## Purdue University

ECE 580: Optimization Methods for Systems and Control

# FunWork #4

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$$A_{1} = \begin{pmatrix} 1 & 1 \end{pmatrix}$$

$$A_{2} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$A_{1}^{\dagger} = A_{1}^{\top} (A_{1} A_{1}^{\top})^{-1} = (2)^{-1} A_{1}^{\top} = \begin{pmatrix} 0.5 \\ 0.5 \end{pmatrix}$$

$$A_{2}^{\dagger} = (A_{2}^{\top} A_{2})^{-1} A_{2}^{\top} = (1)^{-1} A_{2}^{\top} = \begin{pmatrix} 1 & 0 \end{pmatrix}$$

$$(A_{1} A_{2})^{\dagger} = (1)^{\dagger} = (1)$$

$$A_{2}^{\dagger} A_{1}^{\dagger} = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} 0.5 \\ 0.5 \end{pmatrix} = (0.5)$$

$$(A_{1} A_{2})^{\dagger} \neq A_{2}^{\dagger} A_{1}^{\dagger}$$

The Griewank function is defined as:

$$f(x_1, x_2, ..., x_n) = 1 + \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}})$$

Listing 1 shows the source code of the Griewank function:

```
1  function [f] = gk(x)
2
3  sum = 0;
4  prod = 1;
5
6  for i = 1:length(x)
7   sum = sum + x(i)^2/4000;
8   prod = prod * cos(x(i)/sqrt(i));
9  end
10
11  f = sum - prod + 1;
12
13  end
```

Listing 1: The source code of the Griewank function

Listing 2 shows the source code of the PSO function that implements the Particle Swarm Optimization algorithm. It can be used for both minimization and maximization of a given function. The following configurations are used:

- 1. The minimum value for each coordinate of the particle positions is -5, and the maximum is 5. The positions are always clipped to be in that range.
- 2. The minimum value for each coordinate of the particle velocities is -0.5, and the maximum is 0.5. The velocities are always clipped to be in that range.
- 3. The number of iterations is 100.
- 4. The size of the population is 100.
- 5. The inertial constant is 0.8.
- 6. The cognitive coefficient is 2.
- 7. The social coefficient is 2.

```
function [] = pso(f, is_minimize, file_name)
    \min_{\mathbf{x}} = -5;
 4
    \max_{x} = 5;
    \min_{v} = -0.5;
 6
    \max_{v} = 0.5;
9 \text{ max_k} = 100;
10
   d = 100;
11
   w = 0.8;
13 \quad c1 = 2;
14
16 	 x = \min_{x} + (\max_{x} - \min_{x}) \cdot * rand(2, d);
   v = rand(2, d);
18 p = x;
```

```
g = x(:, 1);
20
     for i = 2:d
21
         \begin{tabular}{ll} \bf if & $(f(x(:,\ i)) < f(g) \&\& \ is\_minimize)$ & $|| & $(f(x(:,\ i)) > f(g) \&\& \ \~is\_minimize)$ \\ \end{tabular} 
          g = x(:, i);
23
24
        end
25
     end
26
27
    overall_best = zeros(1, max_k);
28 best = zeros(1, max_k);
    worst = zeros(1, max_k);
29
30
     average = zeros(1, max_k);
31
32
     for k = 1: max_k
33
       r = rand(2, d);
        s = rand(2, d);
34
35
36
        v = w * v + c1 * r .* (p - x) + c2 * s .* bsxfun(@minus, g, x);
        v = max(min_v, min(max_v, v));
37
38
39
        x = x + v;
40
        x = max(min_x, min(max_x, x));
41
        worst(k) = f(x(:, 1));
42
43
        best(k) = f(x(:, 1));
44
45
        for i = 1:d
46
           average\left(\,k\,\right) \;=\; average\left(\,k\,\right) \;+\; f\left(\,x\,\left(\,:\,,\quad i\,\,\right)\,\right);
47
           \begin{array}{l} \mbox{if } (f(x(:,\ i\,)) < f(p(:,\ i\,)) \&\& \ is\_minimize) \ || \ \dots \\ (f(x(:,\ i\,)) > f(p(:,\ i\,)) \&\& \ \~is\_minimize) \end{array}
48
49
50
              p(:, i) = x(:, i);
51
              \label{eq:force_force} \textbf{if} \ (\, f\, (\, x\, (\, :\, , \quad i\, )\, )\, <\, f\, (\, g\, )\, \,\&\& \,\, is\, \underline{\quad } \\ \text{minimize}\, ) \ \mid\, | \quad \dots
52
                 (f(x(:, i)) > f(g) \&\& is\_minimize)
53
                 g = x(:, i);
54
              end
55
           end
56
57
           if \ (f(x(:,\ i\,)) \ > \ worst(k) \ \&\& \ is\_minimize) \ || \ \dots
              (f(x(:, i)) < worst(k) && ~is\_minimize)
58
59
              worst(k) = f(x(:, i));
60
           end
           \label{eq:if_factor} \textbf{if} \ (\texttt{f}(\texttt{x}(:, \ \texttt{i})) \ < \ \texttt{best}(\texttt{k}) \ \&\& \ \texttt{is\_minimize}) \ \mid\mid \ \dots
61
              (f(x(:, i)) > best(k) \&\& ~is\_minimize)
62
              best(k) = f(x(:, i));
63
64
           end
65
        end
67
        average(k) = average(k) / d;
68
        overall_best(k) = f(g);
69
     end
70
71
     f (g)
72
73
74
75
     file_id = fopen(strcat(file_name, '.txt'), 'w');
     \mathbf{fprintf}(\mathbf{file\_id}, 'Final Solution: \mathbf{x} = [\%.10f \%.10f] \setminus \mathbf{nf}(\mathbf{x}) = \%.10f \setminus n', \dots
76
77
        g(1), g(2), f(g);
78
    k = [1: \max_{k}];
79
80 figure
81 plot(k, overall_best)
82 print(strcat(file_name, 'overall_best'), '-dpng')
     figure
    plot(k, best)
84
     print(strcat(file_name, 'best'), '-dpng')
     figure
```

```
87 plot(k, average)
88 print(strcat(file_name, 'average'), '-dpng')
89 figure
90 plot(k, worst)
91 print(strcat(file_name, 'worst'), '-dpng')
92
93 end
```

