

CE3-08 – Process Model Solution and Optimization

Problem Sheet for Topic #2, with Answers

1. Check whether the following functions are convex or concave over the domains specified using the Hessian test. Try to plot the functions in Matlab to validate your answers.

(a) $f(x) = x \sin(x)$, for $x \in [0, \pi]$? for $x \in [\frac{\pi}{2}, \pi]$?

Answers. The second derivative of f is easily calculated as:

$$f''(x) = 2 \cos(x) - x \sin(x)$$

- In the case that $x \in [0, \pi]$, it is found that $f''(0) = 2$ and $f''(\pi) = -2$, thereby showing that f is neither convex nor concave on $[0, \pi]$ (since the curvature of the function is changing sign).
- In the case that $x \in [\frac{\pi}{2}, \pi]$, the following inequalities are easily established:

$$-2 \leq 2 \cos(x) \leq 0, \quad -\pi \leq -x \sin(x) \leq 0,$$

from where we can conclude that $f''(x) \leq 0$. In other words, f is concave on $[\frac{\pi}{2}, \pi]$.

These results are supported by the plot shown in Fig. 1.

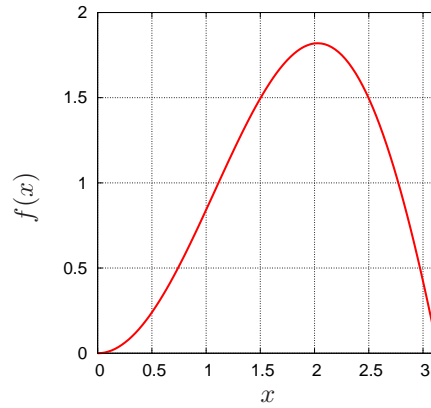


Figure 1: Function f in Question 1a

(b) $f(x_1, x_2) = 1000 + 7x_1 - 700x_2 + 23x_1x_2 + 10x_1^2 + 5.6x_2^2$, for $x_1, x_2 \in \mathbb{R}$?

Answers. The Hessian matrix of f is given by:

$$\mathbf{H}(\mathbf{x}) = \begin{pmatrix} 20 & 23 \\ 23 & 11.2 \end{pmatrix}$$

Notice that \mathbf{H} is independent of the current point \mathbf{x} since f is a second-order polynomial in x_1, x_2 . It can be easily checked whether or not \mathbf{H} is a definite matrix, e.g., by calculating its eigenvalues with Matlab:

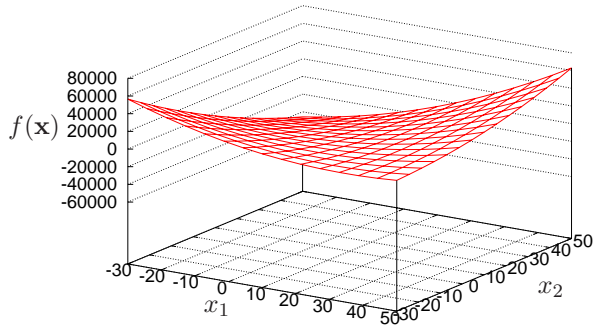


Figure 2: Function f in Question 1b

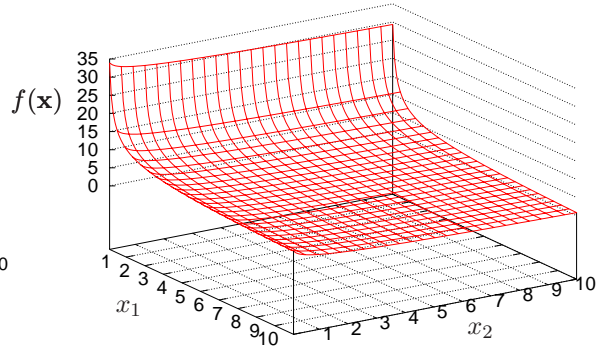


Figure 3: Function f in Question 1c

```
>> eig([[20,23];[23,11.2]])
```

```
ans =
```

```
-7.8171
39.0171
```

Clearly, \mathbf{H} is indefinite, so f is neither convex nor concave. This behavior is confirmed by the plot shown in Fig. 2.

(c) $f(x_1, x_2) = \frac{10}{\sqrt{x_1}} - \log(x_2)$, for $x_1, x_2 > 0$?

Answers. Notice that f is the sum of 2 univariate functions in x_1 and x_2 , respectively. Accordingly, the convexity/concavity of f is determined by the convexity/concavity of these two terms.

- The function $g(z) = \frac{1}{\sqrt{z}}$ is convex since its 2nd-order derivative $g''(z) = \frac{3}{4z^{5/2}}$ is positive for each $z \in (0, +\infty)$.
- Likewise, the function $h(z) = -\log(z)$ is convex since its 2nd-order derivative $h''(z) = \frac{1}{z^2}$ is positive for each $z \in (0, +\infty)$.

Since the sum of two convex functions yield a convex function, f is therefore convex on $(0, +\infty) \times (0, +\infty)$. The plot in Fig. 3 confirms this analysis.

2. For each of the following functions, determine *analytically* whether the specified \mathbf{x} is: (i) definitely a local minimum; (ii) possibly a local minimum; (iii) definitely a local maximum; and/or (iv) possibly a local maximum. Try to validate your answers graphically.

(a) $f(x_1, x_2) = 12x_2 - (x_1)^2 + 3x_1x_2 - 3(x_2)^2$, at $\mathbf{x} = (12, 8)$?

