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OPTMIZATION OF RADIATIVE HEAT TRANSFER INSIDE GREENHOUSES

Washington Braga
Pontifícia Universidade Católica do Rio de Janeiro, PUC-Rio, Rio de Janeiro, Brazil
wbraga@mec.puc-rio.br

Abstract. *This paper presents a multi-objective procedure based on a fully elitist genetic algorithm, GA, able to optimize the radiative heat transfer inside greenhouses used to grow crops. Details of the genetic algorithm used is presented herein but the focus is on the heat transfer. The decision variables are the tube temperature and tube radius, that affects directly the entalphy heating flow, and the tube location. In some studies, the cavity aspect ratio (height to width) is also considered as another decision variable. The influence of the genetic algorithm parameters, such as the size of the initial and following generations, and heat transfer parameters such as cavity aspect ratio and the surface emissivities are discussed herein. A new filter, based on a local gradient, is introduced in order to generate more efficient populations. The results show clearly that with proper consideration, very good results may be obtained with reasonable computational effort.*

Keywords. *Optimization, multi-objective, genetic algorithm, radiation heat transfer, greenhouses*

1. Introduction

Due to the ever increasing fuel and heat production costs coupled to gradually more stringent environmental restrictions, many efficiency analyses in mechanical systems have been developed. Among others, thermal systems have been receiving greater attention lately perhaps due to their widespread applications (e.g. Boehm, 1987). One of the many areas in which Radiative heat transfer is most relevant is on greenhouse thermal designs, in which hot-water circulating inside tubes is used to keep the crop at the desired temperature level and produce the required heating. A preliminary study involving greenhouse efficiency analysis was made by Teitel & Tanny (1998) that analyzed a very simplistic model for the greenhouse thermodynamics and concluded that the heating pipes should be installed as close as possible to the crop. Unfortunately, many simplifications were introduced on their investigation. For instance, their study neglected the blocking effect of radiation coming from one surface (the crop) towards the others surfaces (ground, ceiling and the other crop) due to the presence of the pipe (resulting on a very stringent criteria for the tube radius), the likely solar heating occurring mostly over one of the surfaces, the influence of gas participation on the radiation heat transfer, and the convective heat transfer. Recently, the present author implemented a multi-objective genetic algorithm able to handle the many objetive functions that appear during the optimization study for greenhouses. This allowed a more realistic study that removed some of those restrictions and investigated how to increase greenhouse efficiency using adequate tube sizing and its location (Braga, 2006).

From the literature, only the work developed by Vollebregt & Braak (1995) that modelled the internal greenhouse radiative and convective flows was found, although without any optimization analysis. However, the internal heating configuration (bank of 5 vertical tubes) used in their study was quite different from the one used by Teitel & Tanny (1998) and their results could not be used for comparison. The main objective of the present paper is to describe details not shown previously about the implementation of the genetic algorithm and on the optimization of the radiative heat transfer. The optimization study of the combined Radiative + Convective thermal effects will be made in a subsequent phase of the present investigation.

2. Physical Model

Consider a rectangular greenhouse such as the one displayed on Fig. 1. Following Teitel & Tanny (1998), the aspect ratio $H = L_2 / L_1$ may shift from 1 (for roses) to 3 (for tomatoes). At this stage, the enclosure is considered to be infinitely long. Surfaces 2 (left) and 4 (right) simulate the crop. The heating pipe, of diameter D, is to be located at a position defined as (x_D, y_D). Results shown here were obtained under the assuption that all plane surfaces have the same emissivity while the tube emissivity is a design parameter, smaller than the others. As it is known from the literature (e.g. Siegel and Howell, 2002), the emissivities for nonconductors are usually higher than for conductors. Results shown herein were obtained considering T_1 = 293 K = T_2 = T_4 and T_3 (the ambient) = 283 K. The tube temperature, T_{tube}, is considered to be one of the parameters to be estimated following the optimization analysis. External radiation (coming from the Sun, for instance) reaches the greenhouse at a specified angle. For simplicity, in the present work, surface 3 is a virtual one, although it could be modified to be a physical one, such as a glass panel, for instance.

