

Analysis of a thermal conductivity measurement technique formulated as an inverse heat conduction problem

Vishal Ramnath

Department of Mechanical and Industrial Engineering, University of South Africa (UNISA), Private Bag X6, Florida 1710, Gauteng Province, South Africa

E-mail: ramnav@unisa.ac.za

Abstract. Thermal analysis and solution of heat problems most often utilizes known thermal conductivity material data which is typically experimentally determined from heat flux measurements through the application of Fourier's law. The challenge posed by this approach is the need for known thermal conductivity reference materials which may be inhomogeneous and have large associated uncertainties in industrial physics applications. In this paper we investigate the feasibility of developing a thermal conductivity measurement system that utilizes known radiometric input sources and temperature output measurements which may have smaller relative uncertainties by formulating the system as an inverse heat conduction problem utilizing recently reported research results from the fields of geophysics and mathematical optimization.

1. Introduction

Thermal physics analysis and solution of heat problems often utilizes known thermal conductivity material data which is typically experimentally determined from heat flux measurements through the application of Fourier's law $q'' = -k\nabla T$, where $q''/[\text{W m}^{-2}]$ is the heat flux, $k/[\text{W m}^{-1} \text{K}^{-1}]$ is the thermal conductivity, and $T/[\text{K}]$ is the absolute temperature following the nomenclature in [1]. The use of Fourier's law presents a straight forward mechanism to define and infer the thermal conductivity through the ratio of the heat flux measured using standard techniques as discussed in [2], and the temperature gradient for a specified direction of heat flow where the unknown thermal conductivity may be expressed in terms of known reference quantities such as thermal conductivity, wall thickness and wall temperature amongst other experimental measurements for homogeneous isotropic materials as illustrated in figure 1.

Unfortunately materials such as aluminium/steel thermal properties may be inhomogeneous and/or non-isotropic either from physical effects in the smelting process or manufacturing effects from the fabrication of structures requiring knowledge of thermal conductivity such as reflectors/concentrators in for example solar plants [6] where in addition the thermal conductivity may vary with temperature [7, 8] as illustrated in figure 2 for a selection of materials.

As a result it is desirable in applied industrial research contexts to infer thermal conductivity information directly by an inverse problem formulation using direct temperature measurements which are more practical and experimentally convenient, either when reference thermal

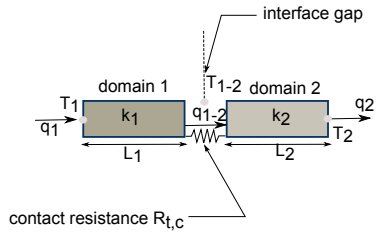


Figure 1. Composite wall system modelled as a 1D thermal circuit. In this model the unknown thermal conductivity k_2 is expressed as $k_2 = \frac{L_2}{A} \left(\frac{T_1 - T_2}{q} - \frac{L_1}{k_1 A} - R_{t,c} \right)^{-1}$ and the uncertainty may be estimated by standard techniques such as the GUM and GS1 as discussed in [3, 4, 5]

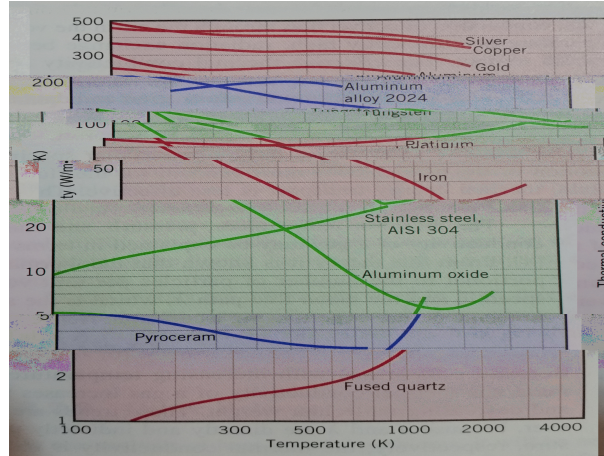


Figure 2. Illustration of thermal conductivity temperature dependence for selection of industrial/engineering materials (Graphic source: [1, page 47])

conductivity materials are unavailable for prior testing, impractical due to prevailing operating conditions, or when in situ process or condition monitoring measurements are necessary.

In general accurate heat sources such as calibrated lasers or electrical resistance heating elements, and temperature measurement devices such as thermocouples or resistance thermometers, are simple and straightforward to procure and utilize. As a result in this paper we opt to analyze a system in which the thermal conductivity may be inferred through an Inverse Heat Conduction Problem (IHCP) modelling approach utilizing just radiometric/electrical heating sources and temperature measurements which are easily accessible and which avoids the need for specific reference thermal conductivity material components, and specialist heat flux instruments and blackbody equipment [9].

