0.1	1.31 %
7	non-ideal 1	0.2	0.1	1.33 %
8	non-ideal 1	0.28	0.1	1.46 %
9	non-ideal 2	0.0	0.0	0.68 %
10	non-ideal 2	0.4	0.1	1.48 %

Table 3: Estimated parameters from optimization and linear regression for all tests in the test set

Test	$R_{b\,opt}$		$k_{g\,opt}$		$R_{b\,reg}$		$k_{g\,reg}$	
	[m·K/W]	% deviation from true value	[W/(m·K)]	% deviation from true value	[m·K/W]	% deviation from true value	[W/(m·K)]	% deviation from true value
1	0.1270	-6.65 %	2.7950	-6.83 %	0.1280	-5.92 %	2.8193	-6.02 %
2	0.1240	-8.86 %	2.7200	-9.33 %	0.1279	-5.99 %	2.8209	-5.97 %
3	0.1240	-8.86 %	2.7200	-9.33 %	0.1252	-8.00 %	2.7456	-8.48 %
4	0.1130	-16.94 %	2.4500	-18.33 %	0.1272	-6.53 %	2.7862	-7.13 %
5	0.1270	-6.65 %	2.7950	-6.83 %	0.1509	10.94 %	3.6067	20.22 %
6	0.1270	-6.65 %	2.7900	-7.00 %	0.1517	11.49 %	3.6334	21.11 %
7	0.1300	-4.45 %	2.8800	-4.00 %	0.1548	13.75 %	3.7770	25.90 %
8	0.1250	-8.12 %	2.7400	-8.67 %	0.1489	9.46 %	3.5247	17.49 %
9	0.1280	-5.92 %	2.8250	-5.83 %	0.1390	2.20 %	3.1673	5.58 %
10	0.1250	-8.12 %	2.7400	-8.67 %	0.1397	2.65 %	3.1814	6.05 %



(a) Test 1



(b) Test 2

Figure 3: Results from tests of ideal input signals without noise (test 1) and with noise on the heat rate (test 2).

3.2. Non-ideal signal

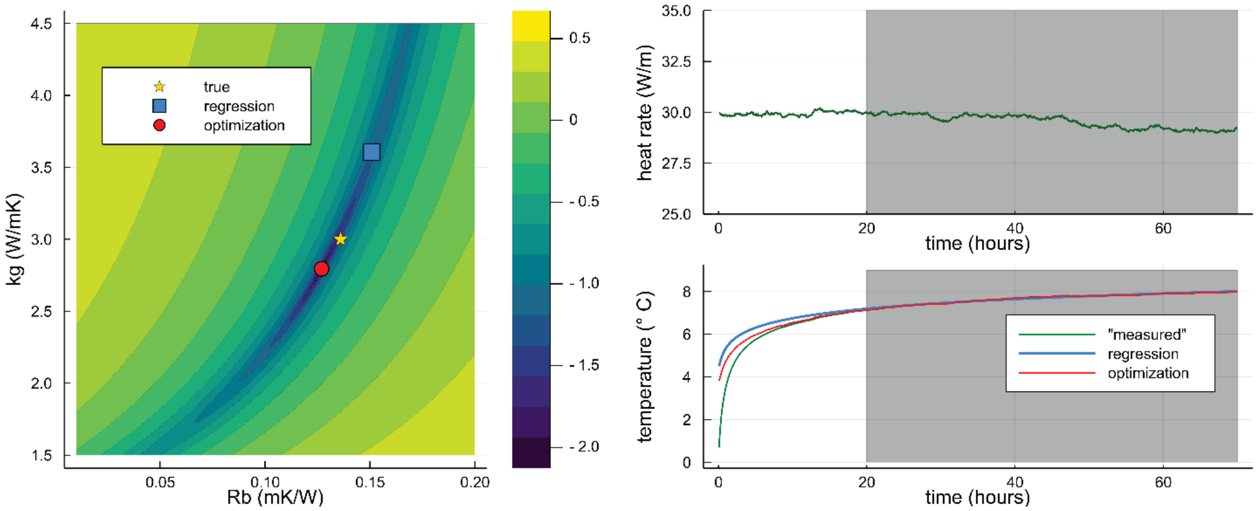
The last six tests reported in table 3 considers TRT datasets with two non-ideal signals. Figure 4 illustrates tests 5,7 and 9. In test 5, the first signal ("non-ideal-1") is tested with no noise on the loading condition nor on the temperature. Although the load standard deviation is well below 1.5%, the regression does not perform well and yields an error of around 20% compared to the "true" conductivity value. On the other hand, the optimization procedure is more robust and yields an error of about 7%.

