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HEAT PIPE DESIGN THROUGH GENERALIZED EXTREMAL OPTIMIZATION

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Abstract. *In this paper an application of the Generalized Extremal Optimization (GEO) algorithm to the optimization of a heat pipe (HP) for a space application is presented. The GEO algorithm is a generalization of the Extremal Optimization (EO) algorithm, devised to be applied readily to a broad class of design optimization problems, regardless of the design space complexity it would face. It is of easy implementation, does not make use of derivatives and can be applied to either unconstrained or constrained problems with continuous, discrete or integer variables. The GEO algorithm has been tested in a series of test functions, showing to be competitive to other stochastic algorithms such as the Genetic Algorithm. In this work it is applied to the problem of minimizing the mass of a HP as a function of a desirable heat transport capability and a given temperature on the condenser. The optimal solutions were obtained for different heat loads, heat sink temperatures and three working fluids: ammonia, methanol and ethanol. The present design application highlights the GEO features of being easily implemented and efficient on tackling optimization problems where the objective function presents design variables with strong non-linear interactions and is subject to multiple constraints.*

Keywords. *Self-organized criticality, optimization, optimal design, heat pipe.*

Nomenclature

d	Diameter of wick wire (m)
d_i	Internal diameter of HP (m)
d_o	External diameter of HP (m)
d_v	Diameter of vapor core (m)
F_l	Liquid frictional coefficient (N/W-m)
F_v	Vapor frictional coefficient (N/W-m)
g	Gravitational acceleration (9.81 m/s^2)
K	Permeability (m^2)
k_{eff}	Effective thermal conductivity of wick (W/K-m)
k_l	Thermal conductivity of liquid (W/K-m)
k_t	Thermal conductivity of the heat pipe wall (W/K-m)
k_w	Thermal conductivity of the heat pipe wick material (W/K-m)
L_a	Length of adiabatic section (m)
L_c	Length of condenser section (m)
L_e	Length of evaporator section (m)
L_{eff}	Effective length of HP (m)
L_{total}	Total length (m)
m_{cont}	Mass of the container (Kg)
m_{total}	Total mass of the HP (kg)
m_{wd}	Mass of the dry wick (Kg)
m_{wl}	Mass of the liquid in the wick (Kg)
M_v	Mach number at vapor core
m_{vapor}	Mass of the fluid vapor inside the HP (Kg)
N	Mesh number of wick (1/m)
P_{amb}	Ambient pressure outside the heat pipe (N/m^2)

P_c Maximum capillary pressure (N/m^2)
P_g Hydrostatic pressure (N/m^2)
Q Heat transported (W)
Q_b Boiling limit (W)
Q_c Capillary limit (W)
Q_e Entrainment limit (W)
Q_v Viscous limit (W)
R Thermal resistance of the HP (K/W)
R_{ct} Thermal resistance of the heat pipe wall at the condenser (K/W)
R_{cw} Thermal resistance of the heat pipe wick at the condenser (K/W)
Re_v Reynolds number at vapor core
R_{et} Thermal resistance of the heat pipe wall at evaporator (K/W)
R_{ew} Thermal resistance of the heat pipe wick at the evaporator (K/W)
R_v Gas constant for vapor (J/kg-mol-K)
r_c Capillary radius (m)
r_n Nucleation radius (m)
$r_{h,s}$ Hydraulic radius for wick surface pores (m)
r_v Radius of vapor core (m)
T_{si} Temperature on the outside surface of the condensor section (K)
T_{so} Temperature on the outside surface of the evaporator section (K)
T_v Temperature of saturated vapor (K)
t_t Thickness of HP tube (m)
t_w Thickness of HP wick (m)
u_{ts} Ultimate tensile strength of the heat pipe's wall material
α Angle of inclination of HP (degrees)
ε Porosity
γ_v Specific heat ratio
λ Latent heat of vaporization (J/Kg)
μ_l Liquid viscosity (kg/m-sec)
μ_v Vapor viscosity (kg/m-sec)
ρ_l Density of the liquid (kg/m^3)
ρ_t Density of the material of the HP container (kg/m^3)
ρ_v Density of the vapor (kg/m^3)
ρ_w Density of the material of the HP wick (kg/m^3)
σ Surface tension coefficient (N/m)
τ Free adjustable parameter of the generalized extremal optimization algorithm

1. Introduction

Nature has been inspiring researchers to develop optimization tools to tackle complex problems that pose great difficulties to traditional gradient algorithms. The natural evolution, the annealing of metals, the functioning of the brain and even the behavior of ants, are examples of natural processes that inspired the development of such tools. Among the optimization methods inspired by nature, Simulated Annealing (SA) (Kirkpatrick et al, 1983) and Genetic Algorithms (GA) (Goldberg, 1989) are probably the two most used for tackling optimization problems in engineering and science. Their robustness and ability to be easily implemented to a broad class of problems, regardless of such difficulties as the presence of multiple local minima in the design space and the mixing of continuous and discrete variables, has made them good tools to tackle complex problems, for example, in the aerospace field (Jilla and Miller, 2001, Schoonover et al, 2000). The main disadvantage of these methods is that they usually need a great number of objective function evaluations to be effective. Hence, in problems where the calculation of the objective function is very time consuming, these methods may become impracticable. Nevertheless, the availability of fast computing resources or the use of hybrid techniques (Wang and Damodaran, 2001; Vicini, A. and Quagliarella, 1999), has made the power of those algorithms available even to that kind of problems. There are today many derivatives of the SA and GAs methods, created to give more efficiency to the proposed original algorithms, but that keep essentially their same principles.

Although algorithms such as the SA and GA are inspired by natural processes, their practical implementation to optimization problems shares a common feature: the search for the optimal is done through a stochastic process that is "guided" by the setting of adjustable parameters. Since the proper setting of these parameters are very important to the performance of the algorithms, it is highly desirable that they have few of them, so that the cost of finding the best set to a given optimization problem does not become a costly task in itself.