2. Literature Review

Within the statistical literature simulation problems may typically be classified as either direct/forward or indirect/inverse where in general terms the former are cases in which PDE parameters are known and one utilizes this information to solve for the PDE solution, whilst in the latter one utilizes the PDE solution to infer the underlying PDE parameters.

In the context of thermal physics a direct/forward problem would correspond to using known thermophysical properties such as thermal conductivity and/or specific heat capacity as inputs with suitable boundary conditions for a boundary $\Gamma = \partial\Omega$ to solve the heat diffusion equation $\nabla \cdot (k \nabla T) + \dot{q} = \rho c_p \frac{\partial T}{\partial t}$ for some problem domain Ω whilst an indirect/inverse problem would in a certain sense “work backwards” to use the PDE temperature field solution to infer the corresponding thermophysical parameters as discussed in [10]. Traditionally inverse problem

studies have been common in the geophysical sciences to determine rock densities, gravitational field strengths, and in oil and gas exploration as discussed in [11, 12, 13] with newer insights into Monte Carlo based inverse parameter uncertainties reported in [14], and which has generally been formulated and solved using the Monte Carlo and Levenberg-Marquardt techniques as outlined in [15, 14].

For IHCP studies methods of solution have mainly to date traditionally consisted of the Levenberg-Marquardt and conjugate gradient techniques for mixtures of problems in laboratory thermophysical testing and space vehicle atmospheric reentry design and research studies after the development of techniques such as Tikhonov regularization which were able to modify and reformulate the original ill-posed/unstable inverse problems as approximate well-posed problems.

More recently investigations in inverse theory problems across different fields has involved applications of newly developed techniques such as the variational iteration method or (VIM) [16], the method of fundamental solutions or MFS [17, 18, 19, 20, 21, 22, 23, 24, 25], the lattice Boltzmann method or LBM [26], heuristic approaches drawing from a mixture of techniques [27, 28], and meshfree approaches [29]. Finite difference methods for IHCP studies are further discussed in [30, 31] who explore how the Tikhonov regularization method may be used to regularize the ill-conditioned linear system of equations for a non-steady two dimensional heat conduction problem, and a iteration approach to determine the regularization parameter was explored in [32]. A measurement methodology for infrared thermography of inverse models that used a maximum entropy principle was reported in [33] for a die forging application in order to deduce the unknown boundary condition of a heat flux using a finite difference discretization.

3. Mathematical Development

Based on the literature review we opt for simplicity since the underlying problem is nonlinear to use a Levenberg-Marquardt optimization in our formulation to avoid a Tikhonov regularization. Utilizing the heat diffusion equation $\nabla \cdot (k \nabla T) + \dot{q} = \rho c_p \frac{\partial T}{\partial t}$ which reduces to a generalized two dimensional Poisson equation $\frac{\partial}{\partial x}(k \frac{\partial T}{\partial x}) + \frac{\partial}{\partial y}(k \frac{\partial T}{\partial y}) = -\dot{q}$ in the special case for steady-state conditions for a planar domain for the particular geometry of the experimental system illustrated in figure 2 where the domain Ω is a circular region of diameter D where the boundary Γ is held at a constant temperature T_f , where $T/[K]$ is the temperature, $k/[W m^{-1} K^{-1}]$ the thermal conductivity of the sample, and \dot{q} is an energy sink/source term which is positive if energy is generated within the medium and negative if energy is being consumed.

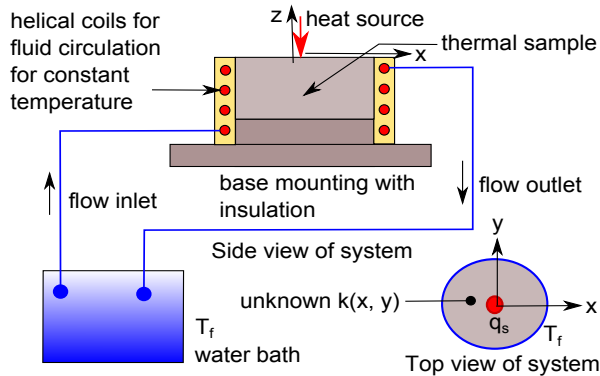


Figure 3. Experimental inverse heat conduction problem (IHCP) system to test for thermal conductivity

