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Application of the hybrid particle swarm optimization algorithms for simultaneous estimation of multi-parameters in a transient conduction–radiation problem

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ABSTRACT

A Simplex Bare-bones Particle Swarm Optimization (KSM-BBPSO) algorithm based on the K-means clustering was introduced, and on this basis, an improved hybrid Simplex-Particle Swarm Optimization algorithm based on K-means clustering (KSM-PSO) was developed to retrieve the multi-parameters of the semi-transparent media simultaneously in a transient conduction–radiation problem. The conduction–radiation parameter, scattering albedo, and boundary emissivity in a one-dimensional (1-D) homogenous semitransparent slab were estimated simultaneously to illustrate the performances of the KSM-BBPSO and KSM-PSO algorithms. The transient temperature responses on both sides of the medium boundaries exposed to the pulse laser irradiation, which was simulated directly by Finite Volume Method (FVM), were served as input for the inverse analysis. By the KSM-BBPSO algorithm introduced and KSM-PSO algorithm developed, all the thermophysical parameters could be estimated with reasonable accuracy, even with noisy temperature measurements. The KSM-PSO algorithm was proved to be fast, accurate, and robust, while the KSM-BBPSO algorithm has better versatility.

1. Introduction

Recently, the inverse heat transfer problems in semitransparent media have been studied extensively for their widely practical applications in various research fields such as atmosphere science, aerospace engineering, medical imaging, remote sensing, and other engineering areas [1–12]. Theoretically speaking, these inverse problems involve retrieving the boundary conditions, the initial conditions, geometry, the heat source, or the material themophysical properties, etc. Among these problems, the inverse problem of coupled conduction–radiation to determine the material themophysical parameters and/or optical properties has received considerable attention in the last two decades [5–9]. Most of these researches were targeted for establishing the corresponding objective function, which is expressed by the sum of square residuals between the calculated and observed temperature distribution in space or time domain. Consequently, the media's thermophysical parameters and/or optical properties, including the thermal conductivity, absorption coefficient, scattering coefficient, conduction–radiation parameter, and medium's boundary emissivity etc., were estimated by minimizing the objective function using the inverse optimization methods.

To date, the widely used conventional inverse methods are gradient-based methods, including the Conjugate Gradient (CG) method, Gauss–Newton method (G–N) and Levenberg–Marquardt (L–M) method, etc. For instance, Sarvari et al. [9] adopted the CG method to retrieve the boundary conditions of the coupled conduction–radiation heat transfer problem. Daouas et al. [10] retrieved some thermophysical parameters during transient coupled conduction–radiation procedure using the L–M method combined with experimental measurements. Cheng et al. [11] developed a revised Tikhonov regularization method to reconstruct three-dimensional temperature distributions of a gas-fired pilot tubular furnace from the green monochromatic radiative intensity which can be calculated by the DRESOR method based on the radiation image processing technology. However, all these gradient-based algorithms need to solve the first or second derivative of the objective function with respect to the inversion parameters, which maybe computationally expensive in terms of both memory requirements and CPU time. Meanwhile, the retrieval result is highly affected by the initial value. Without correlative experience, it may be difficult to have a reasonable result unless a proper initial

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Nomenclature

bdlow (*j*)	the search lower limit of the *j*th coordinate's corresponding parameter
bdup (*j*)	the search upper limit of the *j*th coordinate's corresponding parameter
C_1, C_2	the two positive acceleration coefficients of PSO-based algorithm
c_p	specific heat capacity, J/(kg K)
F	the objective function of minimization
h_1, h_2	the convective heat transfer coefficient, W/(m^2 K)
I	the radiative intensity, W/(m^2 sr)
I_{w1}, I_{w2}	the intensity on the left and right boundary, W/(m^2 sr)
K	the simplex method interval generation
L	length of the media, m
M	the number of particles in each swarm
mod	the modulus operator
N	the maximum number of generation
n	the dimension of the problem
n_1	the refractive index of the media
$P(i,j)$	the value of the *j*th coordinate of the *i*th vertex in the simplex method
$\mathbf{P}_g(t)$	the global best position discovered by all particles at generation t
$\mathbf{P}_i(t)$	the local best position of particle discovered at generation t or earlier
q_r	the radiation heat flux term, W/m^2
q_{laser}	the laser power density, W/m^2
q'_{laser}	the dimensionless laser power density
q^r_{w1}, q^r_{w2}	the radiation heat flux on the left and right boundary, W/m^2
R_1, R_2	the uniformly distributed random number in $[0,1]$
T	temperature, K
T_s	the ambient temperature, K
T_{w1}, T_{w2}	the temperature on the left and right boundary, K
t	the iteration in PSO-based algorithm or time, s
t_{laser}	the duration of laser action
t'_{laser}	the dimensionless time of laser action
$\mathbf{V}_i(t)$	the velocity array of the *i*th particle at generation t
$v_{ij}(t)$	the velocity of the *i*th particle with the *j*th dimension at generation t ($i = 1,\ldots,M$; $j = 1,\ldots,n$)
$\mathbf{X}_i(t)$	the position vector of the *i*th particle at generation t
x	the *x*-axis coordinate
$x_{ij}(t)$	the position of the *i*th particle with *j*th dimension at generation t ($i = 1,\ldots,M$; $j = 1,\ldots,n$)

