Single and Multi-Objective Bilevel Optimization - An Illustrated Travel Guide

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AGENDA

- I Single-objective bilevel optimization main concepts
- II Multi-objective bilevel optimization
- III Bilevel optimization an application in the energy sector

Part I Single-Objective Bilevel Optimization

BILEVEL OPTIMIZATION - STACKELBERG GAMES

- Hierarchical structure: a second optimization problem is embedded in the constraints of the bilevel programming problem
- Roots from game theory: Stackelberg game
 - Stackelberg (1934, engl. transl 1952) used by the first time a hierarchical model to describe real market situations.
 - Two players: the leader and the follower
 - Sequential decision process: the leader moves first and the follower moves next: The leader makes a decision and commits a strategy before the other player (follower)
 - Full information is available and the game is non-cooperative

BILEVEL PROGRAMMING PROBLEM

 $\max_{x} F(x, y)$ s.t. $G(x, y) \le 0$ $\max_{y} f(x, y)$ s.t. $g(x, y) \le 0$ (BLP)

- x variables controlled by the **leader** (upper level)
- y variables controlled by the **follower** (lower level)
- A **bilevel** program is a "mathematical program that contains an optimization problem in the constraints" (Bracken, 1973)
- Two decision makers: the **leader** and the **follower**, who pursue different objectives in a non-cooperative manner.
- The **leader makes his decision first**. The follower **reacts** by choosing his optimal candidate on the feasible choices restricted by the leader.

EXAMPLE OF APPLICATION

- For example, in a **toll-setting problem**:
 - the owners of a highway system (leader) have to set tolls and they want to maximize revenues
 - but users of highways (follower) want to minimize their travel costs

The leader's decision must take into account that few users will use the highways if tolls are set too high, which may result in small revenues for the leader.



DEFINITIONS

BLP:

$$\max_{x} F(x, y)$$

s.t. $G(x, y) \le 0$
$$\max_{y} f(x, y)$$

s.t. $g(x, y) \le 0$

where $x \in \mathbb{R}^{n1}$ and $y \in \mathbb{R}^{n2}$

• Constraint Region of the BLP

 $S = \{(x, y): G(x, y) \le 0, g(x, y) \le 0\}$

(It is assumed that S is non-empty and compact)

• Follower's **rational reaction set** to a given *x*

$$\Psi(x) = \arg \max_{y} \{ f(x, y) : g(x, y) \le 0 \}$$

It is assumed that $\Psi(x) \neq \emptyset$ for all x taken by the leader

DEFINITIONS

$$\max_{x} F(x, y)$$

s.t. $G(x, y) \le 0$
$$\max_{y} f(x, y)$$

s.t. $g(x, y) \le 0$

where $x \in \mathbb{R}^{n1}$ and $y \in \mathbb{R}^{n2}$

• Inducible region $IR = \{(x, y): (x, y) \in S, y \in \Psi(x)\}$

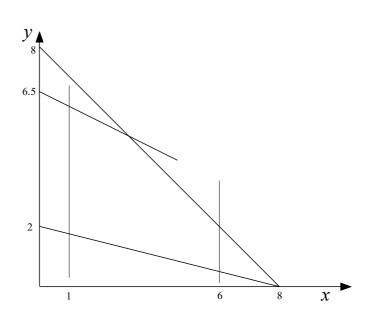
• $(x, y) \in IR$

The BLP can be written as:

 $\max_{x} F(x, y)$
subject to $(x, y) \in IR$

EXAMPLE 1

 $\max_{x} F(x, y) = -x - 3y$ s.t. $1 \le x \le 6$ $\max_{y} f(y) = y$ s.t. $x + y \le 8$ $x + 4y \ge 8$ $x + 2y \le 13$

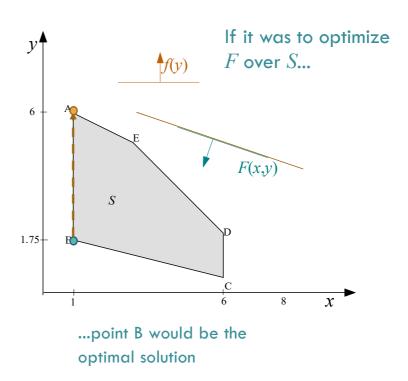


(In: Dempe, 2002)

