Optimal Boundary Design of Radiant Enclosures Using Micro-Genetic Algorithm
(Effects of Refractory Properties and Aspect Ratio of Enclosure on Heaters Setting)*

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Abstract
This study presents an optimization methodology for finding the heaters setting that produce a desired heat flux and temperature distribution over a region of the enclosure surface, called the design surface. Radiation element method by ray emission model (REM²) was used to calculate the radiative heat flux on the design surface, which enables us to handle reflecting surfaces. Micro-genetic algorithm was used to minimize an objective function, which was expressed by the sum of square error between estimated and desired heat fluxes on the design surface. The novel features of this methodology were demonstrated by finding the optimal heaters setting of a three-dimensional enclosure for three aspect ratio. The effects of refractory properties have been studied as well.

Key words: Optimal, Design, Radiant Enclosures, Micro-Genetic Algorithm, Radiation Element Method by Ray Emission Model

1. Introduction

Many thermal processing systems require satisfying two thermal conditions (temperature and heat flux distributions) in one part of the systems, where the process takes place[1]. That is called the design surface. The class of design problems, in which the system geometry and the materials and medium are specified, are called inverse boundary problem. The conditions on the boundaries are parameters that a designer can control to satisfy the design goal. This class of design problems requires finding the energy inputs to the heaters that produce the desired conditions on the design surface.

The traditional method to solve a design problem is to guess an input for the heaters used in the system and then use mathematical models to check whether the desired conditions on the design surface are met. If this heaters setting does not satisfy the problem requirements, the designer modifies the design according to his or her experience and intuition and repeats the analysis. An intuitive understanding of how each individual heater affects conditions on the design surface is elusive due to the complex nature of radiant exchange. Thus, this procedure requires a great deal of effort and time. Furthermore, while
the final solution may be acceptable, it is typically far from optimal. To overcome these drawbacks, recently designers applied regularization and optimization methods to solve these design problems.

A comprehensive review of the regularization methods was reported in literature\(^{(1)}\)-(6). Some examples for design and control of radiation sources can be found in the papers by Erturk et al.\(^{(1)}\), Kudo et al.\(^{(2),(3)}\), Howell et al.\(^{(4)}\), Franca et al.\(^{(5)}\) and Daun et al.\(^{(6)}\). They compared various regularization techniques and applied them to inverse design problems for radiation-dominant environment. The difficulty in imposing design constrains was a significant drawback of these methods, and hence, solutions from regularization often included regions of negative heat flux over the heater surface. This condition could not be realized in practical furnaces. So, these regions were usually taken to be adiabatic, impairing the solution quality\(^{(7)}\).

Optimization methods overcome many drawbacks of regularization methods. The optimization methodology solves the inverse problem implicitly by specifying only one boundary condition (most often temperature) over the design surface, and an assumed heat flux distribution on the heater surface. The remaining boundary condition is used to define an objective function such that its minimum corresponds to the ideal design configuration.

In general, there are two classes of optimization methods for minimizing the objective function: nonlinear programming and metaheuristic. The methods that belong to the former groups and applied to design the radiant-dominant thermal systems include conjugate gradient method, Levenberg-Marquart and Newton’s methods\(^{(7)-(10)}\). The later methods include genetic algorithms, simulated annealing and tabu search.

Recently, metaheuristic methods have received much attention for their outstanding characteristics such as being global and no need for gradient information. Genetic algorithm is one of the popular methods that belong to this category. This method has been applied to various optimization and parameter estimation problems such as chemical laser and airship bodies due to its flexibility, globality, parallelism and simplicity\(^{(11),(12)}\). Genetic algorithm has been applied to a limited number of radiation design problems. Li and Yang applied genetic algorithm to solve the inverse problem for simultaneously determining the single scattering albedo, the optical thickness and the phase function from the knowledge of the exit radiation intensities\(^{(13)}\). Kim et al.\(^{(14),(15)}\) used hybrid genetic algorithm for estimating wall emissivities in two-dimensional irregular geometry and also applied it to inverse surface radiation analysis in an axisymmetric cylindrical enclosure.

