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Inverse boundary design of two-dimensional irregular enclosures using micro-genetic algorithm

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Abstract: - The goal of the inverse analysis is to find a set of heaters over some parts of boundary, called the heater surface, to satisfy the desired heat flux profile over the design surface. Micro-genetic algorithm is employed to inverse design of a radiant enclosure with absorbing-emitting medium. The direct problem of radiative heat transfer is solved by the discrete transfer method. The inverse problem is solved through the minimization of an appropriate objective function using the micro-genetic algorithm. A smoothing criterion is used to achieve a smooth distribution of heaters over the heater surface. The desired heat fluxes over the design surface are well recovered by employing a smooth distribution of heaters over the heater surface. The ability of the method to solve the inverse problem in complex geometries is investigated by a complex problem.

Key-Words: - Micro-genetic-Radiant enclosure-Discrete transfer`

1 Introduction

Radiation is an important, often dominant mode of heat transfer in the design of combustion systems such as furnaces, combustors and jet flames. Design of the radiant enclosures often requires that desired conditions, temperature and heat flux, satisfy over the design surface.

In recent years, optimization methods are widely used to design of radiant enclosures. The main idea in these methods is to minimize an objective function that is defined in such a way that its minimum corresponds to the ideal design configuration. A comprehensive review of the inverse methods for the design and control of radiant sources is reported by Howell et al. [1]. Many algorithms can be used in the procedure of minimizing the objective function. Federov et al. [2] and Sarvari et al. [3] used the Levenberg-Marquart technique to solve the inverse radiation boundary design problem. Conjugate gradient method has been applied to solve the inverse design radiation problem by Daun et al. [4] and Sarvari et al. [5-6].

As the engineering problems are complex and are usually multi-optimum problems, a genetic algorithm (GA) is one of the best techniques that can be used to find the global optimum. It employs the Darwinian survival-of-the-fittest theory to yield the best or better characters among the old population and perform a random information exchange to create superior offspring. A comprehensive study of the genetic algorithm has been reported by Goldberg [7]. Mera et al. [8] used genetic algorithm for solving ill-posed problems. Tsourkas and Rubinsky [9] solved 2-D steady-state conduction by evolutionary-genetic algorithm. Chiwiacowsky and Velho [10] compared the conjugate gradient method with the genetic algorithm for solution of an inverse heat conduction problem. Li and Yang [11] applied genetic algorithm to solve the inverse problem for simultaneously determining the single scattering albedo, the optimal thickness and the phase function, from the knowledge of the exit radiation intensities.

There are several versions of the genetic algorithms. The micro-genetic algorithm developed by Krishnakumar [12] is one of the most widely used GAs. Micro-genetic algorithm is a very robust algorithm in finding the global optimum rather than local optimum for a given domain. Carroll [13] presented the application of the micro-genetic algorithm for optimizing the performance of a laser system. An implementation of the micro-genetic algorithm in a design support tool for solar hot water

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systems is reported by Loomans and Visser [14]. Senecal and Reitz [15] presented the application of the micro-genetic algorithm for computational optimization of a heavy-duty direct-injection diesel engine. In this paper, we present an inverse analysis of radiative heat transfer to produce the desired heat flux and temperature distributions over the design surface of a radiant enclosure with absorbing-emitting media through the genetic algorithm. The direct procedure of solving the radiation transfer equation is based on the discrete transfer method, developed by Lockwood and Shah [16].
A smoothing criterion is applied to absent the fluctuation of solution and achieve a smooth distribution of heat flux over the heater surface. An example problem is presented to show the ability of the method to solve the inverse problem in complex geometries.

2 Problem Formulation

2.1 Nomenclature

a	absorption coefficient, $(1/m)$
A	area, (m^2)
e	error
E	blackbody radiation energy, σT^4, (W/m^2)
F	objective function
I	radiation intensity, $(W/m^2 sr)$
K	optical depth
L	length, (m)
M	number of elements over design surface
N	number of heaters
$\boldsymbol{n}$	unit surface normal
q	heat flux, (W/m^2)
s	geometric path length
$\boldsymbol{s}$	unit vector into a given direction
T	temperature, (K)
W	weighting function
ε	emissivity
γ	peripheral length, (m)
Γ	boundary of solution domain, (m)
σ	stefan-boltzmannconstant, (W/m^2K^4)
Ω	solid angle

