Sections and Chapters

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ENME 625: Multi-Displinary Optimization 5/12/2017

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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

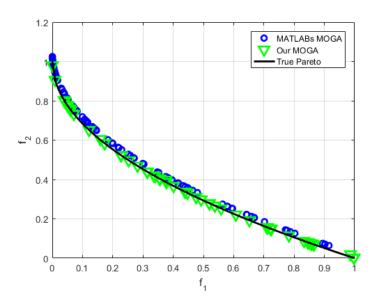
Metric	MATLABs MOGA	Our MOGA
CD	0.3874 (0.0164)	0.3582 (0.0040)
OS	0.9605 (0.1088)	0.9283 (0.0928)

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)

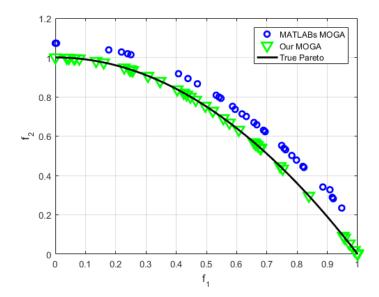


Figure 2: Example Pareto Results for ZDT2

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_i0.05), while the difference is not statistically significant in Pareto Spread (p=0.21).

1.2

O MATLABS MOGA

Our MOGA

Feasible Domain Frontier

0.6

0.4

-0.2

-0.4

-0.6

-0.8

Figure 3: Example Pareto Results for ZDT3

Table 3: Quality Metrics for ZDT3

0.5

 f_1

0.6

0.7

8.0

0.9

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

0

0.1

0.2

0.3

0.4

This test problem, denoted as OSY in (insert reference) is shown below.

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
$$g_1(x) = 1 - \frac{x_1 + x_2}{2} \le 0$$

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

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

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

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

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

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

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

$$0 \le x_4 \le 6$$

The true Pareto frontier for this problem again occurs when $x_i = 0$ for i = 2,...,30. Figure ?? 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		
OS		

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 4.

Minimize
$$f_1(\mathbf{x}) = x_1$$

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

Figure 4: True Pareto Frontier for TNK

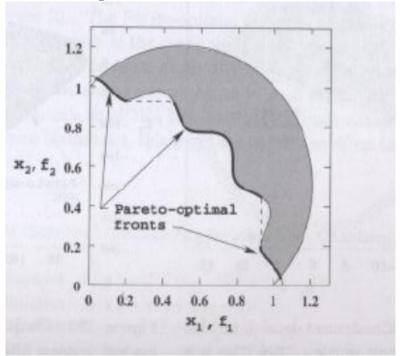


Figure 5 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 5 summarizes the mean quality metrics for each algorithm for ten runs.

Comparing the estimated Pareto frontiers to the true Pareto frontier, is is clear that our MOGA outperforms MATLAB's MOGA. The Pareto spread in our MOGA is significantly higher however the coverage difference is higher in MATLABs MOGA ($p_i^{-1}0.05$).

1.2

0 MATLABS MOGA

Our MOGA

Our MOGA

0.8

0.8

0.4

0.2

Figure 5: Example Pareto Results for TNK

Table 5: Quality Metrics for TNK $\,$

0.6

f₁

0.8

1.2

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

3.2 CTP

0

0

0.2

0.4

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

Minimize
$$f_1(\mathbf{x}) = x_1$$

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

Figure 6: True Pareto Frontier for CTP

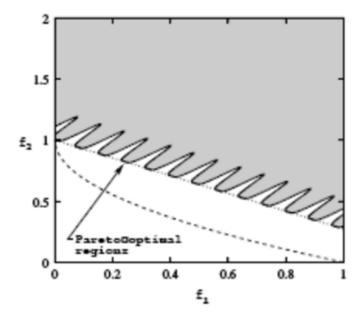


Figure 7 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 6 summarizes the mean quality metrics for each algorithm for ten runs [1].

 MATLABs MOGA Our MOGA 0.9 8 0.8 0.7 **-**~ 0.6 0.4 0.3 0.2 0.1 0.2 0.3 0.5 0.6 0.7 0.8 0.4 0.9 f₁

Figure 7: Example Pareto Results for CTP

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($p_{\dot{\iota}}0.05$). For Pareto spread, MATLAB's MOGA performs the highest.

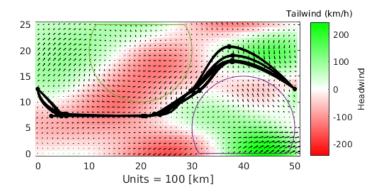
4 Flight Planning Problem (FPP)

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 8. In this figure there are two exclusion zones.

