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Optimization of Hydraulic Cylinder Design used for container lifting device using Genetic Algorithm

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Abstract:

This paper presents the use of different optimization techniques used for the optimization of hydraulic cylinder. These techniques are used to solve a three objective optimization problem in which a hydraulic cylinder is to be designed. It reflects mainly two techniques of Genetic Algorithm using MATLAB R2012a i.e. single and multi-objective optimization with several constraints. Different two dimensional parametric Pareto-optimal plots are obtained for the conflicting objectives like material stress, force on piston, Cylinder wall thickness and cross-sectional area of the cylinder. This optimization analysis strengthens and extends the results suggested by previous works.

Keywords — **Container lifting device (CLD), Algorithm, Genetic algorithm, Cross over, Mutation, Optimization, Single and Multi-objective optimization, Pareto optimization**

1. INTRODUCTION

Mostly the tractor driven container lifting devices (CLD) are used for lifting up to 4.5 cubic meter containers for the transportation of solid waste. The various components of CLD are like hydraulic cylinder, leaf spring, hoisting chain, mechanical jack, cross-rod etc. Hydraulic cylinders are actuation devices that convert the hydraulic energy of pressurized fluids into the mechanical energy needed to control the movement of machine linkages and attachments. Usually, hydraulic cylinder manufactures design them considering buckling load by using Euler equation and safety factor, assuming that the cylinder is column under concentric load. The most known double acting cylinder is using the single rod end. This type of cylinder provides power in both directions, with a pressure port at any end.

Many methods are now available for design optimization of various mechanical elements but no single method gives 100 percent satisfaction. Special design are not standardized as the common sizes and construction of manufacturing methods is not available, that is why if mathematically optimization is not possible in actual practice. This is due to the accessibility of components in standard sizes and constraints due to manufacturing and production practices. Some algorithms have been developed to handle the different nature of design variables. This issue is of the huge importance in solving sensible problems of design optimization. During the last few years lots of mathematical linear and nonlinear programming methods have been developed for solving optimization problems. However, no particular method has been found to be totally capable and strong for all different kinds of engineering optimization problems. Some methods are used for that as

1) penalty-function method,
2) augmented Lagrangian method, and
3) conjugate gradient method,

These methods are not always appropriate in solving all optimization problem used by a mechanical design engineer. Additional methods may apply the first and second order with essential conditions to search for a local minimum by solving a set of nonlinear equations.
These methods usually search for a solution in the region of the starting point. Here the global optimum cannot be assured because the outcome will depend on the selection of the initial point, if there is more than one local optimum in the problem. Moreover gradient search becomes complicated and unsteady, when the objective function and constraints have many sharp peaks.

2. OPTIMIZATION TECHNIQUE - GENETIC ALGORITHM

In the course of the most recent couple of years, genetic algorithms (GAs) have been widely utilized as a hunt and streamlining devices in different issue areas, including the sciences and engineering. The principle purposes behind their prosperity are their expansive materialness, usability and worldwide perspective.
GAs combine the concept of artificial survival of the fittest with genetic operators abstracted from nature to form a robust search mechanism. GAs differs from traditional optimization algorithms in many ways.

- GAs search from population of points, not a single point.
- GAs work with a coding of the parameter set, not the parameters themselves.
- GAs use objective function information, not derivatives, calculus or other auxiliary knowledge.
- GAs use probabilistic transition rules, not deterministic rules.

The genetic algorithm differs from a classical, derivative-based, optimization algorithm in two main ways. This is summarized in the following Table 1.

Table 1: Comparison of Classical and Genetic Algorithm

Classical Algorithm	Genetic Algorithm
Generation of single point at every iteration. The progression of points approaches an optimal solution.	Generation of population of points at every iteration. The best point in the population approaches an optimal solution.
Selects the next point in the progression by a deterministic computation.	Selects the next population by computation which uses random number generators.

2.1 Outline of Genetic Algorithm

This section describes fractural analysis of outline of genetic algorithm. The following stepwise description shows how the genetic algorithm proceeds:

(1) In the beginning, algorithm creating arbitrary initial population.

