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Design and Optimization of Pressure Vessel using Real Coded Genetic Algorithm

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Abstract- This Project aims at achieving global optimal solution of complex problems, such as Pressure vessel, using extended version of real coded genetic algorithms (RCGA). Since genetic algorithm (GA) consists of several genetic operators, namely selection procedure, crossover, and mutation operators, that offers the choice to be modified in order to improve the performance for particular implementation and it is found that the results obtained from RCGA are better as its search is for global optimum as against the local optimum in traditional search methods. The results of the RCGA have been checked using ANSYS, and it is found to perform satisfactorily.

Keywords: Real coded GA, Pressure vessel, Optimization, Non-traditional technique, ANSYS

1. INTRODUCTION

It is well known that the pressure vessel has been widely used in a variety of areas such as chemical engineering, medical treatment, aviation and astronautics as well as nuclear engineering. Currently the pressure vessel tends to be developing in large-scale and high-parameter directions, especially in chemical industry. However, the pressure vessel is generally subjected to a complex environment such as high pressure and high temperature. This means not only a strong challenge regarding the performance of the material and structure, but also concerning the design of the pressure vessel. How to achieve a perfect combination of excellent performance and low cost in the design of a pressure vessel under certain design conditions is an important topic.

2. REAL CODED GENETIC ALGORITHM (RCGA)

2.1 Representationof Design Variables

We have already noted the complicated proceed=ss of encoding and decoding used in binary GA.in real coded GA ,the design variables represented as floating point numbers. If a problem has n design variables, then the design vector can be represented exactly in the same form as used for gradient-based method.

$X=\{x_1,x_2,x_3,\dots,x_n\}$

Note that the binary GA, the design vector was represented by a string and the elements $x_1,x_2,x3,\dots x_n$ were each represented as binary substrings of m bits each. In real GA, we use n floating point numbers while in binary GA, we use m * nbits to represents the design vector. The realGA can use single- or double-precision arithmetic depending on the computer. Since real GA is search algorithm which starts from a population of values, like for binary GA, these move limits have the form $x_i^l \le x_i \le x_i^U$,i =1 to n.

The fitness value of the function is calculated using

$f(x) = f(x_1, x_2, x_3, \dots\dots, x_n)$.

Real GA therefore saves us from the complexity of using the encoding and decoding operations of binary GA.

2.2 Starting population

The starting population is created by taking a floating point number within the design space for each variable. Thus, the starting population with all design variables lying between 1 and 10 may be expressed in the form using random numbers with up to eight decimal places.

Member 1 : 2.34527849 1.342721921.23972398…7.23582302

x_{11} x_{12} x_{13} x_{1n}

Member 2 :7.54989200 3.04011890 2.18998363… 5.82990872

$x_{21}x_{22}$ x_{23} x_{2n}

:

:

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:

Member N :9.82019902 4.023840025.77810282…0.12927494

x_{N1} x_{N2} x_{N3} x_{Nn}

The initial population is therefore a matrix of real numbers of size N*note that random sampling can also be enhanced by uniform sampling to make sure that all parts of the design space are adequately sampled. In addition, a complement approach could be used by subtracting the population of each design variable from its upper bound.

Just as in binary GA, it is advantageous to have a larger initial population compared to the population value used in the GAgenerations. Thus, if we start with a population of 1.2 N-2 N,the N best points can be selected for further operations such as reproduction, crossover rand mutation operations. However, in real GA, some of those operations need to be defined in a new manner compared to binary GA.

2.3 Reproduction

Roulette wheel selection can be used for real GA. The fitness function and cumulative probability can then be calculated in exactly the same manner as for binary GA. Just as in binary GA,we can select the mating pool members as 1,3,2,1 and3 .the mates can then be paired as (1,3) and(2,1) assuming 80 per cent crossover. The only difference in the reproduction operations for realGA is that string i is replaced by design variable i which is the design vector $\{x_{i1},x_{i2},x_{i3},\dots x_{in}\}$.we also see that scaling correction and tournament selection can be applied to real GA .the reproduction operator does not create anynew points.

