Applied Thermal Engineering 129 (2018) 587–595

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research Paper

Estimation of thermal properties of a solid sample during a microwave heating process

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HIGHLIGHTS

- A numerical estimation of thermal properties during microwave heating is presented.
- The Peak Signal-to-Noise Ratio criterion proved to be a valid objective function.
- Prediction of thermal conductivity during microwave heating was achieved.
- Prediction of thermal diffusivity during microwave heating was achieved.

ARTICLE INFO

Article history:
Received 10 July 2017
Revised 3 October 2017
Accepted 5 October 2017
Available online 12 October 2017

Keywords:
Microwave heating
Inverse problems
Parameter estimation
Electromagnetic field

ABSTRACT

This paper addresses the problem of predicting thermal diffusion (α) and conductivity (k) during a microwave heating process. The estimation required the use of "simulated thermal images" for the microwave heating process of a solid parallelepiped sample made of SiC, and the application of the Peak Signal-to-Noise Ratio (PSNR) criterion. White Gaussian noise was also incorporated into the problem to simulate a realistic situation. The inverse problem was solved by applying three global optimization methods such as the Spiral Optimization Algorithm (*SOA*), the Vortex Search (*VS*) algorithm, and the Weighted Attraction Method (*WAM*). Results show that all algorithms converge into the expected solution and, therefore, were completely acceptable. However, the *VS* algorithm was the most accurate, improving the iterations and the parameters for function evaluation in nearly 2.5 times with respect to *SOA* and two times with regard to the *WAM* algorithm.

1. Introduction

Online measurement of process parameters and thermodynamic properties are sometimes difficult and practically impossible in some cases. This is certainly true for the processing of materials using electromagnetic waves in the microwave range. Most electronic temperature sensors are especially susceptible to this kind of radiation, which in turn, results in erroneous measurements and damages of the device. This is the reason why having appropriate methodology and instrumentation for accurate measurement of temperature is so important. This variable is considered of the essence for the prediction of boundary conditions, heat flux, and thermophysical properties, among other properties, through the Inverse Heat Conduction Problem approach (IHCP), [1–27]. Although the analysis of the studies dealing with IHCP and all those aspects is out of the scope of this paper, special focus has been placed on the most interesting aspects according to the authors. For instance, Jolly and Autrique [16] applied a semi-analytic conjugate gradient method (CGM) to estimate heat flux in a problem boundary through temperature readings of the opposite boundary. Their results highlight the fact that CGM acts as low-pass filter, which can be helpful when measuring data with high frequency noise. Then, Davin et al. [9], used inverse modeling to estimate convection coefficients in order to explain heat transfer phenomena when using oil to cool an electric motor. With this approach, the authors could detect the influence of oil temperature on convection coefficients that were undetectable when using direct measurements. Another important finding of their study is a coefficient database that may improve thermal modeling of electrical machines cooled by oil or by a mixture of air and oil. A third document of interest in this paper was published by Unnikrishnakurup et al. [24]. In this study, the authors focused on a welding-operation application. They used an inverse problem for estimating heat flux and, as a result, the process efficiency and

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https://doi.org/10.1016/j.applthermaleng.2017.10.037
1359-4311/

the Gaussian heat radius distribution. Furthermore, they selected the Levenberg-Marquardt method for solving the inverse problem.

The work of Li et al. [7] describe an experimental study for predicting the dynamic conductive heat flux on a concrete block surface when a spill of liquid nitrogen enters in contact with it. They solved the direct problem of thermal boundary conditions. In their findings, the inverse problem aims at the estimation of boundary conditions by knowing the temperature inside of the concrete block; in order to solve this inverse problem, they converted it in an optimization one and used the conjugate gradient method. More recently, Mohebbi et al. [27] proposed to estimate a linearly temperature-dependent thermal conductivity. In such study, they proposed a strategy for predicting the thermal conductivity of a 2D solid at steady state conditions. Furthermore, they developed a method for the computation of sensitivity coefficients. The objective function used in their procedure results from the ordinary least square method where the unknown are the parameters $(a; b)$ of $k(T) = a + bT$. In their conclusion, they report to have achieved the accurate estimation of the temperature-dependent thermal conductivity in the process of heat transfer at steady state. However, there is a gap in all the reported works known to us related to the estimation of thermal properties when a sample is being irradiated with microwaves. Filling this gap is important since it can provide support when designing a batch of experiments to be run.

