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Geothermal Plant Design Optimization By Genetic Algorithms

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ABSTRACT

In this paper a genetic algorithms procedure for solving optimal control system design for a geothermal plant is proposed. The choices for the type of components to be used and their assembly configuration are driven by reliability objective with the economic costs associated with the design implementation, system construction and future operation.

1. INTRODUCTION

When designing a system, several choices must be made concerning the type of components to be used and their assembly configuration. The choice is driven by the interaction of reliability/availability objectives with the economic costs associated with the design implementation, system construction and future operation Marseguerra et al.(2000), Fyffe (1968) and Goldberg (1989). The approach used by us is based on genetic algorithms which are computational tools founded on a direct analogy with the physical evolution of species and capable of exploring the search space in a very efficient manner. They have been used to solve several engineering problems and are particularly effective for combinatorial optimization problems with large, complex search spaces. Within the reliability field, however, there have been very few examples of their use.

In our work, the objective function used to measure the fitness of a proposed solution is the reliability function. Mathematically, then, the problem becomes a search in the system configuration space of that design which maximizes the value of the objective function.

2. GENERATION OF TIME TO FAILURE

At the design stage, analyses are to be performed in order to guide the designer's choices in consideration of the many practical aspects which come into play and which typically generate a conflict between safety requirements and economic needs. This renders the design effort in an optimization when one aims to find the best compromise solution.

The geothermal power plant is a component of the cascaded geothermal energy utilization system, and is used to convert the energy of the geothermal water into electrical energy using CO_2 as working fluid. The elements of the power plant are the following: heat exchangers to vaporize and condense the CO_2, a reciprocating engine connected with the electric generator, a make-up and expansion CO_2 tank, and a CO_2 pump.

A good functioning of the power plant following the required thermodynamic cycle has to insure the heat transfer between the CO_2 and the geothermal water or the cold water. The control has to maintain the constant CO_2 pressure and temperature in all the important states of the thermodynamic cycle. Together with other specialists, we decided that we have to implement loops to control the following parameters: *t1* (CO_2 temperature after vaporization in the heat exchangers), *t3* (CO_2 temperature after the condensation in the heat exchanger), and *h* (level of the liquid CO_2 in the tank). Figure 1 shows the power plant layout, together with the control loops shown by dotted lines.

