

The Effects of Transformations on the Optimal Set in Interval Linear Programming

Elif Garajová¹ (with Milan Hladík¹ & Miroslav Rada²)

¹Department of Applied Mathematics, Faculty of Mathematics and Physics,
Charles University

²Faculty of Informatics and Statistics, University of Economics, Prague

Interval Linear Programming

Consider a linear programming problem...

$$\text{minimize } c^T x \text{ subject to } Ax \leq b$$

Interval Linear Programming

approximation and rounding

$$b \approx 3.14159$$

Consider a linear programming problem...

$$\text{minimize } c^T x \text{ subject to } Ax \leq b$$

estimating the future

$$\text{€}25.6 \leq c \leq \text{€}27.1$$

inexact measurements

$$a = 5 \pm 0.05g$$

Interval Linear Programming

approximation and rounding

$$b = [3.141592, 3.141593]$$

Consider an *interval* linear programming problem...

$$\text{minimize } c^T x \text{ subject to } Ax \leq b$$

estimating the future

$$c = [25.6, 27.1]$$

inexact measurements

$$a = [4.95, 5.05]$$

Interval Linear Programming: Definitions

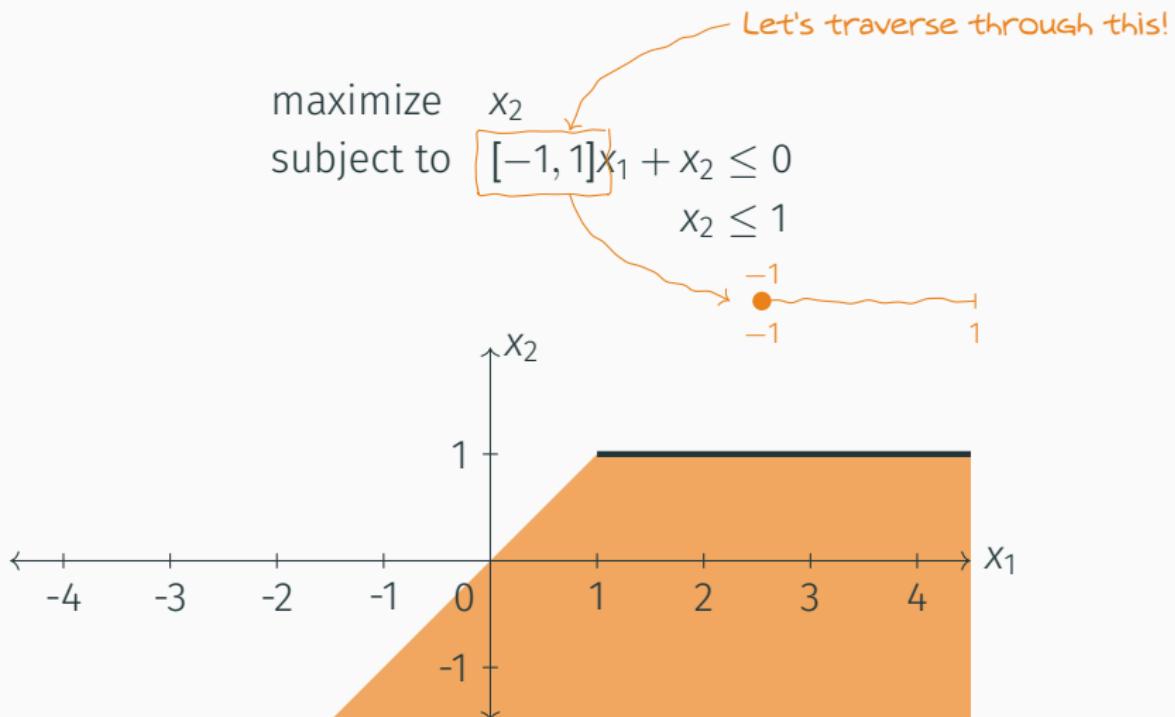
- An **interval linear program** is a family of linear programs
$$\text{minimize } c^T x \text{ subject to } x \in \mathcal{M}(A, b),$$
where $A \in \mathbf{A}, b \in \mathbf{b}, c \in \mathbf{c}$ and $\mathcal{M}(A, b)$ is the feasible set.
- A linear program in the family is called a **scenario**.
- A vector x is a **(weakly) feasible/optimal** solution to the interval program, if x is a feasible/optimal solution for some scenario with $A \in \mathbf{A}, b \in \mathbf{b}, c \in \mathbf{c}$.

Interval Linear Programming: Example

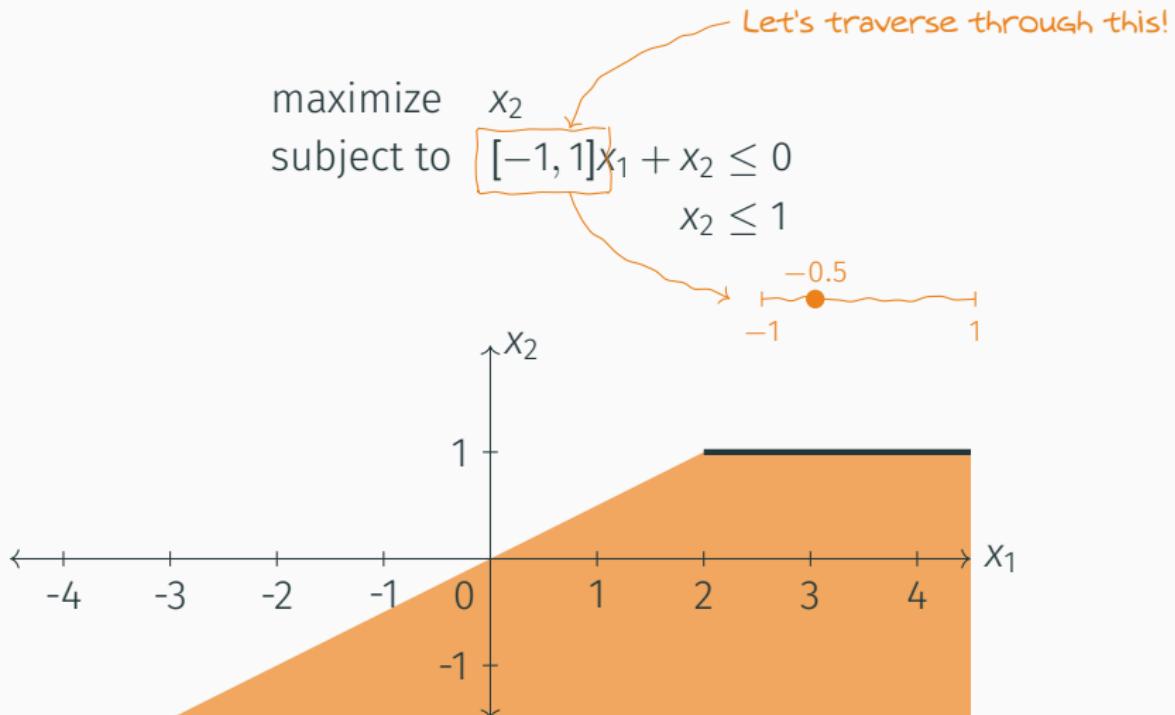
$$\begin{aligned} & \text{maximize} && x_2 \\ & \text{subject to} && [-1, 1]x_1 + x_2 \leq 0 \\ & && x_2 \leq 1 \end{aligned}$$

