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A new approach to designing reduced scale thermal-hydraulic experiments

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Abstract

Reduced scale experiments are often employed in engineering because they are much cheaper than real scale testing. Unfortunately, though, it is difficult to design a thermal-hydraulic circuit or equipment in reduced scale capable of reproducing, both accurately and simultaneously, all the physical phenomena that occur in real scale and operating conditions. This paper presents a methodology to designing thermal-hydraulic experiments in reduced scale based on setting up a constrained optimization problem that is solved using genetic algorithms (GAs). In order to demonstrate the application of the methodology proposed, we performed some investigations in the design of a heater aimed to simulate the transport of heat and momentum in the core of a pressurized water reactor (PWR) at 100% of nominal power and non-accident operating conditions. The results obtained show that the proposed methodology is a promising approach for designing reduced scale experiments.

1. Introduction

Reduced scale experiments for simulating and understanding physical phenomena are often used in engineering wherever there is an interest in designing industrial installations that require expensive investment. Reduced scale experiments are usually much cheaper than real scale testing, but must be suitable to simulate the basic physical phenomena that occur in real scale. Indeed, reduced scale tests must de designed in such a way that the results obtained in the experiments can be used confidently in the development of the real scale installation.

Unfortunately, though, it is difficult to design a thermal-hydraulic circuit or equipment in reduced scale capable of reproducing, both accurately and simultaneously, all the physical phenomena that occur in real scale and operating conditions. Absolute similarity is only possible on a one-to-one scale facility, whilst keeping the same operation conditions of the original system (Ishii and Kataoka, 1984). Therefore, the design of a reduced scale circuit (or test section) must attempt to find the best combination of design parameters (sizes, operating conditions, etc.) capable of simulating the most relevant physical phenomena of the problem in study, whilst respecting practical constraints such as keeping a low cost. Indeed, the problem of designing an experimental test section can be regarded as an optimization problem, subjected to practical constraints, where the designer attempts to find the best compromise solution.

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This paper presents a methodology to designing thermal-hydraulic experiments in reduced scale. The problem is formulated as an optimization task subjected to constraints. The good performance we obtained using genetic algorithms (Holland, 1975) in other optimization problems (Lapa et al., 2000a, 2002; Pereira et al., 1999) led us to apply GA also in this case.

The approach proposed here can be divided into the following steps:

1. Set up the physical model suitable for the problem in study.
2. Obtain the non-dimensional equations and relevant non-dimensional groups from the physical model and operating conditions.
3. Set up the minimization problem with constraints: design a test section attempting to keep the relevant non-dimensional groups of the original problem whilst constrained by cost and constructive restrictions.
4. Apply genetic algorithms (GAs) to solve the constrained optimization problem.
5. Use specialist knowledge to review and criticize the solution found, returning to step 3 if required.

The various steps that comprise the methodology proposed in this work are presented in the following sections. A simple, and yet representative, reduced scale design problem is used to demonstrate the application of the approach proposed here.

2. Physical modeling

As an example of application of the methodology proposed, we performed some investigations in the design of a heater aimed to simulate the transport of heat and momentum in the core of a pressurized water reactor (PWR) at 100% nominal power and non-accident operating conditions.

The physical model considered is represented by the incompressible Navier–Stokes equations, including buoyancy forces, and the convection–diffusion equation of energy. The equations are three-dimensional, instantaneous, and use a first-order (linear) Taylor series to approximate the thermal variation of the transport properties of viscosity and thermal conductivity. Note that the model is valid for both laminar and turbulent flows, whilst the incompressibility approximation is valid for Mach numbers below 0.3, which is clearly the case for the problem at hand.

The incompressible Navier–Stokes and convection–diffusion energy equations are written in non-dimensional form as

$$\nabla^* \cdot \boldsymbol{u}^* = 0 \tag{1}$$

$$\frac{\partial \boldsymbol{u}^*}{\partial t^*} + \boldsymbol{u}^* \cdot \nabla^* \boldsymbol{u}^* + \nabla^* p^* - \frac{1}{Re}\nabla^* \cdot (\nabla^* \boldsymbol{u}^*) + \frac{Bo}{Re}\nabla^* \cdot [T^*(\nabla^* \boldsymbol{u}^*) + (\nabla^* \boldsymbol{u}^*)^{\mathrm{T}}] - \frac{Gr}{Re^2} g^* T^* = 0 \tag{2}$$

