GENETIC ALGORITHMS AND UNCERTAINTY APPLIED TO OPTIMIZATION OF SHIP STRUCTURES

J. M. Vasconcellos, jmarcio@peno.coppe.ufrj.br
M. H. S. Campos, marina-harduim@hotmail.com
Universidade Federal do Rio de Janeiro, Rio de Janeiro, Brasil

Abstract. *Several optimization techniques have been employed to solve naval problems. The development of the technique of Genetic Algorithms (GA) with inclusion of uncertainty in variables has also been recently applied. This article discusses the techniques of G.A. and treatment of variables with a degree of uncertainty in naval problems. A case study is developed for the project of master section of the type of supply vessels. To include uncertainty in the model's variables it has been used the software @risk, which uses a technique called "simulation" to combine all the uncertainties you identify in your modeling situation. @RISK uses simulation, sometimes called Monte Carlo simulation, to do a Risk Analysis. Simulation in this sense refers to a method whereby the distribution of possible outcomes is generated by letting a computer recalculate your worksheet over and over again, each time using different randomly selected sets of values for the probability distributions in your cell values and formulas. In effect, the computer is trying all valid combinations of the values of input variables to simulate all possible outcomes. This is just as if you ran hundreds or thousands of "what-if" analyses on your worksheet, all in one sitting. Then it was used the software RISKoptimizer, that combines simulation and optimization to allow the optimization of models that contain uncertain factors. RISKOptimizer, through the application of powerful genetic algorithm-based optimization techniques and Monte Carlo simulation, can find optimal solutions to problems which are "unsolvable" for standard linear and non-linear optimizers. Genetic algorithms (GAs) are adaptive methods which may be used to solve search and optimization problems. They are based on the genetic processes of biological organisms. A genetic algorithm allows a population of possible solutions composed of many individuals to develop, under specified rules of selection, a state that minimizes the cost function (and HAUPT HAUPT, 2004). According to Fernandes (1996), the selective mechanisms achieve the changes that determine the evolution of a population across generations. Such changes may occur due to interactions between individuals or due to environmental influences on the individual. It derives three basic mechanisms, crossing or recombination, reproduction and mutation, called genetic operators, to carry out the development of the algorithm. The application of these operators is preceded by a process of selection of individuals best adapted, which uses a function to evaluate the individuals named function fitness or, function setting. These methods were applied to the case of a master section of a ship-type supply vessel.*

Keywords: *optimization, uncertainty, naval.*

1. INTRODUCTION

Optimization problems are problems in which one seeks to minimize or maximize a real function by systematically choosing the values of real or integer variables from within an allowed set, with the existence or not of restrictions in the variables. Real problems present uncertainty in their variables: they are inherent to the majority of physical, chemical, biological, geographical systems, etc. Stochastic optimization methods are optimization algorithms which incorporate probabilistic (random) elements, either in the problem data (the objective function, the constraints, etc.), or in the algorithm itself (through random parameter values, random choices, etc.), or in both. The concept contrasts with the deterministic optimization methods, where the values of the objective function are assumed to be exact, and the computation is completely determined by the values sampled so far.

Among the many stochastic optimization techniques existing, it will be used here the Genetic Algorithm and Monte Carlo Simulation methods.

In this article our objective is to minimize the section area of a supply vessel ship as a measure of weight.

A Platform supply vessel (often abbreviated as PSV) is a ship specially designed to supply offshore oil platforms. These ships range from 65 to 350 feet in length and accomplish a variety of tasks. The primary function for most of these vessels is transportation of goods and personnel to and from offshore oil platforms and other offshore structures.

2. METHODOLOGY

2.1. Genetic algorithms

Genetic Algorithms (GAs) are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem.

The selective mechanisms carry out the changes that determine the evolution of a population over generations. Such changes can occur due to the interactions between the individuals or due to the influences of the environment on the individual. Three basic mechanisms derive from this: crossing or crossover, reproduction and mutation. They are called genetic operators and are responsible for carrying out the evolution of the algorithm. The application of these operators is preceded by a selection process of the best adapted individuals, which uses a function called the fitness function, also known as the adaptation function.

An implementation of a genetic algorithm begins with a random population of chromosomes, that is to say, the initial population can be obtained by choosing a value for the parameters or variables of each chromosome randomly between its minimum and maximum value.