Answers. The gradient and the Hessian of f at $\mathbf{x} = (12, 8)$ are easily calculated as:

$$\nabla f(\mathbf{x}) = \begin{pmatrix} -2x_1 + 3x_2 \\ 12 + 3x_1 - 6x_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \mathbf{H}(\mathbf{x}) = \begin{pmatrix} -2 & 3 \\ 3 & -6 \end{pmatrix}.$$

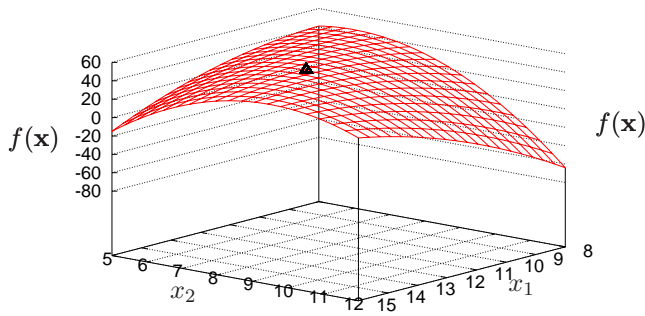


Figure 4: Function f in Question 2a

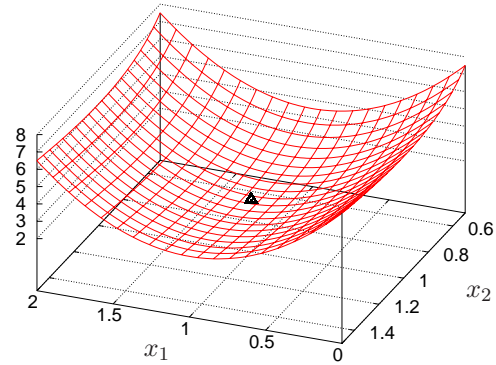


Figure 5: Function f in Question 2b

Clearly, $(12, 8)$ is a stationary point. Moreover, it can be checked that $\mathbf{H}(\mathbf{x})$ is a definite negative matrix using MatLab:

```
>> eig([-2,3];[3,-6])

ans =

-7.6056
-0.3944
```

One can thus conclude that $(12, 8)$ is a strict local maximum based on the second-order sufficient conditions for optimality. This is illustrated in Fig. 4.

(b) $f(x_1, x_2) = 4(x_1)^2 + \frac{3}{x_2} - 8x_1 + 3x_2$, at $\mathbf{x} = (1, 1)$?

Answers. The gradient and the Hessian of f at $\mathbf{x} = (1, 1)$ are given by:

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 8x_1 - 8 \\ -\frac{3}{x_2^2} + 3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \mathbf{H}(\mathbf{x}) = \begin{pmatrix} 8 & 0 \\ 0 & \frac{6}{x_2^3} \end{pmatrix} = \begin{pmatrix} 8 & 0 \\ 0 & 6 \end{pmatrix}.$$

Clearly, $(1, 1)$ is a stationary point, and it is immediately verified that the diagonal matrix $\mathbf{H}(\mathbf{x})$ is definite positive. One can then invoke the second-order sufficient conditions for optimality to conclude that $(1, 1)$ is a strict local minimum. This is illustrated in Fig. 5.

(c) $f(x_1, x_2) = (x_1)^3(x_2)^2$, at $\mathbf{x} = (0, 0)$?

Answers. The gradient and the Hessian of f at $\mathbf{x} = (0, 0)$ are given by:

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 3x_1^2x_2^2 \\ 2x_1^3x_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \mathbf{H}(\mathbf{x}) = \begin{pmatrix} 6x_1x_2^2 & 6x_1^2x_2 \\ 6x_1^2x_2 & 2x_1^3 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}.$$

Here again, $(0, 0)$ is a stationary point, yet the Hessian matrix is equal to zero at that point. According to the second-order *necessary* conditions for optimality, $(0, 0)$ could be either a local minimum, or a local maximum, or a saddle point. Unfortunately, the sufficient second-order conditions do not apply here, so none of these scenarios can be excluded. By visual inspection, it appears that $(0, 0)$ is a saddle point (see Fig. 6).

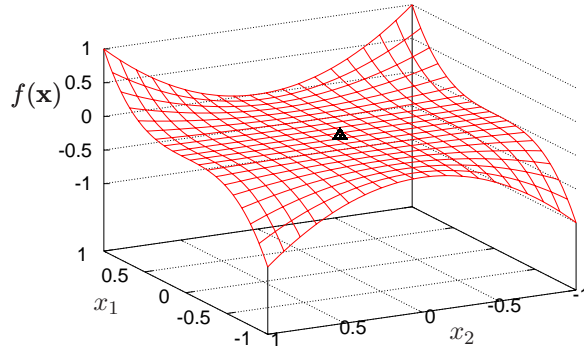
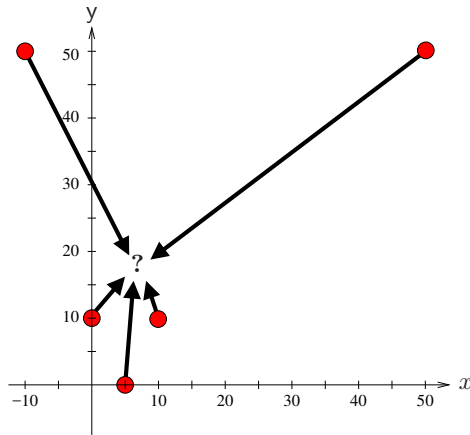


Figure 6: Function f in Question 2c

3. We want to connect five oil wells to a single collection point using the minimum total length of pipe, as shown in the figure below. Each pipe segment will be placed in straight line from the well to the collection point.



The locations of the oil wells in the (x, y) -plane are the following:

- $(x_1, y_1) = (5, 0)$
- $(x_2, y_2) = (0, 10)$
- $(x_3, y_3) = (10, 10)$
- $(x_4, y_4) = (50, 50)$
- $(x_5, y_5) = (-10, 50)$

- (a) Formulate an (unconstrained) NLP model that can be used to determine where the collection point should be located in the plane.

Answers. The decision variables x and y correspond to the position of the collection point. The function to minimize is:

$$\begin{aligned} \min_{x,y} f(x, y) &:= \sum_{k=1}^5 \sqrt{(x - x_k)^2 + (y - y_k)^2} \\ &= \sqrt{(x - 5)^2 + y^2} + \sqrt{x^2 + (y - 10)^2} + \sqrt{(x - 10)^2 + (y - 10)^2} \\ &\quad + \sqrt{(x - 50)^2 + (y - 50)^2} + \sqrt{(x + 10)^2 + (y - 50)^2} \end{aligned}$$

This function is shown in Fig. 7 below.

- (b) Could this problem exhibit multiple local optima? Justify your answer.