Hot fluid (water, for instance) is pumped throughout the tube to heat the greenhouse walls directly by radiation and indirectly by Convection. As it is known, both the radiative and the convective heat transfer depend on physical parameters such as the temperatures, the thermal properties, but also on the geometry and those are to be optimized herein. As previously mentioned, the present work deals only with Radiation and the geometric aspects are handled using configuration factors for diffuse surfaces (specular surfaces could also be handled but those are simply not feasible for greenhouses). This is discussed next.

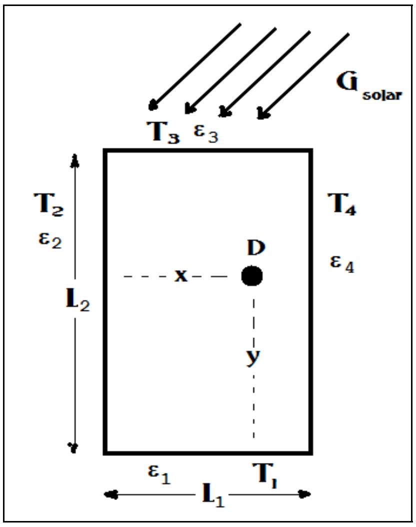

Figure 1. Greenhouse Geometry.

3. Radiative Geometric Configuration Factors

Configuration factors take care of the relative geometry of all surfaces involved in the balance of energy, that is, the First Law of Thermodynamics. In the current situation, a rectangular cavity, most of such factors are easily calculated but not those associated to the tube surface. A careful analysis of Fig. 2 indicates that there are two particular, generically speaking, tube locations to be considered. In the first one, the tube is located to the left of the cavity diagonal linking the corner of surfaces 2 and 3 and the corner of surfaces 1 and 4. This region will be named as region A. In the second, the tube is located to the right of the same diagonal, region B. If the heating tube is located in region A, clearly it will not affect the radiative heat exchange between surfaces 3 and 4, but it will definitely alter the exchange between surfaces 1 and 2. Details of the geometrical considerations involving all such factors are given elsewhere (Bastos & Braga, 2004).

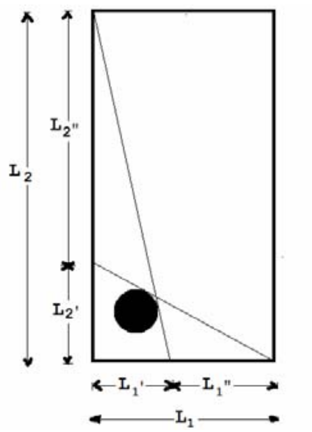

Figure 2. Auxiliary Surfaces for Configuration Factors

4. Mathematical modeling

Defining as usual the radiosity, J, as the total radiant energy leaving a surface, herein considered as a gray diffuse one; E_b as the total, hemispherical emissive power of a black body; ε as the total, hemispherical emissivity of a gray surface; Q as the net radiation transfer from a surface which area is indicated by A; and H_i is the external (i.e. from the sun) heat transfer reaching the i-surface, the energy equation may be written as (e.g. Braga, 2004):

$$\frac{Q_i}{A_i} + H_i = J_i - \sum_{j=1}^{N} F_{ij} J_j \tag{1}$$

The above summation goes from 1 to N (including the pipe surface). The radiosities are obtained from:

$$J_i - (1-\varepsilon_i)\sum_{j=1}^{N} F_{ij} J_j = \varepsilon_i E_{bi} + (1-\varepsilon_i) H_i \tag{2}$$

As it may be noticed, Eq. (2) defines a set of N equations with N unknowns, the radiosities J_i. For the problem under consideration, as all surface temperatures are specified, a set of linear equations are to be solved by standard methods. More interesting situations could be those in which some heat fluxes are considered. However, for a standard greenhouse, such situations have no practical meaning and were, therefore, disregarded.

