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A hybrid method for the inverse heat transfer of estimating fluid thermal conductivity and heat capacity

Fung-Bao Liu*

Department of Mechanical and Automation Engineering, I-Shou University, No. 1, Sec. 1, Syuecheng Rd., Dashu Township, Kaohsiung 84001, Taiwan

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ABSTRACT

In this work, a hybrid method is developed to identify simultaneously the fluid thermal conductivity and heat capacity for a transient inverse heat transfer problem. The proposed method is a combination of the modified genetic algorithm and Levenberg–Marquardt method. A modified genetic algorithm is adopted for searching the better feasible solution which becomes the initial-guessed solution for starting optimization by the Levenberg–Marquardt method. As the cost function is smaller than a default value, the Levenberg–Marquardt method is employed to speed up the convergence speed. Numerical examples are included to demonstrate the performance of the proposed method. In comparison with the modified genetic algorithm and the Levenberg–Marquardt method, the proposed hybrid method is efficiently converged to yield good estimates.

1. Introduction

Transient heat transfer inside ducts with wall heat flux is of interest in the control of heat exchanger equipment. Most of the work available in the literature deals with the solution of direct problems. That is, using the appropriate energy equation, boundary and initial conditions and thermalphysical properties to solve the resulting heat transfer problem for the temperature distribution in the medium. However, the inverse problems arise in the fields where it is not possible to accurately measure the parameters or functions of the process under consideration. They have received increased attention in many thermal engineering applications since 1960s. First, the problems were in the field of heat conduction. Latter, researchers expanded their topics to the thermal radiation. The inverse heat convection problems have been developed mainly since 1990.

Optimization techniques have been widely used to solve the inverse heat transfer problems. An error or cost function is defined first for the optimization procedure, and desired unknown functions or parameters are determined by minimizing the error or cost function. A variety of numerical and analytical techniques for solving the inverse problem have been proposed in the literature [1–5]. Most of them can be classified into two major methods; one is the gradient-based method and the other is the stochastic method.

The advantages of the gradient-based methods are the fast convergence speed and the high accuracy of the estimated solutions. However, the gradient-based methods may fail or not be effective for many reasons such as the cost function of the inverse problems being possible to have multiple minimums for a search range of the desired parameters or functions. In this case, the presence of local minima can trap the inverse procedure into one of the local optimum and the procedure will fail to find the true solutions.

For the gradient-based methods such as Newton method, steepest descent method, Levenberg–Marquardt method (LMM), and the conjugate gradient method, the search for the optimum is based on the gradient direction. Huang et al. [1] investigated the local heat transfer coefficients for plate finned tube heat exchangers in a three-dimensional inverse heat conduction problem. The steepest descent method and a general purpose commercial code were applied successfully based on the simulated measured temperature distributions on fin surface by infrared thermography. The Levenberg–Marquardt algorithm was employed for the inverse convection problem to estimate the unknown spatially nonuniform wall heat flux by Su et al. [2]. The proposed method is tested against several cases and numerical results are encouraging. Based on an advantage of short computational time, the conjugate gradient method has been adopted by many researchers to estimate the inlet flow temperatures [3], surface heat flux [4,5] for the inverse convection problems.

The advantage of the stochastic methods is their capability in searching for the global optimum instead of local optimum. This is because the search for the optimum is stochastic and global. The computation starts with a population of possible solutions rather than a single initial solution, which enables the search to avoid being trapped at any local optimum. However, the stochastic methods

* Tel.: +886 7 6577711x3228; fax: +886 7 6578853.
E-mail address: fliu@isu.edu.tw.

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Nomenclature

C	ρC_p; heat capacity of fluid, kJ/m^{3}K
C_p	specific heat of the fluid, kJ/kg K
$f(p)$	the functional defined by Eq. (2)
J	Jacobian matrix defined by Eq. (6)
k	thermal conductivity, W/m K
L	heated length of the duct, m
m	number of temperature measurements
P	unknown parameter vector defined by Eq. (3)
r	radial coordinate
r_1	random number in the interval [0,1]
r_2	random number in the interval [0,1]
r_3	random number in the interval [0,1]
R	duct radius, m
$T(r,z,t)$	computed temperature, K
T_i	initial temperature of the fluid, K
$u(r)$	fully developed flow velocity, m/s
v	member in the population pool
w	mutated element
Z	axial coordinate along the channel
Greek symbols	
θ	measured temperature, K

generally are poor for a low convergence speed and require a large number of iterations to achieve satisfactory convergent criteria.