Similarly, although other research works deal with the solution of inverse problems by using global optimization algorithms to estimate the missing parameters, only the most relevant studies are mentioned here. Amaya et al. [25] have used a combination of the Unified Particle Swarm Optimization (UPSO) algorithm and the variant of the Harmony Search (HS) algorithm for solving an inverse problem related to microwave heating. In their work, the authors considered a rectangular resonator containing a sample that filled completely the cross section of the device. Thus, only the height of each stage is required to be estimated so the resulting electromagnetic field within the cavity matched a desired field distribution. Another application of global optimization algorithms to inverse problems can be found in the work of Collins and Shen [28] where the authors generalized previous works dealing with a PSO application in robotics. In their study, the algorithm was used for solving an inverse kinematics problem (IK) by estimating the angles at which each joint must be set to guarantee that the end-effector of a robotic manipulator sits at a desired position. Finally, other authors [29] used a global optimization method known as the Cuckoo Search (CS) algorithm for solving the Iterated Function Systems (IFS) inverse problem. This problem appears in the field of fractal imaging because the solution to this problem produces a set of parameters that can be used for generating fractal images.

In this article, we attempt to estimate the thermal diffusion and the thermal conductivity properties after measuring the temperature profile. The proposed numerical strategy converted our inverse problem into an optimization one. The Peak-Signal-to-Noise-Ratio (PSNR) was used to build the objective function, since it is commonly used to compare images. To solve this objective function three global optimization algorithms have been used: the Spiral, Vortex Search and Weighted Attraction algorithms. The rest of the paper is organized as follows: Section 2 is devoted to a brief description of optimization algorithms, the objective function and the declaration of the direct and inverse problem for our specific problem. Section 3 includes our main simulation results and Section 4 is devoted to the conclusions.

2. Materials and methods

A brief description of modern optimization algorithms such as Spiral (SOA), Vortex Search (VS) and Weighted Attraction (WAM) is included in this section. Those algorithms were selected because they did not require many input parameters compared to other classic metaheuristic methods and their straightforwardness for programming. This section also includes a description of the system where the direct and the inverse problem is stated. Then, the solution to the direct problem is shown, including a description of how temperature measurements were created. Finally, the objective function is also declared here.

2.1. Algorithm fundamentals

The SOA [30], VS [31], and WAM [32] are global optimization algorithms that try to mimic natural phenomena such as pressure fronts, vortex pattern created by the vertical flow of stirred fluids, and gravitational attraction between particles. The authors choose them because of their simple structure, the fact that they have just few adjustable coefficients, and they can be easily programmed, among others characteristics. These algorithms are briefly described below.

2.1.1. Spiral optimization algorithm (SOA)

Spiral Optimization is an algorithm that was proposed by Tamura and Yasuda in 2011 [30]. This metaheuristic strives to mimic naturally occurring processes that describe a logarithmic spiral, such as a nautilus shell and a whirling current. The process begins at the outer part of the spiral and makes its way to the center as iterations progress. This migration allows SOA to explore a vast region of the search domain during the early stage of optimization, and then focus on exploiting the best solution found. Moreover, SOA only requires two parameters for its operation: the rotation angle (A_r) and the convergence radius (C_r). In a general sense, SOA can be implemented in five steps:

Step 0: *Algorithm initialization.* Determination of the upper limit (U_{lim}) and the lower limit (L_{lim}) of the search space, number of spirals in the solution space (P_{max}), number of maximum iterations (I_{max}), the rotation angle (A_r) where $0 \leqslant A_r \leqslant 2\pi$, and the convergence radius (C_r) where $0 < C_r < 1$. Then, random placement of every particle (x_i) in the search space, where $2 \leqslant i \leqslant P_{max}$.
Step 1: *Spirals center selection.* Evaluation of each spiral initial point in the objective function *(OF)*. Then, selection of the spiral with minimum value (x^*) as the rotation center.
Step 2: *Spirals rotation.* Rotation of the remaining spirals around the spiral center selected in the previous step as shown in the Eq. (1), where (n) is the dimension of the problem, (j) is the current iteration, ($R^{(n)}$) is the n-dimension matrix rotation, (I_n) is the n-dimension identity matrix and (i) is the current rotated particle.

$$x_i(j+1) = C_r R^{(n)}(A_r) x_i(j) - \left(C_r R^{(n)}(A_r) - I_n\right) x^* \tag{1}$$

Step 3: *New spiral center selection.* Evaluation of the new set of points in the *OF*, and selection of the point with minimum value as the new center (x^*).
Step 4: *Stop criteria check.* If the convergence criteria are satisfied, the algorithm stops. Otherwise, it goes back to Step 2.

2.1.2. Vortex search (VS)

Vortex Search was proposed by Doğan and Ölmez in 2015 [31]. Their approach is based on the vortex-like patterns that appear on nature. Therefore, their metaheuristic operates by creating a series of nested circles and analyzing the response on the objective function. The process begins at the outer layer (i.e. the biggest circle)