When the enclosure contains specular surfaces, the Monte Carlo method (MCM) or radiation element method by ray emission model (REM\(^2\)) is usually used to solve radiation transfer equation. In this study, we used REM\(^2\), because Hayasaka et al.\(^{(16)}\) demonstrated that the use of the ray tracing method results in substantial savings in CPU time compared with the MCM. It is also a very flexible method and has a simple formulation that enables easy handling of a complex geometry and effects of participating and scattering media. In this method, most of the calculation time was consumed by the determination of absorption and diffuse reflection view factors and constant inverse matrix of the system, and only 1% of calculation time was spent on solving radiation heat transfer. In optimization problems many iterative calculations of radiative transfer can be obtained quickly by using the present method because view factors are constant as result of fixed geometry and radiative properties.

In this paper, we use the micro-genetic algorithm to find the optimal heaters setting that provide the desired heat flux and temperature distribution over the design surface of a three-dimensional radiant enclosure containing diffuse and diffuse-specular surfaces with transparent media. The direct procedure of solving the radiation heat transfer is based on the REM\(^2\) method, developed by Maruyama\(^{(17)}\). The effect of distance between heater and design surfaces on the solution is considered. The effects of varying refractory properties to
obtain the desired heat flux and temperature on the design surface are also being studied.

2. Nomenclature

A : area, m²
Err: error
F : view factor matrix
\( F(q_1) \) : objective function
\( F^{\text{ab}}_{ij} \) : absorption view factor from element i to j
\( F^{\text{db}}_{ij} \) : diffuse reflection view factor from element i to j
\( \mathbf{I} \) : unit matrix
H : height
L : length, number of bits for each design variables
m : required precision after the decimal point
N : number of discrete surface elements
\( N_{DS} \) : number of elements on the design surface
\( N_{HS} \) : number of heaters
q : heat flux, W/m²
\( q^* \) : dimensionless heat flux, \( q / \sigma T_r^4 \)
Q : heat transfer rate vector
\( Q_d \) : diffuse radiative heat transfer rate
\( Q_r \) : heat transfer rate of emission
T : temperature, K
\( T^* \) : dimensionless temperature, \( T / T_r \)
W : width
\( \varepsilon \) : emissivity
\( \rho^D \) : diffuse reflectivity
\( \rho^S \) : specular reflectivity
\( \sigma \) : Stefan-Boltzmann constant, \( 5.67 \times 10^{-8} \), W/m².K

Subscripts

d : desired, design
DS : design surface
e : estimated
h : heater
HS : heater surface
i, j : surface element index

Superscripts

L : lower bound
U : upper bound

3. Optimization Strategy

The goal of optimization process is to identify the heaters setting that produce a desired heat flux and temperature distribution over the design surface. Figure 1 shows an example of the radiant enclosure. The design surface is located on the bottom surface and is irradiated by heaters on the top surface. The remainder of the bottom surface around the design surface and sidewalls are insulated in order to prevent leaving the energy provided by the heaters from the system.
The optimization process is accomplished by first specifying the temperature distribution over the design surface and then defining the objective function using the heat flux evaluated at $N_{DS}$ discrete location over the design surface,

$$ F(q_h) = \frac{1}{N_{DS}} \sum_{j=1}^{N_{DS}} (q_{d,j} - q_{e,j})^2 $$

Subject to the following constraints

$$ q_h^L \leq q_{h,i} \leq q_h^U \quad i = 1, 2, ..., N_{HS} $$

where $N_{DS}$ and $N_{HS}$ are the number of surface elements on the design and heater surfaces, respectively. $q_{d,j}$ and $q_{e,j}$ are the desired and estimated heat fluxes over the design surface; respectively at the boundary of surface element $j$. $q_h = (q_{h,1}, q_{h,2}, ..., q_{h,N_{HS}})$ is the vector of heat flux over the heater surface. $q_h^L$ and $q_h^U$ are the lower and upper bounds of $q_{h,i}$ in the feasible region. Unlike gradient based methods, it is fairly easy to impose bound on the heaters setting in genetic algorithm by restricting the domain of possible values that $q_{h,i}$ can assume.

