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Solving inverse problems of radiative heat transfer and phase change in semitransparent medium by using Improved Quantum Particle Swarm Optimization

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ABSTRACT

In the present study, the Quantum Particle Swarm Optimization (QPSO) algorithm is applied to solve the inverse problems of radiative heat transfer and phase change in laser heating semitransparent medium. To increase the efficiency and the accuracy of the original QPSO algorithm, an Improved Quantum Particle Swarm Optimization (IQPSO) algorithm is developed based on the original QPSO algorithm. To illustrate the performance of the proposed IQPSO algorithm, the Stefan number or/and conduction to radiation number of the one-dimensional semitransparent phase change medium are retrieved by measuring the transient boundary temperatures. The Finite Volume Method approximation is treated as the forward model and the sensitivity and measurement error are also analyzed. By the IQPSO algorithm presented, the thermophysical parameters can be estimated accurately, even with noisy data. In conclusion, the IQPSO algorithm is demonstrated to be more effective and robust compared with the Basic Particle Swarm Optimization and QPSO algorithms through function estimation and parameter estimation, it is thus has the potential to be implemented in various fields of inverse heat transfer problems.

1. Introduction

Due to the rapid development of laser technology and wide application of semitransparent material, studying radiative heat transfer in the high-temperature phase change process has important theoretical significance and broad application prospects. Laser heating semitransparent medium has received great attention in the last two decades [1–8]. Since the phase change involves complex thermal physical processes, the temperature is depends on multiple physical mechanisms. Particularly, the radiative heat transfer has to be considered during the high-temperature phase change process in the semitransparent medium. The coupling of radiation and phase change has brought great difficulties to numerical solution. On one hand, the material properties vary with temperature during phase change process; on the other hand, the radiative heat transfer can influence the temperature profile, and this will further affect the phase change process prominently [9].

Most of the previous investigations have used gradient-based optimal methods, such as conjugate gradient method [10,11], Levenberg–Marquardt method [12,13], etc, to solve the inverse radiation and phase change problems. Recently, several heuristic algorithms were developed to solve the inverse radiation and phase change problems, such as genetic algorithm [14,15], particle swarm optimization [16,17], ant colony optimization [18,19], Artificial Neural Network [20,21], etc. Compared with traditional gradient-based methods, these heuristic algorithms have some inherent superiority [22]. Firstly, they are easy to implement using a small number of algorithm control parameters, without the gradient information. Secondly, these algorithms are robust and have less dependence on initial values. Because of their probabilistic nature, the initial guess has little influence on the final optimization result. Finally, these methods are easily to be parallelized.

The Basic Particle Swarm Optimization (BPSO) algorithm was originally inspired by the flocking behavior of birds and used to simulate social behaviors. It is one of the swarm intelligence techniques, which use group intelligence behavior along with individual intelligence to solve the combinatorial optimization problems. The BPSO algorithm is characterized as being simple in concept and easy to implement [23]. It is not necessary to calculate the gradient of the objective function with respect to retrieval variables, and only the functional value of the objective function and primi-