Recently, Boettcher and Percus (2001) have proposed a new optimization method based on a simplified model of biological evolution developed to show the emergence of Self-Organized Criticality (SOC) in ecosystems (Bak and Sneppen, 1993). Called Extremal Optimization (EO), it has been successfully applied to tackle hard problems in combinatorial optimization. The EO algorithm has only one adjustable parameter, which may be an "a priori" advantage

over the SA and GA algorithms, since they use more than one. Sousa and Ramos (2002) have proposed a generalization of the EO method, constructed in a way that makes it easily applicable to a broad class of design optimization problems. It was named the Generalized Extremal Optimization (GEO) algorithm. As the SA and the GA, it is a stochastic method. It does not make use of derivatives and can be applied to nonconvex or disjoint problems. It can also deal in principle with any kind of variable, either continuous, discrete or integer. Having been already tested on a set of test functions commonly used to assess the performance of stochastic algorithms (Sousa and Ramos, 2002), the GEO proved to be competitive to the GA.

In this paper we present an example of an application of the GEO method to a real design problem: The optimization of a heat pipe (HP) for a space application. This problem pose difficulties to the GEO such as an objective function that presents design variables with strong non-linear interactions, subject to multiple constraints, being considered unsuitable to be solved by traditional gradient based optimization methods (Rajesh and Ravindran, 1997). The HP is optimized in regard to its total mass, given a desirable heat transport capability and boundary conditions on the condenser. A total of 18 constraints are taken into account, which include operational, dimensional and structural ones. Temperature dependent fluid properties are considered and the calculations are done for steady state conditions. Several runs were performed under different values of transported heat flux and temperature at the condenser. Integral optimal characteristics were obtained.

The paper is structured as follows: In Section 2 and 3 the EO and GEO methods are described, respectively. On Section 4 the heat pipe design problem is presented, followed by the results on Section 5 and the conclusions on Section 6.

2. The Extremal Optimization Algorithm

Self-organized criticality has been used to explain the behavior of complex systems in such different areas as geology, economy and biology (Bak, 1999). The theory of SOC states that large interactive systems evolves naturally to a critical state where a single change in one of its elements generates "avalanches" that can reach any number of elements on the system. The probability distribution of the sizes "s" of these avalanches is described by a power law in the form $P(s) \sim s^{-\tau}$, where τ is a positive parameter. That is, smaller avalanches are more likely to occur than big ones, but even avalanches as big as the whole system may occur with a non-negligible probability. To show that SOC could explain features of systems like the natural evolution, Bak and Sneepen (1993) developed a simplified model of an ecosystem in which species are placed side by side on a line with periodic boundary conditions. To each species, a fitness number is assigned randomly, with uniform distribution, in the range [0,1]. The least adapted species, the one with the least fitness, is then forced to mutate, and a new random number assigned to it. The change in the fitness of the least adapted species alters the fitness landscape of their neighbors, and to cope with that new random numbers are also assigned to them, even if they are well adapted. After some iterations, the system evolves to a critical state where all species have fitness above a critical threshold. However, the dynamics of the system eventually causes a number of species to fall below the critical threshold in avalanches that can be as big as the whole system.

An optimization heuristic based on a dynamic search that embodies SOC would evolve solutions quickly, systematically mutating the worst individuals. At the same time this approach would preserve throughout the search process, the possibility of probing different regions of the design space (via avalanches), enabling the algorithm to escape local optima. Inspired by the SOC theory, the basic EO algorithm was proposed as follows (Boettcher and Percus, 2001):

1. Initialize configuration C of design variables x_i at will; set $C_{best} = C$.
2. For the current configuration C,
   a) set a fitness F_i to each variable x_i,
   b) find j satisfying $F_j \leq F_i$ for all i,
   c) choose C' in a neighborhood N(C) of C so that x_j must change,
   d) accept C = C' unconditionally,
   e) if $F(C) < F(C_{best})$ then set $C_{best} = C$.
3. Repeat step (2) as long as desired.
4. Return C_{best} and $F(C_{best})$.

The above algorithm shows good performance on problems, such as graph partitioning, where it can choose new configurations randomly among neighborhoods of C, while satisfying step 2c. But when applied to other types of problems, it can lead to a deterministic search (Boettcher and Percus, 2001). To overcome this, the algorithm was modified as follows: in step 2b the N_{var} variables x_i are ranked so that to the variable with the least fitness is assigned rank 1, and to the one with the best fitness rank N. Each time the algorithm passes through step 2c a variable is chosen to be mutated according to a probability distribution of the k ranks, given by:

$$P(k) = k^{-\tau}, \quad 1 \leq k \leq N_{var} \tag{1}$$

where τ is a positive adjustable parameter. For $\tau \to 0$, the algorithm becomes a random walk, while for $\tau \to \infty$, we have a deterministic search. The introduction of the parameter τ, allows the algorithm to choose any variable to mutate, but privileging the ones with low fitness. This implementation of the EO method received the name τ-EO algorithm (Boettcher and Percus, 2001), and showed superior performance to the standard implementation even in cases where the basic EO algorithm would not lead to local minima.

As pointed out by Boettcher and Percus (2001), "a drawback of the EO method is that a general definition of fitness for the individual variables may prove ambiguous or even impossible". What means that for each new optimization problem assessed, a new way to rank the design variables may have to be created and it may happen that for some cases this may not be possible. Moreover, to our knowledge it has been applied so far to combinatorial problems with no implementation to continuous functions. In order to make the EO method applicable to a broad class of design optimization problems, without concern to how the fitness of the design variables would be assigned, and capable to tackle either continuous, discrete or integer variables, a generalization of the EO, the GEO algorithm, was devised (Sousa and Ramos, 2002). In this new algorithm, the fitness assignment is not done directly to the design variables, but to a "population of species" that encodes the variables. Each species receives its fitness, and eventually mutates, following general rules. The GEO algorithm is described in the next Section.