2.4 Crossover

The crossover operator used for real GA is different from that used binary GA. A simple approach we may follow is to take two sites along the parent as the crossover site and then exchange the variables inside the crossover sites. Forexample, if there are two six-variables parents as given below

Father $=\{x_{f1},x_{f2},x_{f3},x_{f4},x_{f5},x_{f6}\}$,

Mother$=\{x_{m1},x_{m2},x_{m3},x_{m4},x_{m5},x_{m6}\}$,

We select two crossover sites randomly and get 1 and 3.the children are then as shown in the following.

Father $= \{ x_{f1}, x_{f2}, x_{f3}, x_{f4}, x_{f5}, x_{f6}\}$,

Mother$= \{ x_{m1}, x_{m2}, x_{m3}, x_{m4}, x_{m5}, x_{m6}\}$,

The above strategy well with binary GA where the variables are coded strings, however in real GA the swapping of design variables does not introduced any new information. We need a method to create new design variables .one approach for creating new design variables is to use the blending method and define the children.

$$x^{(1)}_{new} =\beta x_{mn} + (1-\beta)x_{fn} ,$$

$$x^{(2)}_{new} = \beta x_{fn} + (1-\beta)x_{mn}$$

In the above ,$\beta \in (0,1)$,x_{mn} is the nth design variable in the mother design vector and xfn is the nth design variable in the father design vector .the limiting case occurs when $\beta =0 =x^{(1)}_{new}= x_{fn},x^{(2)}_{new}=x_{mn}$ and when $\beta=0.5$,the two children are the average of the two-parent design variables and are essentially identical twins.in general ,it is a good idea to take a random number $\beta\in(0,1)$ and find the values of the two children. This method is also called the blending method since it combines information from both children. This method is also called the blending method since combines information from both parents to get the children and therefore simulates nature. However, the blending method described in now interpolates between the parent values and is not capable of extrapolating into the design space.

Blending approaches to crossover which extrapolate have also been proposed by some researchers. One such approach is called the linear crossover where there children are created using two parents as follows:

$$x^{(1)}_{new}= 0.5x_{mn}+0.5_{fn},$$

$$x^{(2)}_{new}=1.5x_{mn}-0.5x_{fn},$$

$$X^{(3)}_{new}=-0.5x_{mn}+1.5x_{fn},$$

Here the first child is interpolated while the second and third children are extrapolated. A problem with extrapolation is that sometimes a child may go outside the bounds of the design variable.in such a case, the child is not selected. The best two children among the three are selected for further operations.as an example, consider$x_{mn}=1,x_{fn}=2$.Then,the children are given by $x^{(1)}_{new}=1.5$, $x^{(2)}_{new}=0.5$, $x^{(3)}_{new} =2.5$.thus we see that the linear crossover both interpolates and extrapolates using the parent values .

A further generalization of the concept of the linear crossover in needed to ensure that more than three children can be created in case more than one need to be discarded because they lie outside the move limits for the design variable .we can define any number of children of two parents using heuristic crossover.

$$x_{new} = \beta(x_{mn}-x_{fn}) +x_{mn.}$$

This approach allows generation of children both inside and outside the parent range depending on the value of the random number $\beta \in (0, 1)$. Heuristic crossover also introduces an element of randomness in the crossover process which is absent in linear crossover.

As an example of implementing the two-point heuristic crossover consider the two-point design vectors, shown below:

Father= {2.762, 4.384, 1.236, 0.524},

Mother= {7.310, 8.236, 5.426, 4.316},

Here each design variable has abound of (0, 10) as the lower and upper limit. Using a random number generator, we pick two crossing sites, 2 and 3. Again, we generate three random numbers β ϵ (0, 1) and get 0.1783, 0.8264 and 0.3123, using these values and heuristic crossover, we get three children:

$x^{(1)}_{new}$ =0.1783(8.236-4.384)+8.236=8.9228,

$x^{(2)}_{new}$ =0.8264(8.236-4.384)+8.236=38.0745,

$x^{(3)}_{new}$ = 0.3123(8.236-4.384)+8.236=9.4389.