Listing 2: The source code of the PSO function

```
1  clc;
2  clear;
3  
4  f = @gk;
5  pso(f, 1, 'problem2');
6  pso(f, 0, 'problem3');
```

Listing 3: The main source code of problems 2 and 3. It invokes the PSO for both minimization and maximization.

```
1 Final Solution: x* = [-0.0001206289 \ 0.0002274571]
2 f(x*) = 0.0000000202
```

Listing 4: The output of Problem 2

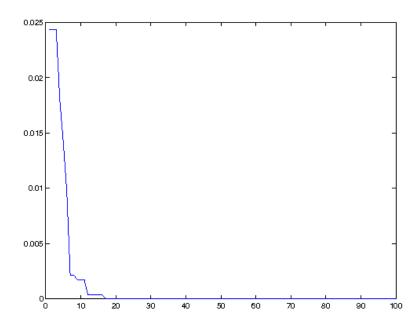


Figure 1: The objective function of the global best over the generations. This function is always decreasing because the global best is maintained.

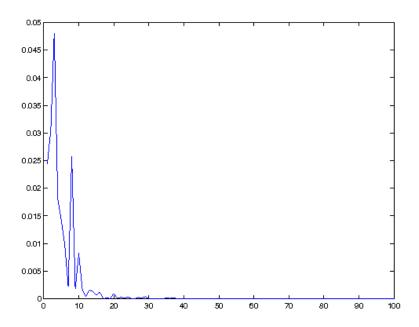


Figure 2: The objective function of the best particle in each generation.

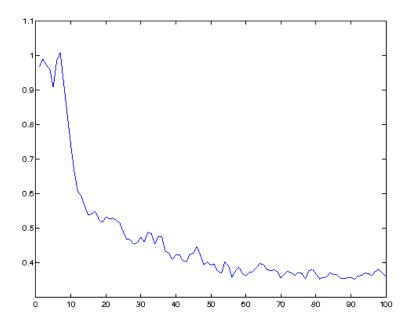


Figure 3: The average objective function of all the particles over the generations.