Answers. It can be shown that every norm in \mathbb{R}^n is a strictly convex function on \mathbb{R}^n . In particular, the Euclidean norm defined as $\|\mathbf{x}\|_2 = \sqrt{x_1^2 + x_2^2}$ is convex. Since the

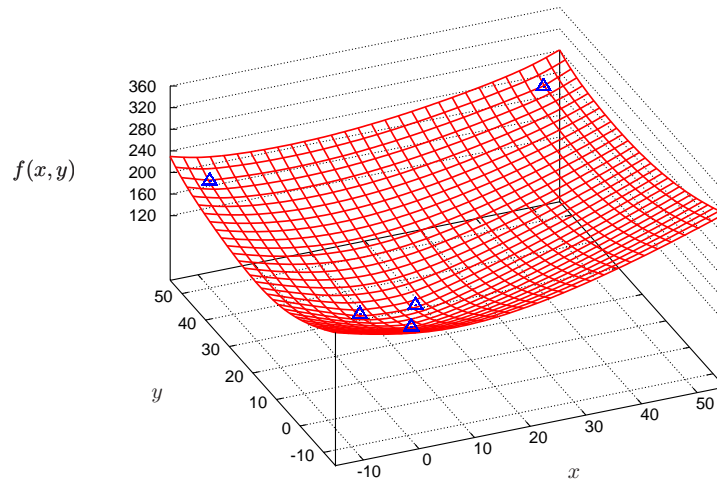


Figure 7: Objective function in Question 3a.

summation of convex functions preserves (strict) convexity, the objective function f is strictly convex on \mathbb{R}^2 . By convexity, it follows that the optimization problem cannot have local optima that are not global optima, and by strict convexity, that the global optimum is unique.

- (c) Implement this problem in Matlab and solve it using the `fminunc` function. In particular:
- try to provide the gradient of the objective function (see option `GradObj`)
 - set the termination tolerances on the variables and the objective gradient value to $1e-7$ (options `TolX` and `TolFun`)
 - select a 'good' initial guess (e.g., the origin $(0,0)$)

Report the optimal point and solution value found by `fminunc`, as well as the termination flag, total number of iterations, and measure of first-order optimality. Plot the objective function and compare the actual maximum with the numerical solution.

Answers. A possible implementation based on `fminunc` is as follows:

```

oilWells.m
1  % Set options (gradient + tolerances)
2  Options = optimoptions( @fminunc, 'GradObj', 'on', 'TolFun', 1e-7, 'TolX', 1e-7 );
3
4  % Initial guess
5  p0 = [0; 0];
6
7  % Call fminunc
8  [popt, fopt, Flag, Info] = fminunc( @oilWells_obj, p0, Options )

```

```

oilWells_obj.m
1  function [ f, df ] = oilWells_obj( p )
2  % This function calculates the value (f) and first derivative (df)
3  % of the objective function for a given collection point p
4

```

```

5      % Well (x,y) locations
6      w1 = [ 5; 0 ];
7      w2 = [ 0; 10 ];
8      w3 = [ 10; 10 ];
9      w4 = [ 50; 50 ];
10     w5 = [ -10; 50 ];
11
12     % Total length of pipe
13     f = norm(p-w1) + norm(p-w2) + norm(p-w3) + norm(p-w4) + norm(p-w5);
14     df = (p-w1)/norm(p-w1) + (p-w2)/norm(p-w2) + (p-w3)/norm(p-w3) + ...
15          (p-w4)/norm(p-w4) + (p-w5)/norm(p-w5);
16
17     end

```

The following results are obtained on calling the m-file `oilWells.m` from the command line in Matlab:

```

Command Line
1      >> oilWells
2
3      Local minimum found.
4
5      Optimization completed because the size of the gradient is less than
6      the selected value of the function tolerance.
7
8      popt =
9
10         7.618835813588754
11        11.214511402349354
12
13
14      fopt =
15
16         1.219537866491946e+02
17
18
19      Flag =
20
21         1
22
23
24      Info =
25
26         iterations: 8
27         funcCount: 9
28         cgiterations: 8
29         firstorderopt: 2.233649931682180e-10
30         algorithm: 'large-scale: trust-region Newton'
31         message: [1x498 char]
32         constrviolation: []

```

These results indicate that an optimum has been found (Flag=1), after 8 iterations. The optimal collection point is $\mathbf{p}^* \approx (7.6188, 11.2145)$ and the corresponding minimal total length of pipe $f^* \approx 121.9538$. Moreover, a measure of first-order optimality by the solver is 2.2×10^{-10} , thereby confirming that the algorithm has converged to a stationary point.

A plot of the optimal solution is shown in Fig. 8 below.

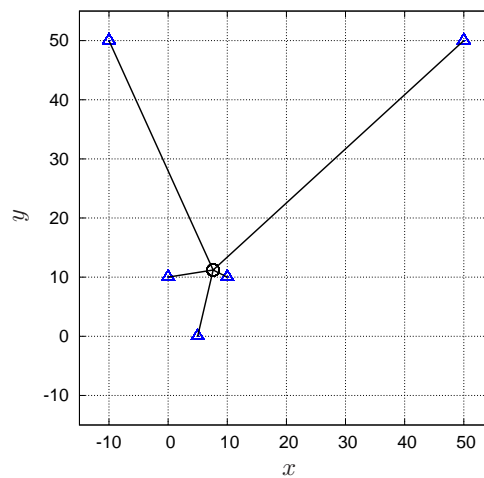


Figure 8: Optimal solution in Question 3c.

(d) Repeat Question 3c using GAMS instead of MATLAB.

Answers. A possible GAMS implementation is as follows:

```

oilWells.gms
1  SETS
2    w  wells / W1*W5 /
3
4  PARAMETERS
5    x(w)  x-coordinate of wells
6    / W1   5
7      W2   0
8      W3  10
9      W4  50
10     W5 -10 /
11   y(w)  y-coordinate of wells
12   / W1   0
13     W2  10
14     W3  10
15     W4  50
16     W5  50 /;
17
18  VARIABLES
19    xc  x-coordinate of collection point
20    yc  y-coordinate of collection point
21    l   total length of pipe;
22
23  EQUATIONS
24    length  objective function;
25
26    length..  l =E= SUM(w, SQRT(POWER(x(w)-xc,2)+POWER(y(w)-yc,2)));
27
28  MODEL collector /ALL/;
29  SOLVE collector USING NLP MINIMIZING l;

```

The following results can be found in the GAMS report:

oilWells.lst				
EXIT - Optimal Solution found, objective:		121.9538		
	LOWER	LEVEL	UPPER	MARGINAL
---- EQU length	.	.	.	1.0000
length objective function				
	LOWER	LEVEL	UPPER	MARGINAL
---- VAR xc	-INF	7.6188	+INF	1.0046939E-8
---- VAR yc	-INF	11.2145	+INF	-1.775206E-8
---- VAR l	-INF	121.9538	+INF	.
xc x-coordinate of collection point				
yc y-coordinate of collection point				
l total length of pipe				
**** REPORT SUMMARY :	0	NONOPT		
	0	INFEASIBLE		
	0	UNBOUNDED		
	0	ERRORS		
EXECUTION TIME	=	0.000 SECONDS	2 Mb	LEX237-237 Aug 23, 2011

These results indicate that an optimum has been found. The optimal collection point is $\mathbf{p}^* \approx (7.6188, 11.2145)$ and the corresponding minimal total length of pipe $f^* \approx 121.9538$ is identical to the solution found previously with MATLAB.