The stochastic techniques such as genetic algorithm (GA) and simulated annealing (SA) have received increasingly more attention in science and engineering fields in recent years. Raudensky et al. [6] have demonstrated two novel approaches to the inverse problems. These approaches use two artificial intelligence mechanisms: neural network and genetic algorithm.

Both of the presented approaches can lead to a solution without having problems with the stability of the inverse task. An inverse procedure is presented based on the improved genetic algorithm and is applied in electronic system cooling simulation to identify heat transfer coefficients through temperature distributions by Liu et al. [7]. Latter, Liu and his colleagues [8] developed a reduced-basis method combined with an IP-GA (intergeneration-projection genetic-algorithm) to inversely identify heat convection constants for complex engineering systems. Yang et al. [9] studied the inverse heat conduction of quenching process based on finite element method and genetic algorithm. An improved genetic algorithm is adopted to solve the nonlinear optimization problem. Das et al. [10] investigated the application of the inverse method for simultaneous retrieval of parameters and reconstruction of the temperature field in a transient conduction–radiation problem with mixed boundary conditions. A method involving lattice Boltzmann method (LBM), the finite volume method (FVM) was used to obtain the temperature field in the mixed boundary problem which in the present work is termed as the direct method. The objective function is minimized using the genetic algorithm (GA). The impact of different genetic parameters on the accuracy of the estimation is also discussed. It is observed that subject to the proper selection of the genetic parameters, simultaneous reconstruction of the temperature field along with a reasonably good estimation of the unknown parameters can be achieved by using the LBM–FVM–GA method.

Silva Neto and Soeiro [11] studied the inverse analysis of heat conduction and radiative heat transfer problems. A combination of a gradient based deterministic method and stochastic global optimization method has been employed to get the best features of each approach. The test results demonstrated the effectiveness of the proposed method leading to good approximation for the global optimization.

In this work we examine the inverse heat convection problem by utilizing simulated transient measured temperatures taken at a single location in the downstream region. A hybrid method based on a combination of modified genetic algorithm and Levenberg–Marquardt method is proposed for the minimization procedure. The proposed hybrid algorithm employs both the merits of the genetic and the Levenberg–Marquardt algorithms to find the unknown parameters. Numerical experiments are performed to demonstrate the accuracy and efficiency of the proposed method.

2. The direct heat transfer problem

Consider transient heat transfer to hydrodynamically developed, thermally developing laminar flow inside a circular duct resulting from an application of constant wall heat flux of the duct. Viscous dissipation and fluid axial conduction effects are neglected. The thermal properties are assumed to be constant. Initially, the temperature of the flow is constant. Because of symmetry, only half of the region is considered for the analysis. The mathematical formulation of the problem is defined as follows.

$$k\frac{1}{r}\frac{\partial}{\partial r}\left(r\frac{\partial T(r,z,t)}{\partial r}\right) = C\frac{\partial T(r,z,t)}{\partial t} + Cu(r)\frac{\partial T(r,z,t)}{\partial z}, \quad 0 < z < L,\ 0 < r < R,\ t > 0, \tag{1a}$$

and subjected to the following boundary and initial conditions.

$$k\frac{\partial T(R,z,t)}{\partial r} = -q, \quad \text{at } r = R,\ 0 \le z \le L,\ \text{for } t > 0 \tag{1b}$$

$$\frac{\partial T(0,z,t)}{\partial r} = 0, \quad \text{at } r = 0,\ 0 \le z \le L,\ \text{for } t > 0, \tag{1c}$$

$$T(r,0,t) = T_i, \quad \text{at } z = 0,\ 0 \le r \le R,\ \text{for } t > 0, \tag{1d}$$

$$T(r,z,0) = T_i, \quad \text{at } 0 \le z \le L,\ 0 \le r \le R,\ \text{for } t = 0, \tag{1e}$$

where the fully developed velocity distribution is given by $u(r) = 2u_m[1-(r/R)^2]$ and the heat capacity is defined as $C = \rho C_p$. The problem defined by equations (1a)–(1e) is called a direct problem in which the downstream temperature $T(r,z,t)$ is determined when the thermal conductivity k, heat capacity C, initial and boundary conditions are known. The classical method for solving the direct problem is conducted by the separation of variables. Also, Mikhailov and Ozisik [12] proposed a different method to solve the same problem by integrate transform technique.

3. The inverse analysis

For the inverse problem, the thermal properties of conductivity k and the heat capacity C of the fluid are regarded as two unknown parameters to be determined from the knowledge of transient temperature readings taken at a single location in the downstream region. A cost function is defined as a sum of squared differences between the measured temperatures and those from the computational results using guess or estimated solutions as follows:

$$f(P) = \sum_{j=1}^{m}\left[T_j(P) - \theta_j\right]^2, \tag{2}$$

and