Retrieval of Heat Radiative Property Parameters in Semitransparent Media Using Improved Stochastic Particle Swarm Optimization

FANG Hongyi[1,2], *JIANG Xinyu*[3], *HE Zhenzong*[3*], *WANG Dengkui*[1], *MAO Junkui*[3], *CHEN Tao*[1]

1. AECC Sichuan Gas Turbine Establishment, Mianyang 621000, P. R. China;
2. School of Power and Energy, Northwestern Polytechnical University, Xi'an 710129, P. R. China;
3. College of Energy and Power Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, P. R. China

(Received 25 January 2022; revised 2 August 2022; accepted 12 October 2022)

Abstract: Semitransparent media widely exist in industrial and chemical equipment, and their heat radiative properties usually play a vital role in studying the heat transfer process in the media. In the paper, an improved stochastic particle swarm optimization (ISPSO) is proposed to determine heat radiative property parameters of semitransparent media, i.e. absorption coefficient, scattering coefficient and asymmetry factor, from the angular light-scattering measurement signals. The results show that compared with the stochastic particle swarm optimization (SPSO) algorithm, the ISPSO algorithm can avoid the phenomenon of local optima and low convergence accuracy, and reasonable retrieval results can be obtained even with 5% random measurement errors. Moreover, the robustness of the inverse results is satisfactory when there are only two parameters needed to be studied. The inverse accuracy will be decreased when more parameters needed to be retrieved. However, the results are still acceptable even with 5% random measurement errors, when the absorption coefficient, scattering coefficient and asymmetry factor are retrieved simultaneously. All the results confirm that the proposed technique is an effective and reliable technique in estimating multiple radiative property parameters in semitransparent media simultaneously.

Key words: inverse radiation problem; radiative property parameter; improved stochastic particle swarm optimization; semitransparent media; angular light-scattering measurement method

CLC number: TK123 **Document code:** A **Article ID:** 1005-1120(2023)01-0037-10

0 Introduction

Radiative properties in the semitransparent media play an important role in studying the optical tomography in medical imaging, laser-based nondestructive testing, remote sensing of the atmosphere and the prediction of the temperature distribution of high luminous flame[1]. Generally, multiple radiative property parameters are used to study the semitransparent media, e. g. scattering albedo, phase function, absorption coefficient and scattering coefficient. The determination of multiple radiative property parameters is regarded as a problem of synergetic reconstruction of multi-parameters, which easily leads to local optimal solution and multi-value characteristics of retrieval results[2-4]. So retrieving multiple heat radiative property parameters in semitransparent media accurately is still an unsolved problem and needs further study.

The laser measurement technology combined with inverse problem optimization algorithms has been introduced to obtain heat radiative properties of semitransparent media. Common measurement lasers can be divided into two categories, i.e. steady-

*Corresponding author, E-mail address: hezhenzong@nuaa.edu.cn.

How to cite this article: FANG Hongyi, JIANG Xinyu, HE Zhenzong, et al. Retrieval of heat radiative property parameters in semitransparent media using improved stochastic particle swarm optimization[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2023, 40(1): 37-46.

http://dx.doi.org/10.16356/j.1005-1120.2023.01.004

state laser and transient laser (e.g. time-domain laser and frequency-domain laser)[5]. For supplying abundant and useful transient measurement information about the measured media, more accurate results can be obtained by using transient laser than by using steady-state laser, and corresponding transient laser measurement technology has attracted widely attention in estimating heat radiative property parameters[6-9]. Unfortunately, there are also some disadvantages in transient lasers measurement technique simultaneously, e.g. complicated optical layout and time-consuming simulation of transient radiative transfer equation (RTE), which means the technique cannot satisfy the needs of in-situ measuring heat radiative properties of media, e.g. in-situ monitoring heat radiation properties of flame. Therefore, to find a kind of simple, the efficient and accurate measurement technique is necessary and worthwhile.

In present study, the steady-state angular light-scattering measurement (ALSM) method has been proposed to retrieve multiple radiative property parameters of semitransparent media simultaneously, for it has been demonstrated to provide abundant angular measurement information about the media and show satisfactory convergence accuracy in studying the particle size distribution[10]. The inverse problem is solved by an improved stochastic particle swarm optimization (ISPSO) algorithm. The remainder of this research is organized as follows. First, the ALSM method is introduced. Then, the convergence properties of ISPSO algorithm are compared with those of stochastic particle swarm optimization (SPSO) algorithm, and the radiative property parameters, i.e. the absorption coefficient α, the scattering coefficient σ and the asymmetry factor g, of semitransparent media are estimated simultaneously under different random measurement errors. Generally, the absorption coefficient shows the absorptive capacity of the medium to incident radiation energy. The scattering coefficient shows the scattering capacity of the medium to incident radiation energy. For the absorption coefficient and the scattering coefficient, the higher the value, the stronger the absorption/scattering capacity. The asymmetry factor shows the anisotropic scattering characteristics of the medium. The value range of the asymmetry factor g is set as $[-1, 1]$. For $g=0$, the medium is isotropic scattering. For $g<0$, the backscattering of the medium is dominant. For $g>0$, the forward scattering of the medium is dominant. Finally, the main conclusions and perspectives are provided.