The second child is outside the movie limit of the design variable and is not selected, we then take the other two values to farm the children:

Father= {2.762, 4.384, 1.236, 0.524},

Mother={7.310, 8.236, 5.426, 4.316},

The tow point heuristic crossover is good approach to use for real coded GA and is recommended for applications.

2.5 Mutation

As binary GA, mutation is needed in real GA to ensure that the algorithm does get stuck or coverage to a local minimum. To apply mutation with probability p_m. We change n× N× p_m designvariables in a random manner .recall that n× N is the number of real numbers in the population .as an example, consider design vectors of size n =6 and N=10 to make up the population. Taking a mutation probability ,p_m=0.05,we need to change three design variables , that is (6×10×0.05=3).to do this, we randomly select three variables from the population and replace them by a random number lying between the move limits corresponding to these variables.

In summary, we point out that many problems involving a low level of discretization can be solved using binary GA, even when the variables are real. However, as the desired accuracy of the optimal point increases, real GA becomes advantageous in terms of storage requirements. Recent research literature shows a growing popularity of real GA over binary GA.

3. PROBLEM FORMULATION

The Problem is to design a compressed air storage tank with a working pressure of 1000 psiand a minimum volume of 750 ft³. The schematic of a pressure vessel is shown in Fig.7.1. The cylindrical pressure vessel is capped at both ends by hemispherical heads. Using rolled steel plate (SAEJ 2340 TYPE 830 R), the shell isto be made in two halves that are joined by two longitudinal welds to form a cylinder. Each head is forged and then welded to the shell. Let the design variables be denoted by the vector

$\boldsymbol{X}=[x_1, x_2, x_3, x_4]$

Where

x_1 is the spherical head thickness,

x_2 is the shell thickness,

$x_3$andx_4 are the radius and length of the shell, respectively.

The objective in this Project is to minimize the manufacturing cost of the pressurevessel. The manufacturing cost of the pressure vessel is a combination of material cost, welding costand forming cost. That can be refer inSandgren (1990) for more details on how cost is determined.

The constraints are set in accordance with respective ASME codes. The mathematical model of theproblem is:

3.1 Objective function

Here our main objective is to reduce the cost by reducing weight of Pressure Vessel. So the objective function

$$f(x) = 0.6224x_1x_2x_3 + 1.7781x_1^{\,2}x_3 + 3.1661x_2x_4^{\,2} + 19.84x_4x_1^{\,2}$$

$x_1 = R =$ Radius of the shell

$x_2 = L =$ Length of the shell

$x_3 = T_s =$ Thickness of the shell

$x_4 = T_b =$ Thickness of the dish end

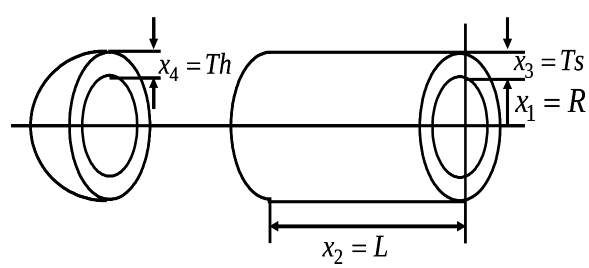

Fig: 3.1: Cylindrical pressure vessel

3.2 Design variables

1. Radius (R)
2. Length (L)

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3.Thickness of the shell

4.Thickness of the dish end

3.3 Design parameters

1. Circumferential or Hoop Stress
2. Longitudinal Stress
3. Volume

3.4 Design constraints

The four important constraints under consideration are

1. Hoop stress≤ Allowable stress

$$g_1(x) = 0.0193x_1 - x_4 \leq 0$$

2. Longitudinal stress≤ Allowable stress

$$g_2(x) = 0.00954x_1 - x_3 \leq 0$$

3. Volume≤750×1728inch^3

$$g_3(x) = 750 \times 1728 - \frac{4}{3}\pi x_1^{\,3} - \pi x_1^{\,2} x_2 \leq 0$$