The radiative heat flux specified on the design surface must be applied by the heaters, thus:

$$ \sum_{i=1}^{N_{DS}} A_i q_{h,i} = \sum_{j=1}^{N_{DS}} A_j |q_{d,j}| $$

where $A_i$ and $A_j$ are the area of the $i$th and $j$th elements of heater and design surfaces, respectively. The area weighted heat flux on the heater and design surfaces can be written as:

$$ \bar{q}_h = \frac{\sum_{i=1}^{N_{DS}} A_i q_{h,i}}{\sum_{i=1}^{N_{DS}} A_i} $$
\[
\sum_{j=1}^{N_{qj}} A_j q_{d,j} = \frac{\sum_{j=1}^{N_{qj}} A_j}{\sum_{j=1}^{N_{qj}} A_j} \quad (5)
\]

By combining the above equations, the following relationship is achieved.

\[
\bar{q}_h = \frac{\sum_{i=1}^{N_{DS}} A_i}{\sum_{i=1}^{N_{DS}} A_i} |\bar{q}_d| \quad (6)
\]

As shall be shown later, we discretize the enclosure surfaces into equal square elements to solve this problem, thus:

\[
\bar{q}_h = \frac{N_{DS}}{N_{HS}} |\bar{q}_d| \quad (7)
\]

Therefore, all values of \( q_{h,i} \) will fluctuate around their mean values, \( \bar{q}_h \); and to insure the heat flux distribution over the heater surface from assuming negative values we should impose the following conditions:

\[
0 \leq q_{h,i}^L < \bar{q}_h \quad \text{and} \quad q_{h,i}^U > \bar{q}_h \quad (8)
\]

The designer can select the value of \( q_{h,i}^L \) and \( q_{h,i}^U \) based on the above relations. It is possible to find more than one solution for a design problem. The designer will select a solution with a physical meaning that is both accurate and smooth among several possible solutions.

### 3.1 Micro-genetic algorithm

Genetic Algorithms (GAs) are stochastic global search methods based on the concepts of natural genetics and Darwinian survival of the fittest. Typically, for a basic GA also called Simple GA (SGA), if the population size is too large, the GA takes longer to converge upon a solution. On the other hand, if the population size is too small, then the GA might converge to a suboptimal solution. The SGA cannot work with a small population as there is not enough diversity in the population pool to allow the GA escape the local optima. The population size of SGA depends on the length of chromosomes and the number of parameters used. If the length of chromosome is big and/or if the number of parameters is big for a particular problem, then the population size will be big.

The numbers of function evaluations increases proportionally with the population size, however, it will require more computational time to find the optimum solution. This is the main drawback of SGA and hence it is less attractive. However different methods are available for reducing the computational time; one such methods, known as the micro-genetic algorithm, developed by Krishnakumar, reduces the computational time considerably (18). As it is obvious from the name of micro-genetic algorithm, it requires smaller population (5 to 10 individual) than the SGA for the same optimal solution. Moreover, micro-genetic algorithm uses elitism and convergence checking with re-initialization to obtain the optimal or near optimal solution. This characteristic of micro genetic algorithm is very important where the objective function involves complicated calculations such as three dimensional radiative heat transfer simulations. Flow chart in Fig. 2 shows the micro-genetic algorithm calculation procedure. In this section, the necessary micro-genetic algorithm concepts associates with the optimal heaters setting in radiant enclosures will be established.
3.1.1 Encoding and decoding

The first step of the GAs to solve a practical design problem is to encode each design variable as a finite length binary string. If there are \(m\) design variables, then a set of \(m\) binary string, each aligned end by end, is thought of as a complete chromosome that represent an individual. In this work, an individual means heater strength. In general, the length of the binary string for a variable is determined by the required precision. One can determine the number of bits used for each design variable base the specified number of significant digits from the following relation:

\[
2^{-L_h - 1} \leq (q_h^U - q_h^L) \times 10^m \leq 2^{L_h} - 1
\]

(9)

where \(L_h\) is the number of bits used for each design variables and \(m\) is the required precision after the decimal point. In the present work, we have set \(m\) equal to 4.