1 ALSM Method

Fig.1 shows a beam of collimated laser impinging on a slab filled with common temperature, homogeneous, absorbing, and scattering semitransparent media. In Fig.1, I_0 is the total incident light intensity; θ the polar angle, which is defined as the angle between Ω and positive x axis; and L the geometrical thickness of the slab.

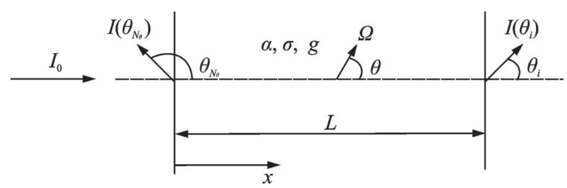


Fig.1 Schematic model of ALSM method

The refractive index of the slab is assumed to be identical to that of the surroundings and equal to unity. So the emitting of the media can be ignored, and the radiative transfer process in the slab can be described by the one-dimensional steady-state radiative transfer equation (RTE)[11]

$$s\cdot\frac{\partial I(z,s)}{\partial z}=-(\alpha+\sigma)I(z,s)+\frac{\sigma}{4\pi}\int_{4\pi}I(z,s_i)\Phi(s_i,s)\mathrm{d}\Omega_i \quad (1)$$

where $I(z,s)$ is the radiative intensity in direction s at location z; $\Phi(s_i,s)$ the scattering phase function, which describes the probability that heat radiation traveling in the solid angle $\mathrm{d}\Omega_i$ around the direction s will be scattered into the solid angle $\mathrm{d}\Omega$ around direction s. In this paper, to simplify the physical problem and make the problem trackable, the scattering phase function $\Phi(s_i,s)$ is assumed to obey the Henyey-Greenstein scattering phase function, and can be expressed as[12]

$$\Phi(s_i,s)=\frac{1-g^2}{[1+g^2-2g\cos(s_i,s)]^{3/2}} \quad (2)$$

In present manuscript, the boundaries are taken as cold and nonreflecting, and the boundary conditions can be expressed as

$$I^{+}(0,\theta)=\begin{cases} I_0 & \theta=0 \\ 0 & 0<\theta\leqslant 90^{\circ} \end{cases} \tag{3}$$

$$I^{-}(L,\theta)=0 \quad 90^{\circ}<\theta<180^{\circ} \tag{4}$$

where $I^{+}(0,\theta)$ is the light intensity incident to the internal media from the left side of the sample; $I^{-}(L,\theta)$ the light intensity incident to the internal medium from the right side of the sample. When the RTE and boundary conditions are solved by numerical methods such as finite volume method (FVM) and Monte-Carlo method (MCM), the ALSM signals $I^{-}(0,\theta)$ on the left side of the slab and the ALSM signals $I^{+}(L,\theta)$ on the right side of the slab can be obtained. In the category of accurate radiative transfer algorithms, FVM can provide the most flexible trade-off between precision and computation time. Thus, in the present study, FVM is employed to solve the direct problem. The detail of FVM is available in Ref. [11], and not repeated here. In this study, α, σ and g are the unsolved heat radiative property parameters in semitransparent media and need to be retrieved.

2 Inverse Problem Models

2.1 Principle of SPSO

By incorporating swarm behaviors observed in flocks of birds, schools of fish, and even human social behaviors, the standard particle swarm optimization (PSO) algorithm, first introduced by Eberhart and Kennedy[13] in 1995, is an optimization technique that can be easily implemented and only needs to adjust a small number of parameters. However, since there is only one term which regulates historic velocity during the evolution process, the particle can only fly along one direction until it finds a better solution, which will result in premature convergence. To overcome the difficulty, the SPSO algorithm was introduced, and showed better retrieval accuracy in solving the problem of estimating the inverse radiation[14-15].

According to the SPSO algorithm, the velocity-update formula and the position-update formula can be described as[14]

$$\boldsymbol{V}_i(t+1)=C_1\cdot \text{rand}_1\cdot[\boldsymbol{P}_i(t)-\boldsymbol{X}_i(t)]+C_2\cdot \text{rand}_2\cdot[\boldsymbol{P}_g(t)-\boldsymbol{X}_i(t)] \tag{5}$$

$$\boldsymbol{X}_i(t+1)=\boldsymbol{X}_i(t)+\boldsymbol{V}_i(t+1) \tag{6}$$

where rand_1 and rand_2 are the two uniformly distributed random numbers in the range of [0, 1]; C_1 and C_2 the two positive constants called acceleration coefficients; $\boldsymbol{P}_i(t)$ and $\boldsymbol{P}_g(t)$ the personal best position of the ith particle and the global best position of all the particles at the tth iteration, respectively; and $\boldsymbol{X}_i(t)$ and $\boldsymbol{X}_i(t+1)$ the old and new position of the ith particle at the tth and $(t+1)$th iteration, respectively. The detail description of the SPSO algorithm is available in Ref. [14].