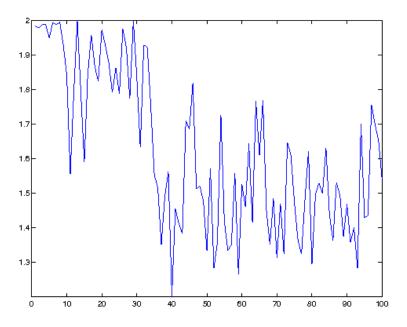


Figure 4: The worst objective function over the generations.

The same source code and the configurations of Problem 2 is used in Problem 3 as well. Listing 5 shows the output of Problem 3.

```
1 Final Solution: x* = [-3.1431671864 \ 0.0003048406]
2 f(x*) = 2.0024686122
```

Listing 5: The output of Problem 3

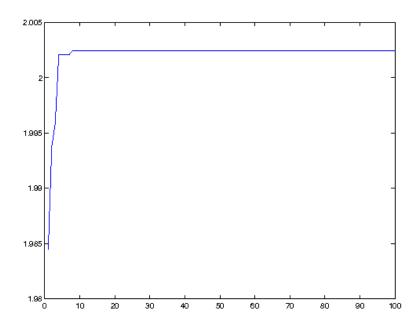


Figure 5: The objective function of the global best over the generations. This function is always decreasing because the global best is maintained.

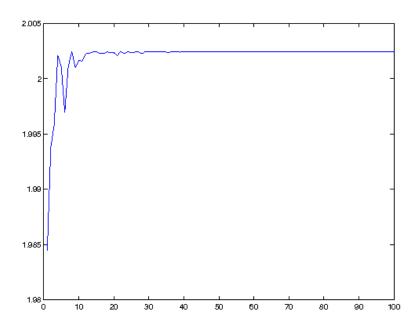


Figure 6: The objective function of the best particle in each generation.

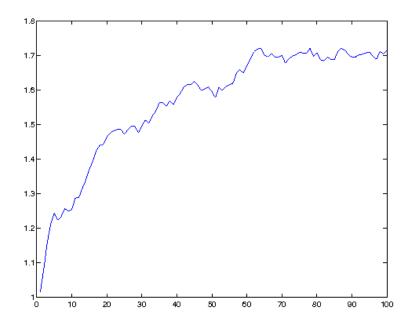


Figure 7: The average objective function of all the particles over the generations.

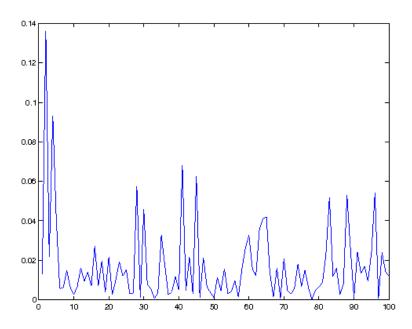


Figure 8: The worst objective function over the generations.

There are 10! different possible paths for 10 cities. Listing 6 shows the main source code of Problem 4. It implements the Genetic algorithm with the following configurations:

- 1. The number of iterations is 200.
- 2. The size of the population is 200.
- 3. The probability of crossover is 0.8.
- 4. The number of elites that are kept at each generation is 5.
- 5. The fitness function is the inverse of the distance along the route among the cities. The function used to calculate the fitness function is shown in Listing 7.

```
1
    clc;
    clear;
3
   \max_{-k} = 200;
4
  d = 200;
6
   p_c = 0.8;
    elites_num = 5;
   cities = [0.4306 \ 3.7094 \ 6.9330 \ 9.3582 \ 4.7758 \ 1.2910 \ 4.83831 \ 9.4560 \ 3.6774 \ 3.2849;
      7.7288 \ 2.9727 \ 1.7785 \ 6.9080 \ 2.6394 \ 4.5774 \ 8.43692 \ 8.8150 \ 7.0002 \ 7.5569];
10
11
   cities_num = size(cities, 2);
12
13
   x = zeros(d, cities_num);
  m = zeros(d, cities_num);
15
   f = zeros(d, 1);
16
17
    for i = 1:d
      x(i, :) = randperm(cities_num);
18
19
      f(i) = tsp_fitness(cities, x(i, :));
20
   end
21
    for k = 1:max_k
22
23
24
      [sorted_values, sort_index] = sort(f(:), 'descend');
25
      for i = 1:elites_num
26
       m(i, :) = x(sort\_index(i), :);
27
      end
28
29
      for i = elites_num + 1:d
        j = find(cumsum(f) / sum(f) - rand() > 0, 1);
30
31
        m(i, :) = x(j, :);
32
33
        if(rand() < p_c)
34
          j = randi([1 cities_num]);
          k = randi([1 cities_num]);
35
36
37
          temp = m(i, j);
          m(i, j) = m(i, k);
38
          m(i, k) = temp;
39
40
        end
41
      end
42
43
      x = m;
44
      for i = 1:d
45
        f(i) = tsp_fitness(cities, x(i, :));
46
      end
47
    end
48
49
   best = x(find(f = max(f), 1), :)
    best_distance = 1 / tsp_fitness(cities, best)
```

```
51
52  x = cities(1, best);
53  x(cities_num + 1) = cities(1, best(1));
54  y = cities(2, best);
55  y(cities_num + 1) = cities(2, best(1));
56  figure
57  plot(x, y, 'b-o')
58  print('problem4', '-dpng')
```

Listing 6: The source code of Problem 4

```
1  function [f] = tsp_fitness(cities, order)
2
3  cities_num = size(cities, 2);
4
5  f = norm(cities(:, order(1)) - cities(:, order(cities_num)));
6
7  for i = 2:cities_num
8     f = f + norm(cities(:, order(i)) - cities(:, order(i - 1)));
9   end
10
11  f = 1 / f;
12
13  end
```

Listing 7: The source code of the function to evaluate the fitness function of a chromosome

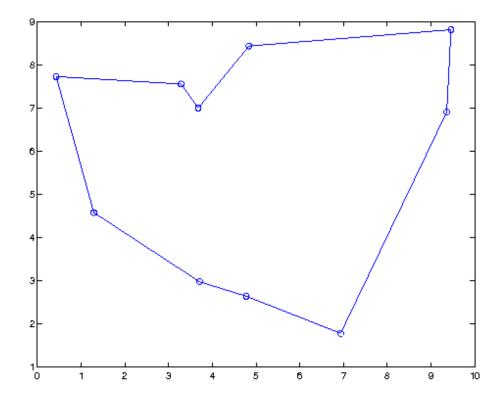


Figure 9: The optimal route among the cities

To solve the problem, I use the linprog method in Matlab as shown in Listing 8. Listing 9 shows the output of the problem. It is worth mentioning that the output values are double. However the problem indicates that some of the products should be integers, such as the number of boxes. This shows the need for integer linear programming. So the provided answer is the optimal double solution. If we round the values, this might not be the optimal integer solution.

```
clc;
 2
    clear;
3
    f = [-6; -4; -7; -5];
4
   A = \begin{bmatrix} 1 & 2 & 1 & 2 \\ 6 & 5 & 3 & 2 \\ 3 & 4 & 9 & 12 \end{bmatrix};
7
    b = [20; 100; 75];
    lb = \mathbf{zeros}(4,1);
10
   [x, fval, exitflag, output, lambda] = linprog(f, A, b, [], [], lb);
11
12
    file_id = fopen('problem5.txt', 'w');
    fprintf(file_id ,
                          Solution: x* = [\%.10f \%.10f \%.10f \%.10f] \ 
14
    x(1), x(2), x(3), x(4);

fprintf(file_id, 'Revenue: f(x*) = \%.10 f\n', ...
15
16
       6 * x(1) + 4 * x(2) + 7 * x(3) + 5 * x(4));
```

Listing 8: The source code of Problem 5

```
1 Solution: x* = [14.9999999999 \ 0.00000000001 \ 3.333333333 \ 0.0000000001]
2 Revenue: f(x*) = 113.33333333326
```

Listing 9: The output of Problem 5