$$\frac{\partial T^*}{\partial t^*} + \boldsymbol{u}^* \cdot \nabla^* T^* - \frac{1}{Re\,Pr}\nabla^* \cdot (\nabla^* T^*) - \frac{La}{Re\,Pr}\nabla^* \cdot (T^* \nabla^* T^*) = 0 \tag{3}$$

where $\boldsymbol{u}^*$, p^* and T^* denote non-dimensional velocity, pressure and temperature fields, respectively, and the following non-dimensional numbers have been introduced:

$$Re = \frac{\rho_0 u_0 D_{\mathrm{h}}}{\mu_0} \quad \text{(Reynolds)} \tag{4}$$

$$Gr = \frac{\rho_0^2 ||\boldsymbol{g}|| \beta\, \Delta T D_{\mathrm{h}}^3}{\mu_0^2} \quad \text{(Grashof)} \tag{5}$$

$$Pr = \frac{\mu_0 c_{\mathrm{p}}}{\kappa_0} \quad \text{(Prandtl)} \tag{6}$$

$$Bo = -\frac{\Delta T}{\mu_0}\left(\frac{\partial \mu}{\partial T}\right)_{T_0} \quad \text{(viscosity thermal variation number)} \tag{7}$$

$$La = \frac{\Delta T}{\kappa_0}\left(\frac{\partial \kappa}{\partial T}\right)_{T_0} \quad \text{(conductivity thermal variation number)} \tag{8}$$

The relationship between the dimensional and the non-dimensional variables is $\boldsymbol{u} = u_0 \boldsymbol{u}^*$, $T = T_0 + T^* \Delta T$, $\boldsymbol{g} = ||\boldsymbol{g}|| \boldsymbol{g}^*$, $\boldsymbol{x} = D_{\mathrm{h}} \boldsymbol{x}^*$ and $t = D_{\mathrm{h}}/u_0 t^*$, where $\boldsymbol{u}$ is velocity, p is pressure and T is temperature. The gravity acceleration is $\boldsymbol{g}$. Density, viscosity, thermal conductivity and the volumetric expansion coefficient are represented by ρ, μ, κ and β, respectively. The specific heat at constant pressure is c_p. The viscosity and thermal conductivity at temperature T_0 are denoted by μ_0 and κ_0, respectively. The reference scale used for non-dimensionalizing length is the wetted diameter D_h. The reference scale used for non-dimensionalizing temperature is ΔT.

In the methodology proposed we do not have to solve the equations that define the physical model. Thus, solvability of the governing equations is not a concern and we do not need to bother to simplify the model in order to render it amenable to solution procedures, either analytical or numerical. Rather, we are free to define the model as complete and general as the application demands.

3. Test section optimization

The design of a thermal-hydraulic test section is formulated as a constrained optimization problem. The objective is to adjust a set of parameters (operating pressure, temperatures, test section sizes, fuel pin diameters, etc.) in the reduced scale design, in such a way that the non-dimensional numbers in the experiment approximate the non-dimensional numbers of the real scale problem.

3.1. The objective function

The objective function measures the distance between a trial test section design and the real scale problem, in the light of the non-dimensional numbers that arise from the physical model. It is convenient to introduce weights in the definition of the objective function in order to be able to indicate which numbers should be prioritized in the optimization of the test section design. Here we use the following objective function,

$$s=\sum_{i=1}^{N_g} w_i(G_i-\bar{G}_i)^2, \quad \text{where} \sum_{i=1}^{N_g} w_i=1 \tag{9}$$

where N_g is the number of non-dimensional groups considered for approximation, $\bar{G}_i$ is the aimed value for the non-dimensional group "i" and G_i is the value for the non-dimensional group "i" corresponding to a given trial design. The value of the G_i parameters depend on the choice of the design parameters, where restrictions are incorporated from the start through ranges of admissible design parameter values. Therefore, practical constraints are not introduced in the objective function itself, but on the definition of the space of admissible solutions. The relative importance of each non-dimensional group is defined by the corresponding normalized weights w_i.

The objective of the optimization problem is to minimize the distance between the test section design and the real scale problem, the function s given by Eq. (9), over the space of admissible design solutions.

