# Sections and Chapters

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#### 1 Introduction

This is the first section.

#### 2 Unconstrained MOGA Problems

We used this textbook [1]

#### 2.1 ZDT1

The first test problem, denoted as ZDT1 in (insert reference) is shown below.

Minimize 
$$f_1(\mathbf{x}) = x_1$$
Minimize 
$$f_2(\mathbf{x}) = g(x) * h(x)$$
where 
$$g(x) = 1 + \frac{9}{(n-1)} \sum_{i=2}^n x_i$$

$$h(x) = 1 - \sqrt{\frac{f_1(x)}{g(x)}}$$

$$n = 30$$

$$0 \le \mathbf{x} \le 1$$

The true Pareto frontier for this problem occurs when  $x_i = 0$  for i = 2,...,30. Figure 1 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. The quality metrics chosen to evaluate this problem are Coverage Difference (CD)and Pareto Spread (OS). Ten runs for each algorithm were performed and the mean and standard deviation of each metric are tabulated in Table 1.

Table 1: Quality Metrics for ZDT1

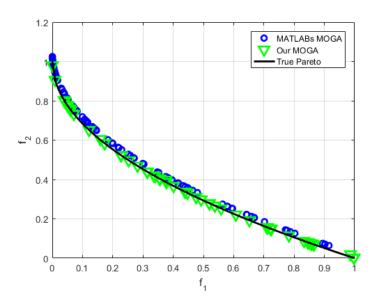
Metric	MATLABs MOGA	Our MOGA
CD	0.3874 (0.0164)	0.3582 (0.0040)
OS	0.9605 (0.1088)	0.9283 (0.0928)

From these metrics, there is certainly a trade-off between MATLABs MOGA and the MOGA developed in this project. The coverage difference of the new MOGA is better in this problem whereas the Pareto spread is improved when using MATLABs MOGA.

#### 2.2 ZDT2

The second test problem, denoted as ZDT2 in (insert reference) is shown below.

Figure 1: Example Pareto Results for ZDT1



Minimize 
$$f_1(\mathbf{x}) = x_1$$
Minimize 
$$f_2(\mathbf{x}) = g(x) * h(x)$$
where 
$$g(x) = 1 + \frac{9}{(n-1)} \sum_{i=2}^n x_i$$

$$h(x) = 1 - \frac{f_1(x)}{g(x)}^2$$

$$n = 30$$

$$0 \le \mathbf{x} \le 1$$

The true Pareto frontier for this problem, similar to ZDT1, occurs when  $x_i = 0$  for i = 2,...,30. Figure 2 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 2 summarizes the mean quality metrics for each algorithm for ten runs.

Table 2: Quality Metrics for ZDT2

<u> </u>		
Metric	MATLABs MOGA	Our MOGA
CD	0.7832 (0.0821)	0.6971 (0.0094)
OS	0.8781 (0.0946)	1.0086 (0.0278)

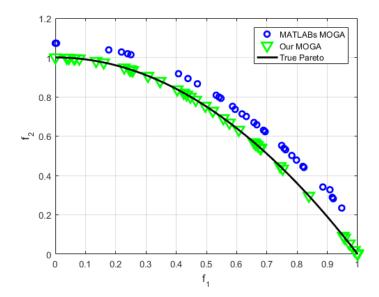


Figure 2: Example Pareto Results for ZDT2

#### 2.3 ZDT3

The third test problem, denoted as ZDT3 in (insert reference) is shown below.

Minimize 
$$f_1(\mathbf{x}) = x_1$$
Minimize 
$$f_2(\mathbf{x}) = g(x) * h(x)$$
where 
$$g(x) = 1 + \frac{9}{(n-1)} \sum_{i=2}^n x_i$$

$$h(x) = 1 - \sqrt{\frac{f_1(x)}{g(x)}} - \frac{f_1(x)}{g(x)} \sin(10\pi f_1)$$

$$n = 30$$

$$0 \le \mathbf{x} \le 1$$

The true Pareto frontier for this problem again occurs when  $x_i = 0$  for i = 2,...,30. Figure 3 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 3 summarizes the mean quality metrics for each algorithm for ten runs.