- (e) Check that the first- and second-order necessary conditions for optimality are satisfied at the optimum point found previously.

Answers. The gradient and the Hessian of the objective function f are given by:

$$\nabla f(x, y) = \begin{pmatrix} \sum_{k=1}^5 \frac{x - x_k}{\sqrt{(x - x_k)^2 + (y - y_k)^2}} \\ \sum_{k=1}^5 \frac{y - y_k}{\sqrt{(x - x_k)^2 + (y - y_k)^2}} \end{pmatrix}$$

$$\mathbf{H}(x, y) = \begin{pmatrix} \sum_{k=1}^5 \frac{(y - y_k)^2}{((x - x_k)^2 + (y - y_k)^2)^{\frac{3}{2}}} & \sum_{k=1}^5 \frac{(x - x_k)(y - y_k)}{((x - x_k)^2 + (y - y_k)^2)^{\frac{3}{2}}} \\ \sum_{k=1}^5 \frac{(x - x_k)(y - y_k)}{((x - x_k)^2 + (y - y_k)^2)^{\frac{3}{2}}} & \sum_{k=1}^5 \frac{(x - x_k)^2}{((x - x_k)^2 + (y - y_k)^2)^{\frac{3}{2}}} \end{pmatrix}$$

The second-order derivatives can be added to the m-file `oilWells_obj.m` as follows:

```
oilWells_obj.m
1 function [ f, df, d2f ] = oilWells_obj( p )
2 % This function calculates the value (f), first derivative (df), and
```



```

3      % second derivative (d2f) of the objective function for a given
4      % collection point p
5
6      % Well (x,y) locations
7      w1 = [ 5; 0 ];
8      w2 = [ 0; 10 ];
9      w3 = [ 10; 10 ];
10     w4 = [ 50; 50 ];
11     w5 = [ -10; 50 ];
12
13     % Total length of pipe
14     f = norm(p-w1) + norm(p-w2) + norm(p-w3) + norm(p-w4) + norm(p-w5);
15     df = (p-w1)/norm(p-w1) + (p-w2)/norm(p-w2) + (p-w3)/norm(p-w3) + ...
16          (p-w4)/norm(p-w4) + (p-w5)/norm(p-w5);
17     Q = ones(2)-eye(2); % Permutation matrix
18     d2f = Q* ( (p-w1)*(p-w1)'/norm(p-w1)^3 + (p-w2)*(p-w2)'/norm(p-w2)^3 + ...
19               (p-w3)*(p-w3)'/norm(p-w3)^3 + (p-w4)*(p-w4)'/norm(p-w4)^3 + ...
20               (p-w5)*(p-w5)'/norm(p-w5)^3 ) * Q';
21
22     end

```

The following results are obtained upon calling the m-file `oilWells_obj.m` with the optimum point \mathbf{p}^* found in Question 3c:

```

Command Line
1      >> [fopt,dfopt,d2fopt] = oilWells_obj( popt )
2
3      fopt =
4
5          121.9538
6
7
8      dfopt =
9
10     1.0e-09 *
11
12         0.2067
13         0.2234
14
15
16     d2fopt =
17
18         0.1902   -0.1122
19        -0.1122    0.4413
20
21     >> eig( d2fopt )
22
23     ans =
24
25         0.1473
26         0.4841

```

It is checked that the gradient elements are both very close to zero. Moreover, both eigenvalues of the Hessian matrix are positive, thereby confirming that \mathbf{p}^* is indeed a strict local minimum – in fact, a strict global minimum by convexity.

4. Consider the following QP problem:

$$\begin{aligned} \min_{\mathbf{x}} \quad & x_1^2 + x_2^2 - 8x_1 - 16x_2 + 32 \\ \text{s.t.} \quad & x_1 + x_2 \leq 5 \\ & x_1 \geq 0 \end{aligned}$$

- (a) Write down the KKT conditions for this QP. Identify such KKT points, by successively considering *all* possible active sets (4 possibilities).

Answers. The conditions for $(\mathbf{x}, \boldsymbol{\nu})$ to be a KKT point for this problem are the following:

$$\begin{aligned} x_1 + x_2 &\leq 5, & \nu_1(x_1 + x_2 - 5) &= 0, & \nu_1 &\geq 0, \\ -x_1 &\leq 0, & \nu_2 x_1 &= 0, & \nu_2 &\geq 0, \\ 2x_1 - 8 + \nu_1 - \nu_2 &= 0, & 2x_2 - 16 + \nu_1 &= 0, \end{aligned}$$

Next, we search KKT points for different active-set configuration:

Constraints #1 & #2 Inactive: This case corresponds to $\nu_1 = \nu_2 = 0$. The dual feasibility conditions therefore reduce to the system:

$$2x_1 - 8 = 0, \quad 2x_2 - 16 = 0,$$

the unique solution of which is $x_1 = 4$ and $x_2 = 8$. However, this point violates the first inequality constraint since $4 + 8 = 12 > 5$. Therefore, a KKT point cannot exist in this active-set configuration.

Constraint #1 Active & #2 Inactive: This case corresponds to $\nu_2 = 0$, and $x_1 + x_2 = 5$. This later condition along with the dual feasibility conditions yield the following (linear) system:

$$x_1 + x_2 = 5, \quad 2x_1 - 8 + \nu_1 = 0, \quad 2x_2 - 16 + \nu_1 = 0,$$

the unique solution of which is $x_1 = \frac{1}{2}$, $x_2 = \frac{9}{2}$ and $\nu_1 = 7$. Note that $\nu_1 = 7 \geq 0$ also satisfies the sign restriction of the dual feasibility conditions. All the KKT conditions being satisfied, we have thus found a KKT point.