4. Length

$$g_4(x) = x_2 - 240 \leq 0$$

3.5 Variable bounds

The upper and lower bounds on two design variables are

1. $25 \leq x_1 \leq 150$
2. $25 \leq x_2 \leq 240$
3. $0.0625 \leq x_3 \leq 1.25$
4. $0.0625 \leq x_4 \leq 1.25$

Note: All are in inch

4. PROBLEM DESCRIPTION

A typical input data required to develop a mathematical model for pressure vessel design is

1. Pressure vesselmaterial= SAE J2340 – 830R

   Where R=High Strength Recovery Annealed
2. Modulus of elasticity (E) = 200x10^9 N/mm^2
3. Yield Strength=960MPA
4. Factor of safety=1.78
5. Allowable Yield Strength = 540 MPA
6. Applied Pressure=6.80272N/mm^2(1000 Psi)

4.1 Input for Real coded GA

Binary GA, mutation is needed in real GA to ensure that the algorithm does get stuck or coverage to a local minimum. To apply mutation with probability p_m. We change n× N× p_m design variables in a random manner recall that n× N is the number of real numbers in the population as an example, consider design vectors of size n =6 and N=10 to make up the population. Taking a mutation probability, p_m=0.05, we need to change three design variables, that is (6×10×0.05=3).

5. RESULTS AND DISCUSSIONS

The values of best design variables and the constraints for the 500 iteration obtained after running the program for Real coded Genetic Algorithm written in the C-language is given below.

5.1 Program Results

Table: 5.1: Programming Results

S.No	f(x)in $	X_1	X_2	X_3	X_4	g_1	g_2	g_3	g_4
1	115339.8198	6.1190	5.8798	46.4278	197.4326	5.222965	5.436842	460144.3	42.5674
2	112644.9246	6.1243	5.8850	46.4623	187.5280	5.227579	5.441793	395894.7	52.4720
.	.	.	.	.	.	.	.	.	.
22	115339.8198	6.1190	5.8798	46.4278	197.4326	5.22965	5.436842	406144.3	42.5674
23	103103.1814	4.3550	1.0431	86.2090	193.6479	2.691221	0.220628	5908975	463521
.	.	.	.	.	.	.	.	.	.
155	15161.8598	1.5539	195.28	0.775	0.894	0.760824	0.928576	27686.69	45.2360
156	13590.1317	44.167	173.78	0.537	0.894	0.361261	1.584072	27686.69	45.2360
.	.	.	.	.	.	.	.	.	.
1993	6064.0452	0.8121	0.3924	41.0906	190.2364	0.019067	0.00037	3670.959	49.7636
1994	6006.5315	0.8041	0.3924	41.0906	190.2364	0.01103	0.00037	3670.959	49.7636
.	.	.	.	.	.	.	.	.	.
3655	5985.6915	0.8014	0.3924	41.0906	190.1739	0.008309	0.00037	333.146	49.8261
3656	5946.7682	0.7959	0.3924	41.0906	190.1739	0.002848	0.00037	3339.146	49.8261
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
10499	5940.3633	0.7959	0.3924	41.0906	189.8874	0.002848	0.00037	1819.803	50.1126

Table 5.2: Comparison of RCGA with other Optimization Methods.

