# Geothermal Plant Design Optimization By Genetic Algorithms

Corneliu Popescu, Daniela E. Popescu
University of Oradea, Str. Armatei Romane nr.5, Oradea, România
corneliu_popescu@uoradea.ro, depopescu@uoradea.ro

**Abstract**

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

***Keywords***: *Genetic algorithms, system design optimization, systems reliability*

## 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 to the design implementation, system construction and future operation "Marseguerra et al.(2000)" "Fyffe (1968)" "Goldberg (1989)". Optimization approaches to determine optimal solutions to design problems have included gradient methods, dynamic programming, integer programming, mixed integer and nonlinear programming, and heuristics.

Genetic algorithms 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 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 an optimization one aiming at finding 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 constant the $CO_2$ 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 using dotted lines. The reliability model of this structure is given in Figure 2.2.

In the block scheme presented in Figure 2.1 we assume that the vaporizers and condensers form a series-parallel reliability connection, connectors system is a series reliability connection and motor, generator, CO2 pump and motor for CO2 pump are in 2 out of 3 (or 3 out of 4) connection. We analyzed the system considering that the vaporizers system contains 30 vaporizers.

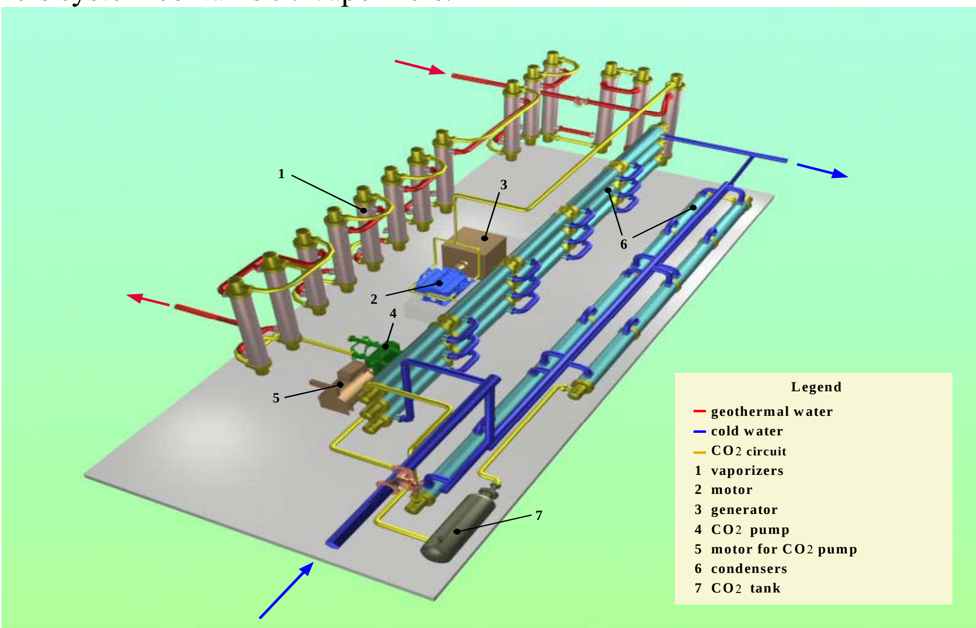
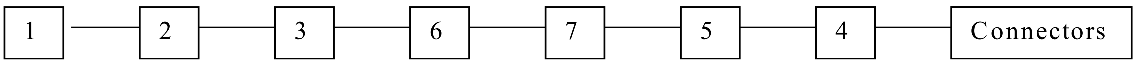



**Figure 2.1. Geothermal power plant block scheme**




1. vaporizers
2. motor
3. generator
4. $CO_2$ pump
5. motor for $CO_2$ pump
6. condensors
7. $CO_2$ tank

**Figure 2.2 The RBD for the geothermal plant**

# 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 that of selecting 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:

- 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 for lower purchase costs but loose availability and may increase the risk of costly accidents.
- 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 but 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 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: $q_1, q_2, ... q_i, ... q_n$ and by their costs: $c_1, c_2, ... c_i, ... c_n$ (Figure 3.1)