Constraint #1 Inactive & #2 Active: This case corresponds to $\nu_1 = 0$, and $x_1 = 0$. This later condition along with the dual feasibility conditions yield the following (linear) system:

$$x_1 = 0, \quad 2x_1 - 8 - \nu_2 = 0, \quad 2x_2 - 16 = 0,$$

the unique solution of which is $x_1 = 0$, $x_2 = 8$ and $\nu_2 = -8$. Note that $\nu_2 = -8 < 0$ violates the sign condition imposed by the dual feasibility conditions. Therefore, a KKT point cannot exist in this active-set configuration.

Constraints #1 & #2 Active: This case corresponds to $x_1 + x_2 = 5$, and $x_1 = 0$, i.e., $x_2 = 5$. The dual feasibility conditions therefore reduce to the system:

$$-8 + \nu_1 - \nu_2 = 0, \quad -6 + \nu_1 = 0,$$

the unique solution of which is $\nu_1 = 6$ and $\nu_2 = -2$. Here again, $\nu_2 = -2 < 0$ violates the sign condition imposed by the dual feasibility, so no KKT point can exist in this active-set configuration.

Overall, the unique KKT point for this NLP problem is:

$$x_1^* = \frac{1}{2}, \quad x_2^* = \frac{9}{2}, \quad \nu_1^* = 7, \quad \nu_2^* = 0$$

(b) Check whether the QP is convex. Conclude.

Answers. A convex optimization problem involves the minimization of a convex objective function over a convex region. A convex domain is obtained when (i) *all* the functions participating in constraints of ≤ 0 type are convex on the search space, and those participating in constraints of ≥ 0 type are concave; and (ii) *all* the functions participating in constraints of $= 0$ type are affine.

In the problem at hand, both inequality constraints are affine, and therefore define a convex domain. Moreover, the objective function is a quadratic polynomial in the variables x_1, x_2 ; its Hessian matrix,

$$\mathbf{H}(\mathbf{x}) := \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix},$$

being positive definite, this function is (strictly) convex. Overall, this optimization problem is therefore a convex QP.

From the first-order sufficient conditions of optimality, it follows that any KKT point yields a *global* optimum for that problem (no matter of the constraints being regular or not). The KKT point determined previously in Question 4a, $\mathbf{x}^* := \left(\frac{1}{2} \quad \frac{9}{2}\right)^T$, is therefore the unique global optimum for our problem.

5. In this question, you are to develop and test an implementation of the active-set method for QP optimization, as described on Slide #63 of Lecture 3. Your function will comply with the following:

```

1      function [xopt, fopt] = qp.m( c, Q, Ae, be, Ai, bi )
2
3          % <- TO BE COMPLETED
4
5      end

```

The input arguments of this function are as follows:

- \mathbf{c} , the linear part of the objective function

- Q , the quadratic part of the objective function
- A_e , the coefficient matrix of equality constraints
- b_e , the right-hand-side vector of equality constraints
- A_i , the coefficient matrix of inequality constraints
- b_i , the right-hand-side vector of inequality constraints

On successful completion, `xopt` and `fopt` should contain, respectively, an (approximate) optimum point and the corresponding solution value.

- (a) Develop the m-file `qp.m` in order to implement the implementing to active-set method, in the case of a minimization problem. Make sure to test that the QP is convex inside the function.

Answers. A possible implementation of the active-set QP algorithm is given below. In addition to returning the optimal point and solution value of the QP, we have defined an extra output argument returning the optimal multipliers for the linear equality and inequality constraints here.

```

1  function [xopt, fopt, lopt] = qp( c, Q, Ae, be, Ai, bi )
2
3  % Check positive semi-definiteness
4  if( eigs( Q, 1, 'SA' ) < 0 )
5      error('Objective function is nonconvex');
6  end
7
8  % Initialization
9  n = length( c );
10 me = length( be );
11 mi = length( bi );
12 act = []; % start with no active inequality constraints
13
14 % Main loop - repeat until active set does not change anymore
15 cnt = true;
16 while( cnt )
17     % Check feasibility
18     ma = length( act );
19     if( me+ma > n )
20         error('Infeasible problem');
21     end
22
23     % Solve equality constrained QP with current active set
24     if( me )
25         M = [ [ Q          Ae'  Ai(act,:)'] ]
26              [ Ae          zeros(me,me+ma) ]
27              [ Ai(act,:) zeros(ma,me+ma) ] ];
28         N = [ -c; be; bi(act) ];
29     else
30         M = [ [ Q          Ai(act,:)'] ]
31              [ Ai(act,:) zeros(ma,ma) ] ];
32         N = [ -c; bi(act) ];
33     end
34     y = M \ N;
35     cnt = false;
36

```

```

37     % Remove inequality constraints with negative multipliers
38     for i = 1:ma
39         if( y(n+me+i) < 0. )
40             cnt = true;
41             act = [ act(1:n+me+i-1) act(n+me+i+1:end) ];
42         end
43     end
44
45     % Append violated inequality constraints
46     for j = 1:mi
47         if( Ai(j,:)*y(1:n) > bi(j) )
48             cnt = true;
49             act = [ act j ];
50         end
51     end
52 end
53
54 % Gather results
55 xopt = y(1:n);
56 lopt = struct('eqlin',y(n+1:n+me),'ineqlin',zeros(mi,1));
57 lopt.ineqlin(act) = y(n+me+1:end);
58 fopt = c'*xopt + 0.5*xopt'*Q*xopt;
59
60 end

```

(b) Debug and test your m-file by considering the same problem as in Question 4 above.