3.2. Genetic algorithms

Genetic algorithms (GAs) are powerful optimization techniques inspired on the natural selection principles and Darwin's species evolution theory (Darwin, 1859). Because of their robustness and easy customization for different kinds of optimization problems, GAs have been successfully used in a wide range of engineering applications. These include important complex problems found in the nuclear engineering field, such as: core reloading (Chapot et al., 1999), maintenance scheduling optimization (Lapa et al., 2000a,b), surveillance tests planing (Lapa et al., 2002), diagnosis systems design (Pereira and Schirru, 2000), and nuclear reactor design (Pereira et al., 1999; Pereira and Lapa, 2003), among others. The non-linearity and multi-modality inherent to the optimization of a reduced scale test section design are characteristics that render GA an attractive technique for the job.

The GAs manipulate populations of symbolic structures, evolving them to their best adaptation. In other words, they adapt populations of solution candidates to the objectives and constraints of the optimization problem. These solution candidates are encoded into symbolic structures, metaphorically called genotypes (or chromosomes) that carry intrinsic characteristics of the symbolic individual. Such characteristics dictate the adaptability (or fitness) of the individual to the environment (associated to the objective function), in which it may survive or perish. The selection and evolution are made in such a way that stronger (more fit) individuals have better chances to be selected, transferring their characteristics to their offspring (new solution candidates). Then, from generation to generation, the average fitness of the individuals increase, leading the population to its optimum adaptation.

The main advantage of GAs over traditional methods is that they provide a global scanning of the search space, requiring no prior knowledge about it. Genetic algorithms start the adaptation process from a randomly generated population of individuals. Then, the fitness is assigned to each individual, defining its adaptability, and finally, natural selection, crossover and mutation are simulated. The selection probability of a given individual is related to its fitness. In the canonical GA, a binary fixed length string represents the genotype. Crossover is performed by exchanging parts of the strings (sub-strings) between two parents. Mutation is simulated by the inversion of one of the bits of the genotype according to a given mutation probability. By selection, crossover and mutation, the population becomes more adapted, generally concentrating in a near-optimum region. Modeling an optimization problem by a GA consists of defining both the fitness function that determines how fit a solution candidate is, and the data structure (or genotype) that encodes the solution candidates.

3.3. Fitness function and genotype structure

In order to minimize the function s given by Eq. (9) we define the following fitness function:

$$f = -s = -\sum_{i=1}^{N_g} w_i (G_i - \bar{G}_i)^2, \quad \text{where} \sum_{i=1}^{N_g} w_i = 1 \qquad (10)$$

Note that the fitness of a candidate design increases as its distance to the real scale problem diminishes. The proposed optimization problem consists in searching for combination of variables (operating pressure, test section sizes, etc.) that lead to the maximum value of the fitness f in Eq. (10). The problem variables are the physical dimensions of the heater (test section representative of Angra I power plant reactor core) and operational conditions that affect the non-dimensional groups identified through the physical model. The genetic modeling is performed using a traditional binary discretization of the problem variables. The genotype, as illustrated in Fig. 1, comprises N genes, where each gene encodes, in a binary form, a particular parameter in the search space.

The genotype (Fig. 1) comprises N genes, where each gene is related to a particular parameter in the search space. The binary discretization of these variables is chosen fine enough not to undermine the accuracy of results.

4. Results

In this section we present results of the application of the proposed methodology in three distinct case studies. Initially, in order to check the consistency of the method, we consider a problem where the GA searches for the design of a heater with the same non-dimensional numbers verified for the Angra I nuclear reactor core. Here the GA is allowed to search for the design parameters in large ranges that contain the trivial similarity solution, i.e. the one-to-one scale solution. Thus, although the GA is allowed to try an enormous number of candidate solutions, it must converge to the trivial solution, as the one-to-one design is contained in the search space of this consistency

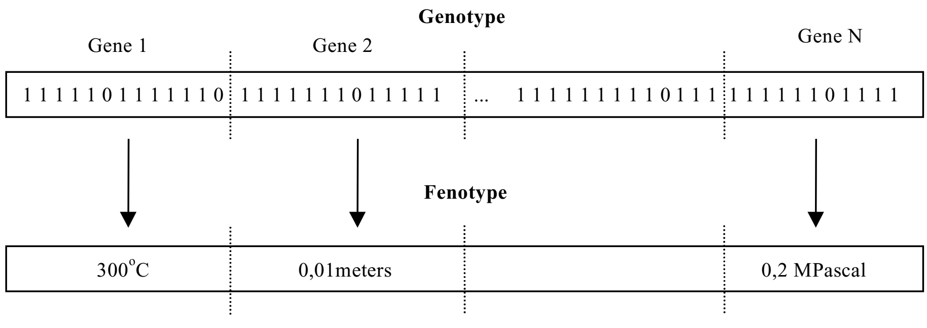

Fig. 1. Example of the proposed genotype and its corresponding phenotype decoding.