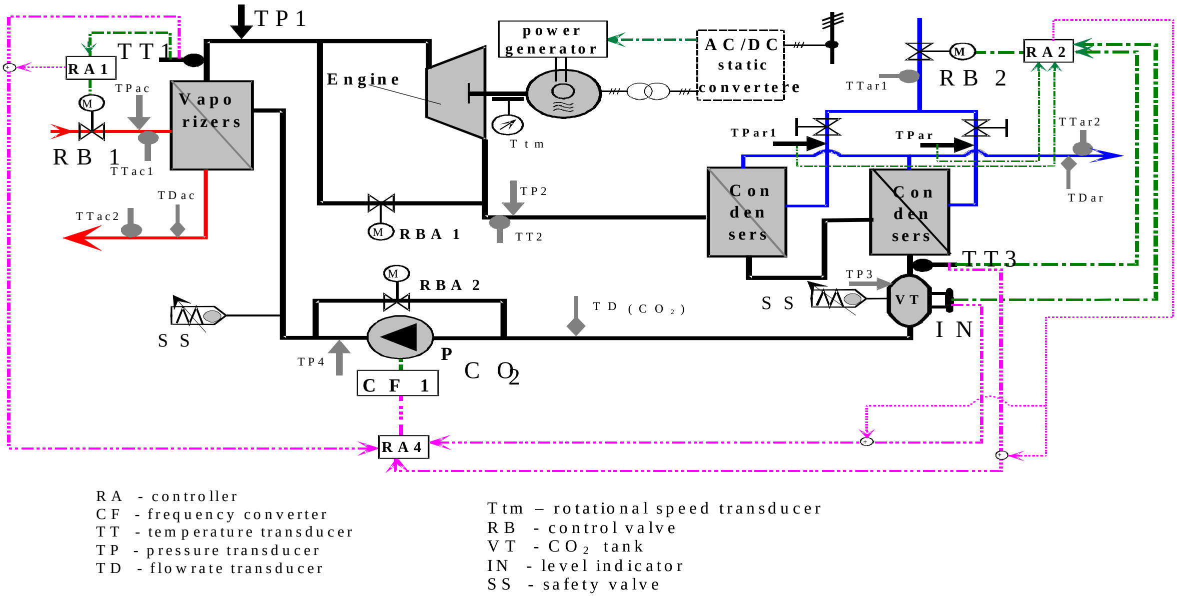

Figure 1 Geothermal power plant block scheme

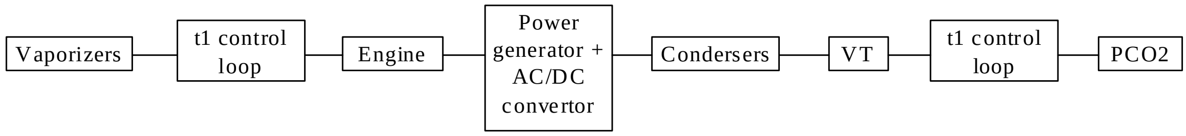

Figure 2 RBD for the control system

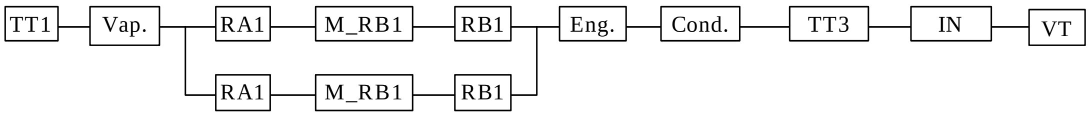

Figure 3 RBD for the t1 control loop

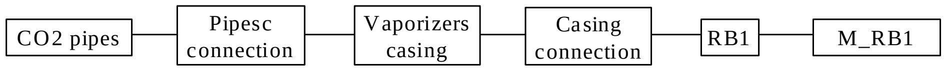

Figure 4 RBD of vaporizers

The reliability of a system depends critically on its individual component reliability and how components are connected in the reliability scheme. To obtain a realistic reliability evaluation of a control system all levels in the system must be examined. For reliability purposes three levels are defined: component level, control loop level and finally the control system level. The reliability model of this structure is given in Figure 2, Figure 3 and Figure 4 above, Gabor and Popescu (2003).

We analyzed the system considering that the vaporizers system contains 30 vaporizers.

3. THE GENERAL PROBLEM FOR OPTIMIZING A SYSTEM

We consider a system made up of a series of n nodes, each one performing a given function. The task of the designer is to select the configuration of each node. This may be done in several ways, e.g. by choosing different series/parallel configurations with components of different failure characteristics and therefore of different costs, Nakagawa (1981). The safety vs. economics conflict rises naturally as follows:

1. Choice of components: choosing the most reliable ones leads to a safe and high-availability design but it may be largely non-economic due to excessive component purchase costs. On the other hand, less reliable components provide lower purchase costs but loose availability and may increase the risk of costly accidents.

2. Choice of redundancy configuration: highly redundant configurations, with active or standby components, guarantee high system availability but suffer from large purchase costs (and perhaps even significant repair costs, if low reliability units are used). Obviously, for assigned component failure and repair characteristics, low redundancies are economic from the point of view of purchase costs. However, they weaken the system availability, thus increasing the risk of significant accidents and the system stoppage time.

In order to find a solution for system optimization, let's consider a system with n components (each one performing a given function) connected as a series reliability connection Vladutiu (1989). The components are characterized by their fault probability: $q_1, q_2, \dots q_i, \dots q_n$ and by their costs: $c_1, c_2, \dots c_i, \dots c_n$ (Figure 5.)

The reliability, P_p, and cost, C_p, functions for this system, are:

$$P_p = \prod_{i=1}^{n} (1 - q_1) \tag{1}$$

$$C_p = \sum_{i=1}^{n} c_i \tag{2}$$

Each group element will be reserved by a number of identical components ($m_1, m_2, \dots m_i, \dots m_n$) connected as a parallel reliability connection (Figure 3.b.). We consider the situation when the groups' elements are identical in their reliability. That is:

$$q_{i1} = q_{i2} = \dots\dots = q_{im_i} = q_i \text{ , where } i = 1, n \tag{3}$$

For our system, P_D, the probability of functioning without faults, is a monotonously ascending function. It has n variables: $m_1, m_2, \dots m_i, \dots m_n$, which are in the following relation:

$$\sum_{i=1}^{n} m_i \cdot c_i = C_{DM} \tag{4}$$

So, m_n can be expressed by:

$$m_n = \frac{C_{DM} - \sum_{i=1}^{n-1} m_i \cdot c_i}{c_n} \tag{5}$$

and it results for P_D:

$$P_D = 1 - \sum_{i=1}^{n-1} q_i^{m_i} - q_n^{\frac{C_{DM} - \sum_{i=1}^{n-1} m_i \cdot c_i}{c_n}} \tag{6}$$