Addition of noise on the heat rate and temperature (Figure 4b) decreases the performance of the regression for both test 6 and 7. On the other hand, the optimization slightly decreases performance in test 6 but increase performance to -4% error in test 7 (compared to about 7% in test 5). In test 8, a further increase in the noise improve the estimation of the regression, while the performance of the optimization decreases to around -9%. These variations demonstrate the randomness introduced in the estimation by the noise. Looking at Figure 4a and 4b an observation can be done regarding the effect of noise on the cost function used in the optimization procedure.

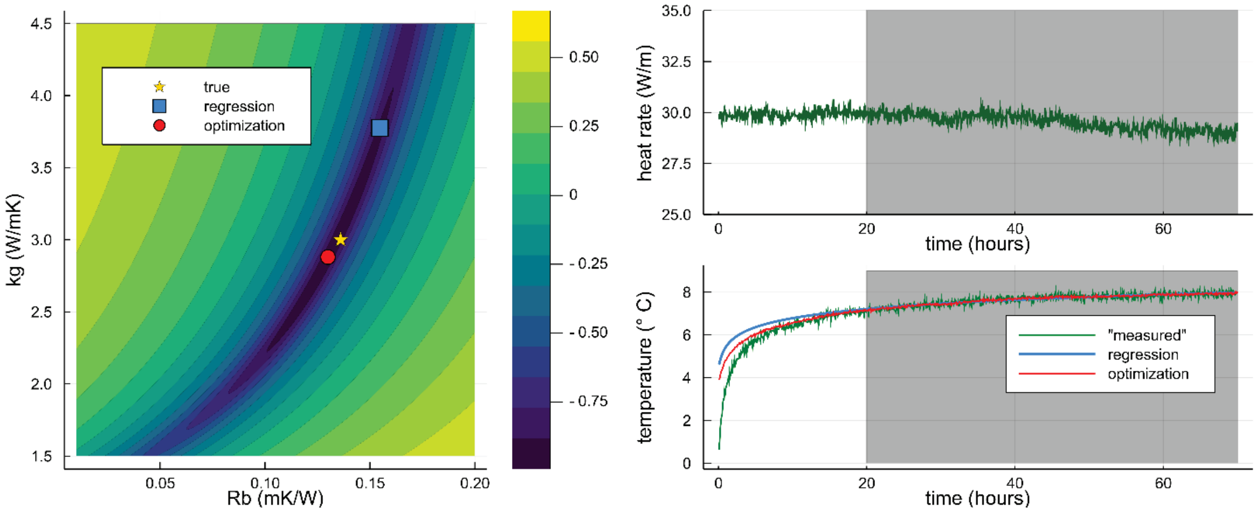
As the amount of noise on the load and on the temperature is increased, the valley of the cost function becomes wider and more flat, meaning that there is a broader range of parameter pairs yielding very low values of RMSE making the parameter estimation procedure more challenging.

The second signal considered ("non-ideal-2") is illustrated in Figure 4c. This signal is somewhat closer to the ideal test compared to "non-ideal-1" and yields very good performance for both optimization and regression. In a sense, this signal has low level of "imperfection"; hence, it yields results that are more comparable to test 1 than test 5.