3. The Generalized Extremal Optimization Algorithm

The GEO algorithm was devised using the same logic of the evolutionary model of Bak and Sneppen (1993), but applying the τ-EO approach to choose the species that will mutate. Following Bak and Sneppen (1993), L species are aligned and for each species is assigned a fitness value that will determine the species that are more prone to mutate. We can think of these species as bits that can assume the values of 0 or 1. Hence, the entire population would consist of a single binary string. The design variables of the optimization problem are encoded in this string that would be similar to a chromosome in a GA, but with each bit considered as a species or individual. To each species (bit) is assigned a fitness number that is proportional to the gain (or loss) the objective function value has in mutating (flipping) the bit. All bits are then ranked from rank 1, for the least adapted bit, to L for the best adapted. A bit is then chosen to mutate (flip) according to the probability distribution (1). This process is repeated until a given stopping criteria is reached and the best configuration of bits (the one that gives the best value for the objective function) found through the process is returned.

The practical implementation of the GEO algorithm to a function optimization problem is as follows:

1. Initialize randomly a binary string of length L that encodes N_{var} design variables of bit length l_j ($j = 1, N_{var}$). For the initial configuration C of bits, calculate the objective function value V and set $C_{best} = C$ and $V_{best} = V$.
2. For each bit i of the string, at a given iteration:
   a) flip the bit (from 0 to 1 or 1 to 0) and calculate the objective function value V_i of the string configuration C_i,
   b) set the bit fitness as $\Delta V_i = (V_i - V_{best})$. It indicates the relative gain (or loss) that one has in mutating the bit, compared to the best objective function value found so far.
   c) return the bit to its original value.
3. Rank the bits according to their fitness values, from k = 1 for the least adapted bit to k = L for the best adapted. In a minimization problem, higher values of ΔV_i will have higher ranking, and otherwise for maximization problems. If two or more bits have the same fitness, rank them randomly.
4. Choose with equal probability a candidate bit i to mutate. Generate a random number RAN with uniform distribution in the range [0,1]. If the mutating probability $P_i(k) = k^{-\tau}$ of the chosen bit is equal or greater than RAN the bit is confirmed to mutate. Otherwise, the process is repeated until a bit is confirmed to mutate.
5. For the bit i chosen to mutate set $C = C_i$ and $V = V_i$.
6. If $V < V_{best}$ ($V > V_{best}$, for a maximization problem) then set $V_{best} = V$ and $C_{best} = C$.
7. Repeat steps 2 to 6 until a given stopping criteria is reached.
8. Return C_{best} and V_{best}.

Equality and inequality constraints can be easily incorporated to the algorithm simply setting a high (for a minimization problem) or low (for a maximization problem) fitness value to the bit that, when flipped, leads the configuration to an unfeasible region of the design space. Side constraints are directly applied through the encoding of the design variables. Note that the move to an infeasible region is not prohibited, since any bit has a chance to mutate according to the P(k) distribution. Moreover, no special condition is posed for the beginning of the search process, which can even start from an infeasible region.

A slightly different implementation of the GEO algorithm can be obtained, changing the way the bits are ranked and mutated. Instead of ranking all the bits according to steps 2-3, we can rank them separately for each variable. In this way the bits of each variable will have a rank ranging from 1 to l_j. In step 4 one bit of each variable is chosen to be flipped according to the probability distribution P(k). We will call this implementation hereinafter GEO_{var}. In the following Section the design problem of the heat pipe is described.

4. Heat Pipe Design Problem Description and formulation

Heat pipes are thermal devices used to transfer high amounts of heat over long distances with a minimum temperature gradient. Its first conception date from the late-1940's, but was from the mid-1960's that it started to be developed and used in engineering applications, that now ranges from oil ducts to spacecraft (Peterson, 1994).

In its basic form, the HP is a hermetically sealed tube-type container with a porous structure placed on its internal walls and filled with a working fluid. Vapor occupies the center of the tube (vapor core) whereas liquid fills the porous structure (wick). When operating, liquid at the evaporator side of the HP evaporates, and vapor moves through the center of the tube to the condenser, where it condenses. At the same time, liquid flows through the wick from the condenser to the evaporator due to the action of capillary forces. This heat-mass transfer mechanism can transport great amounts of heat, as latent heat of vaporization, from the evaporator to the condenser with little temperature drop between the two parts. In Figure 1 a drawing of the HP concept is shown.