Figure 8: True Pareto Frontier for CTP



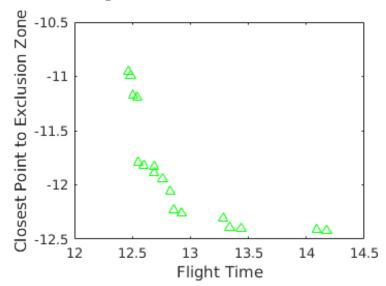


Figure 9: True Pareto Frontier for CTP

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

```
1 %function [optX,optF]=MasterCode(prob,nChrome,nRun,alpha_,sigma_,epsilon_,save_figure,use_matlabs_moga)
2 nargin=0;
3
4 % load .mat file
5 current_dir = pwd;
6 %file_name = 'results_and_params.mat';
7 if(contains(current_dir,'/ENME625_Optimization')) %linux or mac
8 path_prefix = [current_dir, current_dir(1)];
```

```
elseif(contains(current_dir, '/ENME625_Optimization')) %
      windows
       path_prefix = [current_dir, '\'];
10
   e\,l\,s\,e
11
       fprintf('not running from the correct directory')
12
       return
13
  end
14
   file_name = [path_prefix, 'results_and_params.mat'];
   results_and_params = load(file_name);
   results_and_params = results_and_params.
      results_and_params;
18
   global alpha sigma epsilon
19
20
   if(nargin < 1)
21
       prompt = 'Which Test Problem Do You Want To Run? \n 1
22
            - 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);
23
  end
24
   if nargin <2
25
       prompt2 = 'How Many Chromosomes? Suggest 20-30';
26
       nChrome = input (prompt2);
  end
28
     nargin <3
29
       prompt3 = 'How Many Runs? Suggest >40: ';
30
       nRun = input (prompt3);
31
  end
32
   if nargin < 4
33
       prompt4 = 'What value for alpha? ';
34
       alpha = input (prompt4);
35
   else
36
       alpha = alpha_{-};
37
  end
38
   if nargin < 5
39
       prompt5 = 'What value for sigma? (Nominal 0.158) ';
40
       sigma = input (prompt5);
41
   e\,l\,s\,e
       sigma = sigma_-;
43
  end
   i f
      nargin < 6
45
       prompt6 = 'What value for epsilon? (Nominal 0.22) ';
       epsilon = input (prompt6);
47
   else
       epsilon = epsilon_{-};
49
  end
```

```
if nargin <7
       prompt7 = 'Autosave figures [ 1 or 0 ]?';
       save_figure=input(prompt7);
53
  end
  if nargin <8
55
       prompt8 = 'Use Matlabs MOGA [ 1 or 0 ]?';
       use_matlabs_moga=input(prompt8);
57
  end
58
59
   problem = results_and_params{prob,1};
  % ZD-func is our problem function
62
  switch prob
63
       case 1
64
           problem_function = @(X) ZDT1(X);
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
66
           problem_constraints = [];
67
       case 2
68
           problem_function = @(X) ZDT2(X);
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
70
           problem_constraints = [];
       case 3
72
            problem_function = @(X) ZDT3(X);
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
74
           problem_constraints = [];
75
       case 4
76
            problem_function = @(X) OSY(X);
           nvar = 6; LB = [0,0,1,0,1,0]; UB =
78
               [10,10,5,6,5,10];
           problem\_constraints \, = \, @OSY\_constraints \, ; \, \, \% \, \, Only \,
79
               used in matlab test
       case 5
80
           problem_function = @(X) TNK(X);
81
           nvar = 2; LB = [0, 0]; UB = [pi, pi];
           problem_constraints = @TNK_constraints; % Only
83
               used in matlab test
84
       case 6
            problem_function = @(X) CTP(X);
86
           \text{nvar} = 10; \text{LB} = -5*\text{ones}(1,10); \text{UB} = 5*\text{ones}(1,10);
                LB(1,1) = 0; UB(1,1) = 1;
            problem_constraints = @CTP_constraints; % Only
               used in matlab test
       case 7
89
           DP=1:
           problem_function = @(X,DP) TNK_Robust(X,DP);
```

```
nvar = 2; LB = [0,0]; UB = [pi, pi];
92
            robust_fitness = @(X,DP) TNK_NEGCN2(X,DP);
93
        otherwise
94
            problem_function = @(X) 0;
   end
96
   A = []; b = []; Aeq = []; beq = [];
98
   if use_matlabs_moga ==1
       % Modify options setting
100
        options = optimoptions('gamultiobj');
101
        options = optimoptions (options, 'PopulationSize', nRun
102
           );
        options = optimoptions (options, 'CrossoverFcn',
103
           @crossoverscattered);
        options = optimoptions (options, 'Display', 'final');
104
        options = optimoptions (options, 'PlotFcn', {
105
            @gaplotpareto });
        options = optimoptions (options, 'ParetoFraction', 0.9)
106
        indexat = @(expr, index) expr(index);
107
        problem_function = @(X) indexat(problem_function(X),