The mapping from a binary string to a real number for variable \(q_{h,i}\) is straight forward and is as follows:

\[
q_{h,i} = q_h^L + \frac{B_i}{2^{L_h}} (q_h^U - q_h^L)
\]

(10)

where \(B_i\) is the decimal integer value of converted binary string of the \(i\)-th heater strength.

3.1.2 Selection and reproduction

The reproduction operator is a process in which individual strings are copied according
to their objective function values. Coping strings according to their fitness values means that strings with a higher value have a higher probability of contributing one or more offspring to the next generation. As such, by expelling weak individuals from a population and selecting strong individuals, only superior genes are spread to the next generation population. Several types of selection operators have been described in previous literature\(^3\). The two most popular ones are roulette wheel selection and tournament selection. The tournament selection was used for the present study since it is the most effective strategy for many applications. In this selection, a suboptimal \( L \in [2, N] \) of \( N \) individuals is randomly chosen from the population. The individuals of this subpopulation compete on the basis of their fitness and, therefore one which the highest fitness value wins the tournament and becomes the selected individual. All of the subpopulation members are then reinserted into the general population and the process is repeated until \( N \) individual are selected. \( L \) is the tournament size. As such, the selection pressure increases to the extent of the size of \( L \).

### 3.1.3 Crossover

Crossover is the mating process allowing information exchange. Crossover operates on two high-fitness strings (parents) that are produced in the preceding stage and swaps some of their genes. This interchange of the genes leads to the creation of two new chromosomes. These chromosomes represent two new individuals, like the children produced through mating between parents in nature. When crossover takes place, the two new chromosomes will consist of parts of the chromosomes of the parents, as the children inherit some of each of the parent’s genetic material. There are more crossover methods available such as: one-point crossover, two-point crossover, multi-point crossover, uniform crossover, etc. In the current study a uniform crossover with the rate of 0.5 is applied. A crossing mask is employed to determine the crossing location. Two parent individuals will exchange their bits at every location where the corresponding position in the mask is one. The mask comprises a string of 0’s and 1’s bit randomly distributed along its length.

### 3.1.4 Elitism

As there is no guarantee that GA will produce a monotonic improvement in the objective function value with variance of generation, due to its stochastic nature, an elitism strategy is used to ensure a monotonic improvement by copying the best individual of the present generation on to the next generation.

### 3.1.5 Checking and re-initialization

To maintain the genetic diversity in a population, micro-genetic algorithm uses a restart strategy not the conventional mutation operation. That is, the bits of the best fitness parameter set are compared with corresponding bits of all other parameter sets, and if the number of bits which are different from the best parameter set are less than 5% of the total number of bits present in the total population, then the algorithm considers the population as converged and retains only the best fitness parameter set and replaces all other parameter sets with a new parameter set created, randomly as was done in the first step. This evolutionary process would be sequentially conducted until the global is found.

### 4. Solution of Radiative Transfer Equations

Consider the radiative heat transfer in an enclosure comprised of \( N \) surface elements. The diffuse radiation heat transfer rate \( Q_{ji} \) and the net heat loss \( Q_i \) of element \( i \) can be expressed as

\[
Q_{ji} = Q_{T,i} + \sum_{j=1}^{N} F_{ji}^{D} Q_{j,j} \quad \text{and} \quad Q_i = Q_{T,i} - \sum_{j=1}^{N} F_{ji}^{A} Q_{j,j} \quad (11)
\]

in which \( Q_{T,i} = A_i \varepsilon \sigma T_i^4 \) with \( A \) as the area of surface element, \( \varepsilon \) the emissivity
and $\sigma$ the Stefan-Boltzmann constant. In this equation, the absorption view factor $F_{j,i}^A$ and diffuse reflection view factor $F_{j,i}^D$ are defined for analyzing radiation exchange by Maruyama(17). Substituting matrix $F$ and vector $Q$ for $F_{j,i}$ and $Q_i$, respectively, and eliminating $Q_{j,i}$ from Eq. (11), the following relationship is achieved:

$$FQ_T = IQ$$  \hspace{1cm} (12)

where

$$F = I - F^A(I - F^D)^{-1}$$  \hspace{1cm} (13)

where $I$ and $(\cdot)^{-1}$ stand for unit matrix and inverse matrix, respectively. The view factors are calculated by using a ray tracing method based on the ray emission model as described by Maruyama(17). When the system has $n_1$ surfaces with specified temperature $T_i$ as boundary conditions, and the remaining $n_2=N-n_1$ surfaces with specified heat flux $q_i$, the unknown component of $q_i$ ($i=1,\ldots,n_1$) and $T_i$ ($i=n_1+1,\ldots,N$) can be calculated by matrix operation of Eq. (11). In this method, if we single out the treatment for a particular geometry, one can reduce the CPU time of calculation substantially once the view factors are determined. This fact is also conducive to the combination of the present radiation transfer analysis with GAs.