At this part follows an evaluation of each individual through the objective function. The fittest individuals (with the best adaptation values) have the greatest probability of reproducing (selection). Then genetic crossover and mutation operators work on the ones selected. The new individuals replace totally or partially the previous population, thus concluding a generation.

The selection operator allows the transmission of some individuals from the current population to the new one, with greater probability for the individuals with a better performance (fitness value), and with less probability for individuals with a worse performance.

After that the crossover operator interchanges and combines characteristics of the parents during the reproduction process, allowing the next generations to inherit these characteristics. The idea is that the new descendent individuals can be better than their parents if they inherit the best characteristics of each parent.

The next operator is the mutation operator, which is designed to introduce diversity into the chromosomes of the population of the GA, in order to ensure that the latter is not trapped in minimum areas.

In addition to these, there are other factors that influence the performance of a GA, adapted to the particularities of certain classes of problems.

2.2. Monte Carlo simulation

The present study uses the Monte Carlo simulation technique to deal with uncertainty concerning variables in optimization.

The Monte Carlo method is a simulation technique used to solve probabilistic problems in which the entry variables are attributed distributions of probabilities by means of a random process and obtaining as a result the distributions of probabilities of the exit variables. The random process used consists in generating random numbers to select the values of each entry variable for each attempt. This process is repeated numerous times, obtaining numerous results from which one builds a distribution of probability of the exit variables.

An random variable X has a normal distribution, with mean μ $(-\infty < \mu < +\infty)$ and variance $\sigma^2 > 0$, if there is a density function:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \qquad (01)$$

The notation $X \sim N\ (\mu,\ \sigma^2)$ indicates that the random variable X has normal distribution with mean μ, and variance σ^2.

The mean of the normal distribution is determined, making $z = (x - \mu)/\ \sigma$ in the following equation:

$$E(X) = \int_{-\infty}^{\infty} \frac{x}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}\, dx$$

$$E(X) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} (\mu + \sigma z) e^{\frac{-z^2}{2}}\, dz$$

$$= \mu \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}}\, dz + \sigma \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} z e^{\frac{-z^2}{2}}\, dz$$

The normal density appears when integrating the first integral, with $\mu = 0$ and $\sigma^2 = 1$, with this value being equal to one. The second integral has a zero value.

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} z e^{\frac{-z^2}{2}}\, dz = -\frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} \bigg|_{-\infty}^{\infty} = 0$$

$$E(X) = \mu[1] + \sigma[0] = \mu \qquad (02)$$

The variance is determined, making $z = (x - \mu)/ \sigma$ in the following equation:

$$V(X) = E\left[(X-\mu)^2\right] = \int_{-\infty}^{\infty} (x-\mu)^2 \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx$$

$$= \int_{-\infty}^{\infty} \sigma^2 z^2 \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz = \sigma^2 \int_{-\infty}^{\infty} \frac{z^2}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz$$

$$= \sigma^2 \left[\left. \frac{-ze^{\frac{-z^2}{2}}}{\sqrt{2\pi}} \right|_{-\infty}^{\infty} + \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz \right]$$

$$= \sigma^2 [0+1]$$

$$V(X) = \sigma^2 \qquad (03)$$

Applying in the density Equation (9) an average equal to zero and variance 1, and making *Z~N (0,1)*, one has a standardized normal distribution.

$$\varphi(z) = \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} \quad , \quad -\infty < z < \infty \qquad (04)$$

The corresponding distributed function is given by:

$$\phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{\frac{-u^2}{2}} du \qquad (05)$$

And one can say that:

$$F(x) = \phi\left(\frac{x-\mu}{\sigma}\right) = \phi(z)$$

Where:

$$Z = \frac{X-\mu}{\sigma}$$

For example, suppose that *X~N (100,4)* and we wish to find the probability of *X* being less than or equal to *104*; that is to say, *P(X≤104)=F(104)*. Standardizing the point of interest *x = 104*, we obtain:

$$z = \frac{x-\mu}{\sigma} = \frac{104-100}{2} = 2$$

$$F(104) = \phi(2) = 0{,}9772 \qquad (06)$$

This means to say that the probability of the original normal random variable *X,* being less or equal to *104*, is equal to the probability of the standardized normal random variable being less or equal to *2*.

There are tables where we can find accumulated standardized normal probability values for various values of *z*.

3. THE SUPPLY VESSEL SHIP

The supply vessel was used because of its importance nowadays. Petrobras has ordered 200 new supply vessels to the pre-salt area.