Adopting a radial basis function discretization following the discussions in [34, 35, 29] we approximate the thermal conductivity as $k = \sum_{i=1}^{N_k} \alpha_i \varphi_k(\|\mathbf{x} - \mathbf{x}_i\|)$, and the temperature field as $T = \sum_{j=1}^{N_T} \beta_j \varphi_T(\|\mathbf{x} - \mathbf{x}_j\|)$. For the temperature field let N_T be the total number of points composed of N_I interior points and N_B boundary points such that $N_T = N_I + N_B$. In this

approach it is not necessarily the case that $N_k = N_T$ however this will simplify subsequent calculations. The terms α_i ($i = 1, \dots, N$) and β_j ($j = 1, \dots, N$) are coefficients that are used to build up the $k(\mathbf{x})$ and $T(\mathbf{x})$ fields for $\mathbf{x} \in \Omega$ in terms of the RBF's φ_k and φ_T respectively. Utilizing Gaussian RBF's for simplicity to illustrate the approach adopted of form $\varphi_k = e^{-\varepsilon_k^2 r^2}$ and $\varphi_T = e^{-\varepsilon_T^2 r^2}$ where $r = \sqrt{(x - x_i)^2 + (y - y_i)^2}$ and where ε_k and ε_T are suitable shape parameters for the thermal conductivity and temperature fields respectively, and substituting into the generalized two dimensional Poisson equation we then have using the short hand $r_i = r$ for points in the interior that $0 = \frac{\partial k}{\partial x} \frac{\partial T}{\partial x} + k \frac{\partial^2 T}{\partial x^2} + \frac{\partial k}{\partial y} \frac{\partial T}{\partial y} + k \frac{\partial^2 T}{\partial y^2} + \dot{q}$ where $k = \sum_{i=1}^{N_k} [\alpha_i e^{-\varepsilon_k^2 r_i^2}]$, $\frac{\partial k}{\partial x} = \sum_{i=1}^{N_k} [-2\varepsilon_k^2 (x - x_i) \alpha_i e^{-\varepsilon_k^2 r_i^2}]$, $\frac{\partial^2 k}{\partial x^2} = \sum_{i=1}^{N_k} [-2\varepsilon_k^2 \alpha_i \{1 - 2\varepsilon_k^2 (x - x_i)^2\} e^{-\varepsilon_k^2 r_i^2}]$, and similar expressions for the corresponding temperature field.

Let T_k be the experimental measured temperature and θ_k the estimated temperature for some choice of assumed parameter \mathbf{P} , where in our particular problem the parameter is used to specify the thermal conductivity. Constructing an objective function $S(\mathbf{P}) = \sum_{k=1}^N [T_k - \theta_k(\mathbf{P})]^2$ it follows that we solve the IHCP by determining the choice of parameter such that $S(\mathbf{P})$ is minimized. The objective function may be written in matrix form by specifying the measured and estimated temperatures as a column vectors $\mathbf{T}^\top = [T_1, \dots, T_N]$ and $\boldsymbol{\theta}^\top = [\theta_1, \dots, \theta_N]$ and then constructing the objective function as $S(\mathbf{P}) = [\mathbf{T} - \boldsymbol{\theta}(\mathbf{P})]^\top [\mathbf{T} - \boldsymbol{\theta}(\mathbf{P})]$. A solution will occur when $\nabla S(\mathbf{P}) = 0$ which after algebraic manipulations reduces to the following equations

$$-2\mathbf{J}^\top(\mathbf{P})[\mathbf{T} - \boldsymbol{\theta}(\mathbf{P})] = \mathbf{0}$$

$$\mathbf{J} = \begin{bmatrix} \frac{\partial \theta_1}{\partial P_1} & \frac{\partial \theta_1}{\partial P_2} & \frac{\partial \theta_1}{\partial P_3} & \cdots & \frac{\partial \theta_1}{\partial P_M} \\ \frac{\partial \theta_2}{\partial P_1} & \frac{\partial \theta_2}{\partial P_2} & \frac{\partial \theta_2}{\partial P_3} & \cdots & \frac{\partial \theta_2}{\partial P_M} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial \theta_N}{\partial P_1} & \frac{\partial \theta_N}{\partial P_2} & \frac{\partial \theta_N}{\partial P_3} & \cdots & \frac{\partial \theta_N}{\partial P_M} \end{bmatrix}$$