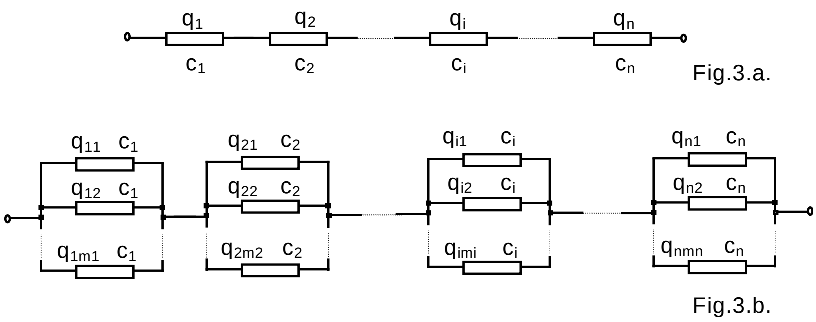



**Figure 3.1 The general reliability model for the n components**

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

$$P_p = \prod_{i=1}^{n} (1 - q_1) \tag{3.1}$$

$$C_p = \sum_{i=1}^{n} c_i \tag{3.2}$$

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

$$q_{i1} = q_{i2} = ..... = q_{im_i} = q_i \text{ , where } i = 1, n \tag{3.3}$$

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

$$\sum_{i=1}^{n} m_i \cdot c_i = C_{DM} \tag{3.4}$$

So, $m_n$ can be expressed by:

$$m_n = \frac{C_{DM} - \sum_{i=1}^{n-1} m_i \cdot c_i}{c_n} \qquad (3.5)$$

and it results for $P_D$ :

$$P_D = 1 - \sum_{i=1}^{n-1} q_i^{\,m_i} - q_n^{\frac{C_{DM} - \sum_{i=1}^{n-1} m_i \cdot c_i}{c_n}} \qquad (3.6)$$

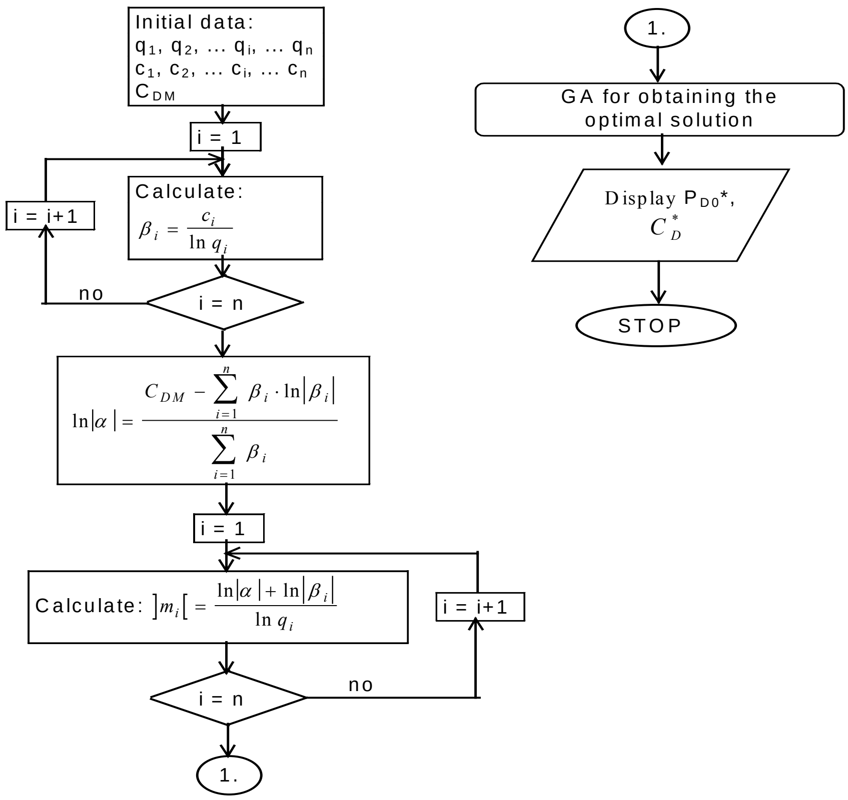



**Figure 3.2 The organigram for the calculus of $m_i$**

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

$$\frac{\partial P_D}{\partial m_i} = -q_i^{m_i} \cdot \ln q_i + q_n^{m_n} \frac{c_i \cdot \ln q_n}{c_n} = 0 \qquad (3.7)$$

$$\Rightarrow \quad \frac{q_i \cdot \ln q_i}{c_i} = \frac{q_n^{\,m_n} \cdot \ln q_n}{c_n} = \alpha \qquad (3.8)$$

Let

$$\beta_i = \frac{c_i}{\ln q_i} \qquad (3.9)$$

$$\Rightarrow \alpha = \frac{q_i^{\,m_i}}{\beta_i} \qquad (3.10)$$

So,

$$m_i = \frac{\ln \alpha \cdot \beta_i}{\ln q_i} = \frac{\beta_i \cdot \ln \alpha \cdot \beta_i}{c_i} \qquad (3.11)$$