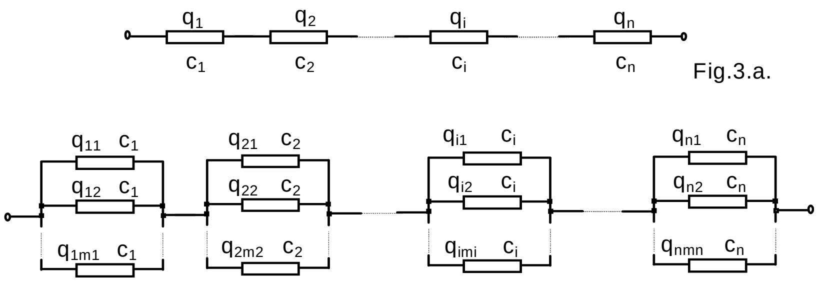

Figure 5 The general reliability model for the n components

We have to find the maximum value for the function $P_D\left(m_1, m_2, \ldots m_i, \ldots m_n\right)$. So,

$$\frac{\partial P_D}{\partial m_i} = -q_i^{m_i} \cdot \ln q_i + q_n^{m_n} \frac{c_i \cdot \ln q_n}{c_n} = 0 \qquad (7)$$

$$\Rightarrow \qquad \frac{q_i \cdot \ln q_i}{c_i} = \frac{q_n^{m_n} \cdot \ln q_n}{c_n} = \alpha \qquad (8)$$

Let

$$\beta_i = \frac{c_i}{\ln q_i} \qquad (9)$$

$$\Rightarrow \alpha = \frac{q_i^{m_i}}{\beta_i} \qquad (10)$$

So,

$$m_i = \frac{\ln \alpha \cdot \beta_i}{\ln q_i} = \frac{\beta_i \cdot \ln \alpha \cdot \beta_i}{c_i} \qquad (11)$$

It results in C_{DM}:

$$C_{DM} = \sum_{i=1}^{n} \beta_i \cdot \ln \alpha \cdot \beta_i = \sum_{i=1}^{n} \beta_i \cdot \ln|\alpha| + \sum_{i=1}^{n} \beta_i \cdot \ln|\beta_i| \qquad (12)$$

and

$$\ln|\alpha| = \frac{C_{DM} - \sum_{i=1}^{n} \beta_i \cdot \ln|\beta_i|}{\sum_{i=1}^{n} \beta_i} \qquad (13)$$

It results in the following expression for m_i:

$$m_i = \frac{\ln|\alpha| + \ln|\beta_i|}{\ln q_i} \qquad (14)$$

Based on relations (3.8), (3.9), (3.13) and (3.14) which are dependent only on the initial data, we obtain the reliability function, P_{D0}, for such system:

$$P_{DO} = 1 - \alpha \cdot \sum_{i=1}^{n} \beta_i \qquad (3.15)$$

The problem is that the m_i values are real numbers and they must be integers. So, they must be rounded to: (m_1^*, m_2^*, ... m_i^*, ... m_{Nc}^*) by respecting the maximum value for the C_{dM} $\left(\sum_{i=1}^{n} m_i^* \cdot c_i\right)$ when the reliability function is maximized.

For calculating the m_i, $i = (1, n)$, values for an optimal static distributed redundancy, we can develop an ordinogram.

By an iterative genetic algorithm procedure we try to obtain a maximum value for the reliability function P_{D0}^*, when $C_D^* \leq C_{DM}$, by selecting k from n m_i values with the $]m_i[$ value, respectively (n-k) m_j $(j \neq i)$ values with the $m_j + 1$ value.

For decision-making purposes, the designer defines an objective function, which accounts for all the relevant aspects. Here we consider as an objective function the reliability for the entire system.

We assume that after an accident the control system cannot be repaired and must be shut down.

For each node a pool of possible configurations is available. The problem is, then, that of choosing a system assembly by selecting one configuration for each node, with the aim of maximizing the objective function.

4. THE GENETIC ALGORITHM OPTIMIZATION APPROACH

The primary target of genetic algorithms is the optimization of an assigned objective function (fitness), Painton (1995).

A population of 100 chromosomes (bit-strings), each representing a possible solution to the problem, is initially considered. This population, then, evolves as dictated by the four fundamental operations of parents selection, crossover, replacement and mutation for 100 generations.

In this work, the selection phase is performed by using the roulette-wheel selection, also called stochastic sampling with replacement. This is a stochastic algorithm and involves the following technique: the individuals are mapped to contiguous segments of a line, such that each individual's segment is equal in size to its fitness. A random number is generated and the individual whose segment spans the random number is selected. The process is repeated until the desired number of individuals is obtained (called mating population). This technique is analogous to a roulette wheel with each slice proportional in size to the fitness.

