Sections and Chapters

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1 Introduction

This is the first section.

2 Unconstrained MOGA Problems

We used this textbook [?]

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

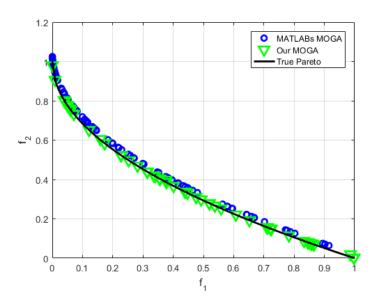
Metric	MATLABs MOGA	Our MOGA
CD	0.3874 (0.0164)	0.3582 (0.0040)
OS	0.9605 (0.1088)	0.9283 (0.0928)

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)

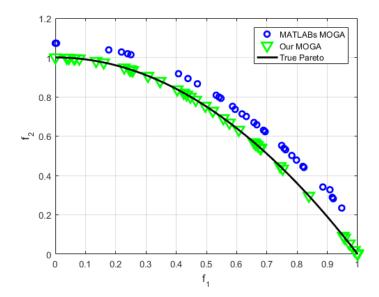


Figure 2: Example Pareto Results for ZDT2

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 [?].

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

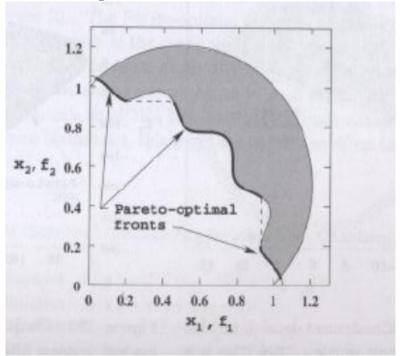


Figure 5 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 5 summarizes the mean quality metrics for each algorithm for ten runs.

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

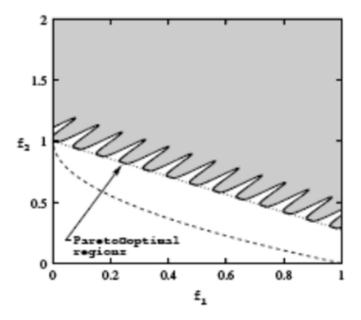


Figure 7 shows a sample result from both MATLABs built in MOGA and the MOGA developed in this project. Table 6 summarizes the mean quality metrics for each algorithm for ten runs.