(2) Afterwards, algorithm creates a progression of novel populations. At every step, the algorithm uses the individuals in the recent generation to create the next population.

3. OPTIMIZATION IN HYDRAULIC CYLINDER DESIGN – A CASE STUDY

Monotonicity and dominance were used to find general principles for designing hydraulic cylinders optimal for a wide class of objective functions and stress conditions. The design method, although guaranteed to give the optimum design.
Optimal cylinders should be designed for minimum force. Only two designs can be optimal—one with maximum pressure and minimum wall thickness; the other with maximum stress.
In the former case, the design is retained if and only if the stress is less than allowable. Otherwise, a one-variable search in a restricted interval is needed. The results suggest the potential importance of monotonicity and dominance in identifying the critical constraints in a design.

(1) Inside diameter, d ⟶ x(1)

(2) Wall thickness, t ⟶ x(2)
(3) Material Stress, s
(4) Force, f
(5) Oil Pressure, p ⟶ x(3)
(6) Cross-sectional area of hydraulic cylinder, A

First Optimum design will be with maximum pressure and minimum wall thickness, second with maximum stress.
Subject to

$$Wall\ thickness,\ t \geq 7\ mm$$

$$Force,\ f \leq 5\ ton\ \left(so\ \ 5000\ kg \cong 49050\ N\right)$$

$$Pressure,\ p \leq 200\ kg/cm^2\ \left(say\ \ 19.62\ N/mm^2\right)$$

There are three physical relations:
First relates force, pressure and area.

$$f = \frac{\pi}{4} \times d^2 \times p$$

The second gives the wall stress,

$$s = \frac{p \times d}{2 \times t}$$

Also to find Cross-sectional area of hydraulic cylinder:
Cross-sectional area,

$$A = \pi.d.t + \pi.t^2$$

$$A = \pi\left(d.t + t^2\right)$$

3.1 Single Objective Optimization Problem – Nonlinear Constrained Minimization

Optimization Toolbox provides widely used algorithms for standard and large-scale optimization. These algorithms solve constrained and unconstrained continuous and discrete problems. The toolbox includes functions for linear programming, quadratic programming, binary integer programming, nonlinear optimization, nonlinear least squares, systems of nonlinear equations, and multi-objective optimization. We can use them to find optimal solutions, perform tradeoff analyses, balance multiple design alternatives, and incorporate optimization methods into algorithms and models.

Using MATLAB 2012 following examples were created and solved related to optimization and design hydraulic cylinder to be used for container lifting device.

Example 1

app2 -- Minimize the force, f

```
ObjectiveFunction = @simple_fitness2;
nvars = 3;    % Number of variables
LB = [50 7 15.696];   % Lower bound
UB = [80 16 19.62];  % Upper bound
ConstraintFunction = @simple_constraint2;
Options=gaoptimset('generations',[50],'PopulationSize',[25],'PlotFcns',{@gaplotbestf,@gaplotmaxconstr},'Display','iter');
[x,fval] = ga(ObjectiveFunction,nvars,[],[],[],[],LB,UB,ConstraintFunction,[1 2],options)
```

```
simple_constraint2
function [c, ceq] = simple_constraint2(x)
c=[0.785*x(1)^2*x(3)-49050;29430-0.785*x(1)^2*x(3);80-x(3)*x(1)/(2*x(2));x(3)*x(1)/(2*x(2))-92];
ceq = [ ];
```

```
simple_fitness2
function y = simple_fitness2(x)
y = 0.785*x(1)^2*x(3);
```

The iteration table in the command window shows how MATLAB searched for the lowest value of force function. This table is the same whether to be used as Optimization Tool or the command line. MATLAB reports the value of three variables (i.e. internal diameter (d), cylinder wall thickness (t), pressure (p) and minimization of force, (f) as below:

Output

```
x =   57.0000    7.0000   19.6200
fval =   5.0040e+04
```

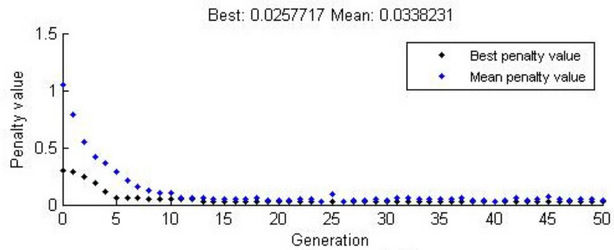

Fig.1 Optimization using MATLAB for the function : Minimization of force value (f) exerted on piston

Example 2

app16 –Minimization of cross-sectional area

```
ObjectiveFunction = @simple_fitness16;
nvars = 3;    % Number of variables
LB = [50 7 15.696];    % Lower bound
UB = [80 16 19.62];   % Upper bound
ConstraintFunction = @simple_constraint16;
options =
gaoptimset('generations',[50],'PopulationS
ize',[25],'PlotFcns',{@gaplotbestf,@gaplot
maxconstr},'Display','iter');
[x,fval] =
ga(ObjectiveFunction,nvars,[],[],[],[],LB,
UB,ConstraintFunction,[1 2],options)
```

simple_constraint16

```
function [c, ceq] = simple_constraint16(x)
c = [0.785*x(1)^2*x(3)-49050;
x(3)*x(1)/(2*x(2))-80];
ceq = [];
```

simple_fitness16

```
function y = simple_fitness16(x)
y = 3.14*((x(1)*x(2)+x(2)^2));
```

Again the iteration table in the command window shows how MATLAB searched for the lowest value of cross-sectional area function. This table is the same whether to be used as Optimization Tool or the command line. MATLAB reports the value of three variables (i.e. internal diameter (d), cylinder wall thickness (t), pressure (p) and minimization of cross-sectional area, (A) as below:

Output

x = 50.0000 7.0000 16.0707

fval = 1.2529e+03

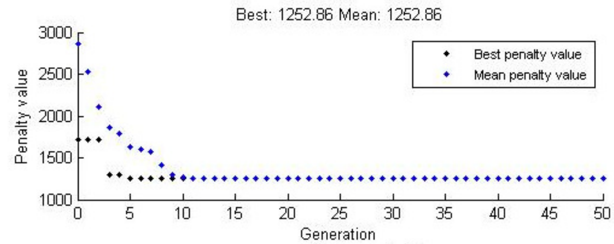

Fig.2 Optimization using MATLAB for the function : Minimization of Cross-sectional area (A) of the Hydraulic Cylinder

4. MULTI OBJECTIVE OPTIMIZATION USING GENETIC ALGORITHM

A multi-objective optimization problem (MOOP) tool deals with more than one objective function. There are fundamental differences between the working principles of single and multi-objective optimization algorithms. However, in a single objective optimization, the task is to find one solution which optimizes the sole objective function.

The general form of Multi-objective optimization problem (MOOP) is stated as follows:

$$\left.\begin{array}{lll} \text{Minimize / Maximize} & f_m(x), & m=1,2,\ldots\ldots,M; \\ \text{subject to} & g_j(x)\geq 0, & j=1,2,\ldots\ldots,J; \\ & h_k(x)=0, & k=1,2,\ldots\ldots,K; \\ & x_i^{[L]}\leq x_i\leq x_i^{[U]}, & i=1,2,\ldots\ldots,n. \end{array}\right\} \quad (1)$$

In many engineering problems we need to find solutions in the presence of conflicting objectives. In such cases, solutions are chosen such that there are reasonable trade-offs among different objectives. In certain problems, it may not be obvious that the objectives are not conflicting to each other. In such combinations of objectives, the resulting Pareto-optimal set will contain only one optimal solution. Pareto optimization is a methodology for solving multi criteria decision problems. This methodology provides a systematic approach towards design problems with multiple conflicting objectives. Pareto optimality is the major concept in multiple criteria optimization and it is defined as follows:

A feasible solution to a multi criteria optimization problem is Pareto optimal (or non-inferior) if there exists no other feasible solution that will yield an improvement in one criterion without causing a decrease in at least one other criterion.