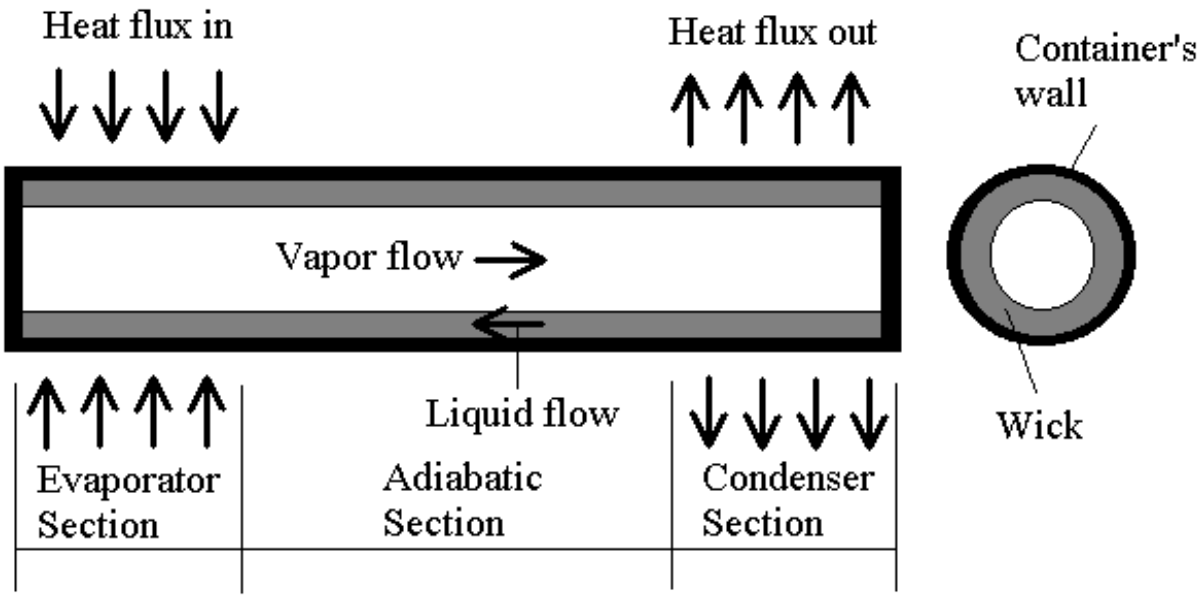

Figure 1. Conceptual drawing of a conventional heat pipe

The materials of the container's wall and wick, as well as the working fluid are chosen depending on the application for the HP and their compatibility. There exists also a variety of wick types available for usage. Altought many combinations of materials and working fluid can be used, there are only two basic types of heat pipes: The Constant Conductance Heat Pipe (CCHP) and the Variable Conductance Heat Pipe (VHCP). Details of their operating, testing and manufacture characteristics can be found elsewhere (for example, Chi, 1976; Peterson, 1994).

The use of HP in satellites date back to the 1970's. In fact, the early development of the HP was motivated by its potential use on those space platforms. Most of the HPs used in satellites are of the CCHP type, using ammonia as the working fluid and a container of Aluminium with a capillary structure formed by axial grooves on its internal wall surface. On space vehicles, HPs are used basically to conduct heat from areas of high heat dissipation to the radiators. Usually, a set of HPs are embedded on some part of the space vehicle, where one or more electronic equipment of high heat dissipation are attached. They transport and spread the heat from these "hot spots" to the radiators that reject it to space.

In any space application, one of the main concerns is to keep the total mass of the space platform as low as possible. In this paper the problem of optimizing a CCHP to be used in the thermal control subsystem of a satellite is tackled. The HP is optimized in regard to its total mass, given a desirable heat transport capability and boundary conditions on the condenser. A total of 18 constraints are taken into account, which include operational, dimensional and structural constraints. Temperature dependent fluid properties are considered and the calculations are done for steady state conditions. Several runs were performed under different values of transported heat flux and temperature at the condenser.

For this problem Stainless Steel (SS 304) is used as the material of the container since it is compatible with all the fluids used here for the analysis, that are ethanol, methanol and ammonia. The wick used is of the mesh type and also made of SS 304. Fluid properties are dependent on the operating temperature of the heat pipe, and data from Dunn and Reay (1976) was used to obtain interpolation curves that were used to calculate the fluid's properties at a given operating temperature.

The objective function to be minimized is the total mass of the HP (m_{total}). The design variables are the wick's mesh number (N), the diameter of the vapor core (d_v), the thickness of wick (t_w), the thickness of the container's wall

(t_t), the length of the evaporator section (L_e) and the length of the condenser section (L_c). The length of the adiabatic section (L_a) is dependent on the application and here was fixed equal to 0.5 m.

The constraints applicable to the HP can be divided into dimensional, operating and structural. The dimensional constraints are mainly concerned with practical aspects of manufacture and installation of the HP, such as defining feasible minimum lengths for the evaporator and condenser section. Operational constraints are posed to assure that the HP will operate properly for a given heat transport load (Q) and at a given sink temperature (T_{si}). Finally, since the HP is essentially a pressurized system, a structural constraint is applied so that the burst of the container is prevented.

The optimization problem can then be formulated as:

Minimize:

$$m_{total} = m_{cont} + m_{wd} + m_{wl} + m_{vapor} \tag{2}$$

where,

m_{cont} is the mass of the container: $m_{cont} = \pi\, t_t\, (d_i + t_t)\, L_{total}\, \rho_t$,

m_{wd} is the mass of the dry wick: $m_{wd} = \pi\, t_w\, (d_v + t_w)\, (1-\varepsilon)\, L_{total}\, \rho_w$,

m_{wl} is the mass of the liquid in the wick: $m_{wl} = \pi\, t_w\, (d_v + t_w)\, \varepsilon\, L_{total}\, \rho_l$ and

m_{vapor} is the mass of the fluid vapor inside the HP: $m_{vapor} = \dfrac{\pi\, d_v^2\, \rho_v\, L_{total}}{4}$

Subject to:

G1: $Q \le Q_c$ (3)

where Q_c is the capillar limit: $Q_c = \dfrac{P_c + P_g}{(F_l + F_v) L_{eff}}$,

$$P_c = \frac{2\sigma}{r_c}\ ;\ r_c = \frac{1}{2N}\ ;\ P_g = \rho_l\, g\, \{L_{total}\sin(\alpha) - d_v\cos(\alpha)\}\ ;\ F_l = \frac{\mu_l}{K\left(\pi\,\frac{d_i^{\,2} - d_v^2}{4}\right)\rho_l\,\lambda}\ ;$$

$$K = \frac{d^2\,\varepsilon^3}{122\,(1-\varepsilon)^2}\ ;\ \varepsilon = 1 - \frac{1.05\pi\cdot N\, d}{4}\ ;\ F_v = \frac{128\,\mu_v}{\pi\, d_v^4\, \rho_v\, \lambda}\ ;\ L_{eff} = \frac{L_e + L_c}{2} + L_a\ ;\ d_i = d_v + 2\,t_w$$

Because the HP is intended for a space application, the gravitational forces are not considered, and hence $P_g = 0.0$.