where as previously mentioned N is the total number of measured/estimated temperatures, M is specified as the total number of parameters such that $\mathbf{P}^\top = [P_1, \dots, P_M]$, and $\mathbf{J}(\mathbf{P}) = [\frac{\partial \boldsymbol{\theta}^\top(\mathbf{P})}{\partial \mathbf{P}}]^\top$ is the corresponding Jacobian matrix of the objective function system. For linear problems the unknown parameter to be determined may be calculated as $\mathbf{P} = (\mathbf{J}^\top \mathbf{J})^{-1} \mathbf{J}^\top \mathbf{T}$ however for a nonlinear inverse problem it may be observed that the Jacobian matrix, also known as the sensitivity matrix, has a functional dependence on the parameter \mathbf{P} and as a result must be solved iteratively using a local linearization. In order for a suitable iteration procedure to converge it is necessary that $|\mathbf{J}^\top \mathbf{J}| \neq 0$ otherwise the IHCP is ill-conditioned. Whilst Tikhonov regularization is possible to solve a resultant ill-conditioned linear system $\boldsymbol{\Lambda} \boldsymbol{\theta} = \mathbf{B}$ of form $\boldsymbol{\theta}_\alpha = [\boldsymbol{\Lambda}^\top \boldsymbol{\Lambda} + \alpha(\mathbf{R}^{(s)})^\top]^{-1} \boldsymbol{\Lambda}^\top \mathbf{B}$ where $\mathbf{R}^{(s)}$ for $s = 0, 1, 2$ is a Tikhonov regularization matrix following the overview presented in [31] where α is the regularization parameter.

Different approaches are possible for estimating α and whilst there is no definitive method the L -curve method appears common within the mathematical literature but is difficult to implement. To avoid these difficulties we opt to use the Levenberg-Marquardt method which is also amenable for potentially ill-conditioned systems and which has the advantage of being well established with existing implementations [36] that are relatively straightforward to implement and which incorporate newer mathematical optimization techniques such as the homotopy approach [37].

Based on our RBF discretization set $N_k = N_T$ to simplify the algebra when constructing the corresponding Jacobian matrix and note that our approach then specifies the parameters as $\mathbf{P}^\top = [\alpha_1, \dots, \alpha_M]$ and the estimated temperature field as $\boldsymbol{\theta}(\mathbf{P})$ as the solution of the generalized Poisson equation as previously indicated. The algorithm to implement the IHCP

formulated thermal conductivity measurement technique may now be conveniently summarized as follows:

- (i) specify the spatial coordinates (x_i, y_i) for the points in the interior Ω and for the points (x_b, y_b) on the boundary Γ
- (ii) assign the associated measured interior temperatures as T_i along with associated heat source/sink terms \dot{q}_i taking note of the known boundary temperatures $T_f(x_b, y_b)$
- (iii) construct the Jacobian matrix \mathbf{J} either symbolically/numerically using the assumed values from the RBF parameterization
- (iv) solve the nonlinear inverse problem using the Levenberg-Marquardt method for the given measured temperature data and assumed parameter values and iterate until convergence to the required accuracy level is achieved
- (v) the associated parameter uncertainties $u(\alpha_i)$ ($i = 1, \dots, M$) in the RBF formulation of the thermal conductivity field may be constructed from Monte Carlo simulations and statistical post-processing of the results using simulation inputs obtained by sampling from the measured temperature values and their associated reported uncertainties
- (vi) the parameter uncertainties may then be used as inputs in a GUM/GS1 uncertainty quantification calculation for the thermal conductivity uncertainty at any particular spatial coordinate within the domain

4. Discussion

In this paper we have investigated how to use an IHCP formulation as a means to determine thermal conductivity values for materials from experimental temperature measurements and numerical simulations. Potential benefits of the method that have been investigated are that there is no need for specialist laboratory reference thermal conductivity material standards, the method can be applied in industrial/plant environments with standard equipment/instruments with minimal physical complexity, and that the numerical algorithm to implement the method may be utilized to accurately relate and estimate the thermal conductivity uncertainties in terms of the input experimental data.