- What are the possible feasible solutions?
- Which solutions are optimal for some scenario?
- What is the set/range of all optimal values?

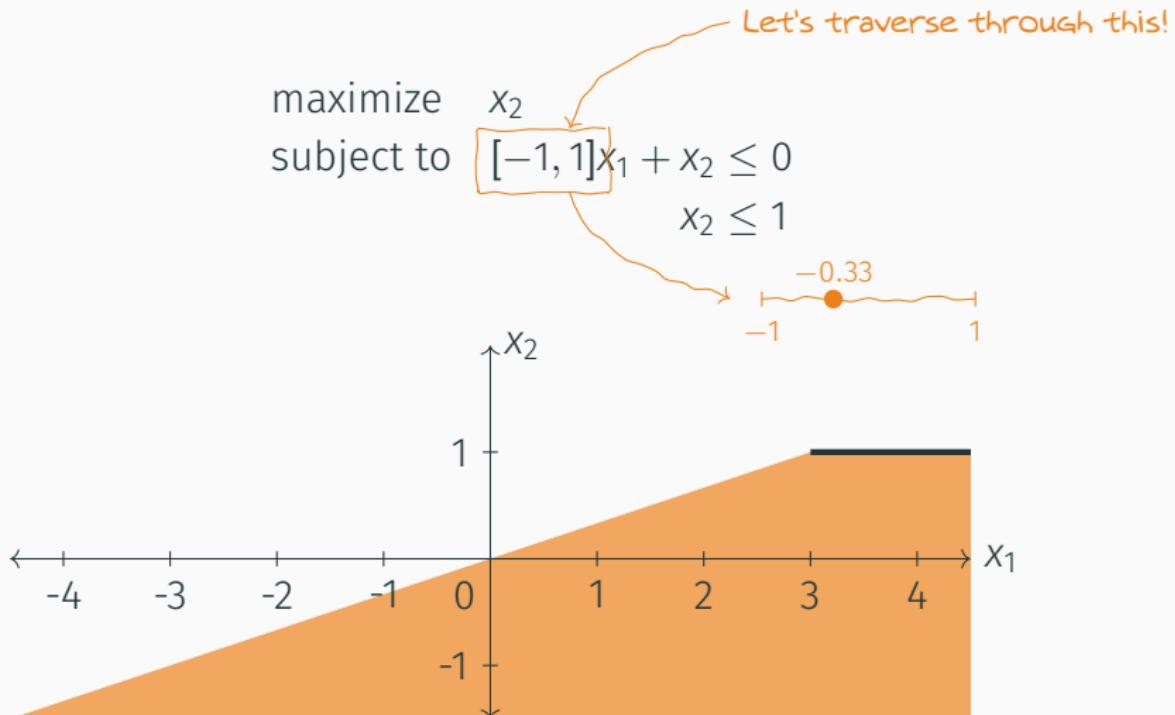
Interval Linear Programming: Example



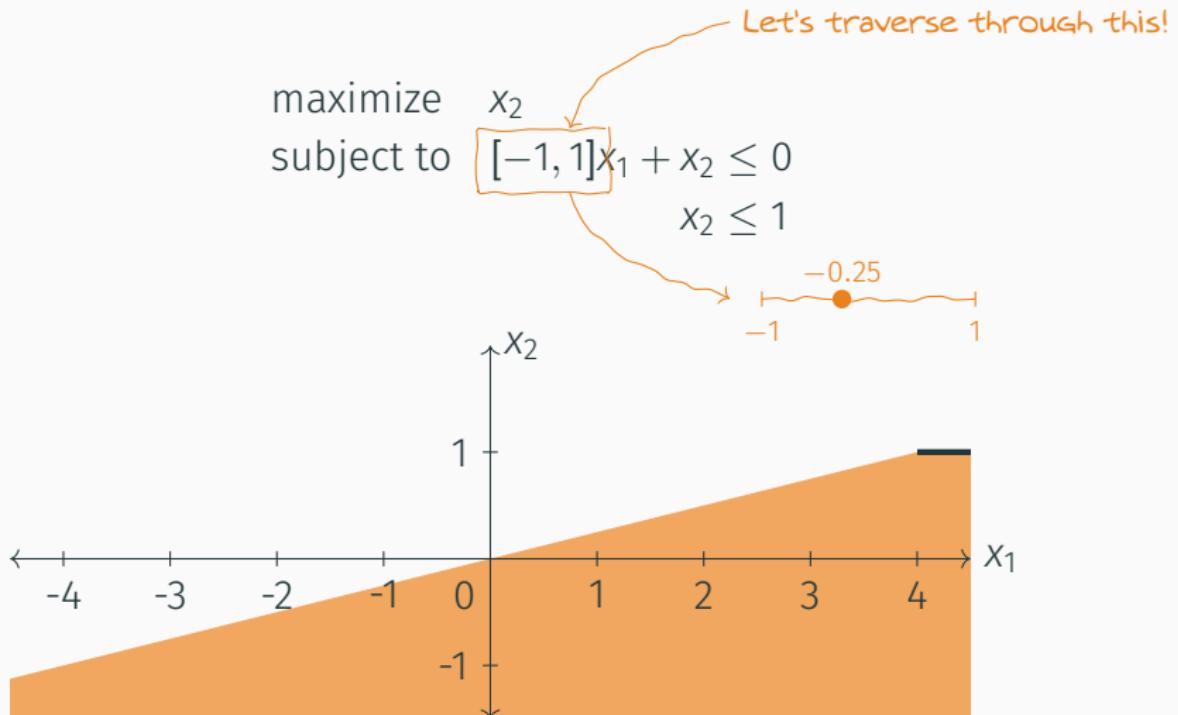
Interval Linear Programming: Example



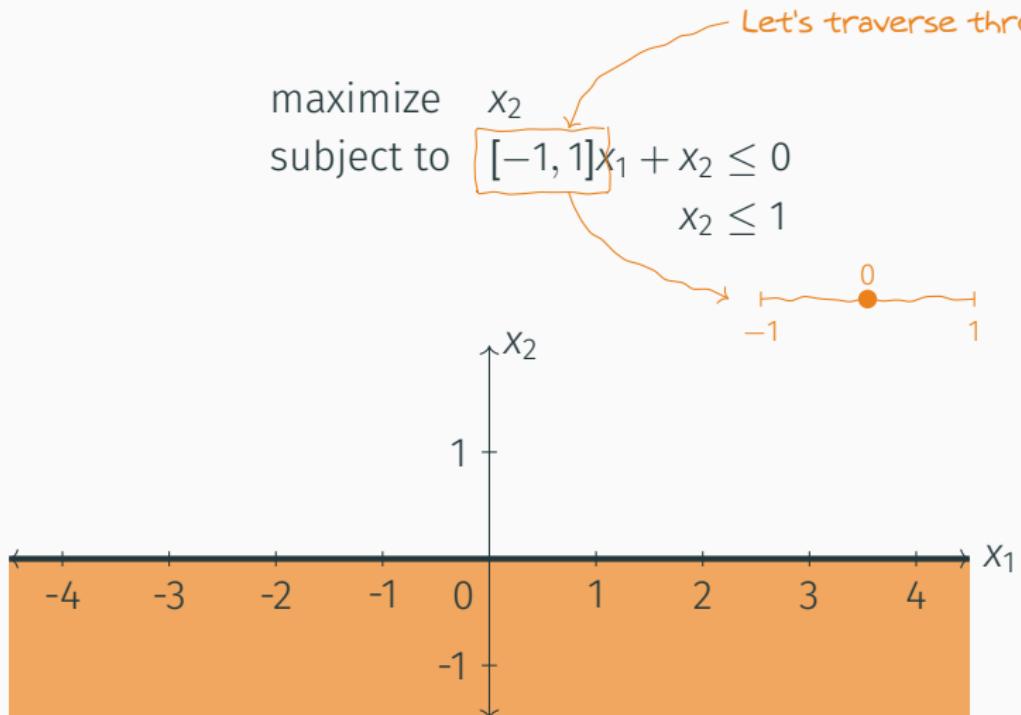
Interval Linear Programming: Example



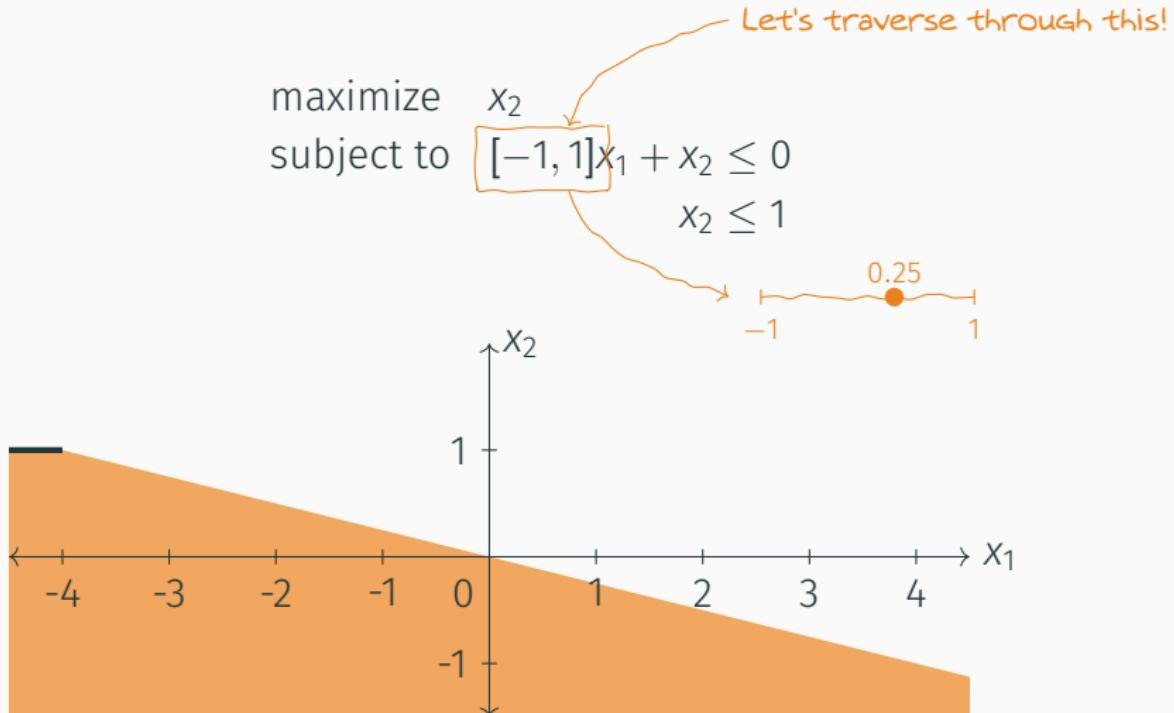
Interval Linear Programming: Example



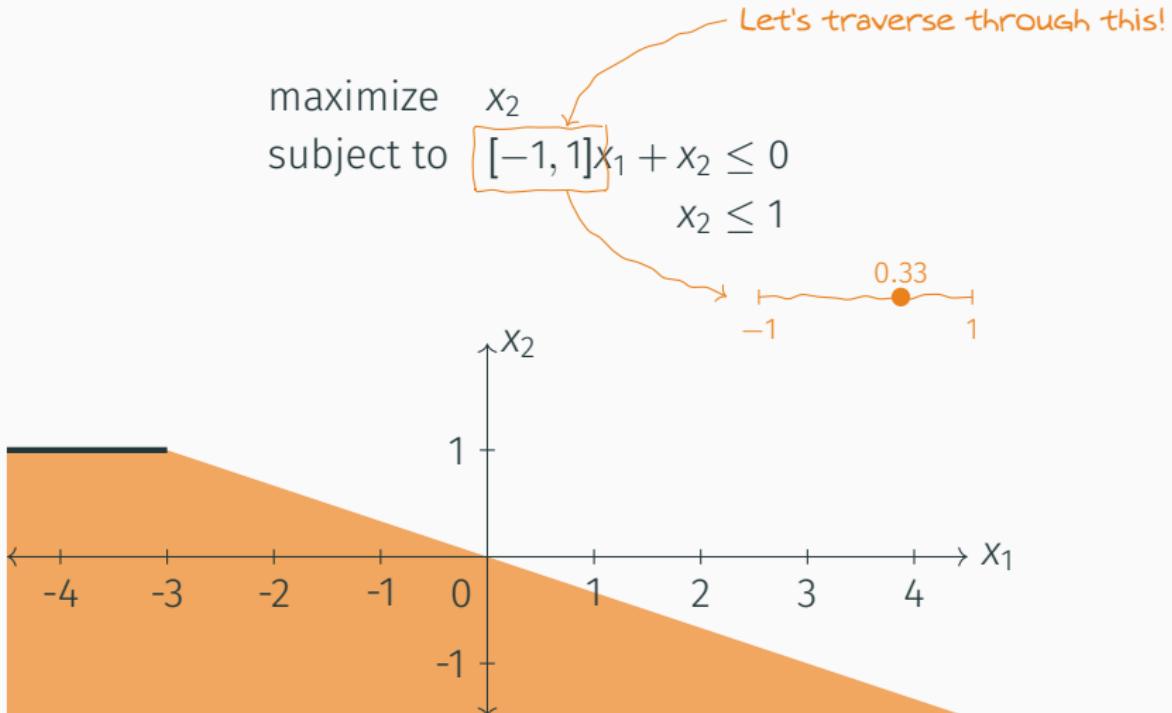
Interval Linear Programming: Example



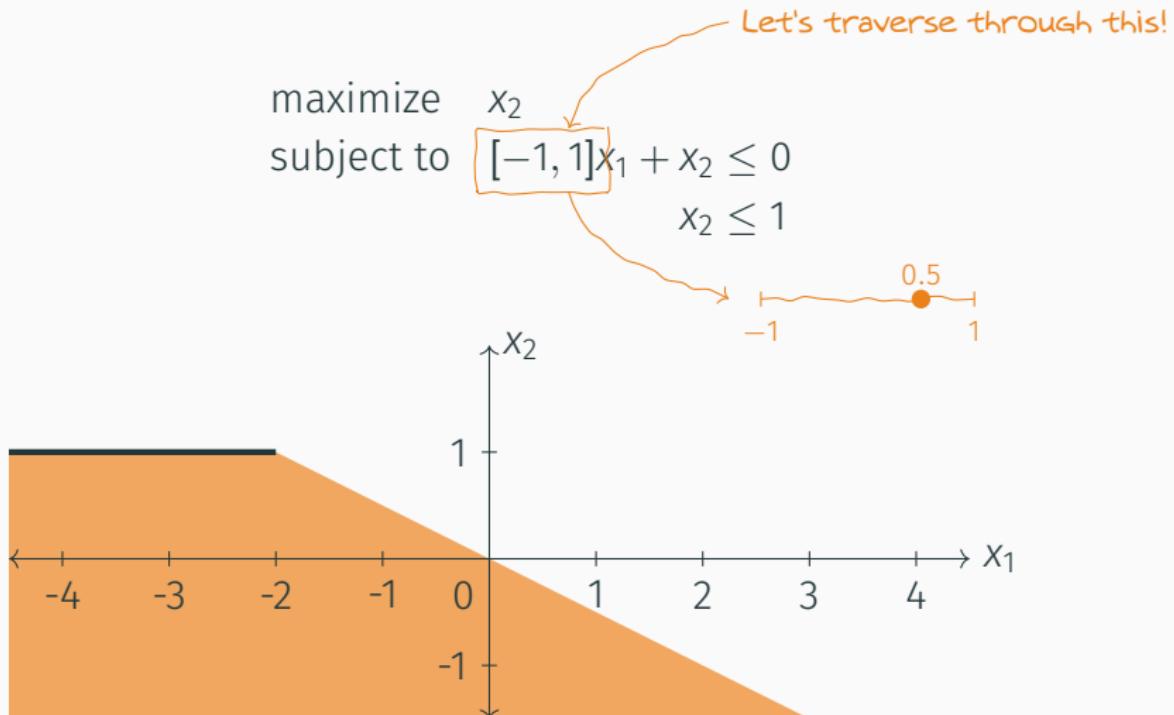
Interval Linear Programming: Example



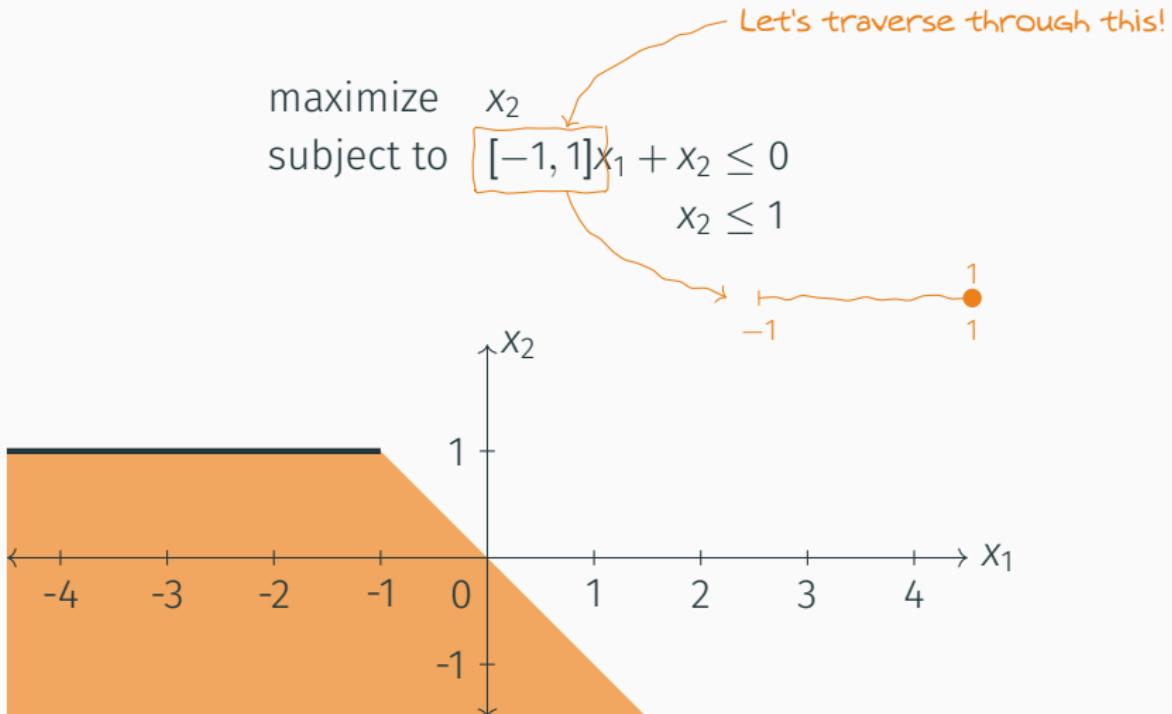
Interval Linear Programming: Example



Interval Linear Programming: Example



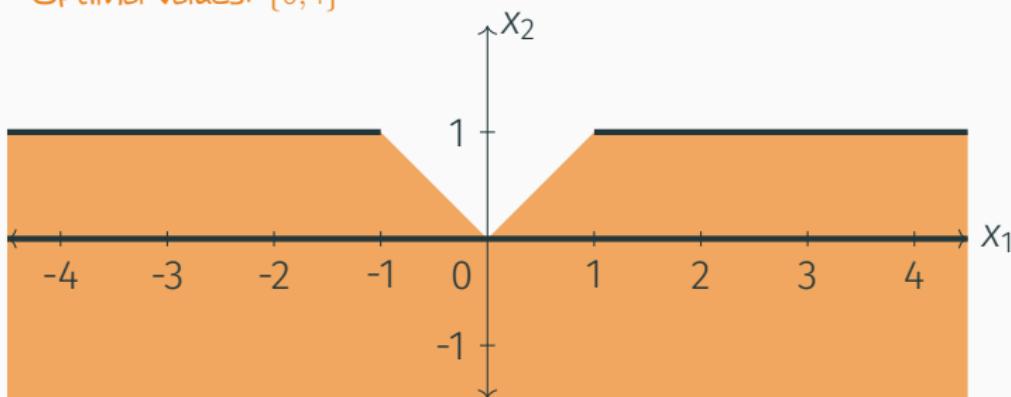