5. Results and Discussions

5.1 Validation procedure

5.1.1 Direct Method

To check the performance and accuracy of the present method in solving the optimal design radiation problems, a traditional test case was considered. First the accuracy of the REM2 in solving the radiative heat transfer was checked by comparing it with the analytical solution. Consider the radiative heat transfer in the enclosure shown in Fig. 1 where $L=2m$, $W=1m$, and $H=0.5m$. This is similar to the imaging enclosure described by Daun et al.(6). As the enclosure has two perpendicular planes of symmetric, we have considered a one-quarter model. In this model, two symmetric surfaces are specified as totally specular with reflection factor of $\rho^S=1$. Figure 3 shows the computational domain. As depicted in this figure the enclosure is divided into finite size square elements where $\Delta x = \Delta y = \Delta z = 0.1$ m.

![Figure 3 Discretization of the computational domain](image)

The emissivity of the surface elements was set to 1.0. The number of rays from each element was set to 8101. The dimensionless heat flux distribution on the design surface was obtained by REM2 and zone method with applying uniform dimensionless heat flux input $q^* = 1.0$ on the top surface, uniform dimensionless temperature on the design surface $T^* = 1.0$ and $q^* = 0.0$ on the sides and the bottom around the design surface. The analytical solution was obtained by using zone method as follows: The view factor $F_{j,i}$ was obtained analytically(20). Then, the radiative heat transfer was obtained by the method...
introduced in the previous section. Figure 4 shows the calculation results. Comparison of
the results with analytical solution showed a good agreement between REM\(^2\) and the
analytical solution.

Figure 4 Comparison of dimensionless heat flux on the design surface

5.1.2 Optimization method

The goal of the optimization process is to find a heat flux distribution, \(q_{b,j}^*, j = 1, 2, ..., 50\) over the heater surface (top surface) so that the heat flux distribution
over the design surface (bottom surface), \(q_{d,j}^*, j = 1, 2, ..., 36\) can be achieved the same as
distribution given by direct solution. Therefore, by assuming the solution of the above direct
problem together with the rest of constraints as known conditions, the optimization method
was validated by determining whether the heat flux distribution on the heater surface of the
direct problem could be recovered uniquely. The results showed that if we put the same
constraints on the heater distribution as in the direct problem (i.e., uniform heaters setting),
we could obtain a unique solution for the heater distributions on the heater surface for any
practical heater ranges. However, if there were not any restricting constraints, then there
would be multiple solutions.

In order to check the effect of restricting constraints on the heaters i.e., selecting range
of heaters setting and non uniformity of the heaters power, we considered three cases with
different ranges. Table 1 shows the value of objective function, the maximum and average
relative error in estimated heat fluxes over the design surface using different ranges of
heaters power for 100 iterations. As shown, the maximum error in heat flux distribution
over the design surface is less than 1%, which is a good value for practical design purposes.

<table>
<thead>
<tr>
<th>Range</th>
<th>Objective function (F)</th>
<th>Maximum relative error (%)</th>
<th>Average relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9-1.1</td>
<td>4.3E-08</td>
<td>0.034</td>
<td>0.012</td>
</tr>
<tr>
<td>0.5-1.5</td>
<td>2.3E-06</td>
<td>0.21</td>
<td>0.09</td>
</tr>
<tr>
<td>0-2</td>
<td>6.9E-06</td>
<td>0.38</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Figure 5 shows the dimensionless heat flux distribution over the heater surface and the
related error over the design surface using three ranges of heaters setting. As shown,
although the desired heat fluxes over the design surface is well recovered by all ranges, the estimated heat flux distribution over the heater surface, especially for case 3 is not exactly the same as the uniform distribution from the direct solution. Therefore, the problem has multiple solutions which satisfy the desired conditions.