Overall, MATLABs MOGA outperforms the MOGA developed in this project in both coverage difference and Pareto spread. A paired t-test shows that the difference in the means for coverage difference is statistically significant (p<sub>i</sub>0.05), while the difference is not statistically significant in Pareto Spread (p=0.21).

1.2 MATLABs MOGA
Our MOGA Feasible Domain Frontie 0.8 0.6 0.4 **⊷**∾ 0.2 0 -0.2 -0.4 -0.6 8.0-0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 8.0 0.9 f<sub>1</sub>

Figure 3: Example Pareto Results for ZDT3

Table 3: Quality Metrics for ZDT3  $\,$ 

Metric	MATLABs MOGA	Our MOGA
CD	0.7407 (0.0050)	0.7554 (0.0031)
OS	$0.8565 \ (0.0098)$	0.8489 (0.0180)

## 2.4 OSY

This test problem, denoted as OSY in (insert reference) is shown below, Figure 4 shows the true Pareto frontier for this problem.

Minimize 
$$f_1(\mathbf{x}) = -(25(x_1 - 2)^2 + (x_2 - 2)^2 + (x_3 - 1)^2 + (x_4 - 4)^2 + (x_5 - 1)^2)$$
Minimize 
$$f_2(\mathbf{x}) = \sum_{i=1}^6 x_i^2$$
Subject to 
$$g_1(x) = 1 - \frac{x_1 + x_2}{2} \le 0$$

$$g_2(x) = \frac{x_1 + x_2}{6} - 1 \le 0$$

$$g_3(x) = \frac{x_2 - x_1}{2} - 1 \le 0$$

$$g_4(x) = \frac{x_1 - 3x_2}{2} - 1 \le 0$$

$$g_5(x) = \frac{(x_3 - 3)^2 + x_4}{4} - 1 \le 0$$

$$g_6(x) = 1 - \frac{(x_5 - 3)^2 + x_6}{4} \le 0$$

$$0 \le x_1, x_2, x_6 \le 10$$

$$1 \le x_3, x_5 \le 5$$

$$0 < x_4 < 6$$

Figure 5 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 4 summarizes the mean quality metrics for each algorithm for ten runs.

Table 4: Quality Metrics for OSY

Metric	MATLABs MOGA	Our MOGA
CD	$0.7882 \ (0.1995)$	$0.5507 \ (0.0685)$
OS	$0.5322 \ (0.3393)$	0.9608 (0.2427)

Overall, our MOGA outperformed MATLABs MOGA in both quality metrics. However, by examining the Pareto frontiers, it is clear that neither algorithm is truely satisfactory in estimating the true Pareto frontier.

#### 3 Constrained MOGA Problems

This is a reference to Azarms constraint paper [2].

#### 3.1 TNK

This test problem, denoted as TNK in (insert reference) is shown below with the true Pareto frontier shown in Figure 6.

30 20 10 -150-100f,

Figure 4: True Pareto Frontier for OSY

$$\begin{array}{ll} \text{Minimize} & f_1(\mathbf{x}) = x_1 \\ \text{Minimize} & f_2(\mathbf{x}) = x_2 \\ \text{Subject to} & g_1(x) = -x_1^2 - x_2^2 + 1 + 0.1\cos(16\arctan(\frac{x_1}{x_2})) \leq 0 \\ & g_2(x) = (x_1 - 0.5)^2 + (x_2 - 0.5)^2 - 0.5 \leq 0 \\ & 0 \leq x_1, x_2 \leq \pi \end{array}$$

Figure 7 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 5 summarizes the mean quality metrics for each algorithm for ten runs.

Table 5: Quality Metrics for TNK

Metric	MATLABs MOGA	Our MOGA
CD	0.8581 (0.0480)	0.7792 (0.0036)
OS	0.4177 (0.3216)	0.9763 (0.0178)

Comparing the estimated Pareto frontiers to the true Pareto frontier, is is clear that our MOGA outperforms MATLAB's MOGA. The Pareto spread in

80 ablaMATLABs MOGA Our MOGA 70 50 **-**∼ 40 a accompany octobro 30 20 10 -300 -250 -200 -150 -100 -50 0  $f_1$ 

Figure 5: Example Pareto Results for OSY

our MOGA is significantly higher however the coverage difference is higher in MATLABs MOGA (p;0.05).