Once the radiosities are found, the heat flux at all surfaces may be calculated, using Eq (1). In order to evaluate the effectiveness of the proposed thermal system in relation to others, a greenhouse thermal efficiency must be defined. For the present considerations, efficiency is defined as the ratio between the total heat reaching both the left and the right crops and the total heat input into the cavity, that is, the sum of the energy transferred by the pipe to the external heating. Clearly, other definitions are available but the one chosen here avoids larger than unity metric and is directly affected by the thermal participants, if you will. So,

$$\eta = \frac{Q_2 + Q_4}{Q_{tube} + G_{solar}} \tag{3}$$

Clearly, for any set of variables (T_{tube}, y_D, D, H), herein called the physical environment (the whole set of these defines the decision or search space), a different solution to the system of equations defined by Eq. (2) will result and a corresponding greenhouse efficiency defined by Eq. (3) will be obtained.

5. Problem Definition

In order to deal with an interesting and realistic situation, the problem to be solved here is stated in terms of finding the optimum for Equation (3) able to satisfy some constraints, both geometric (such as sizes), thermal (such as temperature levels) or specified heat fluxes at both crops and the tube. It may be formulated as:

Maximize $f_1 = \eta = f(H, D, y_D, T_{tube})$ -- the thermal effiency (4)

$f_2 = 1/\left(T_{tube} D^2\right)$ -- the heating function (5)

Eventually, it is also considered that the amount of energy reaching the upper region of the crop (vertical walls of the cavity) has to be equal to (or at least less than) some prefixed value $Q_{upper\,S}$ in order to allow adequate crop growth and to avoid surface burning. This constitutes a restriction, $Q_{upper} = Q_{upper\,S}$ (project specification), implemented as a third objective function as:

$$f_3 = \left|Q_{upperS}\right| / \left|Q_{upperS} - Q_{upperC}\right| \tag{6}$$

In the above set of equations, the symmetry of the problem was considered (the tube is set in the horizontal center of the cavity) without loss of generality. The second objective function, defined by equation (5), indicates that the heating effect, caused by the Convective flow inside the tube, is a function of the enthalpy flow and must be minimized. For the present purposes, this may be represented as:

$$\dot{m}\Delta h \propto T_{tube} A_{tube} \propto T_{tube} D^2 \tag{7}$$

There are also a set of restrictions specified to reduce the search space (and the computational effort). Unless stated elsewhere, they are:

H, the cavity aspect ratio: $1 < H < 4$
R, the radius of the heating tube: $0.02 < R < 0.15$
T_{tube}, the tube temperature: $293K < T_{tube} < 493K$

A feasible solution is one that will satisfy all imposed limits and restrictions. An optimal environment will achieve maximum performance at minimal cost, without violating the imposed heat transfer limitations. Figure 3 indicates a typical distribution of the objectives functions and the imposed restriction as function of the tube radius. As it may be seen, it is not straight finding the best solution in cases like that.

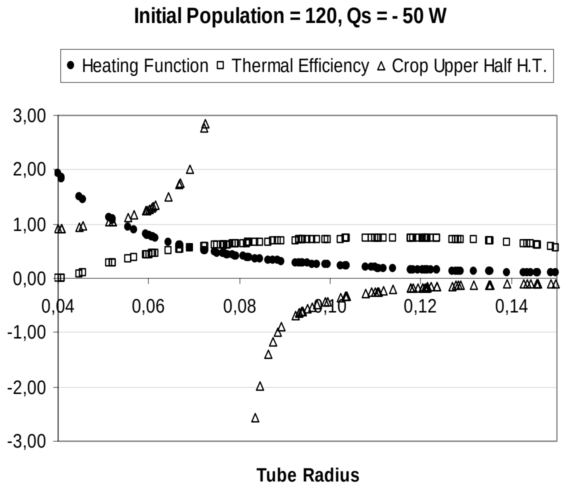

Figure 3. Objective Functions.