check. In the second example we apply the proposed method to designing a modest test section with dimensions and operating conditions close to those of the Instituto de Engenharia Nuclear (IEN) experimental circuit installed, at low cost, a few years ago. The experimental section proposed in this case was designed to simulate forced convection flows. This is a very severe test to the method, as the resulting reduced scale model will be very constrained in both size and operational conditions. Most importantly, we intended to check how similar a design could be achieved in such constrained conditions. Our final investigation involved designing a reduced scale experiment to simulate mixed convection flows. This is a more difficult case than the former forced convection problem, for we have to approximate simultaneously both the Reynolds and Grashof non-dimensional numbers that characterize the prototype.

In all cases presented in this paper we consider designing experimental test sections suitable to simulate heat and momentum transfer in a PWR reactor core. The Brazilian Angra I reactor (630 MWe) was taken as our prototype. The relevant parameters for the study (physical properties and operating conditions) are listed in Table 1.

Using the geometric data and physical properties identified in Table 1, we can write the following derived data: the reference velocity $u_0 = W/(\rho_0 A)$ and the temperature rise $\Delta T = Q/(Wc_p)$. It is also convenient to introduce the definition of heated and wetted diameters, given respectively by $D_q = 4A/\Gamma_q$ and $D_h = 4A/\Gamma_h$. Note that the non-dimensional groups presented in Section 3 concern only the conservation equations and do not account for boundary conditions and geometrical aspects. Thus, we also have to introduce new groups that define aspect ratios. These must be included in the list of non-dimensional groups we want to keep similar in our test section design. Therefore we introduce here the ratio between the heated and the wetted diameters $r_1 = D_q/D_h$ and the ratio between the wetted diameter and the active height $r_2 = D_h/L$.

Table 1
Relevant parameters for thermal-hydraulic analysis

Parameter	Meaning
W	Total mass flow rate
Q	Total heat generation rate
L	Active height of the fuel pins
Γ_h	Wetted perimeter
Γ_q	Heated perimeter
A	Total cross section for flow passage
T_0	Inlet temperature
ρ_0	Inlet density
P_0	System pressure
μ_0	Inlet viscosity
κ_0	Inlet thermal conductivity
c_p	Specific heat at constant pressure

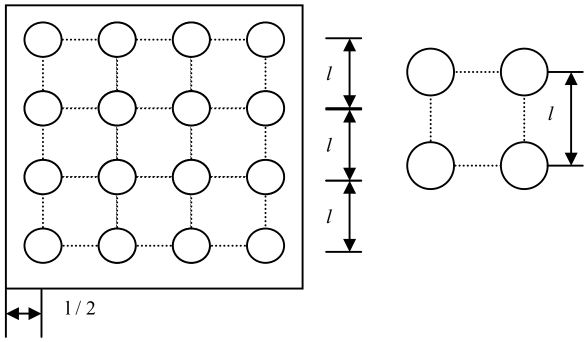

Fig. 2. Transversal view of the square arrangement with nine complete channels.

The shape of heater considered in this study is depicted in Fig. 2. Note that the square shape geometry of the heater proposed for the experiments is not the same used in the Angra I reactor core. Referring to Fig. 2, let N be the number of full (complete) channels. Then, the total number of fuel pins (or electrical heating pins in the experimental prototype) is $N_v = (N+1)^2$ and the total number of channels, including the incomplete channels, is $N_c = (N+1)^2$. Fig. 2 shows an example of test section containing nine complete channels $N = 3$.

Considering this arrangement (square structure), the relevant geometrical data are: $A_c = l^2 - (\pi d^2/4)$ (the channel cross section for flow passage), $A = (N+1)^2 A_c$ (the total cross section for flow passage), $\Gamma_h = 4(N+1)l + (N+1)^2\pi d$ (wetted perimeter) and $\Gamma_q = (N+1)^2\pi d$ (heated perimeter).

Considering the model presented, the search parameters are: the total mass flow rate (W), the total heat generation rate (Q), the active height of the fuel pins (L), the total cross section for flow passage (A), the inlet temperature (T_0), the system pressure (p_0), the fuel pin diameter (d), the pitch (l).