Greeks symbols

α	reflection factor
β	the compression factor or extinction coefficient, m^{-1}
χ	sensitivity coefficient
Δ	the percentage of small change of the inversion parameter
δ	contraction factor
ε	boundary emissivity
ε_{rel}	the measured error of the inversion parameter
Φ	scattering phase function
γ	the extension factor or measurement errors, %
η_t	the ratio of computational time to the laser action time
κ_a	absorption coefficient, m^{-1}
λ	conductivity, W/(m K)
$\mu_{i,j}$	the mean of Gaussian distribution
Θ_w	the dimensionless boundary temperature
θ	temperature excess
ρ	the reflectivity or the mass density, kg/m^3
σ	the standard deviation or the Stefan–Boltzmann constant (5.6703×10^{-8} W m^{-2} K^{-4})
σ_s	scattering coefficient, m^{-1}
Ω	solid angle, sr
ω	scattering albedo or the inertia weight factor
ς	random variable

Subscripts

b	blackbody
est	estimated value
exact	exact value
mea	measured value
w1, w2	the left and right boundary

Superscript

m	the scattering direction or outgoing direction

guess value is available. In a word, these methods are unable to robustly provide solutions close to the global optimal domain [12].

To circumvent this issue, the intelligent optimization algorithms based on the population exhaustive search has been proposed to solve the ill-posed inverse heat transfer problems in recent years, such as the Genetic Algorithm (GA), the Particle Swarm Optimization (PSO), the Ant Colony Optimization (ACO), and the Neural Network Algorithm (NNA) [12–19]. A characteristic feature of these evolutionary search optimization methods is that they can solve the global optimal problem reliably and obtain high quality global solutions with enough computational time. Many literatures for solving inverse conduction–radiation problems have addressed these intelligent evolutionary searching methods. Chopade et al. [12] used the boundary temperatures obtained by solving the forward problem of the coupled conduction–radiation heat transfer in one-dimensional (1-D) participating media to estimate the media's extinction coefficient and scattering albedo using PSO algorithm. The author found that the retrieval results of PSO algorithm were more accurate than those of GA. Verma et al. [13] retrieved conduction–radiation parameter, optical thickness, and the boundary emissivity during the transient coupled conduction and radiation heat transfer in 1-D slab medium using GA. Furthermore, Das et al. [14,15] used the GA for inverse analysis of transient coupled conduction–radiation heat transfer in two-dimensional (2-D) medium to estimate the conduction–radiation parameter, scattering albedo, and boundary emissivity. Recently, they adopted the Lattice Boltzmann method (LBM) and the Finite Volume Method (FVM) to retrieve the extinction coefficient and conduction–radiation parameter of non-Fourier coupled conduction–radiation heat transfer combining with GA [15]. Our research group has demonstrated the use of several PSO-based algorithms to determine the radiative properties, particle size distributions and geometry conditions in various inverse radiation problems [18–21]. More recently, some new intelligent optimization techniques have been proposed to solve the coupled conduction–radiation problems to look for improvements besides GA and PSO. Chopade et al. [22] investigated the transient inverse problem of coupled conduction–radiation heat transfer using Differential Evolution algorithm. A new Homogenous Continuous ACO algorithm was developed by our group to retrieve the thermophysical parameters of participating medium in the problem of coupled conduction–radiation [23].

However, to the best of author's knowledge, the intelligent optimization methods are mostly limited to retrieve the single or