Subscripts

b	blackbody value
d	desired, design
e	estimated
h	heater
i	ray direction
j	surface element
m	design surface element
n	heater surface element
w	wall
k	entry into an element
$k+1$	exit from an element

2.2 Direct problem

Consider an absorbing-emitting gray two-dimensional medium in radiation equilibrium. The equation of radiative heat transfer and the boundary conditions can be written as:

$$\frac{dI}{ds} = a(I_b - I)$$
$$I = \varepsilon_w I_b + \frac{(1-\varepsilon)}{\pi}\int_{\Omega} I(\mathbf{s})\mathbf{n.s}\, d\Omega \quad at \quad s = 0 \tag{1}$$

where the subscript w denotes the values at the wall. Using the discrete transfer method, the solution for the radiation intensity through an element is expressed in the form

$$I_{k+1,i} = I_{k,i} e^{-a\Delta s} + I_b\left(1 - e^{-a\Delta s}\right) \tag{2}$$

where $I_{k,i}$ and $I_{k+1,i}$ are the intensities along the direction of irradiation ray i on entry and exit , respectively, and Δs is the distance traveled by the ray through the element.
Given a wall temperature distribution, the boundary condition can be expressed as follows:

$$I_j = \varepsilon_j I_{b,j} + \frac{(1-\varepsilon_j)}{\pi}\sum_i I_{j,i} W_{j,i} \tag{3}$$

where $I_{j,i}$ is the radiation intensity at surface element j of the irradiation ray i and $W_{j,i}$ is the weighting applied to $I_{j,i}$. The radiant heat flux at the boundaries is

$$q_j = \varepsilon_j\left(E_{b,j} - \sum_i I_{j,i} W_{j,i}\right) \tag{4}$$

The computational algorithm for the DTM is described in detail in [5] and will not be repeated.

2.3 Inverse problem

The inverse radiation problem involves the determination of the heat fluxes over the heater surface, $\mathbf{q}_h = \{q_{h,1}, q_{h,2}, ..., q_{h,N}\}$, from the knowledge of the desired heat fluxes, $\mathbf{q}_d = \{q_{d,1}, q_{d,2}, ..., q_{d,M}\}$, over the design surface. The objective function is defined as:

$$F(\mathbf{q}_h) = [\mathbf{q}_d - \mathbf{q}_e]^T [\mathbf{q}_d - \mathbf{q}_e] \tag{5}$$

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where $\mathbf{q}_d$ and $\mathbf{q}_e$ are the vectors of the desired and estimated heat fluxes over the design surface, respectively. The solution of the inverse problem is based on the minimization of the objective function with respect to the unknown parameters. A genetic algorithm is used for this optimization process, which is described next.

The standard GA uses a population (i.e. a group of possible solutions) of individuals (i.e. parameter sets) that is represented in a binary format. Each parameter is encoded in a binary string. The strings for the separate parameters then are grouped into one long string. The individuals are randomly determined from the search space. The genetic algorithm consists of three basic operations: reproduction, crossover, and mutation.

Reproduction is simply a process to decide which strings should survive and how many copies of them should be produced. The decision is made by comparing the fitness of each string with the average fitness of the population. The fitness is an indicator of the survival potential and reproduction capability of the string in the subsequent generations. For an optimization problem, the fitness is the objective function. In minimization problems, a string with smaller fitness will receive correspondingly more copies in the new population.

Crossover is a means for two high-fitness strings (parents) to produce two offspring by mixing and matching their desirable qualities through a random process.

Mutation plays an important role as a safeguard. Mutation occurs with a small probability in the genetic algorithm to reflect the small rate of mutation existing in the real world. In mutation phase, some bits will be changed in all strings according to mutation rate.