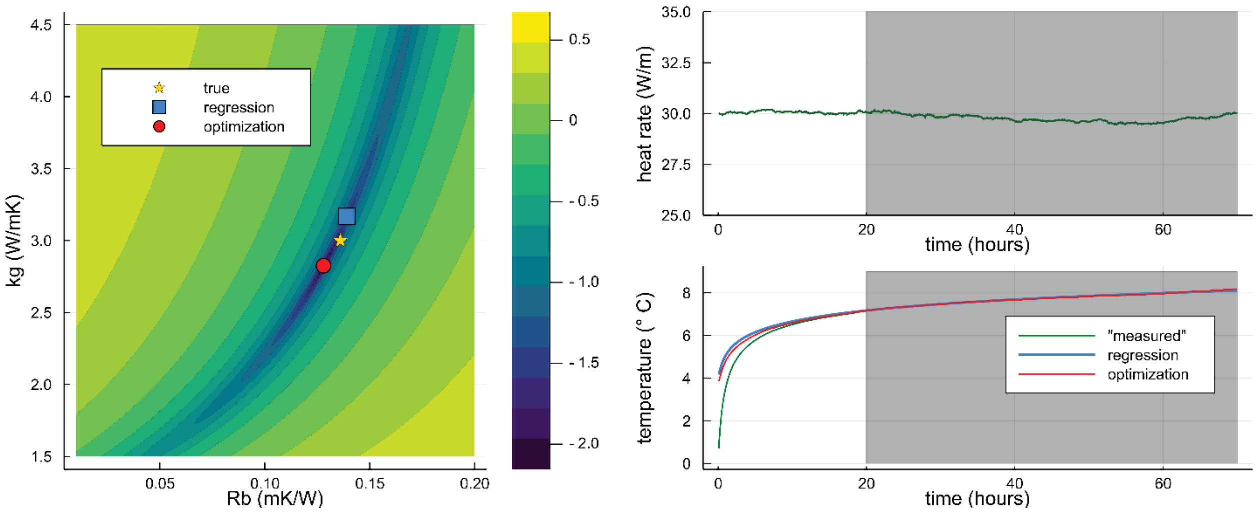
For the cases investigated in this paper, the ASHRAE criterion of maximum 1.5% standard deviation seems to control quite well the effect of noise, although the combined effect of model and measurement errors did lead to non-negligible bias in the estimation of k_g and R_b. On the other hand, the effect of time correlation has a much greater impact on the estimation error even when the ASHRAE criterion is met showing that the classical linear regression method is not suitable in such cases.



(a) Test 5



(a) Test 7



(a) Test 9

Figure 4: Results from tests of non-ideal input signal

It is important to keep in mind that the values obtained in this paper are only an indication and are by no means general since they are specific to the choice of "true model" used in this work. Yet, these results give an estimation of how sensitive is the inverse modeling procedure to imperfection of heat rate, noise and model error.

4. CONCLUSIONS

The high correlation between borehole thermal resistance, R_b, and ground thermal conductivity, k_g, in the TRT analysis is a well-known problem in literature. This study introduces a procedure for simulating TRTs and evaluating the robustness of the analysis utilized to infer the parameters k_g and R_b. A virtual test-bed based on the Javed-Claesson model for short time-step g-fucntions was used to generate TRT datasets from a borehole configuration with known k_g and R_b. Random walks were utilized to simulate variations in the load and to resemble common signal behavior in TRTs. In addition the effect of measurement noise both in the load and temperature was evaluated.

The pair (k_g, R_b) is estimated using both the ILS linear regression and a brute force optimization procedure coupled to the ZOH time-superposed ILS.

The results showed that, even for an ideal test, i.e. step heat rate without any noise, the obtained values for k_g and R_b through the parameter estimation procedures can be biased compared to the true value with differences as high as 7%. This is due to model error. For ideal signals, the regression procedure is less sensitive to noise compared to the optimization procedure with a maximum relative difference of 7% and 18%, respectively. On the other hand, linear regression can perform very poorly for non-ideal signals as it does not account for the actual variations in the load. Relative differences between estimated parameters and true values as high as 25% are noticed for the linear regression, even though the test respect the ASHRAE criterion of ±1.5% standard deviation in the heat rate. In comparison, the optimization procedure lead to a relative error of 4% and is thus more robust and yields better results in this context.

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