G2: $T_{somin} \le T_{so} \le T_{somax}$ (4)

where T_{so} is the temperature of the heat source measured on the external wall of the evaporator section. On a practical application T_{somin} and T_{somax} would be, for example, the limits of the operating range for an electronic equipment. For most electronic equipment used in space applications they are T_{somin} = -10.0 °C and T_{somax} = + 45.0 °C, and these are the limits used on the present problem. The temperature T_{so} can be obtained from the overall thermal balance between the evaporator section and the condenser section, in steady state conditions:

$$T_{so} = R\, Q + T_{si} \tag{5}$$

where,

$$R = R_{et} + R_{ct} + R_{ew} + R_{cw}\ ;$$

$$R_{et} = \frac{\ln\left(\frac{d_o}{d_i}\right)}{2\pi\, L_e\, k_t}\ ;\ R_{ct} = \frac{\ln\left(\frac{d_o}{d_i}\right)}{2\pi\, L_c\, k_t}\ ;\ R_{ev} = \frac{\ln\left(\frac{d_i}{d_v}\right)}{2\pi\, L_e\, k_{eq}}\ ;\ R_{ev} = \frac{\ln\left(\frac{d_i}{d_v}\right)}{2\pi\, L_c\, k_{eq}}\ ;$$

$$k_{eq} = \frac{k[(k_l + k_w) - (1-\varepsilon)(k_l - k_w)]}{[(k_l + k_w) + (1-\varepsilon)(k_l - k_w)]}$$

$$G3: Q \le Q_b \tag{6}$$

where Q_b is the boiling limit: $$Q_b = \frac{2\pi L_e k_{eq} T_v}{\lambda \rho_v \ln\left(\frac{d_i}{d_v}\right)}\left(\frac{2\sigma}{r_n} - P_c\right)$$

$$G4: Q \le Q_e \tag{7}$$

where Q_e is the entrainment limit: $$Q_e = \frac{\pi d_v^2}{4}\lambda\left(\frac{\sigma \rho_v}{2 r_{h,s}}\right)^{0.5}$$

$$r_{h,s} = \frac{1}{2N} - \frac{d}{2}$$

$$G5: Q \le Q_v \tag{8}$$

where Q_v is the viscous limit: $$Q_v = \frac{\pi d_v^4 \rho_v \lambda P_v}{256 \mu_v L_{eff}}$$

$$G6: M_v \le 0.2\ , \tag{9}$$

where M_v is the Mach number limit: $$M_v = \frac{8Q}{\pi d_v^3 \lambda \sqrt{\gamma_v R_v T_v}}$$

$$G7: Re_v \le 2300, \tag{10}$$

where Re_r is the Reynolds number limit: $$Re_v = \frac{4Q}{\pi d_v \mu_v \lambda}$$

Constraints G6 and G7 were put in to assure a laminar incompressible flow inside the vapor core.

$$G8: 0.0001 \le \varepsilon \le 0.9999 \tag{11}$$

$$G9: 2d \le t_w \tag{12}$$

$$G10: 314 \le N \le 15000 \tag{13}$$

$$G11: 0.025\cdot10^{-3} \le d \le 1.0\cdot10^{-3} \tag{14}$$

$$G12: 5.0\cdot10^{-3} \le d_v \le 80.0\cdot10^{-3} \tag{15}$$

$$G13: 0.05\cdot10^{-3} \le t_w \le 10.0\cdot10^{-3} \tag{16}$$

$$G14: 50.0\cdot10^{-3} \le L_e \le 400.0\cdot10^{-3} \tag{17}$$

$$G15: 50.0\cdot10^{-3} \le L_c \le 400.0\cdot10^{-3} \tag{18}$$

$$G16: 0.3\cdot10^{-3} \le t_t \le 3.0\cdot10^{-3} \tag{19}$$

$$G17: \frac{\Delta P\left(d_o^2 + d_i^2\right)}{d_o^2 - d_i^2} \le \frac{u_{ts}}{4} \tag{20}$$

where $\Delta P = P_v - P_{amb}$

Since the HP will be operating in vacuum $P_{amb} = 0.0$.

$$G18: \frac{\Delta P\left(d_o^3 + 2 d_i^3\right)}{2\left(d_o^3 - d_i^3\right)} \le \frac{u_{ts}}{4} \tag{21}$$

The above 18 constraints take into account operational (G1 to G7), dimensional (G8 to G16) and structural (G17 and G18) limits to the HP being optimized here. All operational constraints, but G2, are posed to assure the proper functioning of the HP. G2 was posed so that the temperature on the heat source would be kept inside a given desired range, what is the primary objective of any satellite thermal control system. The dimensional limits assure that the HP can be physically constructed and mounted, while also restrict the search for the optimal values of the design variables to practical ranges. Finally, the structural constraints prevent designs that would lead to a burst of the tube. In the next section the results of the optimization are presented and analyzed.

5. Results

In this paper, we are optimizing the heat pipe for a desired heat transport, given a constant temperature at the outside surface of the condenser section T_{si}. In a practical application, this would be the temperature of the radiator that is rejecting the heat to space, and it would depend also on the external heat loads incident on the radiator, its area and thermal optical properties. Because the present analysis is focused on the HP and intended mainly to show the features of the GEO method, these external factors are translated into a range of constant temperatures at the condenser section. It goes from –15.0 ^{o}C to +30.0 ^{o}C with steps of 15.0 ^{o}C. Three working fluids were used: Ethanol, methanol and ammonia, and the heat transport range under analysis is from 25.0 W to 100.0 W.

The first decision to be made on the utilization of GEO is the number of bits used to each design variable. This would depend on the precision one desires for each variable. For the present problem, the design parameter that required the bigger number of bits to encode its value within the desired precision was L_c. It required 14 bits and, for the sake of simplicity and considering that the computational cost of estimating the objective function was small, that was the number also used for the other design variables.