108
            1:2);
        [~, optF] = gamultiobj(problem_function, nvar
109
            ,[],[],[],[],LB,UB, problem_constraints, options);
       %problem.prob = prob; problem.nChrome = nChrome;
110
           problem.nRun = nRun;
        problem.matlab_optF = optF;
        results_and_params{prob,1} = problem;
112
        save(file_name, 'results_and_params')
113
        return
114
   end
115
116
   Pareto = [];
117
   options = optimoptions (@ga, 'PopulationSize', nChrome, '
       UseVectorized', true, 'CrossoverFraction', 0.90);
   optF = [];
119
   for gen = 1:nRun
120
        Obj_fcn = @(X) fitFCN5(X, problem_function);
        if(prob==7); Obj_fcn = @(X) fitFCN5(X, problem_function)
122
           , robust_fitness); end
        [X, \tilde{x}, \tilde{x}, \tilde{x}] = ga(Obj\_fcn, nvar, A, b, Aeq, beq, LB, UB, [],
123
           options);
        if(prob==7)
124
            [optF(gen,:)] = problem_function(X,[0,0]);
        else
126
            [optF(gen,:)] = problem_function(X);
127
```

```
end
128
        optX(gen,:) = X;
129
   end
130
   nfunc = 2; % Making this static because it will not
131
        change in this project
132
   P = paretoset(optF(:,1:nfunc));
133
   m = 1;
    for k = 1: length(P)
135
         if P(k) == 1
              Pareto (m,:) = optF(k,1:2); m = m+1;
137
        end
138
   end
139
140
   % figure
141
    hold on;
142
    if isempty (problem) == false
         if (isfield (problem, 'matlab_optF'))
144
              ml_optF = problem.matlab_optF;
145
              plot(ml_optF(:,1), ml_optF(:,2), 'b*')
146
        \quad \text{end} \quad
147
   end
148
    if(isempty(Pareto) == false)
150
         plot (Pareto (:,1), Pareto (:,2), 'gv', 'LineWidth',2,'
151
             MarkerSize',10)
152
   end
     plot (optF (:,1), optF (:,2), 'r*', 'LineWidth',2)
153
   hold on; grid on;
    xlabel('f<sub>-1</sub>'); ylabel('f<sub>-2</sub>')
155
156
    handle = gcf;
157
       save_figure == 1
158
        %Save the figures
159
         dir_val = pwd;
160
         saveFigure(handle, [dir_val, dir_val(1), num2str(prob), '
161
              ', num2str (nChrome, '%03.0 f'), ', ', num2str (nRun,
             \%04.0 \,\mathrm{f}')]);
         {\tt print} \; (\; [\; {\tt path\_prefix} \; , {\tt num2str} (\; {\tt prob} ) \; , \; \lq\_ \; \lq \; , {\tt num2str} (\; {\tt nChrome} \; , \\
162
             '%03.0f'), '-', num2str(nRun, '%04.0f'), '.png'], '-
             dpng');
        %Save the .mat file
164
        problem.prob = prob; problem.nChrome = nChrome;
165
             problem.nRun = nRun;
        problem.alpha = alpha; problem.sigma = sigma; problem
166
```

```
.epsilon = epsilon;
       problem.optF = optF; problem.Pareto= Pareto;
167
       results_and_params{prob,1} = problem;
168
       save(file_name, 'results_and_params')
   end
170
  %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,
       robust_constraint_fitness)
  %NSGA algorithm. Use Approach 1 for sorting
   global alpha sigma epsilon
   cheat = 1;
   if nargin < 3
       robust_constraint_fitness = [];
 9
   end
10
  %Check is this is a robust problem
   delta_P = [];
12
   if isempty(robust_constraint_fitness)
13
       func = ZD_func(X);
14
   else%Evaluates feasible solutions with uncertaintly
15
       applied in problems with
   %uncertainy
16
       if cheat ==1
17
            delta_P = [0.5708*ones(length(X),1),-1*ones(
18
               length(X),1)];
       else
19
            [M, \tilde{}] = size(X);
20
            for k = 1:M
21
                options = optimoptions (@ga, 'PopulationSize'
22
                    ,10, 'UseVectorized', true);
                1b = [-2, -2]; ub = [2, 2];
23
                fitnessfn = @(DP) -TNK.NEGCN2(X(k,:),DP);
24
                [d_p, \tilde{}] = ga(fitnessfn, 2, [], [], [], [], lb, ub
                    ,[], options);
                delta_P = [delta_P ; d_p];
            end
27
       end
       func = ZD_func(X, delta_P);
29
   end
31
32
```

```
33
34
35
  % if isempty (existing_points)
  %
         fit = sum(ZD_func(X));
  %
         return
39
  % end
41
  % Find Dominate Points
43
  % Modify existing code to find Pareto points to find
44
      dominant layers
45
  % func = [existing_points; ZD_func(X)];
46
47
  nfunc = func(1, end - 3);
48