Answers. The following results are obtained upon calling the m-file `qp.m` to solve the QP in Question 4:

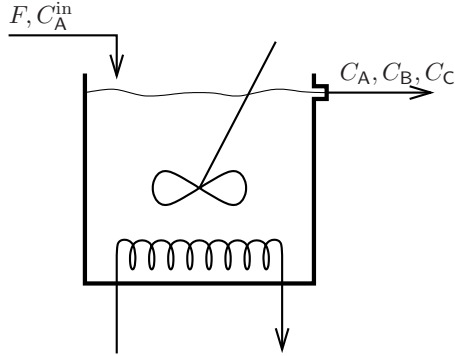
```

Command Line
1  >> [popt, fopt, lopt] = qp( [-8;-16], 2.*eye(2), [], [], [[1 1];[-1 0]], [5;0] )
2
3  popt =
4
5      0.5000
6      4.5000
7
8
9  fopt =
10
11     -55.5000
12
13
14  lopt =
15
16      eqlin: [0x1 double]
17      ineqlin: [2x1 double]
18
19  >> lopt.ineqlin
20
21  ans =
22
23      7
24      0

```

Note that the numerical values match the global optimum determined analytically in Question 4.

6. Consider the isothermal, constant volume CSTR with series reaction $A \xrightarrow{k_1} B \xrightarrow{k_2} C$ shown in the figure below. Our goal is to maximize the concentration of species B, C_B , by adjusting the flow rate F and inlet concentration C_A^{in} simultaneously, while keeping all other variables and parameters constant (see table below). Both manipulated variables F and C_A^{in} should be nonnegative and their maximum allowable levels are F^U and $C_A^{\text{in},U}$, respectively.



Param.	Value
k_1	5.0 min^{-1}
k_2	2.0 min^{-1}
V	1.0 L
C_A^U	0.2 mol L^{-1}
$C_A^{\text{in},U}$	1.0 mol L^{-1}
F^U	20.0 L min^{-1}

Figure 9: CSTR with series reaction and problem data.

- (a) This optimization problem is first modeled as the following constrained NLP:

$$\begin{aligned}
 \max_{F, C_A^{\text{in}}} \quad & C_A^{\text{in}} \frac{F k_1 V}{(F + k_1 V)(F + k_2 V)} \\
 \text{s.t.} \quad & C_A^{\text{in}} \frac{F}{F + k_1 V} \leq C_A^U \\
 & 0 \leq F \leq F^U \\
 & 0 \leq C_A^{\text{in}} \leq C_A^{\text{in},U}
 \end{aligned}$$

- i. Implement this optimization problem in Matlab, then solve it using the `fmincon` function, starting from the initial values $F = 10 \text{ L min}^{-1}$, $C_A^{\text{in}} = 0.5 \text{ mol L}^{-1}$. Check that the solver terminated successfully. Report the optimal point and solution value found by `fmincon`, as well as the optimal active set. Comment.

Indications. Use finite difference approximations for the gradients of the objective and constraint functions for simplicity (see options `GradObj` and `GradCon`); set the termination tolerances on the variables, constraints and KKT conditions value to $1e-7$ (options `TolX`, `TolCtr` and `TolFun`).

Answers. A possible implementation based on `fmincon` is as follows:

```

CSTR.m
1  % Parameters
2  global k1 k2 V CAU
3  k1 = 5.; % kinetic constant (min-1)
4  k2 = 2.; % kinetic constant (min-1)
5  V = 1.; % reactor volume (L)
6  CAU = 0.2; % max. outlet conc. of A (mol L-1)

```

```

7 CAinU = 1.; % max. inlet conc. of A (mol L-1)
8 FU = 20.; % max. inlet flow rate (L min-1)
9
10 % Set options (gradient + tolerances)
11 Options = optimoptions( @fmincon, 'GradObj', 'off', 'GradConstr', 'off', ...
12 'TolFun', 1e-7, 'TolCon', 1e-7, 'TolX', 1e-7, 'display', 'iter', ...
13 'algorithm', 'active-set' );
14
15 % Variables are: x = [ F CAin ]
16 % Initial guess: F = 10 L/min, CAin = 0.5 mol/L
17 x0 = [ 10; 0.5 ];
18
19 % Call fmincon
20 [xopt, fopt, flag, out, lopt] = fmincon( @(x)CSTR_obj(x), x0, [], [], [], [], ...
21 zeros(2,1), [FU; CAinU], @(x)CSTR_ctr(x), Options )

```

CSTR_obj.m

```

1 function f = CSTR_obj( x )
2
3 % Variables are: x = [ F CAin ]
4 global k1 k2 V
5 f = -x(2)*x(1)*k1*V/(x(1)+k1*V)/(x(1)+k2*V);
6
7 end

```

CSTR_ctr.m

```

1 function [ gin, geq ] = CSTR_ctr( x )
2
3 % Variables are: x = [ F CAin ]
4 global k1 V CAU
5 gin = [ x(2)*x(1)/(x(1)+k1*V) - CAU ];
6 geq = [];
7
8 end

```

The following results are obtained on calling the m-file CSTR.m from the command line in Matlab:

```

>> CSTR

```

Iter	F-count	f(x)	Max constraint	Line search steplength	Directional derivative	First-order optimality	Procedure
0	3	-0.138889	0.1333				Infeasible start point
1	6	-0.0834645	6.606e-05	1	0.276	0.199	
2	9	-0.0834776	-9.916e-09	1	-0.00224	0.00696	Hessian modified
3	12	-0.0860956	-9.396e-05	1	-0.00697	0.00741	Hessian modified twice
4	15	-0.08894	-0.0001065	1	-0.00752	0.00823	Hessian modified twice
5	18	-0.0921848	-0.0001351	1	-0.00803	0.00928	Hessian modified twice
6	21	-0.0959395	-0.0001757	1	-0.00865	0.0113	Hessian modified twice
7	24	-0.100359	-0.0002359	1	-0.00939	0.013	Hessian modified twice
8	27	-0.105674	-0.0003296	1	-0.0103	0.0158	Hessian modified twice
9	30	-0.112246	-0.0004853	1	-0.0115	0.019	Hessian modified twice
10	33	-0.120669	-0.0007662	1	-0.0131	0.0238	Hessian modified twice
11	36	-0.132019	-0.001336	1	-0.0152	0.0308	Hessian modified twice
12	39	-0.148411	-0.002706	1	-0.0185	0.0424	Hessian modified twice
13	42	-0.174402	-0.007032	1	-0.0241	0.0634	Hessian modified twice
14	45	-0.214993	-0.02953	1	-0.0354	0.102	Hessian modified twice
15	48	-0.216396	0	1	-0.079	0.0859	Hessian modified twice
16	51	-0.301523	0	1	-0.214	0.0299	
17	54	-0.307637	0	1	-0.11	0.00243	
18	57	-0.307692	0	1	-0.102	2.81e-06	Hessian modified