A primary function of a platform supply vessel is to transport supplies to the oil platform and return other cargoes to shore. Cargo tanks for drilling mud, pulverized cement, diesel fuel, potable and non-potable water, and chemicals used in the drilling process comprise the bulk of the cargo spaces. Fuel, water, and chemicals are almost always required by oil platforms. Certain other chemicals must be returned to shore for proper recycling or disposal, however, crude oil product from the rig is usually not a supply vessel cargo.

Common and specialty tools are carried on the large decks of these vessels. Most carry a combination of deck cargoes and bulk cargo in tanks below deck. Many ships are constructed (or re-fitted) to accomplish a particular job. Some of these vessels are equipped with a firefighting capability and fire monitors for fighting platform fires. Some vessels are equipped with oil containment and recovery equipment to assist in the cleanup of a spill at sea. Other vessels are equipped with tools, chemicals and personnel to "work-over" existing oil wells for the purpose of increasing the wells' production.

The optimization procedure applied to this kind of ship is important in many design phases. Preliminary design, hull design and structural ship design are some examples of optimization techniques possible application.

Optimization is not a commonly used procedure among the national ship design offices. It is still under the research and academic area. Recently in a very important design conference in Trondheim- Norway (IMDC-2009) the main theme in many papers was the optimization application in different ship and offshore design areas.

We have chosen the structural design phase, in special the section modulus calculation, to highlight the optimization under uncertainty application.

The section modulus calculation is an important phase in the structural design. We assume the ship as beam and we design the section to resist the main wave loads. The section modulus is directly associated with the beam strength and the geometric material distribution.

$$SM = I / y \tag{07}$$

Where:

I – Second moment f area, m^4
y – Distance from the neutral axis, m

4. CASE STUDY

To illustrate the application of optimization under uncertainty techniques, we select a ship section modulus calculation. This normally is done in a spreadsheet. Table 1 presents the original and the optimized midship section elements values. Table 2 presents the original and optimized main results for the ship section modulus calculation.

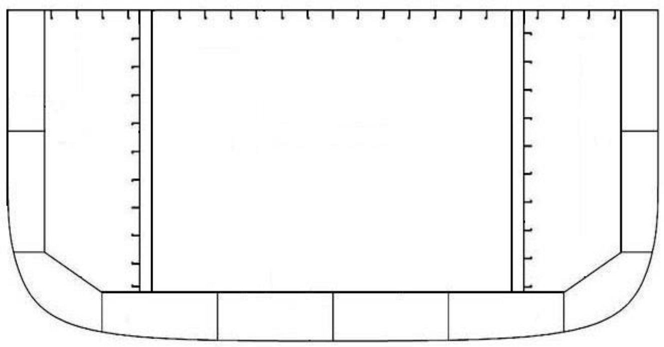

Figure 1: The Midship Section Example

Table 1: Main Elements

Element	width	thickness	Optimized thickness
	(mm)	(mm)	(mm)
Bottom shell plates	10470.0	16.0	10.0
Deck plates	12255.0	16.0	21.0
Inner bottom shell plates	13000.0	14.0	10.0
Longitudinal bulkhead	9357.0	14.0	11.1
Side shell Plates	10839.0	14.0	10.0
Double hull side shell plates	10600.0	14.0	10.0
Wing tank plates	3394.0	14.0	10.0
Floor 1	1730.0	12.0	10.0
Floor 2	1730.0	12.0	10.0
Floor 3	1730.0	12.0	10.0
Floor 4	1730.0	12.0	10.0
Girder 1	1300.0	16.0	10.0
Girder 2	1300.0	16.0	12.6
Girder 3	1300.0	16.0	10.0
Central Longitudinal	1730.0	16.0	10.1
Longitudinal Girder 1	1730.0	12.5	10.0
Longitudinal Girder 2	1730.0	12.5	10.0
Longitudinal Girder 3	1730.0	12.5	10.0
Longitudinal Girder 4	1730.0	12.5	19.4
	radius	**thickness**	**Optimized thickness**
Element	**(mm)**	**(mm)**	**(mm)**
Bilge keel plate	1730	18	19.0
CH. CINTADO CURVO	800	16	17.3

Table 2: Main Results

RESULTS	Half Section			Full Section	
Section Material Area	17815.708	cm^2			
Neutral line height	6.169	m	46%	from the depth	
Moment of Inertia	52.010	m^4		104.022	m^4
Section Modulus	6.71	m^3		13.419	m^3
Optimized Results	Half Section			Full Section	
Section Material Area	15606.025	cm^2			
Neutral line height	7.019	m	53%	from the depth	
Moment of Inertia	48.890	m^4		97.780	m^4
Section Modulus	7.08	m3		14.169124	m3

Following the optimization procedure we include uncertainty in some variables. The graphics shown in figures 2-6 presents the normal distribution used to model the uncertainty in the design variable.