The initial attempts to solve this problem involved the search for a single objective function, combined properly scaled the (first) two or the three functions previously mentioned. Several combinations were tried but the results were always poor and were dropped. It was understood that obtaining a suitable combination of weights is not an easy task. The usage of Lagrange multipliers did not work but in a small number of cases, due to a very ill conditioned Hessian matrix. A good candidate for an optimization method should have at least some characteristics, besides being able to handle the problem. It has to be robust, easy and cheap to be implemented, and it should not depend heavily on the numerical aspects, specially considering that the next phase of this project will involve some computational fluid dynamics code. In order to avoid handling ill conditioned matrices, a search algorithm based on evolutionary algorithms (Davalos & Rubinsky, 1996) was implemented. As it is known, such algorithms are adaptive search procedures loosely based on the Darwinian notion of evolution and have a clear advantage over those based on the Hessian matrix as they do not require singular or near singular matrix inversions. In what follows, a very brief general description on the methodology behind such algorithms will be made in order to properly pose the modifications introduced together with the discussion towards the use on such a complex situation.

6. Optimization Method

Evolutionary algorithms (EAs) are being used to allow quick and efficient optimization studies, having already achieved a reference level among other optimization methods. Beginning with an initial, perhaps randomly chosen population of possible solutions, chromosomes in EAs parlance, those set of variables that result on the best, most suitable values for the fitness (or objective) function are selected according to some pre-specified criterion, to breed the next generation. For situations in which a single fitness function is available (for instance, whenever a single function combining all the requirements is obtained), standard EAs procedures involving selection, pairing, crossover and mutation operators take care of the optimization procedure with proven results (Goldberg, 1999). However, in many real world problems, there is more than a single objective function. In the present situation, for instance, one is interested in finding the environment (the set of design or decision variables) that represents a trade off between the quality (highest possible thermal efficiency) and that at the same time, the low cost (or correspondingly, the smallest possible heating condition) amont all feasible solutions. That is, often, there are more than one objective functions and they are competing ones (see Fig. 3).

In such problems, in general, there is no more sense to talk about a single, best (optimum) solution. Instead, the goal now is to calculate an assembly of solutions, generically called the Pareto set, hopefully with small (computational) effort, in which no other solution in the search space is superior to those in the Pareto set, when all objectives are considered. To illustrate this, figure 4 represents three feasible solutions for a situation having two objective functions.

After an analysis of the results, environment 3 may be discarted as environment 2 is clearly a better solution. However, among envs 1 and 2, no elimination is possible. The set of feasible solutions obtained after some generations (the iterative procedure) usually contain some solutions that may be discarted due to the concept of dominance, Deb (1999) that indicates that solution A is said to dominate solution B if all objective components of A is bigger (for a maximization problem) than those of B. In figure 4, environment 2 dominates environment 3. The set of non-dominated solutions is theoretically but not necessarily the optimal set of solutions. Two metrics are available to indicate if the optimal Pareto set is actually obtained: diversity and convergence. As the size of this set may become larger than practical, solution niching is the additional size reduction mechanism used, dropping solutions that are too close to others, according to some criterion.

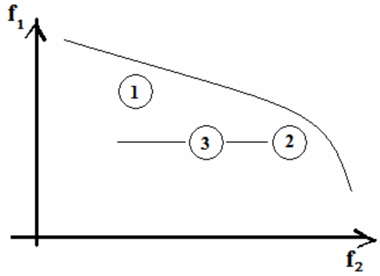

Figure 4. Assembly of Solutions.

7. Solution Procedure and Results Analysis

All results to be shown were obtained following roughly the same routine. Initially, physical parameters (such as emissivities, Solar Radiation, cavity surface temperatures) are set as well as the size of the initial population (from 25 to 120. Subsequent populations could have as few as 26 individuals going up to 110), the crossover and the mutation probabilites. The number of generations was set to 5, considered sufficient for the present purposes assuring convergence in all situations. Table 1 indicates best results for a single run, indicating that 5 generations are sufficient for engineering purposes to allow convergence. Such result is not affected by the number of individuals in each generation.

Table 1. Partial Results for the first 5 generations. Two Objective Functions Case.
Shaded areas indicate the heating function and the
thermal efficiency obtained for the best result for each generation.