#### 3.2 CTP

This test problem, denoted as CTP in (insert reference) is shown below and the true Pareto frontier is shown in Figure 8.

$$\begin{array}{ll} \text{Minimize} & f_1(\mathbf{x}) = x_1 \\ \\ \text{Minimize} & f_2(\mathbf{x}) = g(x)(1 - \sqrt{\frac{f_1(x)}{g(x)}} \\ \\ \text{Subject to} & g_1(x) = a |\sin(b\pi(\sin(\theta)(f_2(x) - e) + \cos(\theta)f_1(x))^c)|^d \\ & - \cos(\theta)(f_2(x) - e) - \sin(\theta)f_1(x) \leq 0 \\ \\ \text{where} & \theta = -0.2\pi, a = 0.2, b = 10, c = 1, d = 6, e = 1 \\ \\ & g(x) = |1 + (\sum_{i=2}^{10} x_i)^{0.25}| \\ & 0 \leq x_1 \leq 1 \\ & -5 \leq x_i \leq 5, i = 2, ..., 10 \end{array}$$

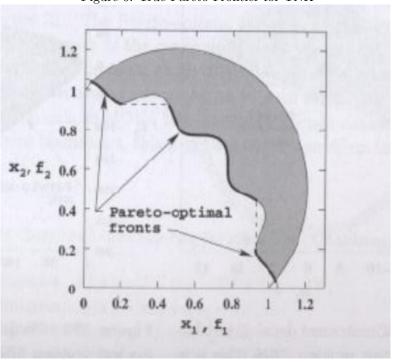


Figure 6: True Pareto Frontier for TNK

Figure 9 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 6 summarizes the mean quality metrics for each algorithm for ten runs [1].

Table 6: Quality Metrics for CTP

Metric	MATLABs MOGA	Our MOGA
CD	0.6802 (0.0067)	0.6802 (0.0092)
OS	0.7901 (0.0734)	0.5959 (0.1324)

The mean values for coverage difference are exactly the same for both algorithms. In fact a paired t-test also shows the means are not statistically difference( $p_{\dot{t}}0.05$ ). For Pareto spread, MATLAB's MOGA performs the highest.

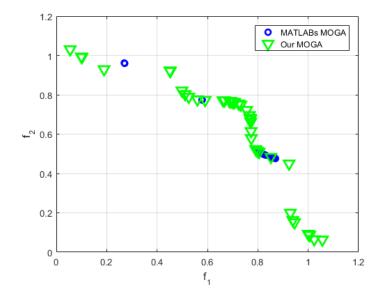


Figure 7: Example Pareto Results for TNK

### 4 Robust Problems

#### 4.1 Robust TNK

This test problem, denoted as TNK in (insert reference) is shown below with the true Pareto frontier shown in Figure 6.

Minimize 
$$f_1(\mathbf{x}) = x_1$$
  
Minimize  $f_2(\mathbf{x}) = x_2$   
Subject to  $g_1(x) = 1 + 0.1\cos(16\arctan(\frac{x_1}{x_2})) + 0.2\sin p_1\cos p_2 - x_1^2 - x_2^2 \le 0$   
 $g_2(x) = (x_1 - 0.5)^2 + (x_2 - 0.5)^2 - 0.5 \le 0$   
 $0 \le x_1, x_2 \le \pi$   
 $-1 \le p \le 3$ 

Figure ?? shows a sample result from both MATLABs built in MOGA and the robust MOGA developed in this project. Table 7 summarizes the mean quality metrics for each algorithm for ten runs.

Comparing the estimated Pareto frontiers to the true Pareto frontier, is is clear that our MOGA outperforms MATLAB's MOGA. The Pareto spread in

Figure 8: True Pareto Frontier for CTP

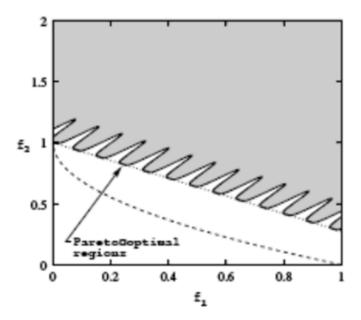


Table 7: Quality Metrics for Robust TNK (10 Runs)

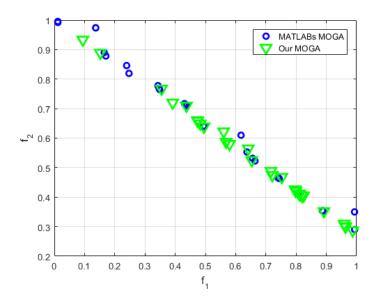
Metric	Our MOGA
CD	0.95 (0.014)
OS	0.66 (0.012)

our MOGA is significantly higher however the coverage difference is higher in MATLABs MOGA ( $p_i0.05$ ).