2.2 Principle of ISPSO

In original SPSO algorithm, initial positions are usually generated by random numbers that may allow some of initial positions too close to each other. To overcome these difficulties, the chaos theory, the highly unstable motion of deterministic systems in finite phase space that often exists in nonlinear systems, is used to initialize the positions of particles. The chaos theory studies the behavior of dynamical systems that are highly sensitive to initial conditions, the effect that is popularly referred to as the butterfly effect[16], and the typical logistic mapping to generate the chaos signal is described as follows

$$\begin{cases} r(0)=\text{rand}_3 \\ r(k+1)=\mu r(k)(1-r(k)) \quad k=0,1,\cdots,N_c-1 \end{cases} \tag{7}$$

where rand_3 is the uniformly distributed random number in the range of [0, 1]; and μ the control number, when $\mu=4.0$, the logistic mapping is in a fully chaotic state.

Moreover, the fast information flow between particles seems to be the reason for clustering of particles, which will also lead to the diversity decline rapidly and leave the algorithm with great difficulties of escaping local optima. Therefore, to remedy this problem, the differential evolution (DE) algorithm is introduced to improve the personal best positions. The DE algorithm, developed by Storn and

Price[17] , is an evolutionary optimization algorithm based on population cooperation and competition of individuals and has been successfully used to solve optimization problems particularly involving non-smooth objective function[18-19]. The basic optimization process in the DE algorithm is carried out by combing simple arithmetic operators with classical evolution operators of mutation, crossover and selection to evolve from a randomly generated population to a final solution[19].

According to the DE algorithm, the mutant vector can be generated as[17]

$$\boldsymbol{P}_{i,\mathrm{mut}}(t)=\boldsymbol{P}_k(t)+F\cdot[\boldsymbol{P}_l(t)-\boldsymbol{P}_m(t)] \quad (8)$$

where k, l, m are random integers uniformly selected from $[1, N_\mathrm{s}]$ and $i\neq k\neq l\neq m$; and F, the mutant factor, is a real and constant value, $F\in[0, 2]$, which controls the amplification of the differential variation $[\boldsymbol{P}_l(t)-\boldsymbol{P}_m(t)]$. In order to increase the diversity of the perturbed parameter vectors, crossover is introduced and the trial vector $\boldsymbol{P}_{i,\mathrm{tri}}(t)=(p_{i1,\mathrm{tri}}, p_{i2,\mathrm{tri}}, p_{i3,\mathrm{tri}}, \cdots, p_{iN_\mathrm{p},\mathrm{tri}})$ can be derived from[17]

$$p_{ij,\mathrm{tri}}(t)=\begin{cases} p_{ij,\mathrm{mut}}(t) & \mathrm{rand}_4(j)\leqslant C_\mathrm{R} \text{ or } j=\mathrm{rnbr}(i) \\ p_{ij}(t) & \mathrm{rand}_4(j)> C_\mathrm{R} \text{ or } j\neq \mathrm{rnbr}(i) \end{cases} \quad (9)$$

where $\mathrm{rand}_4(j)$ is the jth evaluation of a uniform random number generator, $\mathrm{rand}_4(j)\in[0, 1]$; C_R the crossover constant $C_\mathrm{R}\in[0, 1]$, determined by the user; and $\mathrm{rnbr}(i)$ the random integer uniformly selected from $[1, N_\mathrm{s}]$. The detail search procedures are shown below.

Step 1 Input system control parameters of the ISPSO algorithm, i.e. the total number of the particles in the swarm N_s, the maximum number of iterations N_c, the number of the inversion parameters (dimensions) N_p, the searching space $[\mathrm{low}_i, \mathrm{high}_i]$ of each inversion parameter, the tolerance for minimizing the objective function value ε and the values of C_1, C_2, F and C_R.

Step 2 Initialize a population of particles with random positions in the N_p dimensional problem by mapping the chaotic sequence, which is generated by Eq.(13), to the search space. Evaluate the objective function value of each particle $F_{\mathrm{obj},i}$. Obtain the initial personal best position of each particle $\boldsymbol{P}_i$ and the global best position $\boldsymbol{P}_\mathrm{g}$, and record corresponding objective function values p_{best_i} and g_best. Set the number of current iteration $t=0$.

Step 3 Determine whether the program matches one of the following two stop criterions. If so, end the calculation and record the estimated values; if not, proceed to Step 4.

(1) The objective value of global best position is less than the tolerance, $g_\mathrm{best}<\varepsilon$;

(2) The number of the iteration reaches the user-defined iteration limit N_c, $\mathrm{iter}(t)>N_\mathrm{c}$.

Step 4 Update the velocity $\boldsymbol{V}_i$ and positions $\boldsymbol{X}_i$ of all the particles according to Eqs.(11, 12). If the new position exceeds the search space, make it equal to the low or high limit of the search space.

Step 5 Evaluate the positions of particles and calculate the corresponding objective function values $F_{\mathrm{obj},i}$.

Step 6 Determine whether the objective function value of each particle is superior to current p_{best_i}. If so, update the value p_{best_i} and corresponding personal best position $\boldsymbol{P}_i$.

Step 7 Calculate the mutant vectors for all the particles using Eq.(14). Operate the crossover and calculate the trial vector $\boldsymbol{P}_{i,\mathrm{tri}}$ using Eq.(15). Finally, evaluate the trial vector and compare the objective function value of the trial vector and that of the target vector. If the trial vector is superior, update the value p_{best_i} and corresponding personal best position $\boldsymbol{P}_i$.