Using Pareto search instead of generating a single optimal solution, many solutions are generated that satisfy Pareto Optimality Criterion. The set of all Pareto optimal solutions form a surface known as a Pareto front. The Pareto front helps engineers to realize the nature of trade-offs that require to be made in order to select superior solutions. Thus Pareto optimization techniques usually generate a large number of alternatives which the decision maker should investigate to arrive at his best compromise solution.

4.1 Difference with Single-Objective Optimization

Besides having multiple objectives there are number of primary variances between single objective and multi objective optimization, as under:[16]

4.1.1 Two goals Instead of one[16]

In a single-objective optimization, there is one goal that looks for an optimum solution. In the case of multi-modal optimization, the goal is to find a number of local and global optimal solutions, instead of finding one optimum solution. However, most single-objective optimization algorithms aim at finding one optimum solution, even when there exist a number of optimal solutions.

However, in multi-objective optimization, there are clearly two goals. Progressing towards the Pareto-optimal front is definitely an important goal. An algorithm that finds a closely packed set of solutions on the Pareto-optimal front satisfies the first goal of convergence to the Pareto-optimal front, but does not satisfy maintenance of a diverse set of solutions. Since all objectives are important in a multi-objective optimization, a diverse set of obtained solutions close to the Pareto-optimal front provides a variety of optimal solutions, trading objectives differently. A multi-objective optimization algorithm that cannot find a diverse set of solutions in a problem is as good as a single-objective optimization algorithm. Since both goals are essential, a proficient multi-objective optimization algorithm must work on fulfilling both of them. Because of these dual tasks, multi-objective optimization is more difficult than single-objective optimization.

4.1.2 Dealing with two search spaces[16]

Another difficulty is that multi-objective optimization involves two search spaces, instead of one. In a single-objective optimization, there is only one search space – the decision variable space. An algorithm works in this space by accepting and rejecting solutions based on their objective function values. Here in addition to the decision variable space, there is also the objective function space. When this happens, the proceedings in both spaces must be coordinated in such a way that the creation of new solutions in the decision variable space is complimentary to the diversity needed in the objective space. This by no means, is an easy task and more importantly is dependent on the mapping between the decision variables and objective function values.

4.1.3 No Artificial Fix-Ups[16]

The most real world optimization problems are naturally posed as a multi-objective optimization problem. Multi-objective optimization for finding multiple Pareto-optimal solutions eliminates all such fix-ups and can, in principle, find a set of optimal solutions corresponding to different weight and e-vectors. It is true that a multi-objective optimization is, in general more complex than a single-objective optimization, but the avoidance of multiple simulation runs, no artificial fix-ups, availability of efficient population based optimization algorithms, and above all, the concept of dominance helps to overcome some of the difficulties and give a user the practical means to handle multiple objectives, a matter which was not possible to achieve in the past.

5. MULTI – OBJECTIVE OPTIMIZATION

Definition: Point $x^* \in \Omega$ is a non-inferior solution if for some region of x^* there does not exist a Δx such that $\left(x^* + \Delta x\right) \in \Omega$ and

$$F_i\left(x^* + \Delta x\right) \le F_i\left(x^*\right),\ i = 1, ..., m,\ \ and$$

$$F_j\left(x^* + \Delta x\right) < F_j\left(x^*\right)\ \ for\ at\ least\ one\ j.$$

In the two-dimensional representation of Figure 4 the set of non-inferior solutions lies on the curve between C and D. Points A and B represent specific non inferior points.

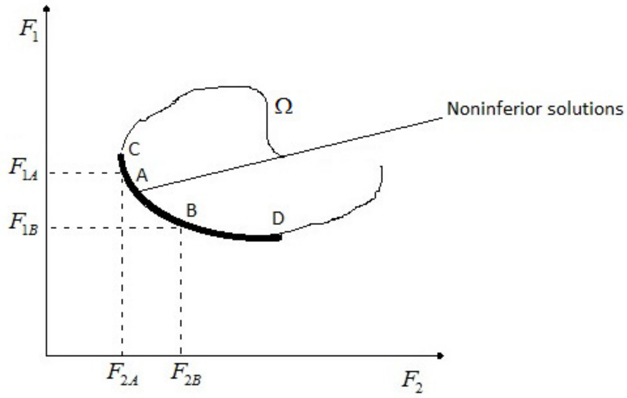

Fig.4 Set of Non inferior Solutions

A and B are clearly non inferior solution points because an improvement in one objective, F_1, requires a degradation in the other objective, F_2, i.e. , $F_{1B} < F_{1A}$, $F_{2B} > F_{2A}$.