Since the performance of the GEO algorithm is dependent on the parameter τ, we first made a study to determine its best value for the HP problem. We set T_{si} = 0.0 ^{o}C and Q = 25.0 W and run GEO and GEO_{var} for 10^5 function evaluations. Fifty independent runs were made for each algorithm. The initialization of the string of bits at each run was done randomly. The parameter τ was varied in the range 0.25 to 3.00, in steps of 0.25, and the results are shown in Figures 2 and 3.

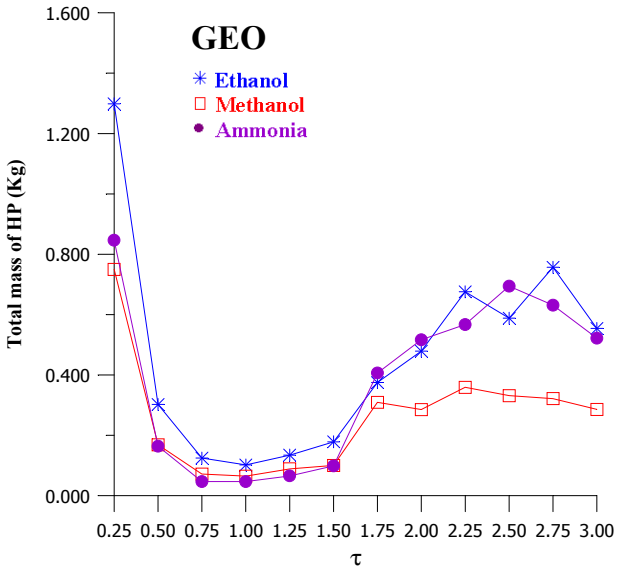

Figure 2. Minimum total mass of HP after 10^5 function evaluations as a function of τ for GEO. Average of 50 idependent runs.

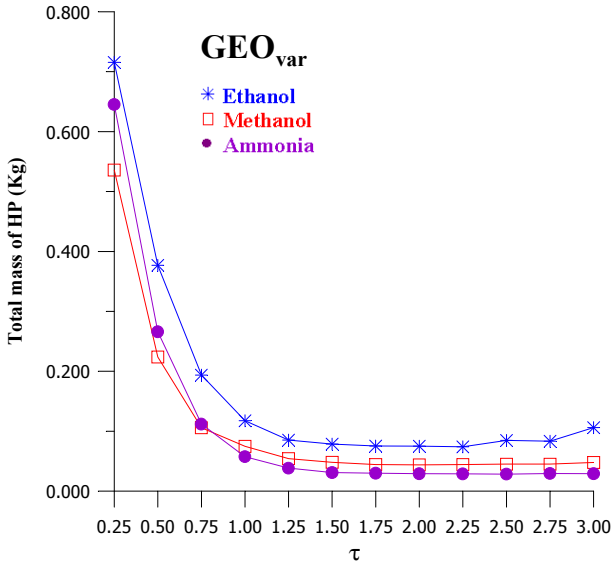

Figure 3. Minimum total mass of HP after 10^5 function evaluations as a function of τ for GEO_{var}. Average of 50 idependent runs.

From Figures 1 and 2 it can be seen that the best value of τ for GEO and GEO_{var} lies in the ranges 0.75-1.25 and 1.75-2.25, respectively, considering all working fluids. That is, the best results are obtained with a smaller value of τ for GEO than for GEO_{var}. It was also observed that GEO_{var} was more efficient than the GEO on the search for the optimum. That is, it converged on average faster to the better results than GEO. These characteristics were also observed in the test functions results (Sousa and Ramos, 2002). It interesting to note also that the range for the search of the best τ used for the HP problem was the same used for the test functions. In this relatively narrow range the best values of τ for all test functions and the HP problem were found, either for the GEO or GEO_{var}. This may indicate a very interesting general characteristic of the algorithm, that is to have the ideal τ to a broad class of problems confined to a relatively narrow range, what pretty much facilitates the processing of finding its best value for a specific design problem.

For the problem being dealt here, we decided to use τ = 1.0 and τ = 2.0 for GEO and GEO_{var}, respectively, on all subsequent runs for the search of the optimal HP design. On these, the stopping criteria used to halt the search for the

optimal was when the number of function evaluations (NFE) reached 10^6. This number was defined from observation, for the same boundary conditions used to find the "optimal" τ, that the average value of m_{total} had apparently converged close to a global minimum after that NFE. This was particularly true for the methanol and ammonia. In Figure 4, the variation of m_{total} as a function of NFE is shown for the three working fluids.

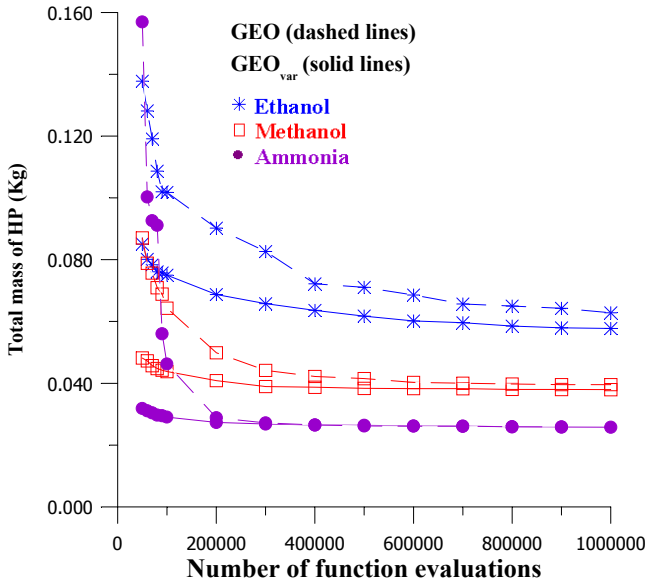

Figure 4. Minimum total HP mass as a function of NFE. Average of 50 idependent runs.