Step 8 Determine whether the objective function values of the personal best positions p_{best_i} are superior to that of the current global best position g_best for all particles. If so, update the value g_best and corresponding location $\boldsymbol{P}_\mathrm{g}$. Loop to Step 3.

3 Numerical Simulation

In this manuscript, the measurement angles are set as $\theta=10°$, $40°$ for there are two parameters needs to studied, and set as $\theta=10°$, $40°$, $70°$ for there are three parameters, i.e. α, σ and g needs to be determined. The inverse problem is solved by minimizing the objective function value F_obj, which is defined as the sum of the square residual between the simulated and measured signal ratios. The mathematical expression of F_{obj} is derived as

$$F_{obj}=\sqrt{\frac{1}{N_\theta}\sum_{i=1}^{N_\theta}\left(\frac{I(\theta_i)_{sim}-I(\theta_i)_{mea}}{I(\theta_i)_{mea}}\right)^2} \tag{10}$$

where N_θ denotes the number of measurement angles; and $I(\theta_i)_{sim}$ and $I(\theta_i)_{mea}$ denote simulated and measured ALSM signals, respectively. The system control parameters of SPSO and ISPSO algorithms are listed in Table 1.

Table 1 System control parameters of SPSO and ISPSO algorithms

Parameter	N_s	N_p	N_c	ε	C_1	C_2	F	C_R
SPSO	50	3	3 000	10^{-8}	1.0	1.0		
ISPSO	50	3	3 000	10^{-8}	1.0	1.0	0.5	0.4

Considering that the inverse algorithm is a stochastic optimization method and the optimization process has certain randomness, all the calculations are repeated 20 times. Numerical simulation procedure is illustrated in Fig.2. According to the procedure, it can be found that the proposed unsolved parameters α, σ and g are inputted into the radiative transfer equation. Then, the measured angular light-scattering signals are simulated by solving the radiative transfer equation. The objective function of the inverse problem model is established. The inverse problem model will use its own iteration mechanism to search for optimal results that minimize the objective function value. Finally, the optimal results, i.e. parameters α, σ and g, are obtained and outputted. The standard deviation η_X is investigated to evaluate the reliability and feasibility of the inverse results, and the mathematical expressions are described as

$$\eta_X=\sqrt{\frac{1}{20}\sum_{i=1}^{20}\left(\bar{X}_{sim}-X_{sim,i}\right)^2}$$
$$\bar{X}_{sim}=\frac{1}{20}\times\sum_{i=1}^{20}X_{sim,i} \qquad X=\alpha,\sigma,g \tag{11}$$

At first, the performance of the ISPSO algorithm is investigated through comparison with the SPSO algorithm. Fig.3 displays the comparison of objective function values between SPSO and ISPSO algorithms.

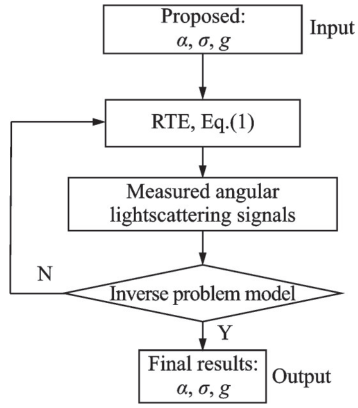


Fig.2 Flowchart of the whole numerical simulation procedure

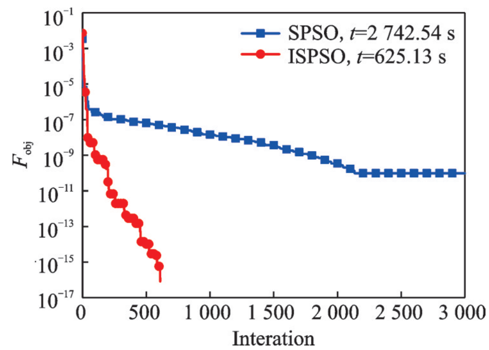


Fig.3 Comparison of objective function values of SPSO and ISPSO algorithms

The detailed average searching paths of the computation process of the algorithms are described in Fig.4.

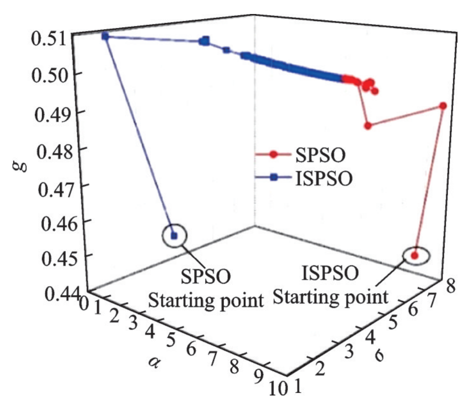


Fig.4 Solving paths of calculation processes of SPSO and ISPSO algorithms

The searching ranges of absorption coefficient α and scattering coefficient σ are all set as [0.01, 10]. The searching ranges of asymmetry factor g is set as [0.0, 1.0] for the medium in the present work. The real values for unsolved parameters are set as $\alpha=4$, $\sigma=7$ and $g=0.1$. The corresponding system control parameters are listed in Table 2.