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Nomenclature

c_1, c_2	two acceleration coefficients in Eq. (16)
c_p	specific heat capacity, J/(kg K)
E	estimated value
f_l	liquid fraction
F_{obj}	the objective function value
h	total enthalpy, J/kg
h_{f1}, h_{f2}	convective heat transfer coefficient, W/(m^2 K)
H	Heaviside function
I	radiative intensity, W/(m^2 sr)
I^-	radiative intensity when $0 \leqslant \theta < \pi/2$, W/(m^2 sr)
I^+	radiative intensity when $\pi/2 < \theta \leqslant \pi$, W/(m^2 sr)
I_b	blackbody radiative intensity, W/(m^2 sr)
L	the latent heat, J/kg
L_x	length of the media, m
low_i, $high_i$	low and high limit of the initial search space of the ith retrieval parameter
M, $\tilde{M}$	measured value and the exact measured value
n	refraction index
N	total number of retrieval parameters or conduction-to-radiation parameter
$\mathbf{n}$	outward normal direction of the wall
N_c	maximum number of the iterations
N_s	number of the particles
N_τ	grids number
N_θ	number of the polar angles
obj_j, obj_g	objective function value of the individual and global best position
$\mathbf{P}_i$, $\mathbf{P}_g$, $\mathbf{P}_m$	the individual, global and mean best position
$\mathbf{Q}_i$	local attractor point
q_{in}	the peak heat flux of the incident laser, W/m^2
$\mathbf{q}^r$	radiative heat flux vector, W/m^2
q^r_{w1}, q^r_{w2}	radiative heat flux on the left and right borders, W/m^2
r	the chaos signal generated by the typical logistic mapping
R, $\bar{R}$, $\hat{R}$	retrieval value, the mean retrieval value and the true value of the retrieval parameter
$rand_n$	standard normal distributed random number
$rand_u$	uniform random number in [0, 1]
s	spatial position
t	time or iterations
t_p	the pulse width of the incident laser, s
T	temperature, K
T_0	the initial temperature, K
T_{f1}, T_{f2}	the ambient temperature of the left and right side of the medium, K
T_{w1}, T_{w2}	the boundary temperature of the left and right side of the medium, K
$T_{-\infty}$, $T_{+\infty}$	the surroundings temperature of the left and right side of the medium, K
T_{ref}	the reference temperature, K
$\mathbf{V}_i$	the velocity of the particle
v_{max}	the maximum value of the particle velocity
$\mathbf{X}_i$	the position of the ith particle

Greeks symbols

β	the contraction–expansion coefficient or extinction coefficient, m^{-1}
χ	sensitivity coefficient
Δ	perturbation
ε	setting accuracy of the objective function
ε_{w1}, ε_{w2}	emissivity of the left and the right wall
ε_{rel}	relative error, %
Φ	scattering phase function
γ	measurement error, %
κ_a, κ_s	absorption and scattering coefficient, m^{-1}
λ	thermal conductivity, W/(m K)
μ	the logistic mapping control parameter in Eq. (23) or the direction cosine
θ	polar angle
ρ	density, kg/m^3
σ	standard deviation or Stefan–Boltzmann constant (5.6703×10^{-8} W m^{-2} K^{-4})
τ	optical thickness
ω	scattering albedo
$\mathbf{\Omega}$	radiation direction
Ω	solid angle, sr
ζ	the mutation control parameter in Eq. (25)

Subscripts

i	particle index
j	retrieval parameters index
k	measurement position index
l	liquid zone
m	mushy zone
s	solid zone

Superscripts

m	scattering direction or outgoing direction
m'	incoming direction
T	matrix transpose
$*$	dimensionless term

tive mathematical operators are required. When appropriately handled, BPSO algorithm explores a large portion of solution space, and is unlikely to converge to a local optimum. The disadvantage of BPSO algorithm is its slow convergence speed, which can be much slower than that of gradient-based optimization methods. In addition, separate runs of the BPSO algorithm with exactly the same settings could potentially converge to different similar optimal results because of their probabilistic nature [16]. Therefore, the BPSO algorithm is not suitable for inverse problems requiring high computational efficiency.

Recently, as inspired by quantum mechanics and trajectory analysis of the BPSO algorithm, Sun et al. proposed the Quantum Particle Swarm Optimization (QPSO) algorithm, which is based on a quantum δ potential well model to sample around the previous best points [24], and introduced the mean best position into the algorithm [25]. The updating scheme of the QPSO algorithm is very different from that of the BPSO algorithm. Compared with the BPSO algorithm, the QPSO algorithm does not need velocity vectors for particles, and has fewer parameters to adjust, making it easier to implement. The QPSO algorithm has been used to solve a wide range of continuous optimization problems successfully and many efficient strategies have been proposed to improve the algorithm [26]. However, to the best of our knowledge, there were no reports concerning the application of the QPSO algorithm to solve inverse problems of radiation heat transfer and phase change. In this paper, an Improved Quantum Particle Swarm Optimization (IQPSO) algorithm is developed, which applies logistic mapping to generate chaotic sequence in the initialization, uses Gaussian probability distribution as local attractor point and adds a mutation operation to avoid premature convergence during the