Local minimum found that satisfies the constraints.

```

26 Optimization completed because the objective function is non-decreasing in
27 feasible directions, to within the selected value of the function tolerance,
28 and constraints are satisfied to within the selected value of the constraint tolerance.
29
30 <stopping criteria details>
31
32 Active inequalities (to within options.TolCon = 1e-07):
33   lower      upper      ineqlin      ineqnonlin
34           2           1
35
36 xopt =
37
38     1.2500
39     1.0000
40
41
42 fopt =
43
44    -0.3077
45
46
47 flag =
48
49     1
50
51
52 out =
53
54     iterations: 19
55     funcCount: 57
56     lssteplength: 1
57     stepsize: 4.6997e-08
58     algorithm: [1x44 char]
59     firstorderopt: 4.8054e-09
60     constrviolation: 0
61     message: [1x787 char]
62
63
64 lopt =
65
66     lower: [2x1 double]
67     upper: [2x1 double]
68     eqlin: [0x1 double]
69     eqnonlin: [0x1 double]
70     ineqlin: [0x1 double]
71     ineqnonlin: 0.7988
72
73 >> lopt.ineqnonlin
74
75 ans =
76
77     0.7988
78
79 >> lopt.upper
80
81 ans =
82
83     0
84     0.1479

```

- The optimal solution point for this problem is: $F^* = 1.250 \text{ L min}^{-1}$, $C_A^{\text{in}*} = 1.000 \text{ mol L}^{-1}$
- The corresponding optimal solution value (cost) is: $C_B^* = 0.308 \text{ mol L}^{-1}$ (remember we are minimizing $-C_B$ here)
- The optimal active set consists of the inequality constraints $C_A^{\text{in}} \frac{F}{F+k_1V} \leq C_A^U$ and $C_A^{\text{in}} \leq C_A^{\text{in},U}$; all other inequality constraints being inactive at the optimum

These results are confirmed by the graphical solution shown in Fig. 10.

- Repeat Question 6(a)i using GAMS instead of MATLAB. Compare the results.

Indications. GAMS allows a user to fix the activity levels (values) of variables through the .1 suffix:

```

VARIABLE x1;
x1.1 = 1.0;

```

assigns the value 1 to the variable x1. In particular, values assigned to the variables prior to the SOLVE statement serve as initial values for the solver – default values of 0 are used otherwise. This is particularly important for NLP problems. For further information, you

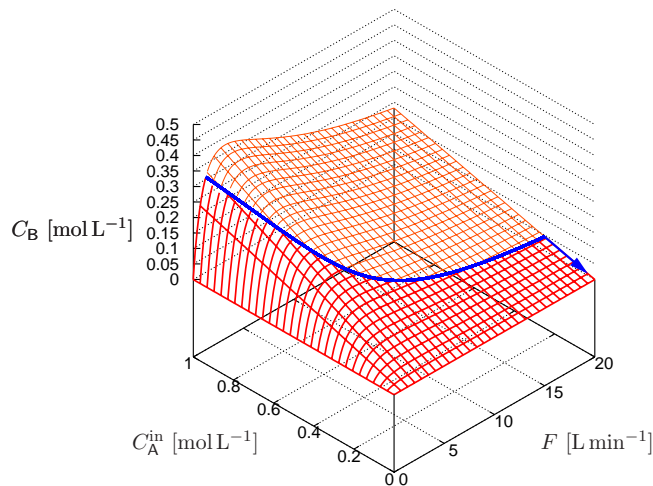


Figure 10: Graphical solution for CSTR with series reaction.

can always refer to the GAMS users guide: <http://www.gams.com/dd/docs/bigdocs/GAMSUsersGuide.pdf>.

Answers. A possible GAMS implementation is as follows:

```

CSTR.gms

1  SCALARS
2    K1      'kinetic constant (min-1)'      / 5.0 /
3    K2      'kinetic constant (min-1)'      / 2.0 /
4    V       'reactor volume (L)'            / 1.0 /
5    CAU     'max. outlet conc. of A (mol L-1)' / 0.2 /
6    CAINU   'max. inlet conc. of A (mol L-1)' / 1.0 /
7    FU      'max. inlet flow rate (L min-1)' / 20.0 /;
8
9  VARIABLES
10   F       'inlet flow rate (L min-1)'
11   CAIN    'inlet conc. of A (mol L-1)'
12   CB      'outlet conc. of B (mol L-1)';
13
14  POSITIVE VARIABLES F, CAIN;
15  F.UP     = FU;
16  CAIN.UP  = CAINU;
17
18  EQUATIONS
19   CBOUT   'objective'
20   CAMAX   'residual concentration constraint';
21
22  CBOUT..  CB =E= CAIN*F*K1*V/((F+K1*V)*(F+K2*V));
23  CAMAX..  CAIN*F/(F+K1*V) =L= CAU;
24
25  MODEL CSTR / CBOUT, CAMAX /;
26
27  F.l      = 10.0;
28  CAIN.l   = 0.5;
29
30  SOLVE CSTR USING NLP MAXIMIZING CB;

```

The following results can be found in the GAMS report:

CSTR.lst				
	LOWER	LEVEL	UPPER	MARGINAL
---- EQU CBOUT	.	.	.	1.000
---- EQU CAMAX	-INF	0.200	0.200	0.799
CBOUT objective				
CAMAX residual concentration constraint				
	LOWER	LEVEL	UPPER	MARGINAL
---- VAR F	.	1.250	20.000	.
---- VAR CAIN	.	1.000	1.000	0.148
---- VAR CB	-INF	0.308	+INF	.
F inlet flow rate (L min-1)				
CAIN inlet conc. of A (mol L-1)				
CB outlet conc. of B (mol L-1)				
**** REPORT SUMMARY :	0	NONOPT		
	0	INFEASIBLE		
	0	UNBOUNDED		
	0	ERRORS		

The optimal point, solution value and active set the same as in Question 6(a)i.

- iii. What is the rate of change in optimal concentration C_B for a variation in the maximum allowable concentration C_A^U ? Using this value (and without any additional calculations in GAMS or MATLAB), estimate the change in C_B incurred by increasing C_A^U to 0.25 mol L⁻¹.