	Temp Tube [K]	y (tube) [m]	D/2 [m]	H [m]	Heating Function	η
1st gen	440,7	2,295	0,116	3,216	**0,1686**	**73,6%**
	433,3	2,112	0,111	3,104	0,1867	73,5%
	428,5	2,000	0,108	3,033	0,1997	73,2%
	422,2	1,856	0,104	2,939	0,2190	72,7%
2nd gen	438,4	2,163	0,114	3,163	**0,1768**	**74,1%**
	433,4	1,999	0,108	3,034	0,1973	73,5%
	429,3	1,999	0,108	3,041	0,1982	73,4%
	428,6	1,999	0,108	3,033	0,1998	73,2%
3rd gen	429,3	1,763	0,102	3,040	**0,2232**	**74,4%**
	422,8	1,763	0,102	3,034	0,2280	74,0%
	441,6	1,249	0,090	2,715	0,2794	72,7%
	405,0	1,546	0,094	2,696	0,2811	69,9%
4th gen	441,9	1,770	0,103	3,042	**0,2145**	**75,1%**
	429,3	1,763	0,102	3,040	0,2232	74,4%
	422,8	1,763	0,102	3,034	0,2280	74,0%
	425,5	1,652	0,100	2,923	0,2359	73,5%
5th gen	441,9	1,770	0,103	3,042	**0,2145**	**75,1%**
	438,8	1,510	0,098	2,936	0,2359	74,5%
	434,5	1,510	0,097	2,907	0,2430	74,1%
	425,9	1,510	0,095	2,849	0,2580	73,0%

At each generation, the dominated solutions were filtered and the following population was generated using the individuals that best obeyed the objective function f_3 (the restriction): elitism has been observed to speed up GA performance, Deb *et al* (2002), and it is used whenever necessary. In the following subsection, generically obtained results will be given. After that, some special considerations were implemented slightly altering this routine and the final results were obtained. The general solution procedure is indicated on Fig. 5.

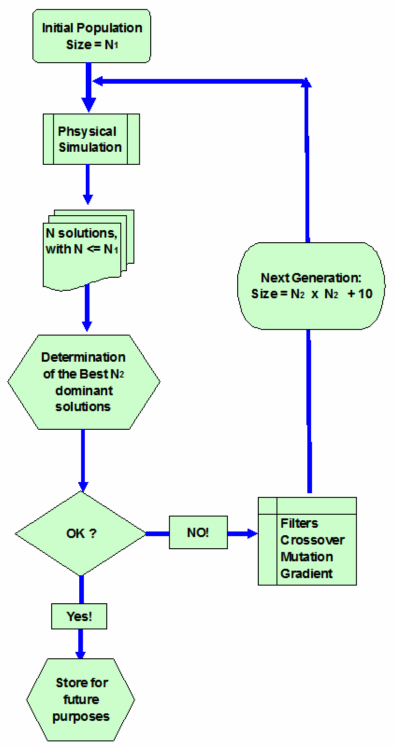

Figure 5. Solution Procedure.

In such figure, N_1 is the size of the initial population, N_2, a number ranging from 4 to 10, that defines the size of the following generations given by $\mathbf{N}_2^2 + \mathbf{N}_3$, where N_3 indicates the number of terms introduced by mutation and by the gradient method introduced here, always kept equal to 10. The gradient filter uses local estimatives for the gradients of the three objective functions to generate new individuals for the following generations. For this problem, this filter gave results quite superior to any other.

7.1. Search for the Unique Solution

As it is known, one of the greatest disadvantages of genetic algorithms is the lack of assurance that the global optimum solution was truly found. This situation is worst for the multi-objective problems in which many decision variables are available. In order to minimize this, during the present work, it was decided to repeat the problem N3 times (using the same genetic algorithm parameters, such as the population size) and after these runs, a final search for the best solution among all best previously found was conducted. This constitutes a final filter for the results. Figure 6 gives the solution after 4, 8, 12, 18 and 24 runs but considering only two objective functions, to help visualize the results. As it may be seen, they do not change if one considers filtering after 12 runs. Before proceeding, it is instructive to recall that the need for such filtering is directly associated to the randomic generation of the first population. Therefore, it was decided to analyse such dependence. Figure 7 gives results similar to those shown on Figure 6 but with a much larger initial population (100 individuals).