From Figure 4, it can be seen that GEO_{var} is more efficient than the GEO on the search for the optimum design, for the HP problem. Hence, it was used to obtain the results for the different combinations of heat transport and T_{si} shown on Figures 5 to 8 below. On these Figures are plotted the variation of m_{total} as a function of Q, for a given T_{si}. The curves for the three working fluids are represented in each graph as solid (for the minimum value of m_{total} found out of 50 runs) and dashed lines (for the average minimum value of m_{total} found in 50 runs).

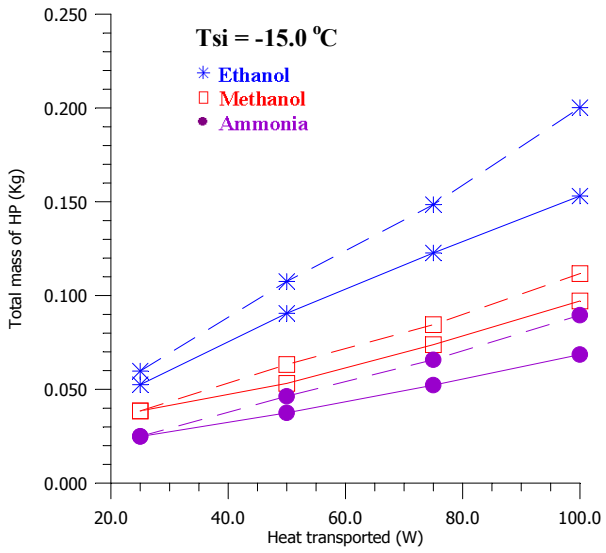

Figure 5. Total mass of HP as a function of Q, for T_{si} = -15.0 °C.

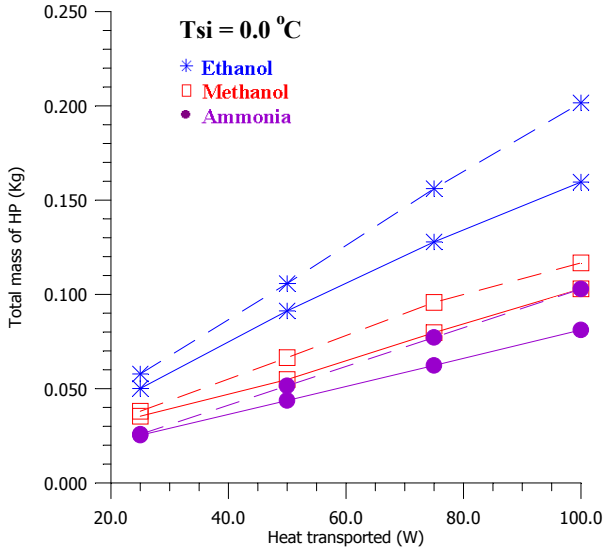

Figure 6. Total mass of HP as a function of Q, for T_{si} = 0.0 °C.

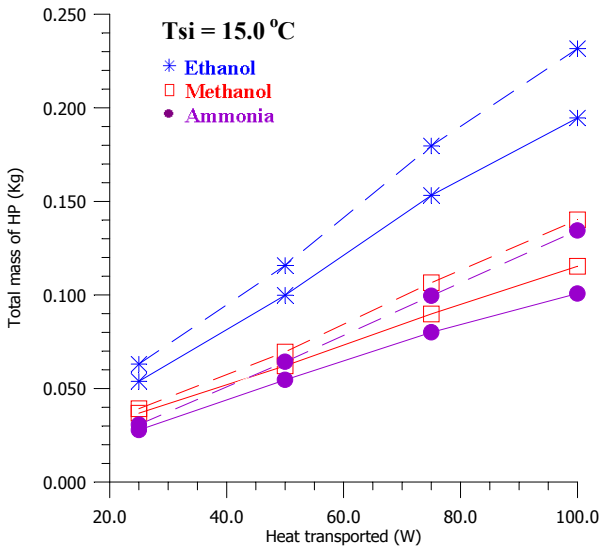

Figure 7. Total mass of HP as a function of Q, for T_{si} = 15.0 °C.

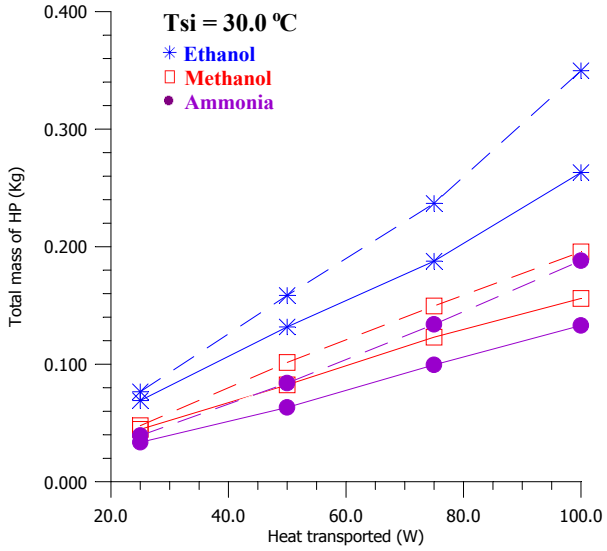

Figure 8. Total mass of HP as a function of Q, for T_{si} = 30.0 °C.

From Figures 5 to 8, it can be seen that, as expected, m_{total} increases as Q increases. A higher T_{si} will also lead to a heavier HP, but with a lesser influence than Q. It can also be observed that the use o methanol does not led to a much heavier HP than when using ammonia, even on high heat loads. This is an interesting result since ammonia is a dangerous and difficult fluid to handle and an alternative slightly heavier but safer, and probably cheaper, would be more advantageous to use.