Answers. The rate of change ν^* in optimal concentration C_B^* for a variation in the maximum allowable concentration C_A^U is given by the marginal value (KKT multiplier) of the constraint $C_A^{\text{in}} \frac{F}{F+k_1V} \leq C_A^U$ (equation CAMAX in the above model):

$$\nu^* \triangleq \frac{\partial C_B^*}{\partial C_A^U} = 0.799 \text{ (mol L}^{-1}\text{)}/\text{(mol L}^{-1}\text{)}.$$

Based on this value, an estimate of the change in C_B incurred by increasing C_A^U to 0.25 mol L⁻¹ is obtained as follows:

$$\Delta C_B^* \approx \nu^* \times \Delta C_A^U = 0.799 \times 0.05 = 0.040 \text{ mol L}^{-1}.$$

In other words, an estimate of the cost value for $C_A^U = 0.25 \text{ mol L}^{-1}$ is: $C_B^* \approx 0.348 \text{ mol L}^{-1}$.

- iv. Modify, then resolve, your GAMS or MATLAB model to reflect the previous change in C_A^U . Report the optimal solution value, and compare it to the estimate calculated in the previous question. Discuss your results.

Answers. We make the modification on the GAMS model here. The only required change is in line #5:

```
CAU      'max. outlet conc. of A (mol L-1)' / 0.25 /
```

The following results are obtained on running the modified GAMS model:

CSTR.lst				
	LOWER	LEVEL	UPPER	MARGINAL
---- EQU CBOUT	.	.	.	1.000
---- EQU CAMAX	-INF	0.250	0.250	0.537
CBOUT objective				
CAMAX residual concentration constraint				
	LOWER	LEVEL	UPPER	MARGINAL
---- VAR F	.	1.667	20.000	.
---- VAR CAIN	.	1.000	1.000	0.207
---- VAR CB	-INF	0.341	+INF	.
F inlet flow rate (L min-1)				
CAIN inlet conc. of A (mol L-1)				
CB outlet conc. of B (mol L-1)				
**** REPORT SUMMARY :	0	NONOPT		
	0	INFEASIBLE		
	0	UNBOUNDED		
	0	ERRORS		

The optimal solution value now is: $C_B^* = 0.341 \text{ mol L}^{-1}$. Observe that this value is rather close to the estimate ($C_B^* \approx 0.348 \text{ mol L}^{-1}$) calculated in the previous question. Observe also that the set of active constraints remains unchanged. However, unlike LP, sensitivity analysis in NLP can only provide an *approximation* of the actual change, due to the nonlinearity.

- (b) You notice that the same optimization problem could be modeled by incorporating the mole-balance equations directly as equality constraints, thereby yielding the *equivalent* NLP:

$$\begin{aligned}
 & \max_{F, C_A^{\text{in}}, C_A, C_B} && C_B \\
 & \text{s.t.} && 0 = F(C_A^{\text{in}} - C_A) - k_1 C_A V \\
 & && 0 = -F C_B + (k_1 C_A - k_2 C_B) V \\
 & && C_A \leq C_A^U \\
 & && 0 \leq F \leq F^U \\
 & && 0 \leq C_A^{\text{in}} \leq C_A^{\text{in}, U}
 \end{aligned}$$

- i. Repeat Question 6(a)ii for this reformulated optimization model.

Answers. A possible GAMS implementation is as follows:

CSTR2.gms				
1	SCALARS			
2	K1	'kinetic constant (min-1)'	/ 5.0 /	
3	K2	'kinetic constant (min-1)'	/ 2.0 /	
4	V	'reactor volume (L)'	/ 1.0 /	
5	CAU	'max. outlet conc. of A (mol L-1)'	/ 0.2 /	
6	CAINU	'max. inlet conc. of A (mol L-1)'	/ 1.0 /	

```

7      FU      'max. inlet flow rate (L min-1)'      / 20.0 /;
8
9  VARIABLES
10     F      'inlet flow rate (L min-1)'
11     CAIN   'inlet conc. of A (mol L-1)'
12     CA     'outlet conc. of A (mol L-1)'
13     CB     'outlet conc. of B (mol L-1)';
14
15  POSITIVE VARIABLES F, CAIN;
16  F.UP      = FU;
17  CAIN.UP   = CAINU;
18  CA.UP     = CAU;
19
20  EQUATIONS
21     MBALA   'mole balance for species A'
22     MBALB   'mole balance for species B';
23
24  MBALA..   F*(CAIN-CA) - K1*CA*V      =E= 0;
25  MBALB..   -F*CB + (K1*CA-K2*CB)*V =E= 0;
26
27  MODEL CSTR / MBALA, MBALB /;
28
29  F.l       = 10.0;
30  CAIN.l    = 0.5;
31
32  SOLVE CSTR USING NLP MAXIMIZING CB;

```

The following results can be found in the GAMS report:

CSTR2.lst				
	LOWER	LEVEL	UPPER	MARGINAL
---- EQU MBALA	.	.	.	-0.118
---- EQU MBALB	.	.	.	-0.308
MBALA mole balance for species A MBALB mole balance for species B				
	LOWER	LEVEL	UPPER	MARGINAL
---- VAR F	.	1.250	20.000	.
---- VAR CAIN	.	1.000	1.000	0.148
---- VAR CA	-INF	0.200	0.200	0.799
---- VAR CB	-INF	0.308	+INF	.
F inlet flow rate (L min-1) CAIN inlet conc. of A (mol L-1) CA outlet conc. of A (mol L-1) CB outlet conc. of B (mol L-1)				
**** REPORT SUMMARY :	0	NONOPT		
	0	INFEASIBLE		
	0	UNBOUNDED		
	0	ERRORS		

- As expected, the optimal solution point for the reformulated problem is identical to the one found previously: $F^* = 1.250 \text{ L min}^{-1}$, $C_A^{\text{in}*} = 1.000 \text{ mol L}^{-1}$

- The corresponding optimal solution value (cost) is also identical: $C_{\mathbf{B}}^* = 0.308 \text{ mol L}^{-1}$
 - The optimal active set consists of the bound constraints $C_{\mathbf{A}} \leq C_{\mathbf{A}}^U$ and $C_{\mathbf{A}}^{\text{in}} \leq C_{\mathbf{A}}^{\text{in},U}$ (with the same marginal values as previously), along with the two equality constraints; all other inequality constraints being inactive at the optimum.
-