

Problem 1

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} \quad \text{s.t.} \quad \mathbf{A}\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}$$

$$\mathbf{c}, \mathbf{x} \in \mathbb{R}^n \quad \mathbf{b} \in \mathbb{R}^m$$

KKT conditions: $L(\mathbf{x}, \lambda, \mathbf{s}) = \mathbf{c}^T \mathbf{x} - \lambda^T (\mathbf{A}\mathbf{x} - \mathbf{b}) - \mathbf{s}^T \mathbf{x}$

- $\nabla_{\mathbf{x}} L(\mathbf{x}^*, \lambda^*, \mathbf{s}^*) = \mathbf{c} - \mathbf{A}^T \lambda^* - \mathbf{s}^* = \mathbf{0}$
- $\mathbf{A}\mathbf{x}^* = \mathbf{b} \quad \hookrightarrow \mathbf{A}^T \lambda^* + \mathbf{s}^* = \mathbf{c}$
- $\mathbf{x}^* \geq \mathbf{0}$
- $\mathbf{s}^* \geq \mathbf{0}$
- $\mathbf{s}^{*T} \mathbf{x}^* = 0$

a) The Newton direction may not be defined because $\nabla^2(\mathbf{c}^T \mathbf{x}) = \mathbf{0} \neq 0$, i.e. $\nabla^2(\mathbf{c}^T \mathbf{x})$ is not positive definite.

b) Definition of convex function

$$f(\alpha \mathbf{x} + (1-\alpha) \mathbf{y}) \leq \alpha f(\mathbf{x}) + (1-\alpha) f(\mathbf{y}) \quad \forall \alpha \in [0,1]$$

In LP: $f(\mathbf{x}) = \mathbf{c}^T \mathbf{x}$

• Objective function convex: ✓

$$\begin{aligned} \mathbf{c}^T (\alpha \mathbf{x} + (1-\alpha) \mathbf{y}) &= \mathbf{c}^T (\alpha \mathbf{x}) + \mathbf{c}^T ((1-\alpha) \mathbf{y}) \\ &= \alpha \mathbf{c}^T \mathbf{x} + (1-\alpha) \mathbf{c}^T \mathbf{y} \end{aligned}$$

To have a convex optimization problem, we need

- convex objective function ✓
- linear equality constraints: $Ax = b$ ✓
- concave inequality constraints: ✓
 $x \geq 0 : f(\alpha x + (1-\alpha)y) \geq \alpha f(x) + (1-\alpha)f(y)$
 $(\alpha x + (1-\alpha)y) \geq \alpha x + (1-\alpha)y$

⇒ The linear program is convex.

c) Dual problem: $\max_{\lambda} b^T \lambda$ s.t. $A^T \lambda \leq c$

Make dual to standard form:

$$\min_{\lambda} -b^T \lambda \text{ s.t. } c - A^T \lambda \geq 0$$

$$L(\lambda, x) = -b^T \lambda - x^T (c - A^T \lambda)$$

KKT conditions:

- $\nabla_{\lambda} L(\lambda^*, x^*) = -b + A x^* = 0$
 $\rightarrow A x^* = b$
- $x^* \geq 0 \quad \rightarrow A^T \lambda^* + s^* = c$
- $s^* \triangleq (c - A^T \lambda^*) \Rightarrow s^* \geq 0$
- $s^{*T} x^* = 0$

$$\text{d) } c^T x^* = (A^T \lambda^* + s^*)^T x^* = \lambda^{*\top} \underbrace{A x^*}_{b} + \underbrace{s^{*\top} x^*}_{=0}$$

$$= \lambda^{*\top} b = b^T \lambda^*$$

$$\Rightarrow \underline{\underline{c^T x^* = b^T \lambda^*}}$$

e) Basic feasible point:

- The possible point that can be optimal points.
- In LP, this is the vertices of the feasible region.
- $B \subseteq \{1, \dots, n\}$ with exactly m indices
s.t. if $i \notin B \Rightarrow x_i = 0$ and $B = [A_i]_{i \in B}$
is a $m \times m$ matrix with columns from A .

f) LICQ: All ∇c_i , $i \in A(x^*)$ are linearly independent.

A is full rank \Leftrightarrow all rows of A linearly independent.

This means all constraints are linearly independent, hence ∇c_i are also linearly independent.

Problem 2

a) $R_I : 2A + 1B \leq 8$

A, B : loading product.