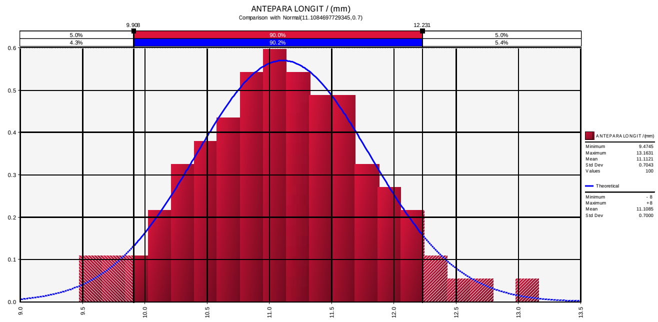

Figure 2: Uncertainty in the longitudinal bulkhead thickness

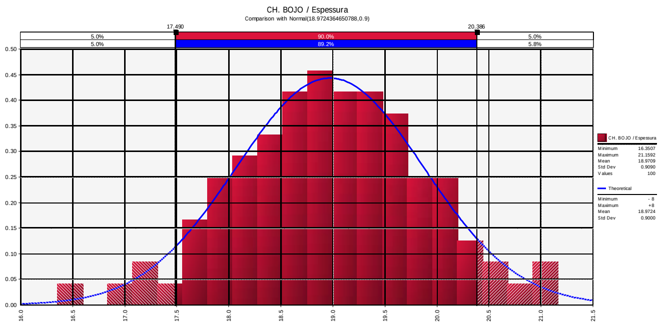

Figure 3: Uncertainty in the Bilge Keel shell thickness

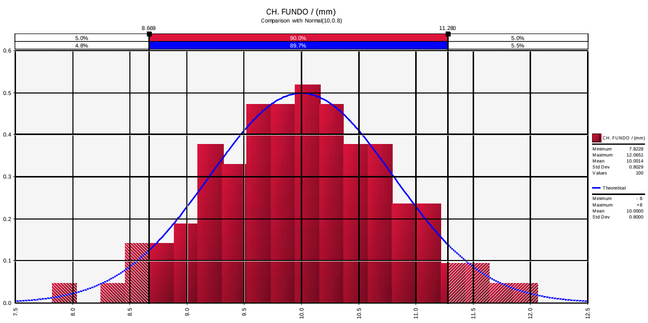

Figure 4: Uncertainty in the bottom shell thickness

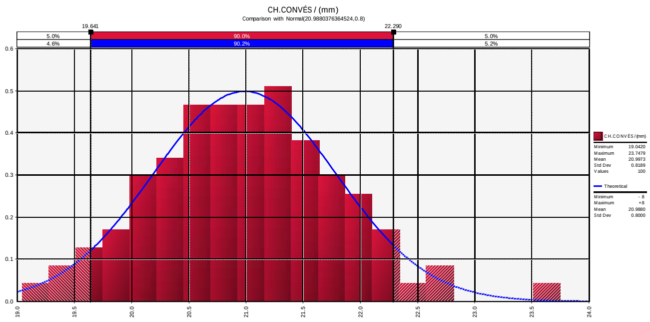

Figure 5: Uncertainty in the deck shell thickness

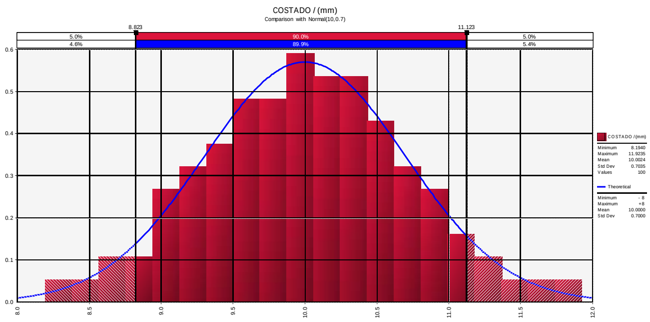

Figure 6: Uncertainty in the side shell thickness

Applying the Monte Carlo procedures in the optimization search using genetic algorithm the results are presented in figures 7-9 for the material area, neural axis height and section modulus output. Table 3 also presents the main results showing the average and standard deviation for each distribution adjusted by a normal curve.