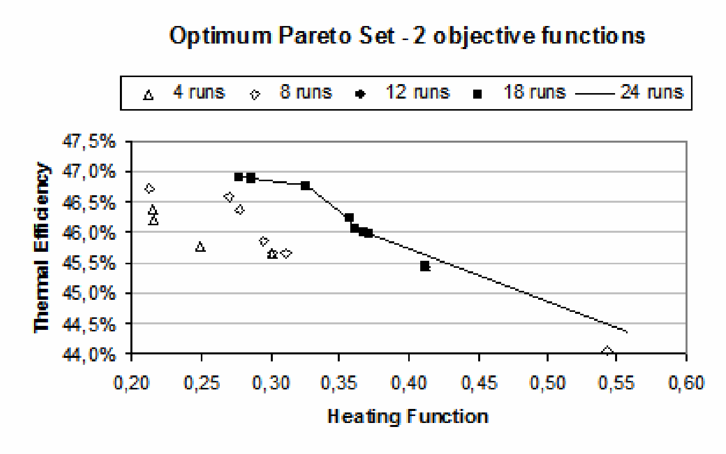

Figure 6. Optimum Pareto Set for 2 Objective Functions.
Population size = 25 individuals

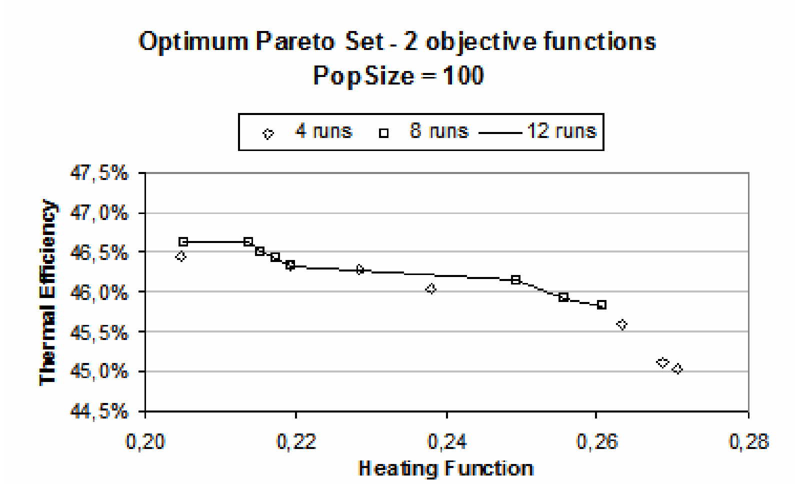

Figure 7. Optimum Pareto Set for 2 Objective Functions.
Population size = 100 individuals

As it may be seen, using a much larger initial population size reduces the fluctuations seen on the previous data. Clearly, this is indicative of the fact that increasing the initial population increases the search space as more solutions are tested during the initial search and this indeed acts like a filter, smoothing the final results profile. It may also be noticed that the final Pareto sets are not significantly different. Another important issue to be considered here is that the random number generator is a matter of facts a pseudo random number generator: a better generator could minimize this undesired effect. Due to the larger diversity (i.e. larger range of heating function values), all further results were obtained using population size equal to 25 individuals (unless whenever stated differently).

8. Heat Transfer Results

Once the genetic procedure was considered to be understood, the radiative heat transfer inside the greenhouse investigation was able to be started. Considering that often the aspect ratio is fixed accordingly to the desired crop, the first study made considered this. Figure 8 next shows the results obtained for two full set of data (filtered accordingly to the previous analysis). Such results were initially obtained for two objective functions, defined by Equations (4) and (5) and later extended to include Equation(6), considering black bodies and (for the three objective functions case) specified upper half crop heat transfer equals to $Qs = -100$ W/m. Figure 8 indicates the filtered (after 12 runs) results for fixed aspect ratios. Increasing the size of the vertical walls implies on more energy reaching the vertical crops, therefore increasing the thermal efficiency. The increase is quite significant from a square cavity to a rectangular cavity but after that, the increase rate reduces significantly, indicating that very tall cavities are in fact not anymore efficient (mainly if one considers costs).