$R_{II} : 1A + 3B \leq 15$

$\rightarrow 2A + 1B + x_3 = 8 \quad x_3, x_4 \geq 0$

$1A + 3B + x_4 = 15 \quad \hookrightarrow \text{slack variables}$

$$x = \begin{bmatrix} A \\ B \\ x_3 \\ x_4 \end{bmatrix}; \quad A = \begin{bmatrix} 2 & 1 & 1 & 0 \\ 1 & 3 & 0 & 1 \end{bmatrix} \quad b = \begin{bmatrix} 8 \\ 15 \end{bmatrix}$$

$c^T = [3/2 \ -1]$ if price of $1B = 1$.

$\Rightarrow LP: \min_{\mathbf{x}} c^T \mathbf{x} \text{ s.t. } A\mathbf{x} = b, \mathbf{x} \geq 0$

c) Yes, x^* is at the intersection of both constraints, making them both active.

(b,d) See figure below.

e) The plot only shows A and B , but we see the iterations move along the constraints $A\mathbf{x} = b$ and $\mathbf{x} = 0$. This fits the theory well.

Problem 3

$$\min_x \quad q(x) = \frac{1}{2} x^T G x + x^T c \quad G: n \times n, \text{ sym.}$$

$$\begin{aligned} \text{s.t.} \quad & a_i^T x = b_i \quad i \in E \\ & a_i^T x \geq b_i \quad i \in I \end{aligned} \quad c, x, a_i \in \mathbb{R}^n$$

a) $\mathcal{A}(x^*) = \{i \in I \mid a_i^T x^* = b_i\}$

where x^* is the optimal point.

b) $L(x^*, \lambda^*) = \frac{1}{2} x^{*T} G x^* + x^{*T} c - \sum_{i \in A(x^*)} \lambda_i (a_i^T x^* - b_i)$

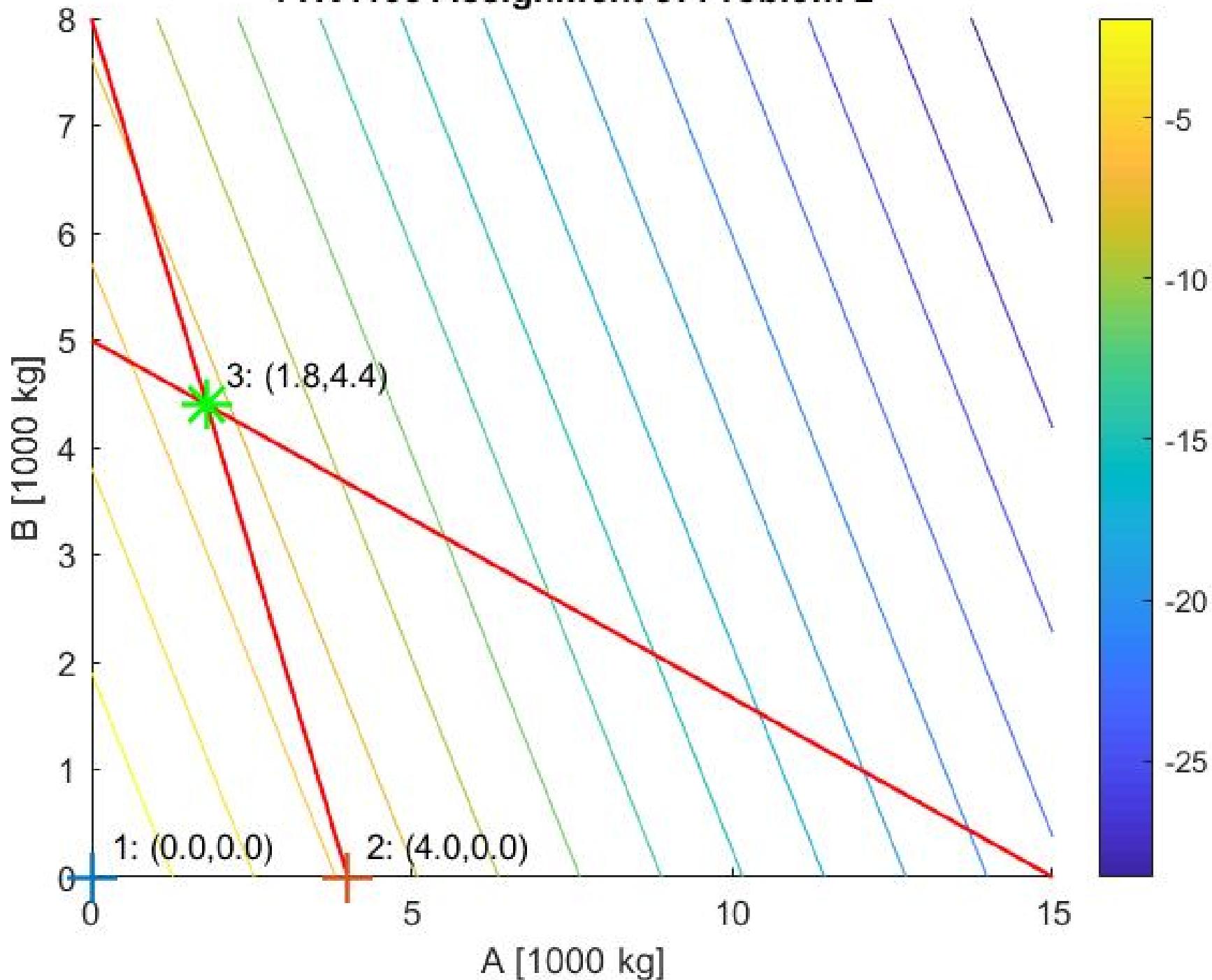
- $\nabla_x L(x^*, \lambda^*) = G x^* + c - \sum_{i \in A(x^*)} a_i \lambda_i = 0$