References

- [1] Incropera F P and DeWitt D P 1996 *Fundamentals of Heat and Mass Transfer* 4th ed (John Wiley & Sons)
- [2] Tsai B K, Gibson C E, Murthy A V, Early E A, DeWitt D P and Saunders R D 2004 Heat flux sensor calibration Tech. rep. National Institute of Standards and Technology nIST Special Publication 250-65 (37 pages)
- [3] JCGM/WG1 2008 Evaluation of measurement data – guide to the expression of uncertainty in measurement (JCGM 100:2008) Tech. rep. BIPM/IEC/IFCC/ILAC/ISO/IUPAC/IUPAP/OIML
- [4] JCGM/WG1 2008 Evaluation of measurement data – supplement 1 to the “guide to the expression of uncertainty in measurement” – propagation of distributions using a Monte Carlo method (JCGM 101:2008) Tech. rep. BIPM/IEC/IFCC/ILAC/ISO/IUPAC/IUPAP/OIML
- [5] JCGM/WG1 2011 Evaluation of measurement data – supplement 2 to the “guide to the expression of uncertainty in measurement” – extension to any number of output quantities (JCGM 102:2011) Tech. rep. BIPM/IEC/IFCC/ILAC/ISO/IUPAC/IUPAP/OIML
- [6] Hasuike H, Yoshizawa Y, Suzuki A and Tamaura Y 2006 *Solar Energy* **80** 1255–1262
- [7] Rodriguez-Sanchez M R, Soria-Verdugo A, Almendros-Ibanez J A, Acosta-Iborra A and Santana D 2014 *Applied Thermal Engineering* **63** 428–438
- [8] Powell R W, Ho C Y and Liley P E 1966 Thermal conductivity of selected materials Tech. rep. National Institute of Standards and Technology (previously NBS) <http://www.nist.gov/data/nsrds/NSRDS-NBS-8.pdf>
- [9] Miklavec A, Pusnik I, Batagelj V and Drnovsek J 2013 *Measurement Science and Technology* **24** 1–8
- [10] Ozisik M N and Orlande H R B 2000 *Inverse Heat Transfer – Fundamentals and Applications* (Taylor and Francis)
- [11] Mosegaard K and Tarantola A 1995 *Journal of Geophysical Research* **100** 12431–12447

- [12] Mosegaard K and Sambridge M 2002 *Inverse Problems* **18** R29–R54
- [13] Mosegaard K 2011 *Geophysics* **76** W51–W61
- [14] Fernandez-Martinez J L, Fernandez-Muniz Z, Pallero J L G and Pedruelo-Gonzalez L M 2013 *Journal of Applied Geophysics* **98** 62–72
- [15] Pujol J 2007 *Geophysics* **72** W1–W16
- [16] Geng F and Lin Y 2009 *Computers and Mathematics with Applications* **58** 2098–2102
- [17] Hon Y C and Wei T 2004 *Engineering Analysis with Boundary Elements* **28** 489–495
- [18] Hon Y C and Wei T 2005 *CMES Comput Model Eng Sci* **7** 119–132
- [19] Jin B and Marin L 2007 *International Journal for Numerical Methods in Engineering* **69** 1570–1589
- [20] Johansson B T, Lesnic D and Reeve T 2011 *International Journal of Computer Mathematics* **88** 1697–1713
- [21] Johansson B T, Lesnic D and Reeve T 2012 *International Communications in Heat and Mass Transfer* **39** 887–895
- [22] Karageorghis A, Lesnic D and Marin L 2011 *Inverse Problems in Science and Engineering* **19** 309–336
- [23] Marin L, Karageorghis A and Lesnic D 2011 *Engineering Analysis with Boundary Elements* **35** 342–354
- [24] Mierzwiczak M and Kolodziej J A 2011 *Inverse Problems in Science and Engineering* **19** 777–792
- [25] Reeve T and Johansson B T 2013 *Engineering Analysis with Boundary Elements* **37** 569–578
- [26] Kameli H and Kowsary F 2012 *International Communications in Heat and Mass Transfer* **39** 1410–1415
- [27] Liao W, Dehghan M and Mohebbi A 2009 *Journal of Computational and Applied Mathematics* **232** 351–360
- [28] Frackowiak A, Botkin N D, Cialkowski M and Hoffman K H 2010 *International Journal of Heat and Mass Transfer* **53** 2123–2127
- [29] Rashedi K, Adibi H, Amani J and Parand K 2014 *Engineering Analysis with Boundary Elements* **40** 1–21
- [30] Pourgholi R, Rostamian M and Emamjome M 2010 *Inverse Problems in Science and Engineering* **18** 1151–1164
- [31] Pourgholi R, Esfahani A and Abtahi M 2013 *Journal of Applied Mathematics Computation* **41** 61–79
- [32] Qian Z and Feng X 2013 *Inverse Problems in Science and Engineering* **21** 467–484
- [33] Lair P, Dumoulin J and Millan P 1998 *Numerical Heat Transfer, Part A: Applications: An International Journal of Computation and Methodology* **33** 267–277
- [34] Fasshauer G E 2007 *Meshfree Approximation Methods with MATLAB* (World Scientific Publishing)
- [35] Fasshauer G E and Zhang J G 2007 *Numerical Algorithms* **45** 345–368
- [36] Press W H, Teukolsky S A, Vetterling W T and Flannery B P 2007 *Numerical Recipes – The Art of Scientific Computing* 3rd ed (Cambridge University Press)
- [37] Burden R L and Faires J D 2001 *Numerical Analysis* 7th ed (Brooks/Cole)