There are several different versions of genetic algorithms. The micro-genetic algorithm (μGA) is one of the most widely used GAs. It is able to avoid the premature convergence and perform better in reaching the optimal region than the traditional GAs. Basically, μGA uses the similar evolutionary strategy as that used in the traditional GAs. Reproduction and crossover are still the basic genetic operations while mutation is usually omitted. Another operation which is recommended to use is called elitism. elitism means the best individual must be replicated among the next generation. The main differences of μGA from the traditional GAs are in the population size and the mechanism to introduce and maintain the genetic diversity. Generally, μGA operates on a very small population. The small population very often converges in a few generations. To maintain the genetic diversity in population, μGA uses a restart strategy not the conventional mutation operation. That is, once the current population converges, a new population would be generated, which has the same population size and consists of the best individual from the previously converged generation and other new randomly generated ones. This evolutionary process would be sequentially conducted until the global is found.

The heater strengths are selected such that $|q_{h,n+1} - q_1| \geq |q_{h,n} - q_1|$. Fig. 1 shows some possible selected profiles using the smoothing criterion.

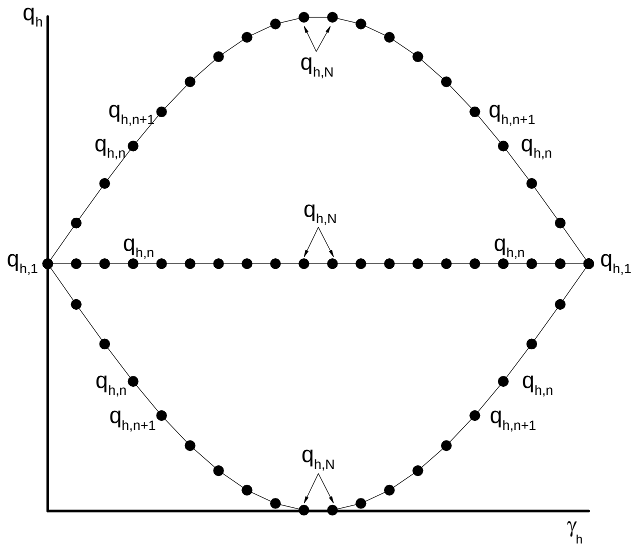

Fig. 1: Some possible selected profiles by using the smoothing criterion

4 Results

Consider the radiative heat transfer in an enclosure shown in Fig. 2. All the walls are diffuse and gray with a unit emissive power ($E = 1\,W/m^2$). The emissivity on the outer and the inner (design) surfaces are 0.8, 0.5, respectively. The enclosure contains an absorbing-emitting medium. The goal of the design problem is then to find a symmetrical arrangement of 30 heaters over the outer boundary surface to produce a uniform dimensionless heat flux of $q_d / E = -2\,W/m^2$ over the design surface.

Fig. 3 shows the estimated heat flux distribution over the design surface for different values of optical depth defined by $K_R = a \times R$. As shown, the uniform desired heat flux distribution is recovered using the inverse method. The estimated heat flux distribution over the heater surface is shown in Fig.

4. Fig. 5 shows the rate of convergence for objective function versus the number of iterations for different optical depth. As shown, the objective function is rapidly converged to a small value. Fig. 6 shows the emissive power contours for optical depth of $K_R = 1.0$.

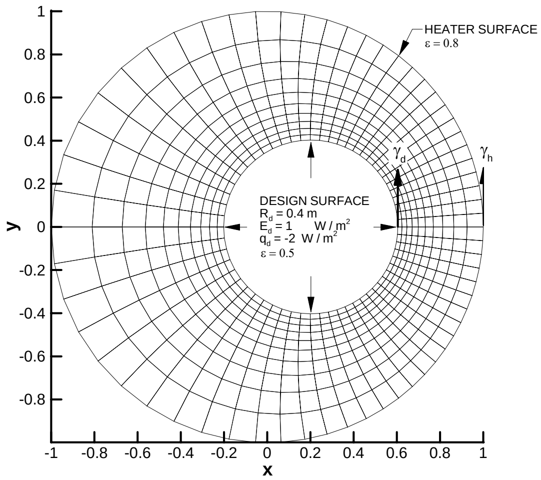

Fig. 2**:** The geometry and wall radiative properties of an enclosure containing an absorbing-emitting medium.