- $a_i^T x^* = b_i \quad i \in A(x^*)$

- $a_i^T x^* \geq b_i \quad i \in I \setminus A(x^*)$

- $\lambda_i^* \geq 0 \quad i \in I \setminus A(x^*)$

TTK4135 Assignment 3: Problem 2



```

1 %% LP definition
2 % x = [A; B; x3; x4];
3 % x3,x4: slack variables
4 Aeq = [2 1 1 0;
5         1 3 0 1];
6 beq = [8; 15];
7 c = [-3/2; -1; 0; 0];
8
9 f = @(a,b) c'*[a; b; 0; 0];
10
11
12 %% Meshgrid and contour
13 [X,Y] = meshgrid(0:1:15,0:1:8);
14 Z = zeros(size(X));
15 % TODO: Is there an easier way to do this?
16 for i = 1:size(X,1)
17     for j = 1:size(X,2)
18         Z(i,j) = f(X(i,j),Y(i,j));
19     end
20 end
21
22 figure(1);
23 hold on;
24 title('TTK4135 Assignment 3: Problem 2');
25 xlabel('A [1000 kg]');
26 ylabel('B [1000 kg]');
27
28 contour(X,Y,Z,15);
29 colorbar;
30
31
32 %% Constraints
33 % see separate file for function: ploteqconstraints
34 ploteqconstraints(Aeq, beq, 'r', 'LineWidth', 1.2);
35
36
37 %% Simplex method
38 x0 = [0 0 beq]';
39 [xo, fval, iterations] = simplex(c, Aeq, beq, x0, 'report');
40
41
42 %% Plot x* and iterations
43 for i = 1:size(iterations, 2)
44     p = [iterations(1,i), iterations(2,i)];
45     ptxt = sprintf('%d: (%.1f,%.1f)', i, p(1), p(2));
46     xshift = 0.3;
47     yshift = 0.3;
48     text(p(1) + xshift, p(2) + yshift, ptxt);
49
50     if i == size(iterations, 2)
51         plot(p(1), p(2), 'g*', 'MarkerSize', 15, 'LineWidth', 1.5);
52     else
53         plot(p(1), p(2), '+', 'MarkerSize', 15, 'LineWidth', 1.5);
54     end
55 end
56
57

```

```

1 function ploteqconstraints(Aeq, beq, varargin)
2 % Plot equality constraints for a 2D linear optimization problem
3 % in standard form
4 %
5 % min c'*x      subject to: A*x = b, x >= 0
6 %   x
7 %
8 %
9 % ploteqconstraints(Aeq, beq, varargin)
10 %
11 % Aeq: Nx2 matrix
12 % beq: Nx1 vector
13 % varargin: Name,Value used for specs for plotting
14
15 N = size(Aeq,1);
16
17 for i = 1:N
18     temp = num2cell(Aeq(i,:));
19     [ai1, ai2] = temp{:};
20     bi = beq(i);
21
22     p1 = [bi / ai1; 0];
23     p2 = [0; bi / ai2];
24
25     x = linspace(p1(1), p2(1));
26     y = linspace(p1(2), p2(2));
27
28     plot(x, y, varargin{:});
29 end % for
30
31 end % function

```