Since any point in Ω that is an inferior point in which enhancement can be attained in all the objectives, it is clear that such a point is of no value.

Multi-objective optimization is, therefore, concerned with the generation and selection of non-inferior solution points.

Non inferior solutions are also called Pareto optima. A general goal in multi-objective optimization is constructing the Pareto optima. [30]

Following three examples are related to multi-objective optimization of same hydraulic cylinder using MATLAB 2012.

Example 3

app9 -- Multi objective Optimization, Pareto Optimization, Minimization the stress, s & Maximization of force, f linked with mymulti4.m. [d = x(1), t = x(2) and p = x(3)]

```
App9
options =
gaoptimset('PopulationSize',60,...
'ParetoFraction',0.7,'PlotFcns',@gaplotpar
eto);
[xfval flag output population] =
gamultiobj(@mymulti4,3,...
[],[],[],[],[55,7,15.696],[70,15,19.62],op
tions)
```

mymulti4.m

```
function f = mymulti4(x)
f(1) = -x(3)*x(1)/(2.0*x(2));
f(2) = 0.785*x(1)^2*x(3);
```

Table 2: Value of each variable Internal diameter (d), Thickness of Cylinder (t) and Internal Pressure (p) after each iteration

Sr. No.	Internal Diameter, d, x(1) in mm	Thickness of Cylinder, t, x(2) in mm	Internal Pressure, p, x(3) in N/mm^2
1	55.0000	7.0000	15.6960
2	55.0000	7.0000	15.6960
3	67.9488	7.0004	19.6177
4	66.0879	7.0006	19.6142
5	62.1038	7.0008	19.6095
6	55.0697	7.0001	18.7284
7	55.0000	7.0000	15.6960
8	61.5011	7.0044	19.5724
9	63.2799	7.0007	19.4776
10	55.1592	7.0002	19.3134
11	60.1210	7.0009	19.2270
12	55.2045	7.0004	17.5064
13	61.5487	7.0005	19.3465
14	62.6038	7.0008	19.6095
15	63.6634	7.0008	19.5930
16	66.7628	7.0882	19.6077
17	67.3658	7.0007	19.6087
18	67.9488	7.0629	19.6177
19	55.3786	7.0004	18.9923
20	63.1262	7.0008	19.3906
21	65.5459	7.0007	19.5991
22	64.5898	7.0014	19.5215
23	68.4488	7.0629	19.6177
24	55.2372	7.0003	16.9682
25	57.5214	7.0014	19.0636
26	56.3554	7.0000	18.9304
27	57.2708	7.0014	18.9802
28	61.4504	7.0005	19.2710
29	65.9134	7.0005	19.4305
30	60.0506	7.0007	19.2578
31	57.0909	7.0000	19.2807
32	55.4016	7.0001	17.8215
33	55.6155	7.0005	19.5148
34	58.6515	7.0005	19.2076
35	66.6374	7.0005	19.6171
36	55.2858	7.0005	18.7972
Sr.	Internal	Thickness of	Internal

No.	Diameter, d, x(1) in mm	Cylinder, t, x(2) in mm	Pressure, p, x(3) in N/mm^2
37	59.1644	7.0004	19.4069
38	61.2350	7.0006	19.5046
39	55.0697	7.0001	18.2284
40	55.4872	7.0003	16.4682
41	59.3659	7.0006	18.6440
42	63.8413	7.0005	19.4967
43	57.2254	7.0003	18.0292
44	61.6910	7.0002	19.6070
45	60.0506	7.0007	19.2578
46	60.6888	7.0006	19.3176
47	57.5941	7.0009	19.4783
48	55.1072	7.0002	18.4943
49	66.8232	7.0563	19.5605
50	61.4631	7.0019	19.1307
51	57.3776	7.0009	19.5002
52	66.8318	7.0054	19.4653
53	55.0000	7.0000	15.6960
54	65.1528	7.0007	19.4174
55	62.9997	7.0002	19.1572
56	56.0235	7.0003	19.1430
57	64.8733	7.0005	19.5825
58	55.0697	7.0626	18.2284
59	58.6515	7.0005	19.4576
60	67.6158	7.0007	19.6087