#### 4.2 Flight Planning Problem (FPP)

Now let us consider the final problem where we try to minimize the total flight time from the start location (0,12.5) to the finish location (40,12.5). In this problem there is a know wind velocity field which changes the total velocity of the aircraft with respect to the ground. At the same time, we want to maximize the distance of the flight path from some group of some exclusion zones. This also introduces a constraint that requires the flight path not intersect the exclusion zone. Each exclusion zone is approximated by a circle with known centers. The radius of each exclusion zone is known to  $\pm 2m$ . As a result this problem can be approached as a bi-objective optimization with a robust feasibility constraint.





$$\begin{aligned} & \text{Minimize} & & f_1(\mathbf{x},\mathbf{y}) = flightTime(\mathbf{x},\mathbf{y}) \\ & \text{Maximize} & & f_2(\mathbf{x},\mathbf{y}) = -\min_{i,j} \sqrt{(\mathbf{x}_i - \mathbf{x}\mathbf{c}_j)^2 + (\mathbf{y}_i - \mathbf{y}\mathbf{c}_j)^2} \\ & \text{Subject to} & & \mathbf{g}_j(\mathbf{x},\mathbf{y}) = -\min_j \left[ \mathbf{r}_j + p_0 + \Delta p - \sqrt{(\mathbf{x}_i - \mathbf{x}\mathbf{c}_j)^2 + (\mathbf{y}_i - \mathbf{y}\mathbf{c}_j)^2} \right] \leq 0 \\ & \text{where} & & 0 \leq x \leq 50, i = 2, ..., 10 \\ & & 0 \leq y \leq 25, i = 2, ..., 10 \\ & & p_0 = 0 \\ & & \Delta p \in [0,2] \end{aligned}$$

The function  $flightTime(\mathbf{x}, \mathbf{y})$  is a black-box. The values  $\mathbf{x}\mathbf{c}_j$  and  $\mathbf{y}\mathbf{c}_j$  specify the exclusion zone centers while  $\mathbf{r}_j$  specify the radii. A solution to this problem is shown in figure 11. In this figure there are two exclusion zones.

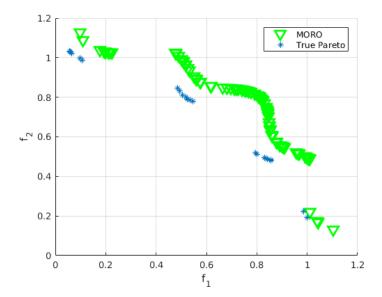


Figure 10: Example Pareto Results for TNK

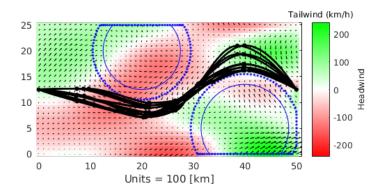
#### References

- [1] K. Deb, "Multi-objective optimization using evolutionary algorithms, 2001," *Chicheter, John-Wiley.*, 2001.
- [2] A. Kurpati, S. Azarm, and J. Wu, "Constraint handling improvements for multiobjective genetic algorithms," *Structural and Multidisciplinary Optimization*, vol. 23, no. 3, pp. 204–213, 2002.