It results for $C_{DM}$:

$$C_{DM} = \sum_{i=1}^{n} \beta_i \cdot \ln \alpha \cdot \beta_i = \sum_{i=1}^{n} \beta_i \cdot \ln|\alpha| + \sum_{i=1}^{n} \beta_i \cdot \ln|\beta_i| \qquad (3.12)$$

and

$$\ln|\alpha| = \frac{C_{DM} - \sum_{i=1}^{n} \beta_i \cdot \ln|\beta_i|}{\sum_{i=1}^{n} \beta_i} \tag{3.13}$$

It results for $m_i$:

$$m_i = \frac{\ln|\alpha| + \ln|\beta_i|}{\ln q_i} \tag{3.14}$$

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 a system as being:

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

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.

In Figure 3.2 we have an organigram for calculating the $m_i,\ i = (1, n)$, values for an optimal static distributed redundancy.

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

We assume that after an accident the danger management 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 parent’s selection, crossover, replacement and mutation, for 100 generations.

Using the roulette-wheel selection, also called stochastic sampling with replacement, performs the selection phase in this work. 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 variable value to change is chosen uniform at random with a probability of $10^{-3}$.

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 either a "1" value, when the number of components for that node is $]m_i[+1$, either a "0" value, 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 nodes all equals 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.

Table 4.1

| Compone nt i | Purchase cost Ci [$10^3$ $] | Failure rate $\lambda_i$ [$10^{-3}$ $y^{-1}$] |
|---|---|---|
| 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 |

The system here considered consists of n = 7 nodes. In TABLE 4.1 we give the failure rates and the costs for the system components. The maximum cost allowed for the system is: 1 000 000 $.

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 $p_m = 0{,}01$, so, on average, 1% of total bit of population would undergo mutation.

Figure 4.1 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 **97,435**% with a total cost of 995 000$.

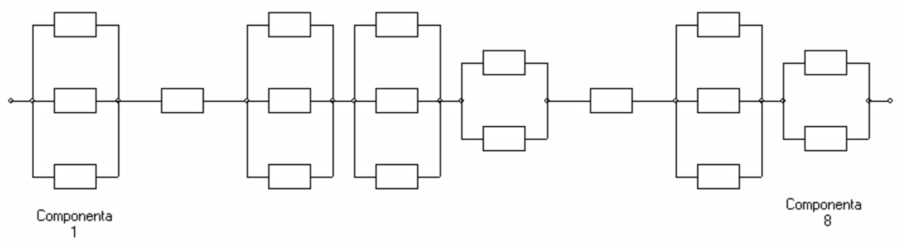



**Figure 4.1. The optimal configuration**

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

It is important to be noted that the optimizing approach presented in this paper can be extended even for the situation of geothermal plant that includes k-out-of-n: 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 were recorded the results of individual Monte Carlo runs. In our case, the resulting reliability was: 97,435%.

# 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, in a few iterations. However, for more realistic models we can use a Monte Carlo method for its evaluation.

It is important to be noted 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).

# References


Marseguerra, M., Zio, E., 2000, *System design optimization by Genetic Algorithms*, Annual Relliability and Maintainability Symposium, Proceedings`, pp.222-227

Vlăduțiu, M., 1989, *Tehnologie de ramură şi fiabilitate*, curs litografiat IPTVT, pp.95-110

Tillman, F. A., Hwang C. L., Kuo, W., 1977, *Optimization Techniques for System Reliability with Redundancy : A Review*, IEEE Trans. Reliability, vol. R-26, Aug, pp 148-155.

Fyffe, D.E., Hines, W. W., Lee, N. K., 1981, *System Reliability Allocation and a Computational Algorithm*, IEEE Trans. Reliability, Vol R-17, 1968 Jun, pp 64-69.

Nakagawa, Y., Miyazaki, S., *Surrogate Constraints Algorithm for Reliability Optimization Problems with Two Constraints*, IEEE Trans. Reliability, Vol R-30, Jun , pp 175-180.

Goldberg, D. E., 1989, *Genetic Algorithms in Search, Optimization, and Machine Learning*,; Addison-Wesley Publishing Company, pp.215-220

Painton, L., Campbell, J., 1995, *Genetic Algorithms in Optimization of system Reliability*, IEEE Trans. On Reliab., Vol 44, N. 2, pp 172-178.