Table 2
Parameters and search limits adopted in first case

	Range of search	Number of bits utilized
d: fuel pin diameter	0.005–0.04 m	9
l: pitch	$d + 0.0005$ to $d + 0.05$ m	9
N_v: number of thermal resists	1–256	8
Q_v: power of one thermal pin	20,000–110,000 W	15
P_0: operation pressure	0.1–17 MPa	12
T_0: inlet temperature	25 °C to T_{sat} (pressure)	8
W: inlet flow	4,000–15,000 kg/s	13
L: active height of the pins	0.2–5.5 m	9

The first case presented (case 1) is the consistency test. The GA looks for parameter values that approximate Angra I non-dimensional numbers. Table 2 presents in its first column the search parameters. In the second column the range chosen for each variable is shown. In the third column we present the number of bits used for each variable. Note that the number of bits defines the resolution adopted for each parameter.

Many simulations, involving different random seeds, were performed. In all cases the GA obtained dimensions and operation conditions very close to the Angra I real design. Note that the trivial similarity solution, i.e. the one-to-one scale solution, exists only in *continuum* space. However, the GA searches in a discretized space and this partially accounts for the small differences observed. Nonetheless, the GA was able to find, in each experiment, near optimal similarity solutions. Among the various solutions obtained by GA, we present in Table 3 three of the solutions found, comparing them with Angra I dimensions and operating conditions.

In the second case study, the GA designed a reduced scale test section (when compared to other experimental circuits, such as APEX) to simulate the phenomena, which occurs in a forced convection situation based on the Angra I reactor core.

Note that the cost constraint is not included in the fitness expression defined by Eq. (9). However, the cost is an important restriction that is included in the space of admissible design solutions through the bounds imposed on design parameter ranges. The definition of ranges for pressure and test section size, for instance, indirectly constrains the cost of the reduced scale experiment. Table 4 shows the ranges of the optimization parameters and the number of bits used in problem discretization.

We may observe that the *La* number represents the variation of the coolant thermal conductivity as a function of the temperature, with first-order (linear) approximation. At high pressure conditions (as found in PWRs) the direction of the temperature changes differs from the one observed at atmospheric pressure. Hence, it is not possible to simulate, at low pressures, the water thermal conductivity behavior at high pres-

Table 3
Results obtained by GA, the Angra I dimensions and operations conditions

	Angra I	Simulation 1	Simulation 2	Simulation 3
d: fuel pin diameter (cm)	0.95	0.9705	0.9605	0.9527
l: pitch (cm)	1.232	1.245	1.241	1.237
N_v: number of thermal pins	169	166	166	167
Q_v: power of one pin (W)	6,4251	60,980	67,223	63,451
P_0: operation pressure (MPa)	15.5	15.2	15.2	15.3
T_0: inlet temperature (°C)	292	292	292	292
W: inlet flow (kg/s)	8,556	8,718	8,719	8,603
L: active height of the pins (m)	3.66	3.68	3.68	3.67
Reynolds number	427,344.9	429,452.1	429,501.3	428,212.8
Grashof number	1.1339E+08	1.1501E+08	1.1501E+08	1.1458E+08
Prandtl number	0.82946	0.82866	0.82866	0.82892
Bo number	0.2516	0.2504	0.2504	0.2508
La number	−0.1646	−0.1620	−0.1620	−0.1629
*R*1 number	1.0098	1.0098	1.0098	1.0098
*R*2 number	2.9336E−03	2.9487E−03	2.9487E−03	2.9392E−03

Table 4
Parameter ranges for the second case study

	Range of search	Number of bits utilized
d: fuel pin diameter	0.008–0.04 m	9
l: pitch	$d + 0.001$ to $d + 0.05$ m	9
N_v: number of thermal pins	1–16	4
Q_v: power of one pin	1–512 W	9
P_0: operation pressure	0.1–0.2 MPa	8
T_0: inlet temperature	25 °C to T_{sat} (pressure)	8
W: inlet flow	1–11 kg/s	10
L: active height of the pins	0.4–1.5 m	8

Table 5
Comparison between the Angra I parameters and non-dimensional numbers and those obtained by the GA in second case study

	Angra I	GA (second case)
d: fuel pin diameter (cm)	0.950	0.962
l: pitch (cm)	1.232	1.062
N_v: number of thermal pins	169	2
Q_v: power of one pin (W)	64,251	89
P_0: operation pressure (MPa)	15.5	0.2
T_0: inlet temperature (°C)	292	106.45
W: inlet flow (kg/s)	8,556	11
L: active height of the pins (m)	3.66	1.2325
Reynolds number	427,344.9	416,886.9
Grashof number	1.1339E+08	–
Prandtl number	0.82946	1.641
Bo number	0.2516	0.1383
La number	−0.1646	–
*R*1 number	1.0098	1.4684
*R*2 number	2.9336E−03	2.9335E−03

sures. For these reasons, setting *La* number weights to zero will not influence the optimization objectives.