The crossover operator used is single-point crossover: one crossover position k[1,2,...,n-1], where n is the number of variables of an individual, is selected uniformly at random and the variables exchanged between the individuals about this point. Then two new offspring are produced.

For binary valued individuals mutation means flipping of variable values. For every individual the new variable value is chosen uniformly at random with probability 10^{-3}.

During the population evolution we eliminate those chromosomes which encode infeasible solutions because they violate the cost constraint. With the assigned rules, which mimic natural selection, the successive generations tend to contain chromosomes with larger fitness values until a near optimal solution is attained.

Recalling that our system is made up of n nodes, we identify the possible configurations of each node by a binary value so that the system configuration is identified by a sequence of n binary numbers, each one indicating a possible node configuration. For the coding, we choose to take a chromosome made up of a single gene containing all the values of the node configurations in a string of n bits.

For example, for a node i we can have the value either equal to one when the number of components for that node is $]m_i[+1$, or zero when the number of components for node i is $]m_i[$.

The choice of this coding strategy, as compared to a coding with one gene dedicated to each node, is such that the crossover generates children-chromosomes with all nodes equal to the parents except for the one in which the splice occurs. This avoids excessive dispersion of the genetic patrimony thus favouring convergence.

5. NUMERICAL APPLICATIONS

The genetic algorithm procedure has been applied to the geothermal simple system. Given the relative small number of solutions to be spanned in this case, the best configuration was found also by inspection.

The results thereby obtained were compared to those obtained by the genetic algorithm and confirmed the good performance of the methodology implemented.

Our genetic algorithm considers a population of chromosomes, each one encoding a different alternative design solution. For a given design solution, the system performance over a specified mission time is evaluated in terms of a pre-defined reliability function. This latter constitutes the objective function to be maximized by the genetic algorithm through the evolution of the successive generations of the population in conditions of not overlapping a cost constraint for the system.

The system here considered consists of n = 7 nodes. In TABLE 1 we give the failure rates and the costs for the system components. The maximum cost allowed for the system is: $1000000.

TABLE 1

Component i	Purchase cost Ci [$$10^3$]	Failure rate λ_i [10^{-3} y^{-1}]
1	67.5	4.8
2	54	4.3
3	81	4.6
4	45	3.6
5	85.5	3.6
6	58.5	3.7
7	13.5	3.8
8	45	4

We considered 75 generations for a population of 100 chromosomes and the evolution was made with a probability for crossovers set as $p_c = 0.25$ and the probability for the simple mutation set as $p_m = 0.01$. Thus, on average, 1% of total bit of population would undergo mutation.

Figure 6 reports the schematic for the optimal configuration found by the genetic algorithm procedure, which converges only after a few iterations. The reliability value obtained is **97.712%** with a total cost of $985,000. The following simplifying assumptions are made: i) all components have exponentially distributed failure times; ii.) all components *a* of node. A are equal; iii) no repair is allowed;

The simple case considered here has allowed us to compute the objective function analytically and the genetic algorithm

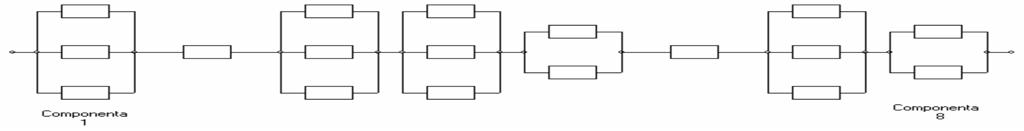

Figure 6 The optimal configuration

was able to converge very rapidly just in a few iterations. However, for more realistic models we can use a Monte Carlo method for its evaluation.

It is important to note that the optimizing approach presented in this paper can be extended even for the situation of geothermal plant that includes k-out-of-n. That is for G schemes (used for reserving the control unit).

The reliability, that is the percentage of successful runs recorded in the simulation of the resulted system was calculated in EXCEL by using the AVERAGE function applied to the columns where the results of individual Monte Carlo runs were recorded. In our case, the resulting reliability was: **97.712**%.

6. CONCLUSION

The genetic algorithm procedure has been applied to a simple system. Given the relative small number of solutions to be spanned in this case, the best configuration was found also by inspection. The results thereby obtained were compared to those obtained by the genetic algorithm and confirmed the good performance of the methodology implemented.

In conclusion, genetic algorithms can be very useful in solving complex design problems. The simple case considered here has allowed us to compute the objective function analytically and the genetic algorithm was able to converge very rapidly just in a few iterations. However, for more realistic models we can use a Monte Carlo method for its evaluation.

It is important to note that the optimizing approach presented in this paper can be extended even for the situation of danger control systems that includes k-out-of-n, G schemes (used for reserving the control unit).

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