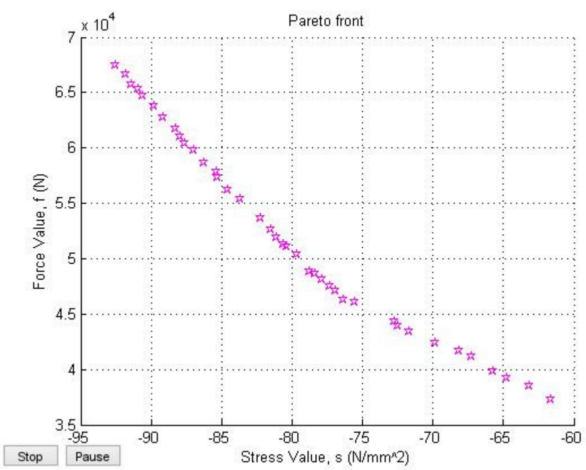

Fig.5 : Pareto optimization using Genetic Algorithm plot of Stress generated(N/mm^2) v/s Force on Piston (N)

Example 4

app6 -- Multiobjective Optimization, Pareto Optimization, Minimization of the force, f & Maximization of thickness, t linked with mymulti1.m. [d = x(1), s = x(2) and p = x(3)]

App6

```
options =
gaoptimset('PopulationSize',60,...
'ParetoFraction',0.7,'PlotFcns',@gaplotpar
eto);
[xfval flag output population] =
gamultiobj(@mymulti1,3,...

[],[],[],[],[55,80,15],[80,92,19.62],optio
ns)
```

mymulti1.m

```
function f = mymulti1(x)
f(1) = -0.785*x(1)^2*x(3);
f(2) = x(3)*x(1)/(2.0*x(2));
```

Table 3 : Value of each variable Internal diameter (d), Stress of Cylinder (s) and Internal Pressure (p) after each iteration

Sr. No.	Internal Diameter, d, x(1) in mm	Stress of Cylinder, s, x(2) in N/mm^2	Internal Pressure, p, x(3) in N/mm^2
1	55.0078	91.6168	15.0018
2	79.9919	91.7703	19.6176
3	79.9919	91.7547	19.6176
4	79.2017	91.7932	16.5609
5	55.0078	91.6480	15.0018
6	55.0078	91.6793	15.0018
7	79.9694	91.8333	19.3448
8	79.8608	91.7727	15.8229
9	66.3763	91.7202	15.1005
10	76.0792	91.7928	15.0875
11	79.4116	91.7394	17.0860
12	79.8643	91.8274	19.0110
13	63.2734	91.7015	15.0096
14	79.8288	91.7790	17.8853
15	65.0628	91.7493	15.2036
16	64.9417	91.6681	15.0416
17	77.6260	91.7956	15.2363
18	67.0868	91.7160	15.3411
Sr. No.	Internal Diameter, d,	Stress of Cylinder, s, x(2)	Internal Pressure,