## 5 Appendix

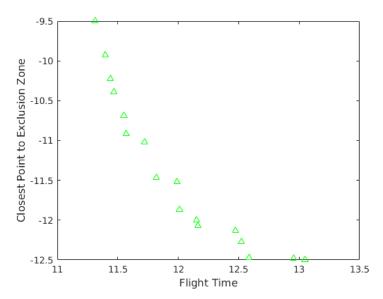
## Matlab Code

Figure 11: True Pareto Frontier for CTP



```
elseif (contains (current_dir, '/ENME625_Optimization')) %
      windows
       path_prefix = [current_dir, '\'];
10
   else
       fprintf('not running from the correct directory')
12
       return
13
14
   file_name = [path_prefix, 'results_and_params.mat'];
15
   results_and_params = load(file_name);
   results_and_params = results_and_params.
      results_and_params;
   global alpha sigma epsilon
19
20
  % helper functions
21
   if(nargin < 1)
22
       prompt = 'Which Test Problem Do You Want To Run? \n 1
            - ZDT1\n 2 - ZDT2 \n 3 - ZDT3 \n 4 - OSY \n 5 -
          TNK \setminus n \ 6 - CTP \setminus n \ 7 - Robust \ TNK \setminus n';
       prob = input(prompt);
24
  end
25
   if nargin <2
26
       prompt2 = 'How Many Chromosomes? Suggest 20-30';
       nChrome = input (prompt2);
28
```