Another interesting result, is that the gap between the absolute and average minimum found on the 50 runs, done for each case, increases as Q increases, with the results for ethanol having the bigger gap. This means that, as the heat load is increased, an increase in the NFE may be necessary to increase the probability of have finding the global minimum at the end of the search.

On Table 1 the values for the design variables correspondent to the maximum and minimum values found for m_{total} in the operational condition of Q = 25.0 W and T_{si} = 0.0 °C are shown. In Table 2 the range of minimum to maximum values of the design variables found on the 50 runs are shown.

Table 1. Value of the design variables for the minimum and maximum value of m_{total} found in 50 runs for the operational condition: Tsi = 0.0 °C and Q = 50.0 W.

		m_{total}	N	d 10^{-3}	d_v 10^{-3}	t_w 10^{-3}	L_e 10^{-3}	L_c 10^{-3}	t_t 10^{-3}
Ethanol	min	0.050	317	0.025	9.7	0.22	50.0	50.0	0.3
	max	0.070	345	0.025	12.1	0.21	50.1	50.2	0.3
Methanol	min	0.035	315	0.025	6.4	0.21	71.9	50.3	0.3
	max	0.039	320	0.025	7.4	0.21	50.0	51.3	0.3
Ammonia	min	0.025	316	0.025	5.0	0.08	50.7	51.1	0.3
	max	0.027	314	0.025	5.0	0.09	93.7	50.0	0.3

Table 2. Range of variation on the values of the design variables for 50 runs on the operational condition: T_{si} = 0.0 °C and Q = 50.0 W.

		m_{total}	N	d 10^{-3}	d_v 10^{-3}	t_w 10^{-3}	L_e 10^{-3}	L_c 10^{-3}	t_t 10^{-3}
Ethanol	range	0.050-0.070	314-375	0.025-0.125	7.3-12.5	0.21-0.41	50.0-225.0	50.0-168.8	0.3-0.3
Methanol	range	0.035-0.039	314-432	0.025-0.048	6.4-7.4	0.17-0.21	50.0-93.8	50.0-57.4	0.3-0.3
Ammonia	range	0.025-0.027	314-343	0.025-0.033	5.0-5.3	0.08-0.09	50.0-72.2	50.0-65.7	0.3-0.3

It can be seen from Table 1 that the parameters that most influence the final weight of the HP are d_v and t_w, which make up the internal diameter d_i. This is clearly seen from the data for ammonia, where there is a great difference between the minimum and maximum L_e, which does not reflect on m_{total}. Moreover, it can be seen that most of the design variables for the three fluids, but d_v and t_w, have the same value. In fact, the bigger part of the weight of the HP is due to the weight of the container, which in turn is more affected by increments in d_i than any other variable. It is interesting to note that the values of N, d and t_t were kept equal or very close to the minimum allowable by its constraints. Low values for N and d allowed ε reach a very high value (0.99) that is greater than the technological feasibility for mesh type wicks. It must also be noted that, in a further development of this work, the expression for the permeability K, used in the G1 constraint, should be reviewed for adequacy with porosity values closed to unity. The relation for K used in this paper was elaborated by Marcus (1972) by the modification of the Schmidt's expansion

(1966) of the Blake-Kozeny equation, initially developed for randomly packed sphere beds (Bird et al, 1960), that was based on Kozeny's theory, developed in the 1930's. As was point out by Ivanovsii et al (1982), the Kozeny's theory is good for small values of the porosity but "… for large porosities it is necessary to take into account of the statistic nature of the distribution of the components of the porous material" (Ivanovskii et al, 1982).

Finally, in Table 2 the range of variation of the objective function and the design variables, for the 50 runs, are shown. Confirming the results from Table 1, it can be seen that great variations on L_e and L_c, does not lead to great variations in m_{total}, as is clear from the ammonia results. From the range of variation of N and d, it can be calculated that ε would range from 0.955 to 0.994, which is a range more appropriate to felt or foam wicks (Faghri, 1995).

6. Conclusions

In this paper the Generalized Extremal Optimization algorithm was presented and an application to a heat pipe optimization problem shown. Inspired by the theory of Self-Organized Criticality, it is an stochastic algorithm devised to tackle complex design optimization problems that presents such features as nonconvex design domains or presence of different kinds of design variables. Had been already applied to a set of test functions, it showed to be competitive to the GA (Sousa and Ramos, 2002). On the present work, it was seen that some general characteristics of the GEO method observed for the test functions also showed up in the heat pipe optimal design problem, such as: i) the best value of τ could be found within the same relatively narrow range for the functions and the HP problem, ii) the best value of τ for a given problem is bigger for GEO_{var} than for GEO and, iii) GEO seems to be less efficient than GEO_{var} on the search for the optimum. The first characteristic may indicate that the range where to search for the best τ (from 0.25 to 3.0) may be the same for a broad class of problems. Having only one free parameter to adjust, that may vary within a narrow range for many problems, gives the GEO method an "a priori" advantage over other popular stochastic algorithms, since the time spent on fine tuning the algorithm to its best performance, would be greatly reduced.

Applied to a real problem, the GEO method showed to be a valuable design tool. It was easily implemented to a highly constrained problem with non-linear interactions between the design variables and was capable to portrait many of its features, such as to identify the more relevant design variables to the problem. One important conclusion of the analysis done here for the HP, is that the difference in weight from a HP system filled with methanol compared with one filled with ammonia may not be so great for a given application. Hence, considering the safety and operational problems of manipulating ammonia, sometimes it would be preferable to use methanol instead. In a sequence of the present work, the type of wick, the HP material and working fluid are intended to be incorporated also as design variables. The algorithm would then, for a given application, search automatically not only for the optimal dimensions of the HP, but also for the best combination of wick, materials and working fluid.

7. Acknowledgements

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