	x(1) in mm	in N/mm²	p, x(3) in N/mm²
19	70.5506	91.6568	15.0636
20	75.3182	91.7606	15.3205
21	67.3269	91.7229	15.0905
22	79.3568	91.7997	16.7358
23	79.6428	91.7405	18.5703
24	79.9240	91.8879	17.5826
25	79.9256	91.8502	18.3170
26	77.3328	91.8284	15.1115
27	72.7814	91.7847	15.0560
28	79.8332	91.8116	18.7950
29	59.9086	91.7026	15.4638
30	56.6810	91.7107	15.0201
31	69.1143	91.7195	15.1666
32	59.2841	91.8107	15.5315
33	79.7091	91.7845	16.0754
34	79.8247	91.7922	17.2598
35	65.0814	91.7806	15.2036
36	79.6472	91.7693	16.2253
37	57.2698	91.7542	15.1802
38	79.6972	91.7660	18.5507
39	61.4632	91.7095	15.1355
40	62.8751	91.6910	15.1317
41	55.0078	91.6793	15.0018
42	57.5984	91.7088	15.0473
43	78.8803	91.7897	15.8159
44	68.5697	91.7179	15.2937
45	79.1919	91.7576	17.0069
46	59.2251	91.6635	15.1759
47	78.6092	91.7721	17.4948
48	73.1853	91.7286	15.5022
49	76.8068	91.7216	15.4737
50	75.4550	91.8006	15.3853
51	68.5267	91.7862	15.0148
52	78.1924	91.7886	15.5452
53	79.9295	91.7737	19.3981
54	72.4331	91.7462	15.4561
55	79.7663	91.7790	17.8853
56	70.4219	91.7718	15.4908
57	79.9240	91.8254	17.5826
58	63.2734	91.6390	15.0643
59	55.0586	91.7418	15.0018
60	79.5994	91.7578	15.6826

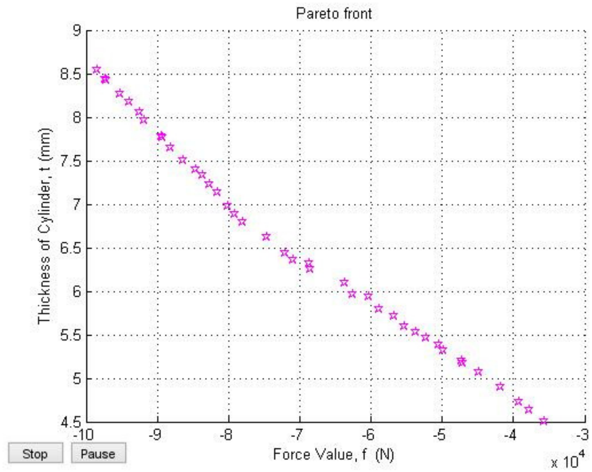

Fig.6 : Pareto optimization using Genetic Algorithm plot of Force (N) v/s Thickness of Cylinder (mm)

Example 5

app17 -- Multiobjective Optimization, Pareto Optimization, Minimization the force, f & Maximization of cross-sectional area, A linked with mymulti17.m. [d = x(1), t = x(2) and p = x(3)]

```
options =
gaoptimset('PopulationSize',60,...
'ParetoFraction',0.7,'PlotFcns',@gaplotpar
eto);
[xfval flag output population] =
gamultiobj(@mymulti17,3,...

[],[],[],[],[55,07,15.696],[70,16,19.62],o
ptions)
```

mymulti17.m

```
function f = mymulti17(x)
f(1) = -0.785*x(1)^2*x(3);
f(2) = 3.14*((x(1)*x(2)+x(2)^2));
```

Table 4 : Value of each variable Internal diameter (d), Thickness of Cylinder (t) and Internal Pressure (p) after each iteration