Interval Linear Programming: Example



Interval Linear Programming: Example

$$\begin{aligned} & \text{maximize} && x_2 \\ & \text{subject to} && [-1, 1]x_1 + x_2 \leq 0 \\ & && x_2 \leq 1 \end{aligned}$$

Optimal values: $\{0, 1\}$



Overview of Basic Results

Feasible solutions:

- **Oettli–Prager:** x solves $Ax = b \Leftrightarrow |A_c x - b_c| \leq A_\Delta |x| + b_\Delta$
- **Gerlach:** x solves $Ax \leq b \Leftrightarrow A_c x - A_\Delta |x| \leq \bar{b}$

Optimal values:

- Best optimal value (inequalities):

For each $s \in \{\pm 1\}^n$ solve

$$\min (c_c - D_s c_\Delta)^T x \text{ s. t. } (A_c - A_\Delta D_s)x \leq \bar{b}, D_s x \geq 0$$

- Worst optimal value (inequalities):

$$\max \underline{b}^T y \text{ s. t. } \bar{A}^T y \leq \bar{c}, \underline{A}^T y \geq \underline{c}, y \leq 0$$

Optimal solutions:

- Special cases, approximations, ...

Dependency Problem (I)

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & [0, 1]x_1 - x_2 = 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

Optimal set: $\{(x_1, x_2) \in \mathbb{R}^2 : x_1 \in [1, \infty) \text{ and } x_2 = 1\}$

Dependency Problem (I)

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & [0, 1]x_1 - x_2 = 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & [0, 1]x_1 - x_2 \leq 0, \\ & [0, 1]x_1 - x_2 \geq 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

Optimal set: $\{(x_1, x_2) \in \mathbb{R}^2 : x_1 \in [1, \infty) \text{ and } x_2 = 1\}$

Dependency Problem (I)

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & [0, 1]x_1 - x_2 = 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & 1x_1 - x_2 \leq 0, \\ & 0x_1 - x_2 \geq 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

Optimal set: $\{(x_1, x_2) \in \mathbb{R}^2 : x_1 \in [1, \infty) \text{ and } x_2 = 1\}$

The solution $(0, 0)$ is now optimal, too!

Dependency Problem (I)

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & [0, 1]x_1 - x_2 = 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

$$\begin{aligned} \max \quad & x_1 \\ \text{s. t.} \quad & [0, 1]x_1 - x_2 \leq 0, \\ & [0, 1]x_1 - x_2 \geq 0, \\ & x_2 \leq 1, \\ & x_1, x_2 \geq 0. \end{aligned}$$

Optimal set: $\{(x_1, x_2) \in \mathbb{R}^2 : x_1 \in [1, \infty) \text{ and } x_2 = 1\}$

The solution $(0, 0)$ is now optimal, too!