Figure 7: Example Pareto Results for CTP

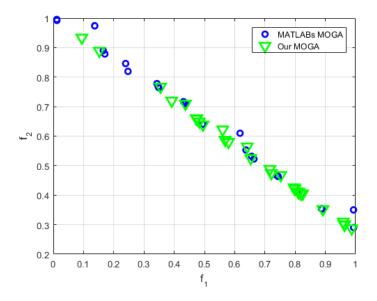


Table 6: Quality Metrics for CTP

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

References

4 Appendix

Matlab Code

```
1 clear all;
2 % close all;
  clc;
  warning off
  global alpha sigma epsilon Mmoga
  prompt = 'Which Test Problem Do You Want To Run? \n 1 -
      ZDT1\n 2 - ZDT2 \n 3 - ZDT3 \n 4 - OSY \n 5 - TNK \n 6
       - CTP \setminus n;
9 prob = input(prompt);
  prompt2 = 'How Many Chromosomes? Suggest 10-20 times #
      variables: ';
  nChrome = input (prompt2);
  prompt3 = 'How Many Runs? Suggest >40: ';
  nRun = input (prompt3);
  prompt4 = 'What value for alpha?';
  alpha = input (prompt4);
  prompt5 = 'What value for sigma? (Nominal 0.158) ';
  sigma = input(prompt5);
  prompt6 = 'What value for epsilon? (Nominal 0.22) ';
  epsilon = input(prompt6);
  prompt7 = 'Save Data? \n 1 - \text{YES} \n 2 - \text{NO} \n';
21
  save_figure = input(prompt7);
22
  \% for test = 1:10
  %%
25
  switch prob
26
       case 1
27
           problem_function = @(X) ZDT1(X);
28
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
           problem\_constraints = [];
30
           A = []; b = []; Aeq = []; beq = [];
31
32
           problem_function = @(X) ZDT2(X);
           nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
34
           problem_constraints = [];
```

```
A = []; b = []; Aeq = []; beq = [];
36
       case 3
37
            problem_function = @(X) ZDT3(X);
38
            nvar = 30; LB = zeros(1, nvar); UB = ones(1, nvar);
            problem_constraints = [];
40
           A = []; b = []; Aeq = []; beq = [];
41
       case 4
42
            problem_function = @(X) OSY(X);
43
            nvar = 6; LB = [0,0,1,0,1,0]; UB =
44
                [10,10,5,6,5,10];
           A = \begin{bmatrix} -1 & -1 & 0 & 0 & 0 & 0; 1 & 1 & 0 & 0 & 0; -1 & 1 & 0 & 0 & 0; 1 & -3 \end{bmatrix}
45
                0 \ 0 \ 0 \ 0; b = [-2;6;2;2];
            Aeq = []; beq = [];
46
            problem_constraints = @OSYcon; % Only used in
47
                matlab test
       case 5
48
            problem_function = @(X) TNK(X);
49
            nvar = 2; LB = [0,0]; UB = [pi, pi];
50
           A = []; b = []; Aeq = []; beq = [];
            problem_constraints = @TNKcon; % Only used in
52
                matlab test
53
       case 6
54
            problem_function = @(X) CTP(X);
55
            \text{nvar} = 10; \text{LB} = -5*\text{ones}(1,10); \text{UB} = 5*\text{ones}(1,10);
56
                LB(1,1) = 0; UB(1,1) = 1;
           A = []; b = []; Aeq = []; beq = [];
            problem_constraints = @CTPcon; % Only used in
58
                matlab test
       case 7
59
           DP=1;
60
            problem\_function = @(X) TNK\_Robust(X,DP);
61
            nvar = 2; LB = [0,0]; UB=[pi,pi];
62
           A = []; b = []; Aeq = []; beq = [];
       otherwise
64
            problem_function = @(X) 0;
65
  end
66
68
  % Matlab's MOGA
70
  options = optimoptions('gamultiobj', 'PopulationSize',
      nChrome, 'CrossoverFcn', @crossoverscattered, 'Display',
        'final', 'PlotFcn', { @gaplotpareto }, 'ParetoFraction'
       , 0.9);
```

```
Mmoga = 1;
   [Xmoga, Fmoga] = gamultiobj (problem_function, nvar, A, b, Aeq,
       beq, LB, UB, problem_constraints, options);
   Mmoga = 0;
   figure
76
   plot (Fmoga(:,1),Fmoga(:,2),'bo','LineWidth',2);
   hold on
   % Our MOGA
   Pareto = [];
   options = optimoptions (@ga, 'PopulationSize', nChrome, '
       UseVectorized', true, 'CrossoverFraction', 0.90);
   optF = [];
   for gen = 1:nRun
84
        gen
85
        Obj_fcn = @(X) fitFCN5(X, problem_function);
86
        [X, fval, exitflag, output] = ga(Obj_fcn, nvar, A, b, Aeq,
87
           beq,LB,UB,[], options);
        [optF(gen,:)] = problem_function(X);
       optX(gen,:) = X;
89
   end
   nfunc = optF(1, end - 3);
91
    P = paretoset(optF(:,1:nfunc));
93
    m = 1;
94
        for k = 1: length(P)
95
            if P(k) = 1
                 Pareto (m,:) = optF(k,1:2); m = m+1;
97
            end
       end
99
   % figure
   hold on;
102
   plot (Pareto (:,1), Pareto (:,2), 'gv', 'LineWidth',2,'
       MarkerSize',10)
   plot (optF(:,1),optF(:,2), 'r*', 'LineWidth',2)
   hold on; grid on; legend ('MATLABs MOGA', 'Our MOGA')
105
   xlabel('f<sub>-</sub>1'); ylabel('f<sub>-</sub>2')
107
108
   handle = gcf;
109
   if save_figure == 1
110
       %Save the figures
111
  %
          dir_val = pwd;
112
        saveFigure(handle, ['prob', num2str(prob), '_nChr',
113
           num2str(nChrome), '_nRun', num2str(nRun)]);
```

```
114
       %Save the .mat file
115
       problem.prob = prob; problem.nChrome = nChrome;
116
           problem.nRun = nRun;
       problem.alpha = alpha; problem.sigma = sigma; problem
117
           .epsilon = epsilon;
       problem.optF = optF; problem.Pareto= Pareto; problem.
118
           Fmoga = Fmoga;
       results_and_params{prob,1} = problem;
119
       save(['results_and_params',num2str(prob),'_nChr',
           num2str(nChrome), '_nRun', num2str(nRun), '_nTest',