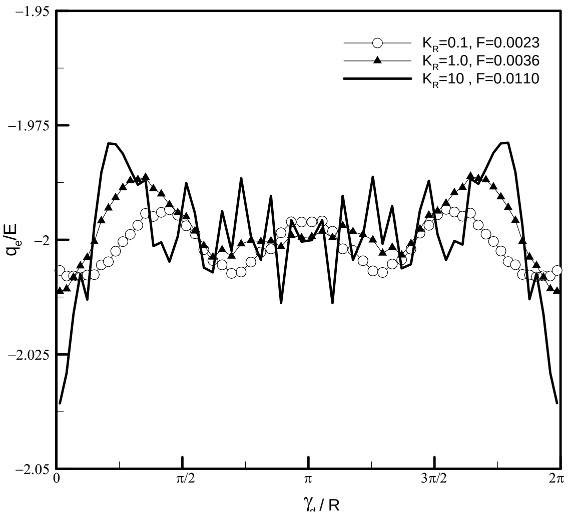

Fig. 3: The dimensionless estimated heat flux distribution over the design surface for different values of optical depth.

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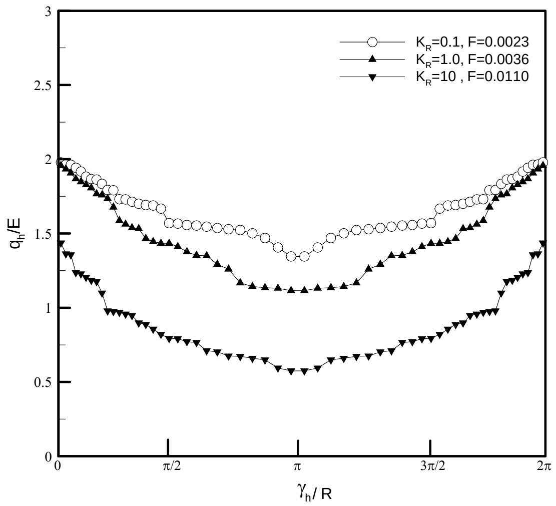

Fig. 4: The dimensionless heat flux distribution over the heater surface for different values of optical depth.

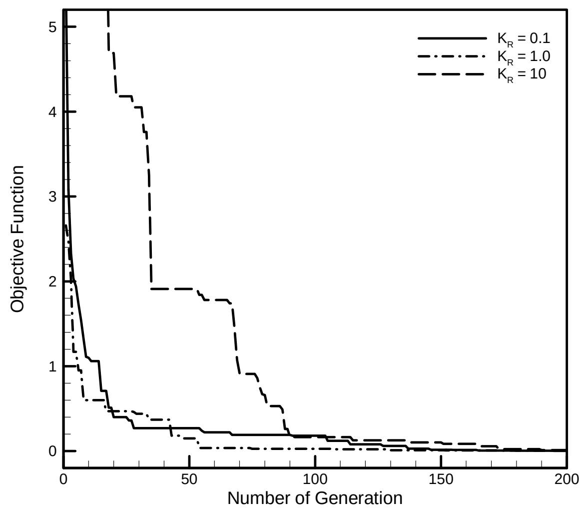

Fig. 5: The rate of convergence for objective function versus the number of iterations for different values optical depth.

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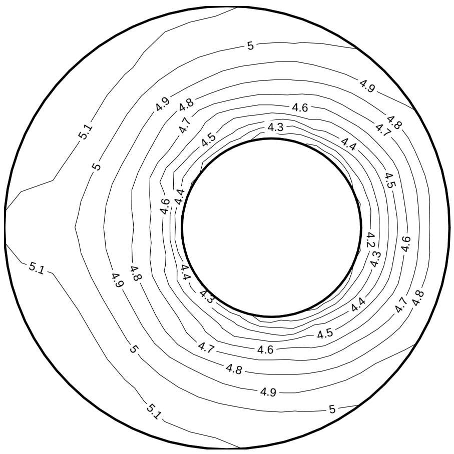

Fig. 6: The emissive power contours in the medium for $K_R = 1.0$.

4 Conclusion

A micro-genetic algorithm has been used to solve the inverse boundary design problem in a radiant enclosure with absorbing-emitting medium. The discrete transfer method has been employed to solve the radiative transfer equation. A smoothing criterion has been applied to GA to achieve a smooth profile of heat flux over the heater surface. The inverse problem has been formulated as an optimization problem that minimizes the errors between desired and estimated heat fluxes over the design surface. An example problem has been investigated to show the ability of the method for solving the inverse problem in complex geometries.

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