(a) Heat flux: $0.9 \leq q_{h,j}^* \leq 1.1$

(b) Error: $0.9 \leq q_{h,j}^* \leq 1.1$

(c) Heat flux: $0.5 \leq q_{h,j}^* \leq 1.5$

(d) Error: $0.5 \leq q_{h,j}^* \leq 1.5$

(e) Heat flux: $0 \leq q_{h,j}^* \leq 2$

(f) Error: $0 \leq q_{h,j}^* \leq 2$

Figure 5 Predicted dimensionless heat flux distribution over the heater surface and the related error over the design surface using three ranges of heaters setting

5.2 Sample problem

In order to see the influence of the distance between the heater surface and design surface, consider the radiative heat transfer in the enclosure shown in Fig. 1 again with dimensions $L=2m$, $W=1m$, and three value for $H$: 0.3, 0.5, and 0.7m. The heater and design surfaces are gray and diffuse on the top and bottom of the enclosure, respectively. The design surface has dimensions of $0.8 \times 1.8m$ (that is, it is set in 0.1m from each boundary). The remainders of bottom surface around the design surface together with the sidewalls are adiabatic, gray, diffuse and specular. Table 2 gives the enclosure properties that were used in the analyses.
The aim of the design problem is to find a set of 50 heaters over the heater surface (top surface) in such a way that the dimensionless temperature and heat flux over the design surface had a uniform distribution of $\frac{dT}{dt} = 0.1$ and $q_h = 0.2$, respectively. In solving this problem the heater strength were between 1 and 4. Figure 6 show the dimensionless heat flux for several enclosure heights: $H=0.3$, 0.5, and 0.7. Table 3 shows the value of objective function, the maximum and average error in estimated heat fluxes over the design surface.

<table>
<thead>
<tr>
<th>Surface</th>
<th>Emissivity</th>
<th>Diffuse reflectivity $\rho^D$</th>
<th>Specular reflectivity $\rho^S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heater</td>
<td>0.9</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>Design</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
</tr>
<tr>
<td>Others</td>
<td>0.3</td>
<td>0.2</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Figure 6 Dimensionless heat flux distribution over heater surface for several enclosure heights
As shown, although the desired heat fluxes over the design surface is well recovered and the solution is physically correct, the heat flux distribution is quite irregular, which is typical characteristic of GAs. These heaters input may be difficult to implement in practical system. The design may become more practical if a smaller number of heaters were employed, even at the expense of accuracy. Multiple solution of design problem allows the designer a choice, and the solution that is cheapest and easiest to implement can be chosen from among them. Therefore, if each heater element was considered as a single design parameter, the resulting optimization problem would have been large and distribution of heaters might be irregular. However, we may smooth and reduce the design parameter by dividing the heater surface into 12 zones as shown in Fig. 7 based on our observation of the physical problem. A uniform heat flux over each region is specified. Figure 8 shows dimensionless heat fluxes of 12 zones and dimensionless estimated heat flux on the design surface for \( H=0.3, 0.5, 0.7 \). Table 4 shows the value of objective function, the maximum and average error in estimated heat fluxes over the design surface. As shown, the distribution of heat flux is smoother than previous solution and but the value of objective function is almost the same. Figure 8 show that the heaters strength becomes more uniform as \( H \) decreases. The involved error is also decreases. The reason for this behavior is that as the distance decreases, the heater surface dominates the heat flux on the design surface, whereas the refractory surfaces will control the heat flux on the design surface as \( H \) increases. The view factor between heater and design surfaces as a function of distance is shown in Fig. 9 which supports the forgoing arguments. Figure 10 shows the rate of convergence for objective function versus the number of iterations for different aspect ratio.