...But the feasible set is the same! (Li, 2015)

Dependency Problem (II)

Example (Hladík, 2012)

$$[1, 2]x \leq 2 \quad \rightarrow \quad [1, 2]x^+ - [1, 2]x^- \leq 2, x^+, x^- \geq 0$$

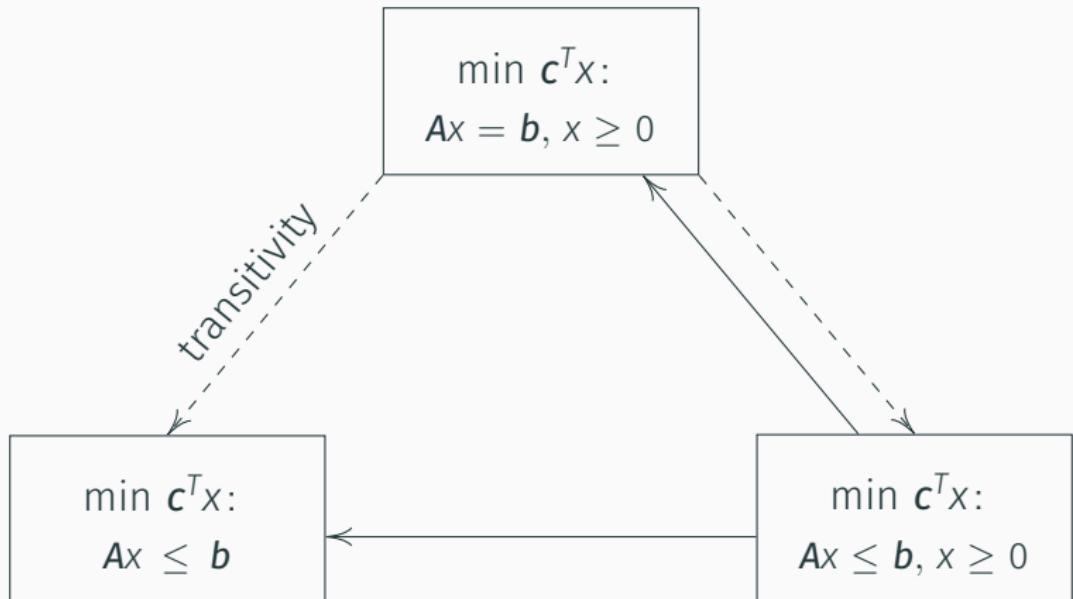
Original feasible set: $(-\infty, 2]$

Consider the new scenario $x^+ - 2x^- \leq 2, x^+, x^- \geq 0\dots$

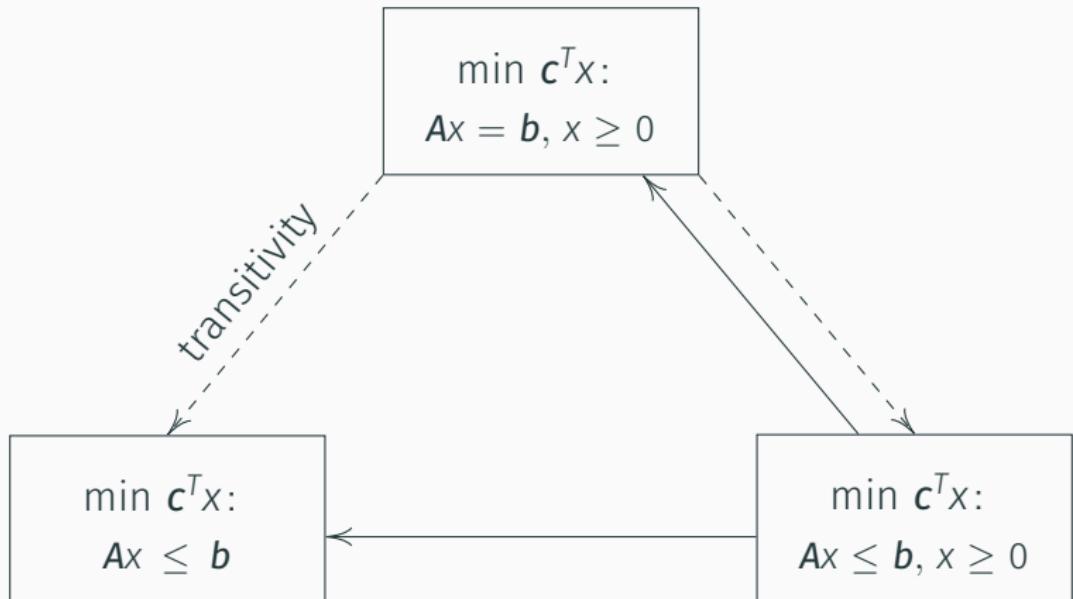
All real numbers are now feasible solutions, because we can express any real x as $x = x^+ - x^-$, where

$$x^+ = \max(2x, 0) \text{ and } x^- = |x|.$$

Transformations: The General Case



Transformations: The General Case



What if A is fixed?

Splitting Equations into Inequalities

Theorem 1

The optimal solution set of the interval linear program

$$\min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}$$

is equal to the optimal solution set of the program

$$\min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} \leq \mathbf{b}_1, -\mathbf{A}\mathbf{x} \leq -\mathbf{b}_2, \mathbf{x} \geq \mathbf{0}$$

with $\mathbf{b}_1 = \mathbf{b}_2 = \mathbf{b}$.

Splitting Equations into Inequalities

Theorem 1

The optimal solution set of the interval linear program

$$\min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} = \mathbf{b}, \mathbf{x} \geq 0$$

is equal to the optimal solution set of the program

$$\min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} \leq \mathbf{b}_1, -\mathbf{A}\mathbf{x} \leq -\mathbf{b}_2, \mathbf{x} \geq 0$$

with $\mathbf{b}_1 = \mathbf{b}_2 = \mathbf{b}$.

Proof idea:

x^* optimal for scenario $\min \mathbf{c}^T \mathbf{x}: \mathbf{b}_2 \leq \mathbf{A}\mathbf{x} \leq \mathbf{b}_1, \mathbf{x} \geq 0$

$\Rightarrow \mathbf{A}\mathbf{x}^* = \mathbf{b}_3 \in \mathbf{b} \quad \Rightarrow x^* \text{ optimal for } \min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} = \mathbf{b}_3, \mathbf{x} \geq 0$

Imposing Non-negativity

Theorem 2

Let \mathcal{S} denote the optimal solution set of $\min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} \leq \mathbf{b}$ and let \mathcal{S}' be the optimal solution set of the program

$$\min \mathbf{c}_1^T \mathbf{x}^+ - \mathbf{c}_2^T \mathbf{x}^- : \mathbf{A}\mathbf{x}^+ - \mathbf{A}\mathbf{x}^- \leq \mathbf{b}, \mathbf{x}^+, \mathbf{x}^- \geq 0$$

with $\mathbf{c}_1 = \mathbf{c}_2 = \mathbf{c}$. Then, the following properties hold:

- If $\mathbf{x} \in \mathcal{S}$, then there is $(\mathbf{x}^+, \mathbf{x}^-) \in \mathcal{S}'$ with $\mathbf{x} = \mathbf{x}^+ - \mathbf{x}^-$.
- If $(\mathbf{x}^+, \mathbf{x}^-) \in \mathcal{S}'$, then $\mathbf{x}^+ - \mathbf{x}^- \in \mathcal{S}$.