On the other hand, in the Grashof and Reynold non-dimensional groups, the relation Gr/Re^2 has fundamental importance in defining the flow pattern to be studied. If such relation is close to unity, it is a mixed (forced/natural) flow. If it is much less than 1, a forced flow is characterized. Instead, when Gr/Re^2 is very large, density variations in the fluid promote resultant components more relevant than the inertia of the flow, increasing the importance of Grashof number for this analysis. Such concepts were applied to the simulations made in this research, modifying the relative importance of the non-dimensional numbers Grashof and Reynolds, according to their relation. Table 5 presents the results obtained by the GA considering this premise and with search ranges defined in Table 4. Note that at 100% of power, in normal operation, the flow in Angra I core is typically forced, hence, in a design aimed to reproduce similar behavior, the Grashof number is an irrelevant parameter.

The results obtained by the GA (Table 5) show that the values found for Reynold and *R*2 numbers are very close to the standard values from Angra I. For the

Table 6
Comparison between the Angra I parameters and those obtained by the GA in case study 3

	Angra I	GA1	GA2	GA3	GA4
d: fuel pin diameter (cm)	0.950	1.286	2.287	0.718	2.567
l: pitch (cm)	1.232	0.990	1.036	0.932	0.237
N_v: number of thermal pins	169	25	20	33	21
Q_v: power of one pin (W)	1800	30	87	207	238
P_0: operation pressure (MPa)	15.5	0.2	0.2	0.2	0.2
T_0: inlet temperature (°C)	292	90	90	86	99
W: inlet flow (kg/s)	85.56	9.22	10.78	9.06	11.74
L: active height of the pins (m)	3.66	4	4	4	4
Reynolds number	4273	4254	4281	4271	4027
Grashof number	1.1339E+08	0.813E+08	0.821E+08	0.985E+08	1.043E+08
Prandtl number	0.82946	1.82	1.82	1.86	1.82
Bo number	0.2516	0.254	0.254	0.284	0.259
La number	−0.1646	–	–	–	–
*R*1 number	1.0098	1.086	1.088	1.085	1.073
*R*2 number	2.9336E−03	8.84E−03	8.87E−03	9.33E−03	9.58E−03

other numbers (Prandtl, *Bo* and *R*1) the results can be considered good due to the constraints of the problems.

Finally, the case study 3 will allow a performance analysis of the methodology in the design of an experimental circuit to simulate mixed flows. Here, the main objective is to establish the operational conditions and design dimensions that lead to non-dimensional numbers near real groups in mixed flow conditions. In this case, by the same reasons mentioned above the *La* number was discharged. In this study, we consider that 60 s after a total stop of the Angra I primary loops circulation pumps, a coolant free flow, propitiated by the head between the core and the steam generator, is established. This scenario results in a situation of the mixed circulation (forced/natural), where the Grashof and Reynolds numbers are relevant for the problem of similarity. Many simulations, involving different random seeds and the same search ranges from the second case, were performed. In all simulations, the GA obtained excellent values to the non-dimensional numbers, but the dimensions of the project and operations conditions suggested by GA were very different case by case. These results are irrefutable evidence of the multi-modality of the search space and demonstrate that the proposed problem is a tough optimization task. Table 6 presents four design suggestion, among others, obtained by the GA. This table shows the hypothetical thermal-hydraulic conditions of the Angra I core in a lost forced circulation incident. Note that the typical mixed flow pattern can be observed.

5. Concluding remarks

The design of a reduced scale test section is a difficult task that involves many possible parameter combinations and practical constraints such as size and limiting operational conditions, among others. The investigations presented in this work indicate that the methodology proposed is a valuable tool that can help experts in their effort to designing reduced scale experiments.

The technique is currently being implemented on a Beowulf-type parallel computing system. The resulting increase in computing power will enable us to address more realistic practical problems, such as designing reduced scale experiments of whole thermal-hydraulic loops.

In the approach proposed herein, cost is not included in the fitness function. Rather, the cost constraint is introduced indirectly in the space of admissible solutions, through the definition of acceptable ranges for the design parameters. Work is underway to develop a multi-objective GA that will allow us to include cost explicitly in our procedure.

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