### Table 3 The value of objective function and maximum and average relative error without zoning

<table>
<thead>
<tr>
<th>( H ) (m)</th>
<th>Objective function (F)</th>
<th>Maximum relative error (%)</th>
<th>Average relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>7.5E-06</td>
<td>0.35</td>
<td>0.11</td>
</tr>
<tr>
<td>0.5</td>
<td>9.2E-06</td>
<td>0.35</td>
<td>0.13</td>
</tr>
<tr>
<td>0.7</td>
<td>6.9E-05</td>
<td>0.85</td>
<td>0.36</td>
</tr>
</tbody>
</table>

![Figure 7 Partitioning of the heater surface into 12 zones](image)

### Table 4 The value of objective function and maximum and average relative error with zoning

<table>
<thead>
<tr>
<th>( H ) (m)</th>
<th>Objective function (F)</th>
<th>Maximum relative error (%)</th>
<th>Average relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \rho = 0.5 )</td>
<td>( \rho = 0.95 )</td>
<td>( \rho = 0.5 )</td>
<td>( \rho = 0.95 )</td>
</tr>
<tr>
<td>0.3</td>
<td>6.4E-06</td>
<td>9.7E-07</td>
<td>0.3</td>
</tr>
<tr>
<td>0.5</td>
<td>7.2E-06</td>
<td>2.8E-07</td>
<td>0.25</td>
</tr>
<tr>
<td>0.7</td>
<td>2.6E-05</td>
<td>8.9E-08</td>
<td>0.6</td>
</tr>
</tbody>
</table>
Figure 8 Dimensionless heat flux distribution over the heater surface for 12 zones and the related dimensionless heat flux over the design surface for several enclosure heights.

Figure 9 View factor between heater and design surface for different distance (H).
Figure 10 The rate of convergence for objective function versus the number of generation for different aspect ratio.

- (a) Heater surface: $H=0.3\ m$
- (b) Design surface: $H=0.3\ m$
- (c) Heater surface: $H=0.5\ m$
- (d) Design surface: $H=0.5\ m$
- (e) Heater surface: $H=0.7\ m$
- (f) Design surface: $H=0.7\ m$

Figure 11 Dimensionless heat flux distribution over the heater surface for the problem with reflector surfaces having $\rho^S = 0.95$ and the related dimensionless heat flux over the design surface for several enclosure heights.
In inverse design problems, analogous to the perturbations in the measured data in the inverse identification problems, some variations should be considered to test the capability of the developed technique. A test with variation in input data is considered in this study. In this test, we have only changed the properties of refractory surfaces to a large value of specularity, i.e., $\rho^S = 0.95$.

Figure 11 shows dimensionless heat fluxes on the heater surface and dimensionless estimated heat fluxes on the design surface for the case with reflector surfaces having $\rho^S = 0.95$. Table 4 shows the value of objective function, the maximum and average error in estimated heat fluxes over the design surface. As shown, the value of objective function and maximum error less than previous case. The results are in agreement with physical intuition, as highly reflecting sidewalls will make it easier to achieve spatially uniform distributions. Furthermore, the ratio of the value of objective function between this and previous case for enclosure with higher height $(H=0.7)$ is more than other cases, thus the refractory has an important effect on the solution when the distance between heater and design surfaces is large.

6. Conclusion

In this paper, an optimization method for finding the optimal heaters setting that produce a desired heat flux and temperature distribution over a region of the enclosure surface, called the design surface in 3-D radiant enclosure has been presented which included some surfaces that were diffuse and other specular-diffuse. Radiation element method by ray emission model (REM²) was used to calculate the Radiative heat flux on the design surface, which enabled us to handle reflecting surfaces. Micro-genetic algorithm was used to minimize an objective function, which was expressed by the sum of square error between estimated and desired heat fluxes on the design surface. The estimated values of heat flux on the design surface were in good agreement with the desired value within an acceptable range of error, but the heat flux distribution on the heater surface was quite irregular. Thus, the heat flux distribution was smoothed a priori by aggregating the heater into regions. The novel features of this methodology were demonstrated by finding the optimal heaters setting of a three dimensional enclosure for three aspect ratio. It showed that the heaters strength became more uniform as the distance (aspect ratio) decreased. The involved error was also decreased. The effects of refractory properties have been studied as well. Therefore, one of the most important advantages of the presented optimization design methodology is the ease of imposing design constraint that ensures the solution can be implemented in a practical setting.

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References