Figure 12: True Pareto Frontier for CTP



```
end
29
   if nargin <3
       prompt3 = 'How Many Runs? Suggest >40: ';
31
       nRun = input (prompt3);
  end
33
   if nargin < 4
       prompt4 = 'What value for alpha?';
35
       alpha = input(prompt4);
36
   else
37
       alpha = alpha_{-};
38
  end
39
   if nargin < 5
40
       prompt5 = 'What value for sigma? (Nominal 0.158) ';
41
       sigma = input (prompt5);
42
   else
43
       sigma = sigma_{-};
44
  end
45
   if nargin < 6
46
       prompt6 = 'What value for epsilon? (Nominal 0.22) ';
       epsilon = input(prompt6);
48
   else
49
       epsilon = epsilon_;
50
  end
  if nargin <7
```

```
prompt7 = 'Autosave figures [ 1 or 0 ]?';
53
       save_figure=input(prompt7);
  end
55
  if nargin <8
       prompt8 = 'Use Matlabs MOGA [ 1 or 0 ]?';
57
       use_matlabs_moga=input(prompt8);
58
  end
59
   problem = results_and_params{prob,1};
61
  % ZD-func is our problem function
63
  switch prob
       case 1
65
           problem_function = @(X) ZDT1(X);
66
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
           problem_constraints = [];
68
       case 2
69
           problem_function = @(X) ZDT2(X);
70
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
           problem_constraints = [];
72
       case 3
           problem_function = @(X) ZDT3(X);
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
           problem_constraints = [];
76
       case 4
           problem_function = @(X) OSY(X);
78
           nvar = 6; LB = [0,0,1,0,1,0]; UB =
               [10,10,5,6,5,10];
           problem_constraints = @OSY_constraints; % Only
80
               used in matlab MOGA test
       case 5
81
           problem_function = @(X) TNK(X);
82
           nvar = 2; LB = [0, 0]; UB = [pi, pi];
83
           problem_constraints = @TNK_constraints; % Only
               used in matlab MOGA test
       case 6
86
           problem_function = @(X) CTP(X);
           \text{nvar} = 10; \text{LB} = -5*\text{ones}(1,10); \text{UB} = 5*\text{ones}(1,10);
88
                LB(1,1) = 0; UB(1,1) = 1;
           problem_constraints = @CTP_constraints; % Only
89
               used in matlab MOGA test
       case 7
90
           DP=1:
           nvar = 2; LB = [0, 0]; UB = [pi, pi];
92
           %Find Maximize DP
```

```
delta_P = maximumDeltaP([pi/2,pi
94
                /2, [-2, -2], [2, 2], @TNK_NEGCN2);
            problem_function = @(X) TNK_Robust(X, delta_P);
95
            problem_constraints = @(X) TNK_NEGCN2(X, delta_P);
       case 8
97
            flightPathOpt;
            return
99
       otherwise
100
            problem_function = @(X) 0;
101
            return
102
   end
103
104
   A = []; b = []; Aeq = []; beq = [];
105
   if use_matlabs_moga ==1
106
       % Modify options setting
107
       options = optimoptions('gamultiobj');
108
       options = optimoptions (options, 'PopulationSize', nRun
109
       options = optimoptions (options, 'CrossoverFcn',
110
           @crossoverscattered);
       options = optimoptions(options, 'Display', 'final');
111
       options = optimoptions (options, 'PlotFcn', {
112
           @gaplotpareto });
       options = optimoptions (options, 'ParetoFraction', 0.9)
113
       indexat = @(expr, index) expr(index);
114
       problem_function = @(X) indexat(problem_function(X),
115
           1:2):
       [optX,optF] = gamultiobj(problem_function, nvar
116
           ,[],[],[],LB,UB, problem_constraints, options);
       %problem.prob = prob; problem.nChrome = nChrome;
117
           problem.nRun = nRun;
       problem.matlab\_optF = optF;
118
       results_and_params{prob,1} = problem;
119
       save(file_name, 'results_and_params')
120
       return
121
   end
122
   Pareto = [];
124
   options = optimoptions (@ga, 'PopulationSize', nChrome, '
       UseVectorized', true, 'CrossoverFraction', 0.90);
   optF = [];
127
129
   for gen = 1:nRun
```

```
Obj_fcn = @(X) fitFCN5(X, problem_function);
131
        [X, \tilde{a}, \tilde{a}, \tilde{a}] = ga(Obj\_fcn, nvar, A, b, Aeq, beq, LB, UB, [],
132
            options):
        [optF(gen,:)] = problem_function(X);
        optX(gen,:) = X;
134
   end
135
   nfunc = 2; % Making this static because it will not
136
       change in this project
137
   P = paretoset(optF(:,1:nfunc));
   m = 1;
139
   for k = 1: length(P)
140
        if P(k) == 1
141
             Pareto(m,:) = optF(k,1:2); m = m+1;
142
        end
143
   end
144
145
   % figure
146
   hold on;
147
   if isempty (problem) == false
148
        if (isfield (problem, 'matlab_optF'))
             ml_optF = problem.matlab_optF;
150
             plot (ml_optF(:,1), ml_optF(:,2), 'b*')
151
        end
152
   end
153
154
   if (isempty (Pareto) == false)
155
        plot (Pareto (:,1), Pareto (:,2), 'gv', 'LineWidth',2,'
156
            MarkerSize',10)
157
    plot (optF(:,1),optF(:,2), 'r*', 'LineWidth',2)
158
   hold on; grid on;
   xlabel('f_1'); ylabel('f_2')
160
161
   handle = gcf;
162