           num2str(test)]);
   end
121
122
123 % end
  function [ fit ] = fitFCN5(X, ZD_func)
  %NSGA algorithm. Use Approach 1 for sorting
   global alpha sigma epsilon
   func = ZD_func(X);
  % Find Dominate Points
  % Modify existing code to find Pareto points to find
      dominant layers
  \% func = [existing_points; ZD_func(X)];
11
12
  XOLin = X;
   UNCT = func(1, end);
   nfunc = func(1, end - 3);
   nconstr = func(1, end - 2);
   g = func(:, nfunc+1:nfunc+nconstr);
   nconstr_eq = func(1, end-1);
   h = func(:, nfunc+nconstr+1:nfunc+nconstr+nconstr_eq);
   func = func(:,1:nfunc);
20
   [M, \tilde{z}] = size(X);
22
24
26
   if nconstr == 0 \&\& nconstr_eq == 0
       nc\_col = nfunc + 3;
28
       init_fit_col = nfunc + 4;
```

```
sim_col = nfunc + 5;
30
       indecies = [1:M];
31
       func = [func, indecies]; Whe need to know indecies
32
           later so this should save time
       P_{\text{temp}} = \text{func};
33
       level = 0;
34
       level\_col = nfunc +2;
35
       func(:, level\_col) = 0;
        while ~isempty(P_temp)
37
            level = level+1;% increment the level value
            if length(P_temp(:,1)) = 1
39
                %If there is only one value left at the end,
40
                     assign this to a level
                 \operatorname{func}(P_{\text{temp}}(:, \operatorname{nfunc}+1), \operatorname{level\_col}) = \operatorname{level};
41
                 break
42
43
            place = paretoset(P_temp(:,1:nfunc)); % get all
44
                the indecies in the lowest layer
            for k = 1:length(place)
                 if place(k) == 1
46
                      current_level_indecies = P_temp(k, nfunc
                          +1); %map them from
                      func(current_level_indecies , level_col) =
48
                           level; % assiged from prtp
                 end
49
            end
50
            P_{\text{temp}}(\text{place}, :) = [];
52
       end
53
       numLayer = level;
55
56
       Make sure all individuals have a layer number
57
       flag = 0;
       for k = 1:M
59
           if func(level_col) == 0
                func(k, level\_col) = numLayer+1;
61
                flag = 1;
           end
63
       end
       if flag == 1, numLayer = numLayer+1; end
65
       % Similarity
67
       %Assess similarity layer-by-layer, assess in
           objective space.
       var_rem = 0;
```

```
F_{\min} = M + epsilon;
70
        for k = 1:numLayer
71
             Fitness = []; incl = [];
72
             incl = find(func(:, level\_col) = k); \% incl =
                 include
             Fitness = func(incl, 1:nfunc);
             var_rem = var_rem+length(Fitness(:,1));
75
             if(isempty(Fitness) == 0)
76
                  if length(incl) == 1
77
                       F_{int} = F_{min} - epsilon;
79
                       Fit_share = F_int;
80
                       func(incl, sim_col+1) = F_int;
81
                       func(incl, sim_col) = F_int;
82
                       func(incl,nc\_col) = 1;
                  else
84
                       for m = 1:nfunc
85
                           \max F(m) = \max(Fitness(:,m));
86
                           minF(m) = min(Fitness(:,m));
                           func(m, init_fit_col) = minF(m);
88
                       end
                      d = []; similar = []; sh = [];
90
                       for i = 1: length(incl)
91
                            F_{int} = F_{min} - epsilon;
92
                            for j = 1: length (incl)
93
                                for p = 1:nfunc
94
                                     similar(p) = ((Fitness(i,p)-
95
                                         Fitness(j,p))/(maxF(p)-
                                         \min F(p))^2;
                                end
96
                                d(i,j) = sqrt(sum(similar));
97
                                if d(i, j) \le sigma
98
                                     \operatorname{sh}(i,j) = 1 - (\operatorname{d}(i,j) / \operatorname{sigma})^{\hat{}}
99
                                         alpha;
                                else sh(i,j) = 0;
100
                                end
101
                           end
102
                           nc(i) = sum(sh(i,:));
                            Fit_share(i) = F_int/nc(i);
104
                            func(incl(i), nc\_col) = nc(i);
105
                           func(incl(i), sim_col) = Fit_share(i);
106
                           func(incl(i), sim_col+1) = F_int;
108
                       end
109
                  end
110
                  F_{\min} = \min(Fit_{\sinh}are);
111
```

```
end
112
113
       end
114
       %Since a greater fitness value is a larger number, we
116
             use the inverse
        fit = -func(:, sim_col);
117
   % Constraint Handling
119
   else
       Cmax = 1.2; Cmin = 0.8; r = 0.8*M;
121
       CF2 = 0.015;
122
       CF1 = 0.005;
123
       rank = zeros(1,M);
124
125