Table 2 Influence of measurement errors on retrieval results by using ISPSO algorithm

Parameter	α=4, σ=7		
	0%	3%	5%
α	$4.00\pm1.09\times10^{-4}$	$4.02\pm3.56\times10^{-3}$	$4.07\pm6.80\times10^{-3}$
R_α	4.89×10^{-4}	3.83×10^{-2}	6.40×10^{-2}
σ	$7.00\pm1.66\times10^{-4}$	$6.95\pm5.37\times10^{-3}$	$6.89\pm9.22\times10^{-3}$
R_σ	6.77×10^{-4}	5.86×10^{-2}	9.74×10^{-2}
Parameter	α=4, g=0.1		
	0%	3%	5%
α	$4.00\pm5.72\times10^{-3}$	$4.01\pm1.44\times10^{-2}$	$4.03\pm3.49\times10^{-2}$
R_α	1.86×10^{-2}	7.19×10^{-2}	1.30×10^{-1}
g	$0.10\pm3.89\times10^{-4}$	$0.10\pm4.72\times10^{-4}$	$0.10\pm1.3\times10^{-3}$
R_g	1.28×10^{-3}	7.68×10^{-4}	2.31×10^{-3}
Parameter	σ=7, g=0.1		
	0%	3%	5%
σ	$6.99\pm1.63\times10^{-3}$	$6.96\pm3.37\times10^{-2}$	$6.95\pm4.65\times10^{-2}$
R_σ	3.07×10^{-3}	1.29×10^{-1}	2.12×10^{-1}
g	$0.10\pm7.89\times10^{-5}$	$0.10\pm1.22\times10^{-3}$	$0.10\pm1.59\times10^{-3}$
R_g	1.47×10^{-4}	1.33×10^{-3}	1.82×10^{-3}

The investigation shows that the objective function value of ISPSO algorithm converges much faster than that of SPSO algorithm. Moreover, the ISPSO algorithm can arrive at lower best objective function value than the SPSO algorithm within a smaller number of generations, which means more accurate results can be obtained by the ISPSO algorithm with less computing resources and costs. The calculation time of the SPSO algorithm is four times as long as that of the ISPSO algorithm. The phenomenon is more conducive to numerical iterative calculation, especially in the inverse radiative problem. All the results demonstrate that the ISPSO algorithm can avoid the phenomenon of local optima and low convergence accuracy which exit in the SPSO algorithm.

With the help of the ISPSO algorithm and the optimized selection principle of measurement angles, the heat radiative property parameters of semi-transparent media, i.e. α, σ and g are reconstructed. The searching ranges of unsolved parameters and the system control parameters of the ISPSO algorithm are mentioned above.

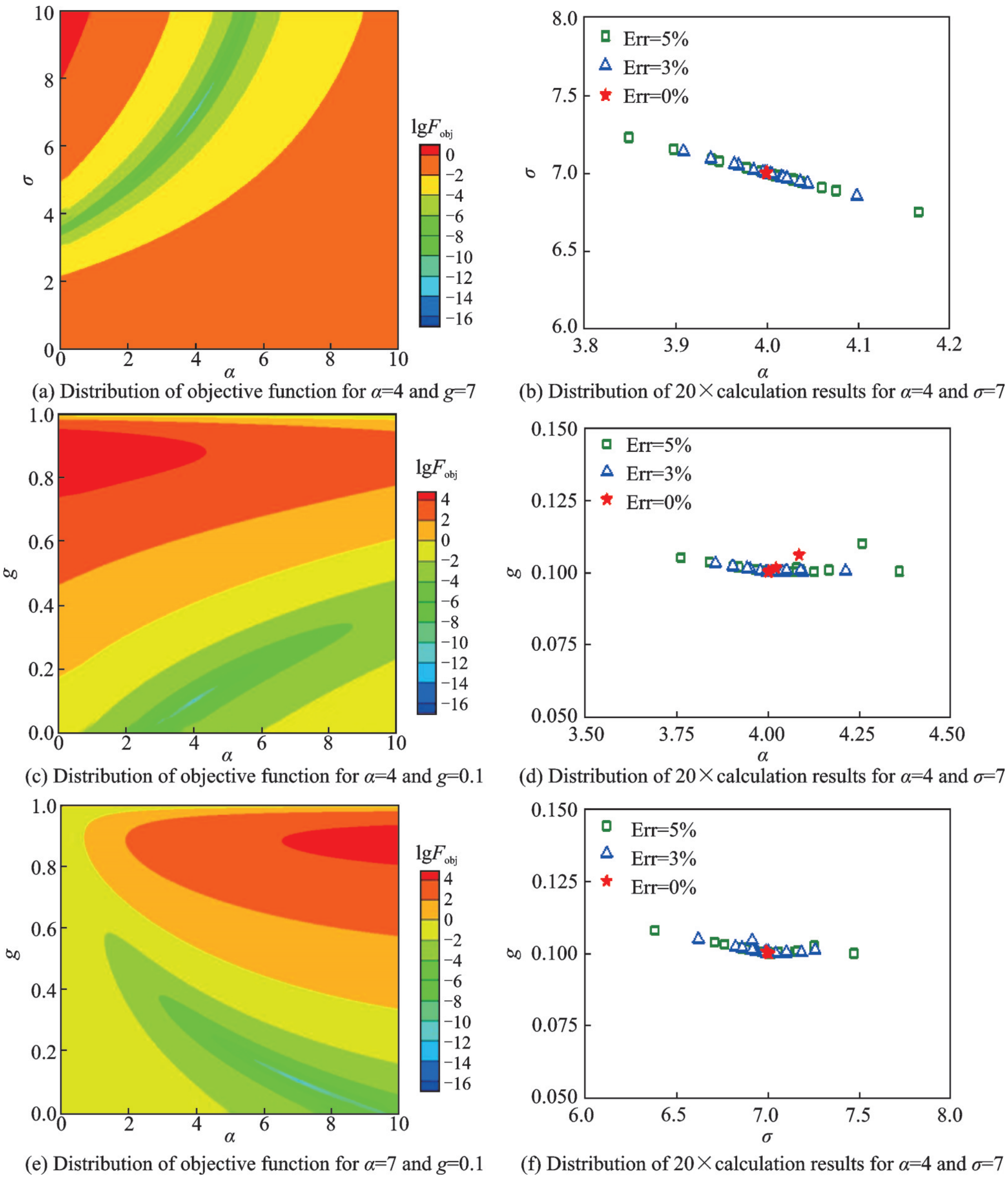
At first, only two parameters are studied, and the effects of different random measurement errors on the measurement results are considered. In the present work, the measurement signals with random measurement noise are obtained by adding normal distribution errors to the exact measurement signals