Sr. No.	Internal Diameter, d, x(1) in mm	Thickness of Cylinder, t, x(2) in mm	Internal Pressure, p, x(3) in N/mm^2
1	55.0000	7.0000	16.0085
2	69.9987	7.0283	19.6200
3	69.9987	7.0127	19.6200
4	57.6986	7.0018	19.5913
5	55.0031	7.0002	18.8725
6	63.5562	7.0312	19.5854
7	55.0000	7.0000	17.5416
8	55.0000	7.0000	16.0085
9	55.0000	7.0000	16.0241
10	55.0000	7.0000	16.9024
11	55.0031	7.0012	18.8725
12	56.7591	7.0100	19.6194
13	69.2413	7.0112	19.6099
14	68.5541	7.0106	19.5913
15	56.3311	7.0160	19.5552
16	55.0000	7.0000	16.3537
17	69.9987	7.0225	19.6200
18	61.9767	7.0049	19.6109
19	69.9987	7.0127	19.6200
20	66.5631	7.0163	19.6021
21	59.7798	7.0104	19.6011
22	55.0012	7.0001	18.3711
23	62.3718	7.0077	19.4629
24	63.9051	7.0162	19.6023
25	67.5167	7.0110	19.4657
26	60.9584	7.0099	19.3632
27	55.0000	7.0000	17.0923
28	67.5035	7.0199	19.6129
29	68.0485	7.0104	19.6050
30	58.8005	7.0098	19.2952
31	55.4372	7.0396	19.2665
32	65.5574	7.0109	19.6028
33	55.9352	7.0152	19.5074
34	55.3623	7.0012	18.9455
Sr. No.	Internal Diameter, d, x(1) in mm	Thickness of Cylinder, t, x(2) in mm	Internal Pressure, p, x(3) in
			N/mm2
35	63.8330	7.0108	19.3648
36	69.6822	7.0121	19.6186
37	64.9928	7.0043	19.5858
38	65.8195	7.0137	19.6042
39	60.3892	7.0092	19.5858
40	59.5785	7.0034	19.2825
41	61.5670	7.0146	19.6042
42	57.3518	7.0055	19.4248
43	65.6511	7.1359	19.6028
44	55.1262	7.0001	18.3711
45	59.4147	7.0100	19.4629
46	58.3674	7.0041	19.2737
47	55.2397	7.0133	19.3382
48	62.2097	7.0236	19.4095
49	63.2301	7.0185	19.6084
50	60.8089	7.0126	19.6011
51	57.7745	7.0087	19.3398
52	59.3529	7.0099	19.3541
53	68.9767	7.0144	19.5854
54	56.8451	7.0144	19.5399
55	67.1126	7.0062	19.5764
56	67.1009	7.0032	19.5319
57	55.7167	7.0280	19.4999
58	62.8502	7.0158	19.6097
59	57.6018	7.0055	19.4248
60	66.5631	7.0163	19.3521

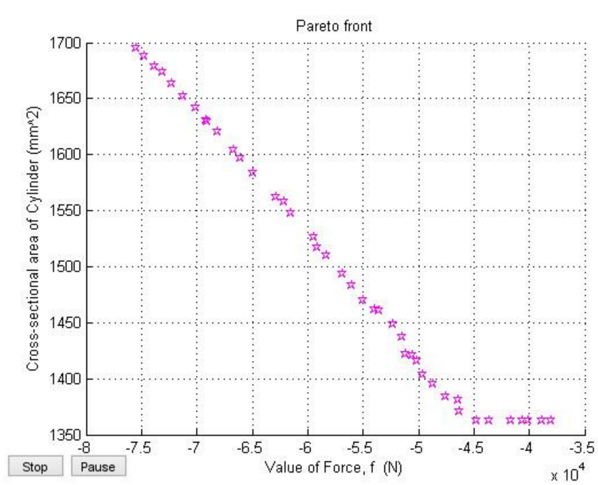

Fig.7 : Pareto optimization using Genetic Algorithm plot of Force (N) v/s Cross-sectional area of Cylinder (mm^2)

6. Conclusion

For the single objective optimization problem (minimizing the force/cross-sectional area/thickness of cylinder), the objective function is monotonic with respect to its variable only (i.e. inside diameter, d). In this case since the constraints pressure (p) and thickness (t) are active. Multi-objective optimization problem results in a number of optimal solutions, known as Pareto-optimal solutions. Pareto optimization is a methodology for solving multi criteria decision problems. This methodology provides a systematic approach towards design problems with multiple conflicting objectives. In Pareto optimal design situations, the designer has more than one performance measure of interest. An optimal solution is generally defined as the best solution. However, with multi criteria problems, the "best" is often dependent upon a designer's preferences. The Pareto optimization methodology usually generates a large number of alternatives which the designer evaluates in order to arrive at his best solution often termed the best compromise solution. The Pareto-optimal curves can be thought of as providing a boundary of efficient solutions. If a design is not on the boundary, the curve shows how much of one objective can be improved without hurting others.

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