Imposing Non-negativity

Theorem 2

Let \mathcal{S} denote the optimal solution set of $\min \mathbf{c}^T \mathbf{x}: \mathbf{A}\mathbf{x} \leq \mathbf{b}$ and let \mathcal{S}' be the optimal solution set of the program

$$\min \mathbf{c}_1^T \mathbf{x}^+ - \mathbf{c}_2^T \mathbf{x}^- : \mathbf{A}\mathbf{x}^+ - \mathbf{A}\mathbf{x}^- \leq \mathbf{b}, \mathbf{x}^+, \mathbf{x}^- \geq 0$$

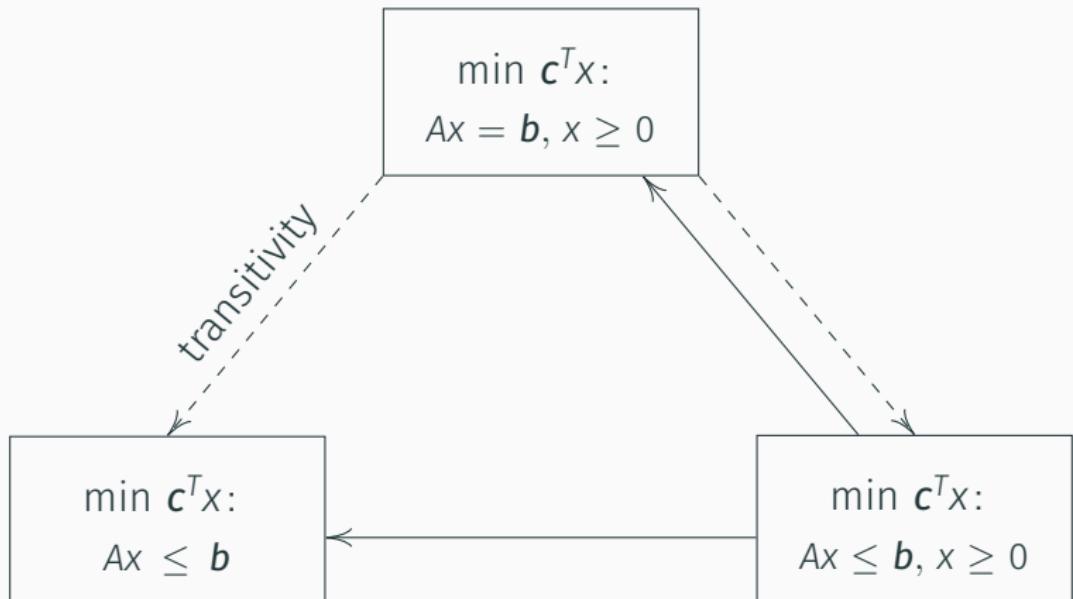
with $\mathbf{c}_1 = \mathbf{c}_2 = \mathbf{c}$. Then, the following properties hold:

- If $\mathbf{x} \in \mathcal{S}$, then there is $(\mathbf{x}^+, \mathbf{x}^-) \in \mathcal{S}'$ with $\mathbf{x} = \mathbf{x}^+ - \mathbf{x}^-$.
- If $(\mathbf{x}^+, \mathbf{x}^-) \in \mathcal{S}'$, then $\mathbf{x}^+ - \mathbf{x}^- \in \mathcal{S}$.

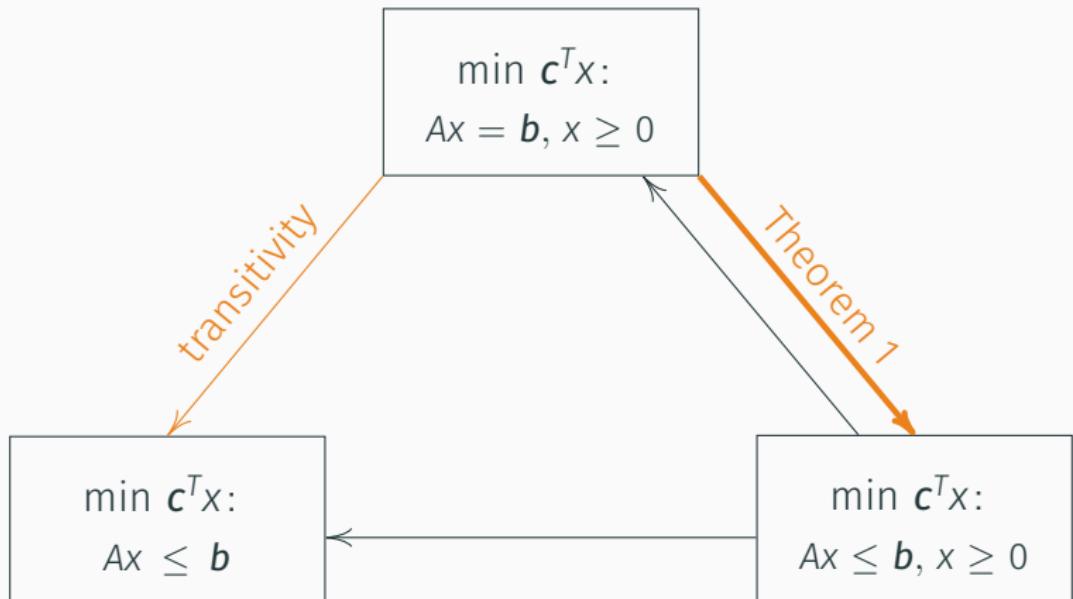
Proof idea:

For an optimal \mathbf{x}^* , we have by dual feasibility some \mathbf{y}^* with $\mathbf{A}^T \mathbf{y}^* = \mathbf{c}_3 \in [\mathbf{c}_2, \mathbf{c}_1] \subseteq \mathbf{c}$. Then, \mathbf{x}^* is optimal for $\min \mathbf{c}_3^T \mathbf{x}: \mathbf{A}\mathbf{x} \leq \mathbf{b}$.