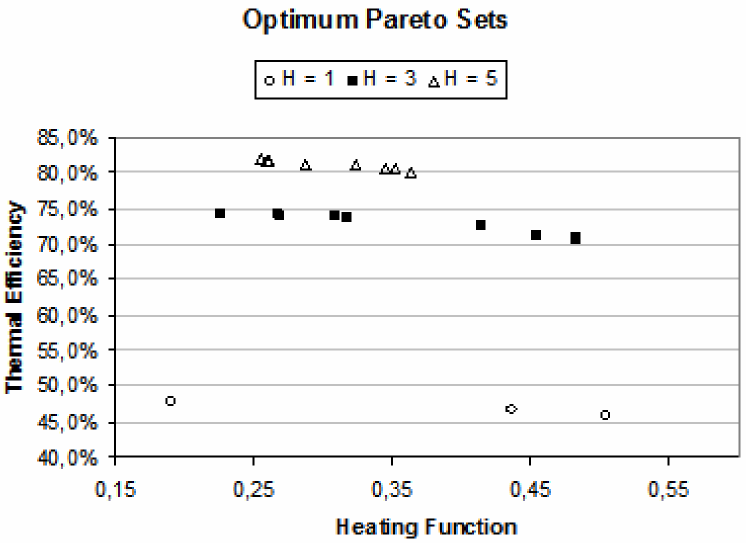

Figure 8. Optimum Pareto Sets for fixed aspect ratios and two objective functions.

After noticing that there seems to have a limit on the cavity aspect ratio effects, it was decided to investigate this optimum aspect ratio. Such results are indicated on Table 2 below.

Table 2. Results obtained for 4 decision variables – Two objective functions
Population Size = 25, filter uses 12 runs

Temp Tube [K]	y (tube) [m]	D/2 [m]	H [m]	Heating Function	η
441,1	1,829	0,108	3,152	0,1938	**75,9%**
438,4	1,831	0,108	3,155	0,1941	**75,8%**
435,6	1,671	0,104	3,065	0,2107	**75,3%**
431,8	1,773	0,104	3,115	0,2150	**75,2%**
424,4	1,792	0,104	3,126	0,2172	**74,8%**
422,1	1,573	0,091	3,048	0,2886	**73,8%**
415,1	1,684	0,089	3,126	0,3043	**73,5%**
414,0	1,616	0,089	3,126	0,3059	**73,4%**

The next investigation considered the influence of the third objective function in the whole optimization process. Figure 9 indicates the results. In this figure, for each specified cavity aspect ratio, H, two full tests, each one consisting of 12 runs were made in order to estimate how the filtering process is affected by the extra objective function. As it may be seen, the filtering process being used is still efficient as the results obtained by two runs (for each specified H-value) give essentially the same trend (i.e., optimum Pareto set). The effects of the aspect ratio are again clearly shown.