$$S_{\text{mea}} = S_{\text{exact}} + \sigma\varsigma \tag{12}$$

where S represents the apparent measurement signals; and ς the normal distribution random variable with zero mean and standard unit deviation. The standard deviation of the measurement signals σ for $\gamma\%$ measured error at 99% confidence is determined from

$$\sigma = \frac{S_{\text{exact}} \times \gamma\%}{2.576} \tag{13}$$

The average retrieval results at different random errors are shown in Table 2. It can be found that there is satisfactory inverse accuracy without random errors, and the inverse results will be deteriorated when more measurement errors added to the measurement signals. Fig.5 depicts the distributions of the objective function values and the distributions of 50 times estimated results with different inverse errors. The minimum value regions of the objective function almost tend to a point, which means the nonambiguity of retrieval results is satisfactory. The phenomenon means more couples of the parameters will satisfy the minimum objective function value, and the solution is not unique. The distributions of the estimated results disperse with increasing random measurement errors. The larger the random error is, the more dispersive the distribution will be. The dispersity of retrieval results for parameter σ is the largest, while that for parameter g is the smallest. The phenomenon means that for a certain parameter g, there will be more values of parameter which match the minimum value of objective function.



(a) Distribution of objective function for α=4 and g=7 (b) Distribution of 20× calculation results for α=4 and σ=7

(c) Distribution of objective function for α=4 and g=0.1 (d) Distribution of 20× calculation results for α=4 and σ=7

(e) Distribution of objective function for α=7 and g=0.1 (f) Distribution of 20× calculation results for α=4 and σ=7

Fig.5 Distribution of retrieval results and the objective function values for different parameters

The average retrieval results, standard deviations and relative errors for studying the absorption coefficient, scattering coefficient and asymmetry factor simultaneously are listed in Table 3. The retrieval accuracy is most satisfactory without random measurement error. Moreover, the retrieval accuracies are still acceptable even if more random measurement errors added to the measurement signals. Moreover, the unsolved parameters show similar retrieval accuracy under the same random measurement errors, which means these retrieval results have the same multi-value characteristics.

Fig.6 depicts the distributions of retrieval results for α=4, σ=7, g=0.1 with different random measurement errors. It can be found that the distributions of estimated results disperse with increasing random measurement errors. The larger the random error is, the more dispersive the distribution will be. The dispersity of retrieval results for parameters α and σ are larger than that for parameter g. The phe-

Table 3 Influence of measurement errors on retrieval results by using ISPSO algorithm

Parameter	α=4, σ=7, g=0.1			α=7, σ=3, g=0.2		
	0%	3%	5%	0%	3%	5%
α	$4.00\pm1.85\times10^{-4}$	$4.04\pm4.04\times10^{-2}$	$3.92\pm1.90\times10^{-1}$	$7.00\pm1.14\times10^{-2}$	$6.93\pm2.71\times10^{-1}$	$6.88\pm2.77\times10^{-1}$
R_α	4.47×10^{-5}	1.06×10^{-2}	1.97×10^{-2}	1.12×10^{-3}	1.18×10^{-2}	1.74×10^{-2}
σ	$7.00\pm3.81\times10^{-4}$	$6.82\pm2.39\times10^{-1}$	$6.72\pm4.09\times10^{-1}$	$3.00\pm8.63\times10^{-3}$	$2.95\pm6.19\times10^{-2}$	$2.92\pm8.52\times10^{-2}$
R_σ	5.06×10^{-5}	1.14×10^{-2}	2.05×10^{-2}	1.81×10^{-3}	1.58×10^{-2}	2.71×10^{-2}
g	$0.100\pm6.84\times10^{-6}$	$0.102\pm5.19\times10^{-3}$	$0.105\pm8.90\times10^{-3}$	$0.200\pm6.86\times10^{-4}$	$0.201\pm1.71\times10^{-3}$	$0.202\pm5.68\times10^{-3}$
R_g	6.54×10^{-5}	2.08×10^{-2}	5.07×10^{-2}	2.80×10^{-3}	5.22×10^{-3}	1.21×10^{-2}