	Sandgren	Fu	Kannan	Lewis	RVR
Method	Penalty	PSO	ALM	NLP	RCGA
R[inch]	47	43.381	58.291	38.2760	**41.0906**
L[inch]	117.701	111.745	43.690	223.299	**189.8874**

Ts[inch]	1.125	1.125	1.125	0.750	**0.7959**
T_h[inch]	0.625	0.625	0.625	0.375	**0.3924**
g1	-0.194	-0.170	0.000	-0.003	**-0.00285**
g2	-0.0283	-0.262	-0.117	-0.014	**-0.0003956**
g3	-0.0510	-0.534	-0.818	-0.070	**-1849.0951**
g4	0.054	-1.046	-1.109	-1.519	**-50.1126**
Objective[$]	8129.800	8048.619	7198.200	5980.950	**5940.3633**

Where

Penalty : Penalty Approach

ALM : Assets Liability Management algorithm

NLP :Non-linear programming Technique

PSO : particle swarm optimization

RCGA : Real coded Genetic Algorithm

From above table it is clear that theReal coded GA gives the best results hence it can have beneficially used for evaluating the cost of the pressure vessel.

6. ANSYS Analysis:

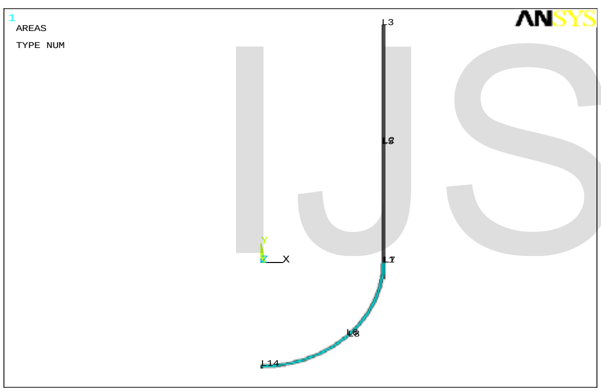

Fig: 6.2: Design of pressure vessel

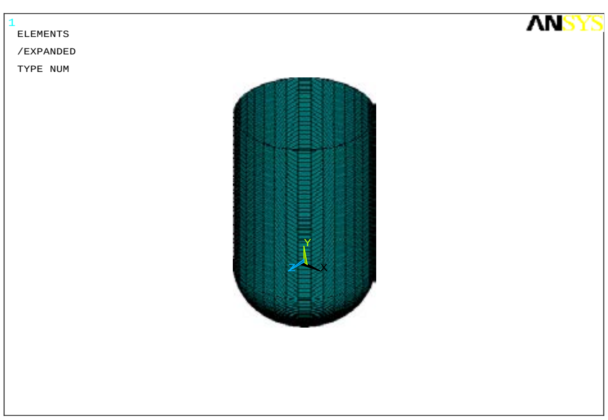

Fig: 6.3: Structure of pressure Vessel

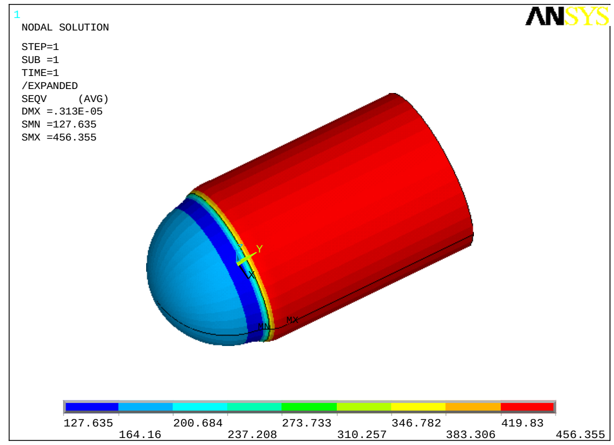

Fig: 6.4: von missesStress of pressure vessel

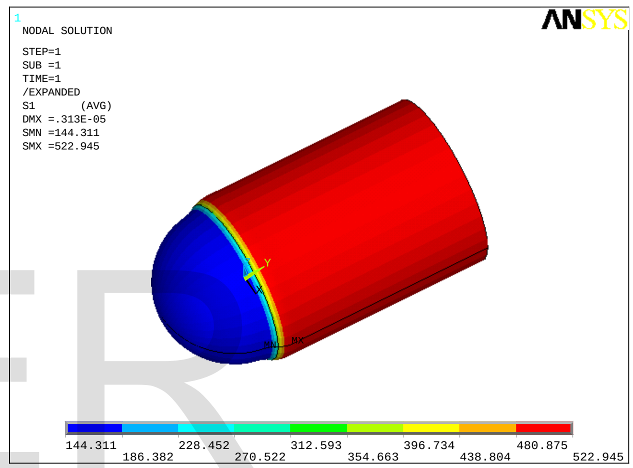

Fig: 6.5: Principle stressesalong X-direction

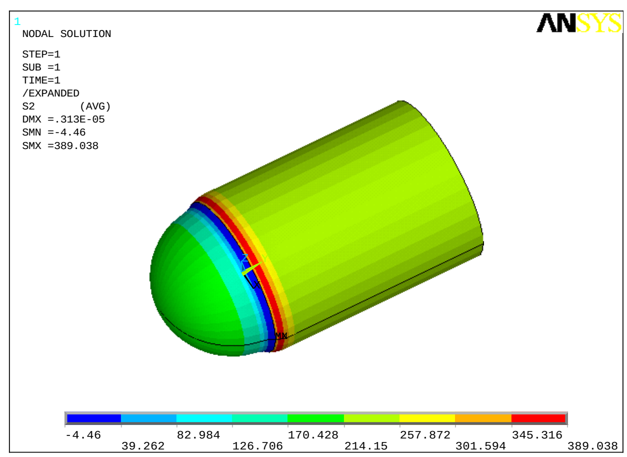

Fig: 6.6 Principle stresses acting along y -direction

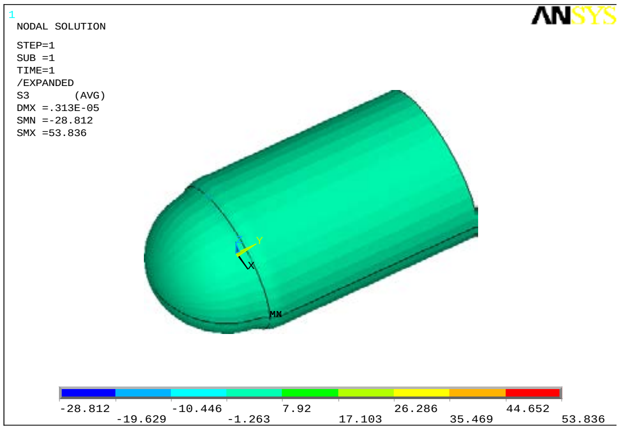

Fig: 6.7 Principle stresses acting along Z–direction

The results of the real coded GA have been checked using ANSYS, and it is found to perform satisfactorily.

7. CONCLUSION AND FUTURE SCOPE

In the present work parameters such as thickness of the shell, and dish end, length and radius of the pressure vessel are optimized by making use of Real coded genetic algorithm powerful non-traditional optimization method and these results are compared with other Optimization Methods.

- It is found that the results obtained from RCGA are better as its search is for global optimum as against the local optimum in traditional search methods. The results of the RCGA have been checked using ANSYS, and it is found to perform satisfactorily.
- The various authors have solved the problem using different algorithms such as Penalty Approach, Assets Liability Management algorithm, Non-linear programming Technique and particle swarm optimization, But it is found that the results obtained by using proposed algorithm is better optimized than any other earlier solutions reported.
- It can be concluded that by applying RCGA, the optimal design parameters for the pressure vessels are obtained and the objective minimization of cost by reducing weight of Pressure vessel is achieved.
- In the present study the application of RCGA has been shown for a Pressure vessel problem with four variables and four design constraints.

Future scope:

- In the proposed study the application of RCGA can be extended for pressure vessels with more than four variables and constraints (including Thermal Stresses).

The present problem can also be extended for the use of the composite materials for weight minimization.

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