  nconstr = func(1, end - 2);
49
  g = func(:, nfunc+1:nfunc+nconstr);
  n constr_lin = func(1, end-1);
  if nconstr_lin > 0
       fprintf('weird error here')
53
  end
  h = func(:, nfunc+nconstr+1:nfunc+nconstr+nconstr_lin);
  func = func(:, 1:nfunc);
56
57
  [M, \tilde{}] = size(X);
59
60
61
62
  if nconstr == 0 && nconstr_lin ==0
63
       nc\_col = nfunc + 3;
64
       init_fit_col = nfunc + 4;
65
       sim_col = nfunc + 5;
66
       indecies = [1:M];
67
       func = [func, indecies]; We need to know indecies
68
           later so this should save time
       P_{\text{temp}} = \text{func};
69
       level = 0;
       level\_col = nfunc +2;
71
       func(:, level\_col) = 0;
       while ~isempty(P_temp)
73
           level = level+1;\% increment the level value
            if length(P_temp(:,1)) = 1
75
                %If there is only one value left at the end,
```

```
assign this to a level
                 func(P_{temp}(:,nfunc+1),level_{col}) = level;
                 break
78
            end
            place = paretoset(P_temp(:,1:nfunc)); % get all
80
                the indecies in the lowest layer
            for k = 1:length(place)
81
                 if place(k) == 1
82
                     current_level_indecies = P_temp(k, nfunc
83
                         +1); %map them from
                     func(current_level_indecies, level_col) =
                          level; % assiged from prtp
                 end
85
            end
86
            P_{\text{-}}\text{temp}(\text{place}, :) = [];
88
       end
89
       numLayer = level;
92
       Make sure all individuals have a layer number
        flag = 0;
        for k = 1:M
           if func(level_col) == 0
96
                func(k, level\_col) = numLayer+1;
                flag = 1;
           end
       end
100
        if flag == 1, numLayer = numLayer+1; end
101
102
       % Similarity
103
       %Assess similarity layer-by-layer, assess in
104
           objective space.
105
          sigma = 0.158;
106
   %
          epsilon = 0.1;
107
   %
          alpha = 1;
108
       var_rem = 0;
       F_{\min} = M_{epsilon};
110
        for k = 1:numLayer
111
            Fitness = []; incl = [];
112
            incl = find(func(:, level\_col) == k); \% incl =
                include
            Fitness = func(incl, 1:nfunc);
            var_rem = var_rem + length(Fitness(:,1));
115
            if (isempty (Fitness) == 0)
116
```

```
if length(incl) == 1
117
118
                        F_{int} = F_{min-epsilon};
119
                        Fit_share = F_int;
                       func(incl, sim_col+1) = F_int;
121
                       func(incl, sim_col) = F_int;
122
                       func(incl,nc\_col) = 1;
123
                   else
124
                        for m = 1:nfunc
125
                            \max F(m) = \max(Fitness(:,m));
126
                            \min F(m) = \min (Fitness(:,m));
127
                            func(m, init_fit_col) = minF(m);
128
                       end
129
                       d = []; similar = []; sh = [];
130
                       for i = 1: length(incl)
131
                            F_{int} = F_{min} - epsilon;
132
                            for j = 1: length(incl)
133
                                 for p = 1:nfunc
134
                                      similar(p) = ((Fitness(i,p)-
135
                                           Fitness(j,p))/(maxF(p)-
                                          \min F(p))^2;
                                 end
136
                                 d(i,j) = sqrt(sum(similar));
137
                                 if d(i, j) \le sigma
138
                                      \operatorname{sh}(i,j) = 1 - (\operatorname{d}(i,j) / \operatorname{sigma})^{\hat{}}
139
                                          alpha;
                                 else sh(i,j) = 0;
140
                                 end
141
                            end
142
                            nc(i) = sum(sh(i,:));
143
                            Fit_share(i) = F_int/nc(i);
144
                            func(incl(i), nc\_col) = nc(i);
145
                            func(incl(i), sim_col) = Fit_share(i);
146
                            func(incl(i), sim_col+1) = F_int;
147
148
                       end