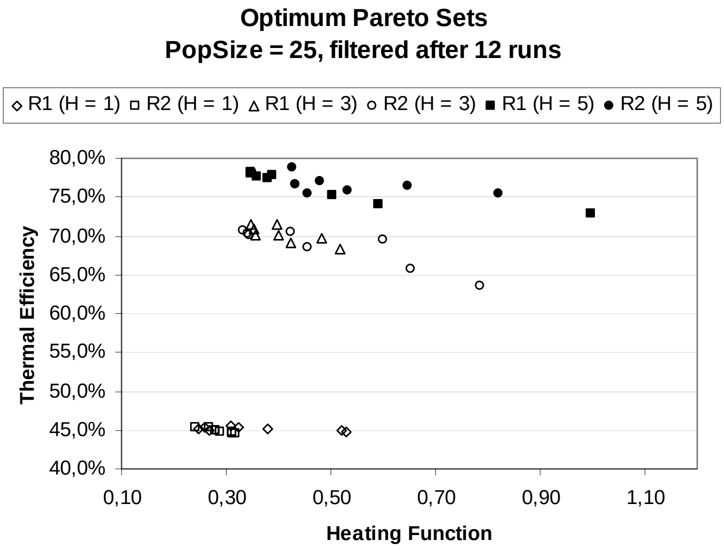

Figure 9. Optimum Pareto Sets for fixed aspect ratios and Qs = - 100 W/m

Table 3 indicates the results obtained considering the cavity aspect ratio as a fourth decision variable. Similar results may be obtained for other heat transfer values and are shown on Figure 10. If one compares the results shown on Table 2 and 3, one will clearly understand the influence of the third objective function. Similar results are obtained for other values for the upper half crop heat transfer.

Table 3. Results obtained for 4 decision variables and for Qs = - 100 W/m
Population Size = 25, filter uses 12 runs

Temp Tube [K]	y (tube) [m]	D/2 [m]	H [m]	Heating Function	η
404,7	1,285	0,087	2,551	0,3279	**68,6%**
403,2	1,279	0,080	2,403	0,3838	**66,5%**
398,0	1,366	0,084	2,471	0,3601	**66,7%**
401,3	1,279	0,080	2,403	0,3856	**66,3%**
400,1	1,263	0,076	2,253	0,4342	**64,1%**
393,2	1,263	0,076	2,243	0,4410	**63,1%**
386,8	1,349	0,081	2,433	0,3914	**64,5%**
388,8	1,300	0,079	2,479	0,4104	**65,1%**

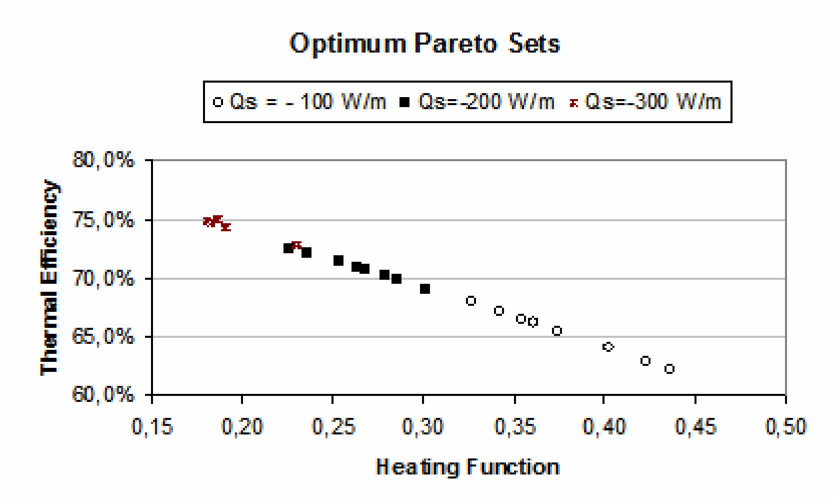

Figure 10. Optimum Pareto Set, obtained considering 4 decision variables

9. Conclusions

The present paper describes the work under development to develop an efficient and not costly, computationally speaking, algorithm to solve the optimization problem associated to the heat transfer inside a greenhouse thermal cavity used to grow different crops. At this stage, a robust multi-objective genetic algorithm has been implemented with good results. The problem dealt herein involved two or three objectives functions, one of them an imposed heat transfer at the upper region of the crop surface treated to work as such, and several geometric and temperature restrictions. The final results are assemblies of solution, usually called the Pareto Set but if desired, a final single solution may be obtained as well, provided a strong weight is allowed for the thermal efficiency (or any other, for that matter). Heat transfer results indicate that following this optimization procedure, significant cost reduction may be achieved.

10. Acknowledgement

The present author would very much thank Mr. Daniel Botelho de Figueiredo, a former student, that first accepted his invitation to a study on genetic algorithms. Mr. Figueiredo´s assistance helped much during the initial efforts towards this interesting optimatization technique.

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