nomenon means that for a certain parameter g, there will be more couples of parameters α and σ which match the minimum value of objective function. Fig.7 shows the distribution of objective function values, and it is obvious that minimum value region of objective function is a point, which indicates that the optimal solution is unique. All these phenomena also confirm the results obtained above. The present methodology provides a very promising technique to solve the problem of simultaneous retrieval of multiple heat radiative property parameters of semitransparent media accurately and reliably.

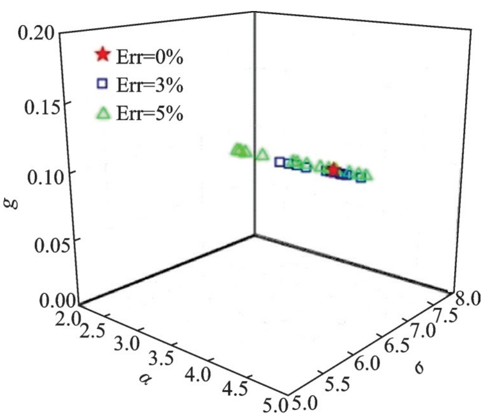


Fig.6 Distribution of 20 retrieval results under different measurement errors with α=4, σ=7 and g=0.1

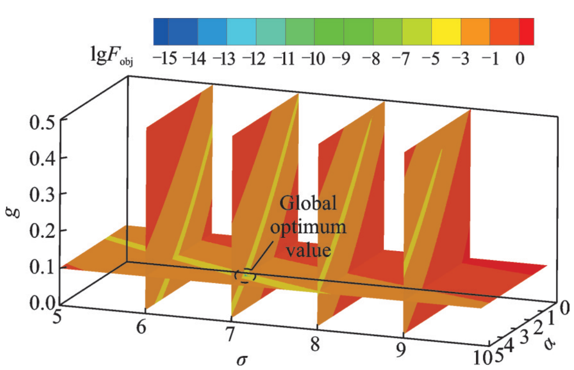


Fig.7 Distribution of objective function values with α=4, σ=7 and g=0.1

4 Conclusions

Combined with the ISPSO algorithm, ALSM signal is developed to determine heat radiative property parameters of semitransparent media simultaneously. The angular light-scattering intensity is served as the input measurement signals to the inverse analysis. The result shows that the ISPSO algorithm can avoid the phenomenon of local optima and low convergence accuracy which exit in the SPSO algorithm. The inverse results are satisfactory even with 5% random measurement errors if only two parameters needed to be retrieved, and the retrieval accuracy will decrease with more parameters needed to be studied. However, the acceptable results can still be obtained by the methodology mentioned in the manuscript even with 5% random measurement errors. As a whole, the proposed ISPSO algorithm combined with ALSM signals mentioned in the manuscript is a promising approach for solving the problem of multiple heat radiative property parameters in semitransparent medium simultaneously.

References

[1] CUI Miao, GAO Xiaowei, CHEN Haigeng. A new inverse approach for the equivalent gray radiative property of a non-gray medium using a modified zonal method and the complex-variable-differentiation method[J]. Journal of Quantitative Spectroscopy and Radiative Transfer, 2011, 112(8): 1336-1342.

[2] QI Hong, WANG Daling, WANG Shengang, et al. Inverse transient radiation analysis in one-dimensional non-homogeneous participating slabs using particle swarm optimization algorithms[J]. Journal of Quantitative Spectroscopy and Radiative Transfer, 2011, 112 (15): 2507-2519.

[3] RUAN Liming, QI Hong, AN Wei, et al. Inverse radiation problem for determination of optical constants

of fly-ash particles[J]. International Journal of Thermophysics, 2007, 28(4): 1322-1341.

[4] GUO Yiming, PANG Shi, LUO Zhou, et al. Measurement of directional spectral emissivity at high temperatures[J]. International Journal of Thermophysics, 2019, 40(10): 1-12.

[5] AN Wei, RUAN Liming, QI Hong. Inverse radiation problem in one-dimensional slab by time-resolved reflected and transmitted signals[J]. Journal of Quantitative Spectroscopy and Radiative Transfer, 2007, 107(1): 47-60.

[6] QI Hong, ZHANG Biao, GONG Shuai, et al. Simultaneous retrieval of multiparameters in a frequency domain radiative transfer problem using an improved PDF-based ACO algorithm[J]. Numerical Heat Transfer Applications, 2015, 69: 727-747.

[7] BRAIEK A, ADILI A, ALBOUCHI F, et al. Estimation of radiative and conductive properties of a semitransparent medium using genetic algorithms[J]. Measurement Science and Technology, 2016, 27(6): 065601.