149
                  end
150
                  F_{\min} = \min(Fit_{\sinh}are);
151
             end
152
153
        end
154
        %Since a greater fitness value is a larger number, we
156
              use the inverse
         fit = -func(:, sim_col);
157
158
```

```
% Constraint Handling
   else
        Cmax = 1.2; Cmin = 0.8; r = 0.8*M;
161
        CF1 = 0.01;
        CF2 = 0.01;
163
        rank = zeros(1,M);
164
165
       % Assign moderate rank to all feasible solutions
166
         for k = 1:M
167
             flag = 0; flag_lin = 0;
168
             for p = 1:nconstr
169
                 if g(k,p)>0, flag = 1;
170
                 end
171
                 if nconstr_lin = 0
172
                      if h(k,p) = 0, flag_lin = 1;
173
                      end
174
                 end
175
            end
176
            if flag == 0 && flag_lin == 0
                 \operatorname{rank}(k) = 0.5*M;
178
            end
         end
180
182
183
        % Collect together feasible population
184
         feas\_pop = []; infeas\_pop = []; m = 1;
         for k = 1:M
186
              if rank(k) = 0
187
                   if isempty(h)
188
                       feas\_pop = [feas\_pop; func(k,:), g(k,:)];
189
                   else
190
                       feas\_pop = [feas\_pop; func(k,:), g(k,:), h(
191
                           k ,:) ];
                  end
192
              else
193
                    if isempty(h)
194
                        infeas_pop = [infeas_pop; func(k,:),g(k
                            ,:)];
                    else
196
                        infeas_pop = [infeas_pop; func(k,:), g(k
197
                            ,:),h(k,:)];
                    end
198
                    loc(m) = k; m = m+1; \% keep track of which
199
                        solutions were infeasible
200
              end
```

```
end
201
202
        % Identify noninferior points
203
         if ~isempty(feas_pop)
              place = paretoset (feas_pop (:,1:nfunc));
205
              m = 1;
206
              for k = 1:length (place)
207
                   if place(k) == 1
208
                       Pareto(m,:) = feas\_pop(k,:); %Assign
209
                           noninferior points along with
                           constraint values
                       rank(k) = 1; m = m+1;
210
                   end
211
              end
212
         end
213
       % Evaluate rank for infeasible individuals
214
       g = infeas_pop(:,nfunc+1:nconstr+nfunc);
215
       h = infeas_pop(:,nconstr+nfunc+1:end);
216
        for k = 1 : length(g(:,1))
218
            for p = 1:nconstr
                 if g(k,p) \le 0
220
                     feas_g(k,p) = 0; delta_g(k,p) = 0;
                 else
222
                     feas_g(k,p) = g(k,p); delta_g(k,p) = 1;
223
                 end
224
            end
            if nconstr_lin = 0
226
                 feas_h = zeros(length(g(:,1)),1);
227
                 delta_h = zeros(length(g(:,1)),1);
228
            else
229
                 for n = 1: nconstr_lin
230
                     feas_h(k,n) = abs(h(k,n));
231
232
                 if h(k,p) == 0, delta_h(k,p) = 0;
233
                 else delta_h(k,p) = 1;
234
                 end
235
            end
237
       num1 = sum(feas_g, 2) + sum(feas_h, 2);
238
       denom1 = (sum(sum(feas_g))+sum(sum(feas_h)))/M;
239
       J = nconstr; K = nconstr_lin;
       num2 = (sum(delta_g, 2) + sum(delta_h, 2));
241
       denom2 = (J+K);
243
        factor1 = CF1.*(num1./denom1);
244
```

```
factor2 = CF2.*(num2./denom2);
245
246
247
        for k = 1: length(g(:,1))
249
             if (factor1(k) > mean(factor1)) && (factor2(k) <
250
                mean(factor2))
                 w1 = 0.75; w2 = 0.25;
251
             elseif (factor1(k) < mean(factor1)) && (factor2(k))
252
                ) > mean(factor 2)
                 w1 = 0.25; w2 = 0.75;
253
             else
254
                 w1 = 0.5; w2 = 0.5;
255
            end
256
             fit_constr(k) = -((Cmax-(Cmax-Cmin)*(r-1)/(M-1))
257
                -(w1.*factor1(k)+w2.*factor2(k)));
        end
258
259
        for k = 1: length(loc)
            rank(loc(k)) = fit_constr(k);
261
        end
        fit = rank;
263
264
265
   \operatorname{end}
266
   end
267
```