      save_figure == 1
163
       %Save the figures
164
        dir_val = pwd;
        saveFigure(handle, [dir_val, dir_val(1), num2str(prob), '
166
             ', num2str (nChrome, '%03.0 f'), '-', num2str (nRun,
            \%04.0 \,\mathrm{f}')]);
        print([path_prefix , num2str(prob), '_ ', num2str(nChrome,
167
            '%03.0f'), '-', num2str(nRun, '%04.0f'), '.png'], '-
            dpng');
168
       %Save the .mat file
169
```

```
problem.prob = prob; problem.nChrome = nChrome;
170
           problem.nRun = nRun;
       problem.alpha = alpha; problem.sigma = sigma; problem
171
           . epsilon = epsilon;
       problem.optF = optF; problem.Pareto= Pareto;
172
       results_and_params{prob,1} = problem;
173
       save(file_name, 'results_and_params')
174
   end
   %save(['ZDT', num2str(prob), '_Nchr', num2str(nChrome), 'run
       ', num2str(nRun), 'alp', num2str(alpha,2), 'epsi', num2str(
       epsilon, 3), 'sig', num2str(sigma, 3)])
  function [ fit ] = fitFCN5(X, ZD_func)
 <sup>2</sup> %NSGA algorithm. Use Approach 1 for sorting
   global alpha sigma epsilon
   func = ZD_{-}func(X);
  % if isempty(existing_points)
         fit = sum(ZD_func(X));
  %
         return
  % end
10
  % Find Dominate Points
13
   % Modify existing code to find Pareto points to find
14
      dominant layers
15
   \% func = [existing_points; ZD_func(X)];
16
17
   nfunc = func(1, end - 3);
   nconstr = func(1, end - 2);
   g = func(:, nfunc+1:nfunc+nconstr);
   n constr_lin = func(1, end-1);
   if nconstr_lin > 0
       fprintf('weird error here')
24
   h = func(:, nfunc+nconstr+1:nfunc+nconstr+nconstr_lin);
   func = func(:, 1:nfunc);
26
   [M, \tilde{}] = size(X);
28
30
32
   if nconstr == 0 && nconstr_lin ==0
```

```
nc\_col = nfunc + 3;
34
       init_fit_col = nfunc + 4;
35
       sim_col = nfunc + 5:
36
       indecies = [1:M];
       func = [func, indecies]; Whe need to know indecies
38
           later so this should save time
       P_{\text{-}}temp = func;
39
       level = 0;
40
       level\_col = nfunc +2;
41
       func(:, level\_col) = 0;
       while ~isempty(P_temp)
43
           level = level+1;% increment the level value
           if length(P_temp(:,1)) = 1
45
               %If there is only one value left at the end,
46
                    assign this to a level
                func(P_{temp}(:, nfunc+1), level_col) = level;
47
                break
48
           end
49
           place = paretoset(P_temp(:,1:nfunc)); % get all
               the indecies in the lowest layer
           for k = 1: length (place)
51
                if place(k) == 1
52
                    current_level_indecies = P_temp(k, nfunc
                        +1); %map them from
                    func(current_level_indecies, level_col) =
54
                         level; % assiged from prtp
                end
           end
56
57
           P_{\text{temp}}(\text{place}, :) = [];
       end
59
60
       numLaver = level;
61
      Make sure all individuals have a layer number
63
       flag = 0;
       for k = 1:M
65
          if func(level_col) == 0
               func(k, level\_col) = numLayer+1;
67
               flag = 1;
          end
       end
       if flag == 1, numLayer = numLayer+1; end
71
       % Similarity
73
      %Assess similarity layer-by-layer, assess in
```

```
objective space.
   %
          sigma = 0.158;
76
   %
          epsilon = 0.1;
   %
          alpha = 1;
78
        var_rem = 0;
        F_{-min} = M + epsilon;
80
        for k = 1:numLayer
81
            Fitness = []; incl = [];
82
            incl = find(func(:, level\_col) == k); \% incl =
83
                include
            Fitness = func(incl, 1:nfunc);
84
            var\_rem = var\_rem + length(Fitness(:,1));
85
             if(isempty(Fitness) == 0)
86
                 if length(incl) == 1
88
                      F_{int} = F_{min} - epsilon;
89
                      Fit_share = F_int;
90
                      func(incl, sim_col+1) = F_int;
                      func(incl, sim_col) = F_int;
92
                      func(incl,nc\_col) = 1;
                 else
94
                      for m = 1:nfunc
95
                          \max F(m) = \max(Fitness(:,m));
96
                          \min F(m) = \min (Fitness(:,m));
97
                          func(m, init_fit_col) = minF(m);
98
                      end
                      d = []; similar = []; sh = [];
100
                      for i = 1: length(incl)
101
                          F_{int} = F_{min} - epsilon;
102
                          for j = 1: length(incl)
103
                               for p = 1:nfunc
104
                                    similar(p) = ((Fitness(i,p)-
105
                                        Fitness(j,p))/(maxF(p)-
                                        \min F(p))^2;
                               end
106
                               d(i,j) = sqrt(sum(similar));
107
                               if d(i, j) \le sigma