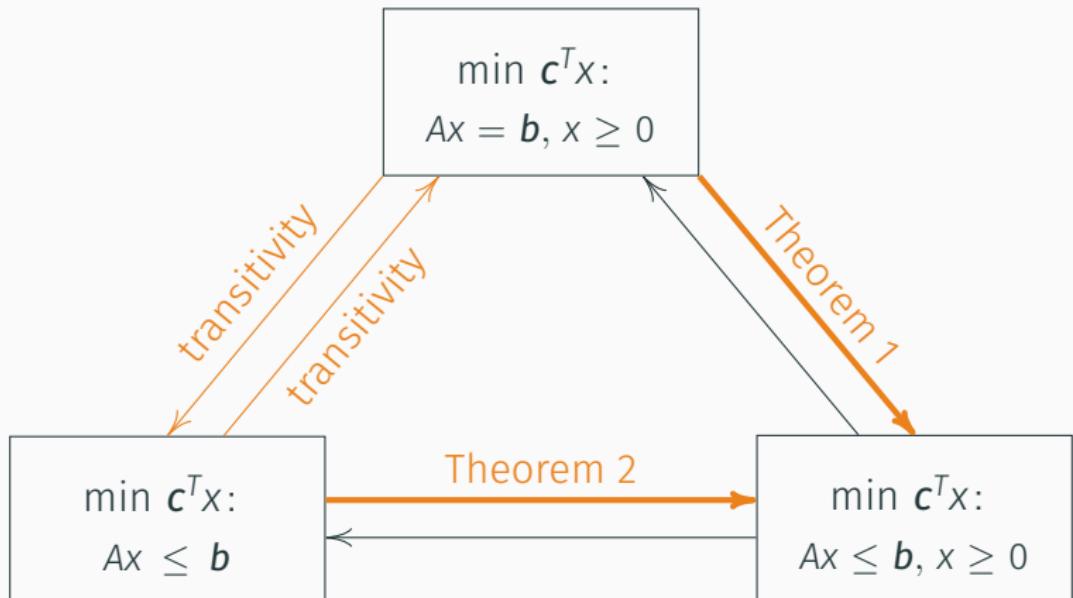
Transformations: The Special Case



Transformations: The Special Case



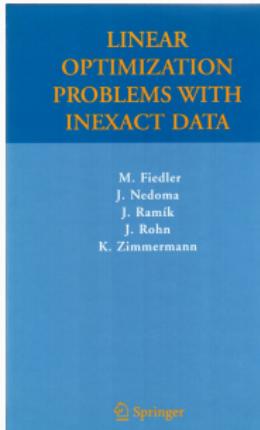
Transformations: The Special Case



Conclusion

- In interval linear programming, the basic transformations may change the feasible/optimal set and other properties of a program.
- We have shown that the transformations do not affect the optimal set for problems with a fixed coefficient matrix (they may still change other properties!).
- Thus, we can directly generalize results concerning the optimal set of a particular type of programs to other types.

References



Linear Optimization Problems with Inexact Data
(2006). Authors: M. Fiedler, J. Nedoma, J. Ramík,
J. Rohn, K. Zimmermann

Interval linear programming: A survey (2012).
M. Hladík. Linear Programming – New Frontiers
in Theory and Applications.

INTERVAL LINEAR PROGRAMMING: A SURVEY

Milan Mihalič¹
Charles University, Faculty of Mathematics and Physics
Department of Applied Mathematics,
Malostranské nám. 25, 118 00 Prague, Czech Republic

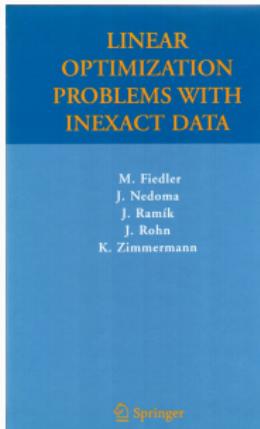
Acknowledgment
Uncertainty is a common phenomenon in practice, but its measurement often we can hardly expect precise values in real-life programming problems. Using estimated quantities may lead to inaccuracy results, nonconvergence issue. In value uncertainty analysis, we can use the interval numbers, e.g. by using the interval arithmetic, interval analysis or fuzzy theory. Each of such methods has its own advantages. In this paper we compare these three approaches and their results on some quantities, and the quantities are partly independently and partly interrelated within these quantities. In the model we discuss the problems of optimum value range, how stability, optimal solutions, preferences, display the problem. Complexity issues are discussed, we come up with some conclusions.

Keywords: Interval linear programming.

1. Introduction

Many practical problems are solved by linear programming. Since real-life problems are subject to uncertainties due to errors, measurements and estimations, we have to reflect this in our model.

References



Linear Optimization Problems with Inexact Data
(2006). Authors: M. Fiedler, J. Nedoma, J. Ramík,
J. Rohn, K. Zimmermann

Interval linear programming: A survey (2012).
M. Hladík. Linear Programming – New Frontiers
in Theory and Applications.

Chapter 2

INTERVAL LINEAR PROGRAMMING: A SURVEY

Milan Hladík
Charles University, Faculty of Mathematics and Physics,
Department of Applied Mathematics,
Malostranská nám. 25, 119 00, Prague, Czech Republic

Abstract
Interval linear programming is a mathematical problem, but its applications often lie in real-life expert practice where a lot of uncertainty occurs. Interval linear programming problems usually have to deal with intervalary models, which means that some data are given in intervals. Interval linear programming is a generalization of standard linear programming, interval analysis or fuzzy methods, each of them has its own pros and cons. In this paper we present the basic concepts and algorithms of interval linear programming. We also discuss the model as a decision support system, interval linear programming is able to handle uncertainty in the input data and to provide the decision maker with a set of solutions, two convex hulls, which are called the inner and outer hulls. These two sets represent the available feasible regions.

In interval analysis, we consider variations of one parameter, which is very useful for sensitivity analysis, but it is not enough for solving interval linear programming problems, since we need to simultaneously all required parameters. We present a brief description of the latest results and the insights, and finally, we give a short bibliography.

Keywords: Linear interval systems, linear programming, interval analysis, optimal value range, interval matrix, linear stability. AMS Subject Classification: 90C15, 90C70, 65G40.

1. Introduction

Many practical problems are solved by linear programming. Since model problems are subject to uncertainties due to errors, measurements and estimation, we have to reflect these

Thank you for your attention!