       % Assign moderate rank to all feasible solutions
126
         for k = 1:M
127
            flag = 0; flag_lin = 0;
128
            for p = 1:nconstr
                 if g(k,p) > 0, flag = 1;
130
131
                 if nconstr_eq = 0
132
                     if h(k,p) = 0, flag_lin = 1;
133
                     end
134
                 end
135
            end
136
            if flag == 0 && flag_lin == 0
                 rank(k) = 0.5*M;
138
            end
139
         end
140
141
        %Evaluates feasible solutions with uncertaintly
142
             applied in problems with
       %uncertainy
143
         if UNCT == 1
144
             for k = 1:M
145
                  if rank(k) = 0.5*M
146
                       options = optimoptions (@ga,
                          PopulationSize', 10, 'UseVectorized',
                          true);
                      1b = -2; ub = 2;
148
                       fitnessfn = @(DP) -TNK_NEGCN2(XOLin(k,:)
149
                           ,DP);
                       [DP, fval] = ga(fitnessfn, 2, [], [], [], [],
                          lb, ub, [], options);
                       Constval = fval;
151
```

```
if Constval > 0
152
                           rank(k) = 0;
153
                       else
154
                           rank(k) = 0.5*M;
                       end
156
                  else
157
                       rank(k) = 0;
158
                  end
159
             end
160
         end
161
162
        % Collect together feasible population
163
         feas\_pop = []; infeas\_pop = []; m = 1;
164
         for k = 1:M
165
              if rank(k) = 0
166
                  if isempty(h)
167
                       feas\_pop = [feas\_pop; func(k,:), g(k,:)];
168
                  else
169
                       feas\_pop = [feas\_pop; func(k,:), g(k,:), h(
                           k,:)];
                  end
171
              else
172
                    if isempty(h)
                        infeas_pop = [infeas_pop; func(k,:),g(k
174
                            ,:) |;
                    else
175
                        infeas_pop = [infeas_pop;func(k,:),g(k
176
                            ,:),h(k,:)];
                   end
177
                   loc(m) = k; m = m+1; \%keep track of which
178
                       solutions were infeasible
             end
179
         end
180
        % Identify noninferior points
182
         if ~isempty(feas_pop)
183
               place = paretoset(feas_pop(:,1:nfunc));
184
              m = 1;
               for k = 1:length(place)
186
                   if place(k) == 1
187
                        rank(k) = 1; m = m+1; \%Assign
188
                            noninferior points along with
                            constraint values
                   end
189
               end
190
191
         end
```

```
% Evaluate rank for infeasible individuals
192
        if ~isempty(infeas_pop)
193
            g = infeas_pop(:,nfunc+1:nconstr+nfunc);
194
            h = infeas_pop(:,nconstr+nfunc+1:end);
196
            for k = 1: length(g(:,1))
197
                 for p = 1:nconstr
198
                     if g(k,p) \le 0
199
                          feas_g(k,p) = 0; delta_g(k,p) = 0;
200
                     else
201
                          feas_g(k,p) = g(k,p); delta_g(k,p) =
202
                             1;
                     end
203
                 end
204
                 if nconstr_{eq} = 0
205
                     feas_h = zeros(length(g(:,1)),1);
206
                     delta_h = zeros(length(g(:,1)),1);
207
                 else
208
                     for n = 1:nconstr_eq
                          feas_h(k,n) = abs(h(k,n));
210
                     end
                     if h(k,p) == 0, delta_h(k,p) = 0;
212
                     else delta_h(k,p) = 1;
                     end
214
                 end
215
            end
216
            num1 = sum(feas_g, 2) + sum(feas_h, 2);
            denom1 = (sum(sum(feas_g)) + sum(sum(feas_h)))/M;
218
            J = nconstr; K = nconstr_eq;
219
            num2 = (sum(delta_g, 2) + sum(delta_h, 2));
220
            denom2 = (J+K);
221
222
            factor1 = CF1.*(num1./denom1);
223
            factor 2 = CF2.*(num2./denom2);
225
226
227
            for k = 1: length(g(:,1))
                 if (factor1(k)> mean(factor1)) && (factor2(k)
229
                     < mean(factor2))
                     w1 = 0.75; w2 = 0.25;
230
                 elseif (factor1(k) < mean(factor1)) && (
                     factor2(k) > mean(factor2))
                     w1 = 0.25; w2 = 0.75;
                 else
233
                     w1 = 0.5; w2 = 0.5;
234
```

```
end
235
                   fit_constr(k) = -((Cmax-(Cmax-Cmin)*(r-1)/(M
236
                       -1))-(w1.*factor1(k)+w2.*factor2(k)));
              \quad \text{end} \quad
237
238
              for k = 1: length(loc)
239
                   rank(loc(k)) = fit_constr(k);
240
              end
241
         end
242
         fit = rank;
243
^{244}
245
   end
246
247 end
```