[8] TILIOUA A, LIBESSART L, JEANDEL G, et al. Determination of radiative properties of polyester batting insulation material from hemispherical transmittance and reflectance measurements[J]. Applied Thermal Engineering, 2016, 105: 594-604.

[9] SUN Shuangcheng, QI Hong, YU Xiaoying, et al. Inverse identification of temperature-dependent thermal properties using improved Krill Herd algorithm[J]. International Journal of Thermophysics, 2018, 39(11): 1-21.

[10] HE Zhenzong, MAO Junkui, HAN Xingsi. Determination of aerosol size distribution from angular light-scattering signals by using a SPSO-DE hybrid algorithm[J]. Computation, 2018, 6(3): 1-14.

[11] MODEST M F. Radiative heat transfer[M]. 3rd ed. New York: McGraw-Hill, 2013.

[12] DOMBROVSKY L A, BAILLIS D. Thermal radiation in disperse systems: An engineering approach[M]. New York: Begell House, 2010.

[13] KENNEDY J, EBERHART R. Particle swarm optimization[C]//Proceedings of IEEE International Conference on Neural Networks. Perth, Australia: IEEE, 1995.

[14] QI Hong, RUAN Liming, ZHANG Hongcheng, et al. Inverse radiation analysis of a one-dimensional participating slab by stochastic particle swarm optimizer algorithm[J]. International journal of thermal sciences, 2007, 46(7): 649-661.

[15] YUAN Yuan, YI Hongliang, SHUAI Yong, et al. Inverse problem for aerosol particle size distribution using SPSO associated with multi-lognormal distribution model[J]. Atmospheric Environment, 2011, 45(28): 4892-4897.

[16] LIU Fang, DUAN Haibin, DENG Yimin. A chaotic quantum-behaved particle swarm optimization based on lateral inhibition for image matching[J]. Optik-International Journal for Light and Electron Optics, 2012, 123(21): 1955-1960.

[17] STORN R, PRICE K. Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces[J]. Journal of Global Optimization, 1997, 11(4): 341-359.

[18] WU Yanling, LU Jiangang, SUN Youxian. An improved differential evolution for optimization of chemical process[J]. Chinese Journal of Chemical Engineering, 2008, 16(2): 228-234.

[19] LU Songfeng, SUN Chengfu, LU Zhengding. An improved quantum-behaved particle swarm optimization method for short-term combined economic emission hydrothermal scheduling[J]. Energy Conversion and Management, 2010, 51(3): 561-571.

Acknowledgements This work was supported by the Aeronautical Science Foundation of China (No.201928052002), and Fundamental Research Funds for the Central Universities (No.NT2021007).

Authors Mr. **FANG Hongyi** received his M.S. degree in engineering thermophysics from Shenyang Aerospace University in 2011. Now he is a senior engineer and his research is focused on aero-engine air system and thermal analysis test technology.

Dr. **HE Zhenzong** received his Ph.D. degree in engineering thermophysics from Harbin Institute of Technology in 2016. He is currently an associate professor in Nanjing University of Aeronautics and Astronautics. His research is focused on the radiative heat transfer of high gas and soot in the aero-engine combustion chamber, soot size inversion prediction and fuel cell system.

Author contributions Mr. **FANG Hongyi** contributed to the discussion and analysis. Mr. **WANG Dengkui** and Mr. **CHEN Tao** contributed to the discussion and analysis as well as prepared all drafts, and draw all the figures. Dr. **HE Zhenzong** and Mr. **JIANG Xinyu** contributed to design of the study and write the manuscript. Prof. **MAO Junkui** contributed to the background, discussion and analysis of the study. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

(Production Editor: SUN Jing)

基于ISPSO的半透明介质中多种辐射特性参数反演

方弘毅[1,2]，蒋新宇[3]，贺振宗[3]，王登奎[1]，毛军逵[3]，陈　涛[1]

(1.中国航发四川燃气涡轮研究院，绵阳 621000，中国；2.西北工业大学动力与能源学院，西安 710129；
3.南京航空航天大学能源与动力学院，南京 210016，中国)

摘要：半透明介质广泛存在于工业和化工设备中，其热辐射特性在研究介质传热过程中起着重要作用。本文提出了一种改进的随机粒子群优化(Stochastic particle swarm optimization, ISPSO)算法，从角度光散射测量信号中反演半透明介质的热辐射特性参数，即吸收系数、散射系数和不对称系数。研究结果表明，与随机粒子群算法(Stochastic particle swarm optimization, SPSO)相比，ISPSO算法避免了局部最优和收敛精度低的现象，即使在5%的随机测量误差下也能获得合理的检索结果。当只需要研究两个参数时，反结果的鲁棒性是令人满意的。当反演的参数较多时，反演精度会降低。此外，在5%随机测量误差下，同时反演多个辐射特性参数时，即吸收系数、散射系数和不对称因子，本文提供的方法仍能得到满意的结果。结果表明，本文提供的反演方法是一种有效可靠的方法，可以同时估计半透明介质中的多个辐射特性参数。

关键词：辐射反问题；辐射特性参数；改进的随机微粒群算法；半透明介质；光角度散射测量方法