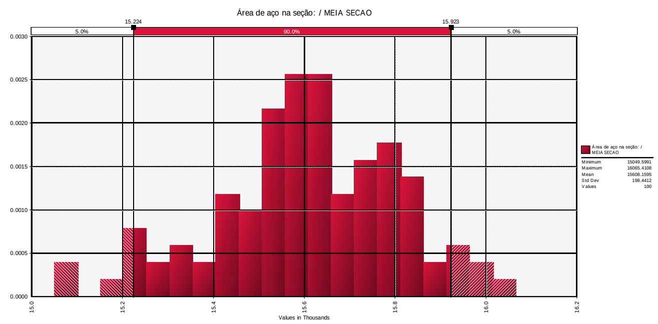

Figure 7: Distribution for Section Area (material) output

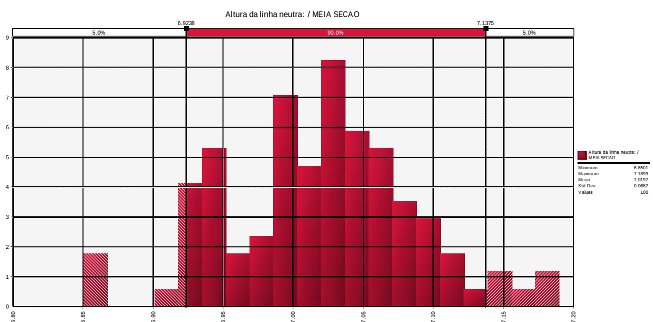

Figure 8: Distribution for Neutral axis height output

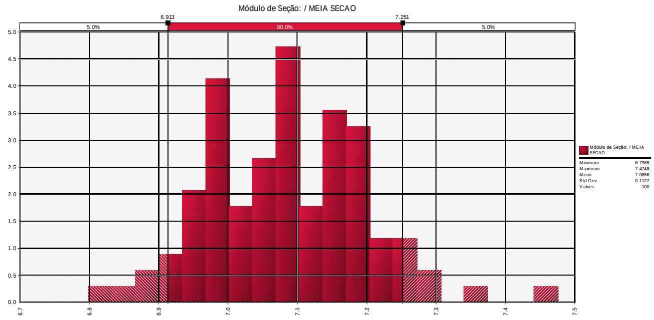

Figure 9: Distribution for Section Modulus output

Table 3: Main results considering uncertainty applied to some variables.

Optimized Results	Half Section average	Standard deviation	90% of Confidence		
Section Material Area	15606	198	15049	16065	cm^2
Neutral line height	7.019	0.068	6.850	7.190	m
Moment of Inertia	48.89	0.697	47.219	51.016	m^4
Section Modulus	7.08	0.113	6.799	7.475	m^3

5. CONCLUSION

The method present here in indicates the possibility to handle optimization problems where uncertainty should be attributing to any variable. The Monte Carlo method associated with genetic algorithms, as optimization procedures, worked well to solve the mathematical model with uncertainty.

The problem we faced was the time consumed using a common computer with duo core processor. The GA algorithm as known is sometimes slow to indicate a solution. We realize the necessity to apply the method in a faster machine and probably using a cluster with some processors.

The application for a section modulus calculation although simple, highlights the main methodology appliance. Naval Architecture designer can expect an interval of confidence for his section modulus and also evaluate the hull resistance characteristic in a risk approach.

6. REFERENCES

[1] Borror, CM. *Probabilidade e Estática na Engenharia***.** 4º Edition. LTC, 2006.

[2] Hines, WW. and Montgomery, DC. and Goldsman, DM. *Marine Technology***.** Oct. 1995.(Volume 32) (Nº4).

[3] Kobylinski, LK. and Kastner S. *Stability And Safety of Ships*. Elsevier, 2005. (Volume 9)

[4] Aror, Jabir S. *Introduction to optimum design*. McGraw-Hill Inc., 1989.

[5] Fonseca, Maurílio M. *Arte Naval*. Ministério da Marinha, 1954.

[6] Kreher, Donald L. and Stinson, Douglas R. *Combinatorial Algorithms: Generation, Enumeration and Search.* CRC Press, 1999.