                                    sh(i,j) = 1-(d(i,j)/sigma)^{\hat{}}
109
                                        alpha;
                               else sh(i,j) = 0;
110
                               end
                          end
112
                          nc(i) = sum(sh(i,:));
113
                          Fit\_share(i) = F\_int/nc(i);
114
                          func(incl(i), nc\_col) = nc(i);
115
```

```
func(incl(i), sim_col) = Fit_share(i);
116
                           func(incl(i), sim_col+1) = F_int;
117
118
                      end
                 end
120
                 F_{min} = \min(Fit_{share});
121
            end
122
123
        end
124
       %Since a greater fitness value is a larger number, we
126
             use the inverse
        fit = -func(:, sim_col);
127
128
   % Constraint Handling
129
   else
130
        Cmax = 1.2; Cmin = 0.8; r = 0.8*M;
131
        CF1 = 0.01;
132
        CF2 = 0.01;
133
        rank = zeros(1,M);
134
135
       % Assign moderate rank to all feasible solutions
136
         for k = 1:M
137
             flag = 0; flag_lin = 0;
138
             for p = 1:nconstr
139
                 if g(k,p) > 0, f \log = 1;
140
                 end
141
                 if nconstr_lin ~= 0
142
                      if h(k,p) = 0, f \log \lim = 1;
143
                      end
144
                 end
145
            end
146
             if flag == 0 && flag_lin == 0
147
                 rank(k) = 0.5*M;
148
            end
149
         end
150
151
153
         % Collect together feasible population
154
         feas\_pop = []; infeas\_pop = []; m = 1;
155
         for k = 1:M
              if rank(k) = 0
157
                  if isempty(h)
158
                       feas\_pop = [feas\_pop; func(k,:), g(k,:)];
159
                   else
160
```

```
feas\_pop = [feas\_pop; func(k,:), g(k,:), h(
161
                          k,:)];
                  end
162
             else
                   if isempty(h)
164
                       infeas_pop = [infeas_pop; func(k,:), g(k,:)]
165
                           ,:)];
                   else
166
                       infeas_pop = [infeas_pop; func(k,:),g(k
167
                           ,:),h(k,:)];
168
                   loc(m) = k; m = m+1; \% keep track of which
169
                       solutions were infeasible
             end
170
        end
171
172
        % Identify noninferior points
173
         if ~isempty(feas_pop)
174
              place = paretoset(feas_pop(:,1:nfunc));
              m = 1;
176
              for k = 1:length(place)
                   if place(k) == 1
178
                       Pareto(m,:) = feas_pop(k,:); %Assign
                           noninferior points along with
                           constraint values
                       rank(k) = 1; m = m+1;
180
                   end
181
              end
182
        end
183
       % Evaluate rank for infeasible individuals
184
       g = infeas_pop(:,nfunc+1:nconstr+nfunc);
185
       h = infeas_pop(:,nconstr+nfunc+1:end);
186
187
        for k = 1: length(g(:,1))
            for p = 1:nconstr
189
                 if g(k,p) \le 0
190
                     feas_g(k,p) = 0; delta_g(k,p) = 0;
191
                 else
                     feas_g(k,p) = g(k,p); delta_g(k,p) = 1;
193
                 end
194
            end
195
            if nconstr_lin = 0
                 feas_h = zeros(length(g(:,1)),1);
197
                 delta_h = zeros(length(g(:,1)),1);
            else
199
                 for n = 1:nconstr_{lin}
200
```

```
feas_h(k,n) = abs(h(k,n));
201
                    end
202
                    if h(k,p) == 0, delta_h(k,p) = 0;
203
                    else delta_h(k,p) = 1;
                    end
205
              end
206
         end
207
         num1 = sum(feas_g, 2) + sum(feas_h, 2);
208
         denom1 = (sum(sum(feas_g))+sum(sum(feas_h)))/M;
209
         J = nconstr; K = nconstr_lin;
         num2 = (sum(delta_g, 2) + sum(delta_h, 2));
211
         denom2 = (J+K);
212
213
         factor1 = CF1.*(num1./denom1);
214
         factor2 = CF2.*(num2./denom2);
215
216
^{217}
218
         for k = 1 : length(g(:,1))
               if (factor1(k)> mean(factor1)) && (factor2(k) <
220
                   mean(factor2))
                    w1 = 0.75; w2 = 0.25;
221
               elseif (factor1(k) < mean(factor1)) && (factor2(k
222
                   ) > mean(factor2))
                    w1 = 0.25; w2 = 0.75;
223
               else
224
                    w1 = 0.5; w2 = 0.5;
              end
226
               \operatorname{fit} \operatorname{constr}(k) = -((\operatorname{Cmax} - (\operatorname{Cmax} - \operatorname{Cmin}) * (r-1) / (\operatorname{M} - 1))
227
                   -(w1.*factor1(k)+w2.*factor2(k)));
         end
228
229
         for k = 1: length(loc)
230
               \operatorname{rank}(\operatorname{loc}(k)) = \operatorname{fit\_constr}(k);
232
         fit = rank;
233
234
    end
236
    end
```