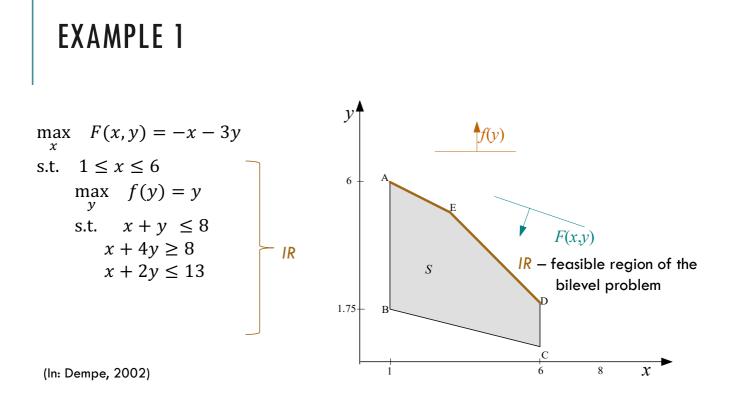
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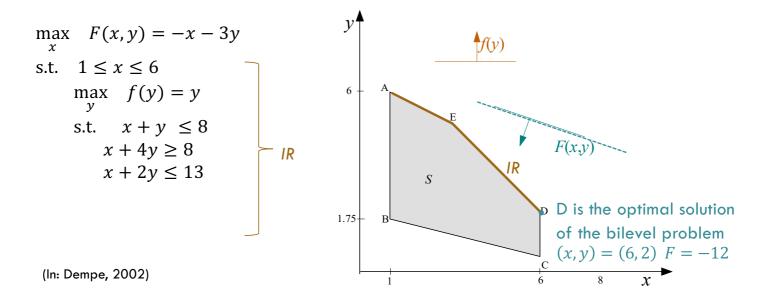
(In: Dempe, 2002)



But, the follower optimizes f(y) for each x chosen by the leader



EXAMPLE 1

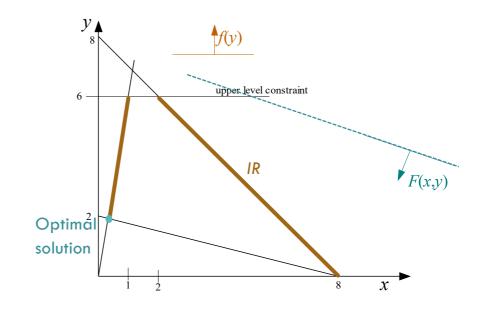


EXAMPLE 2 *Y* **▲** f(y) $\max_{x} F(x, y) = -x - 3y$ 8 x s.t. $0 \le x \le 8$ point chosen by the follower for x=1.5 6 $y \le 6$ However, it does not satisfy $y \leq 6$ $\max_{y} f(y) = y$ s.t. $x + y \leq 8$ F(x,y) $x + 4y \ge 8$ $-6x + y \le 0$ 2 1.5 x 8

(Adap. from Dempe, 2002)

EXAMPLE 2

 $\max_{x} F(x, y) = -x - 3y$ s.t. $0 \le x \le 8$ $y \le 6$ $\max_{y} f(y) = y$ s.t. $x + y \le 8$ $x + 4y \ge 8$ $-6x + y \le 0$



(Adap. from Dempe, 2002)

Problem with disconnected feasible set

PROPERTIES OF THE LINEAR BLP

- The linear BLP is NP-hard
- \circ The **inducible region** IR is composed by the union of faces of S
 - **connected** faces if upper-level constraints do not depend on the lower-level optimal solutions $\max F(x, y) = c_1 x + d_1 y$

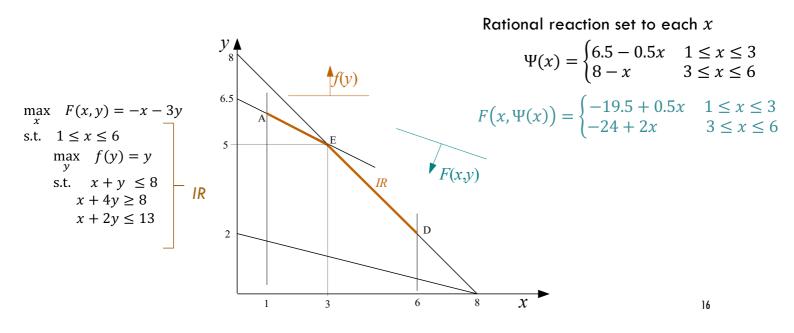
$$\max_{x} F(x, y) = c_1 x + d_1 y$$

s.t.
$$A_1 x + y \leq b_1$$
$$x \geq 0$$
$$\max_{y} f(x, y) = c_2 x + d_2 y$$
s.t.
$$A_2 x + B_2 y \leq b_2$$
$$y \geq 0$$

 \circ The solution occurs at a **vertex** of *IR*

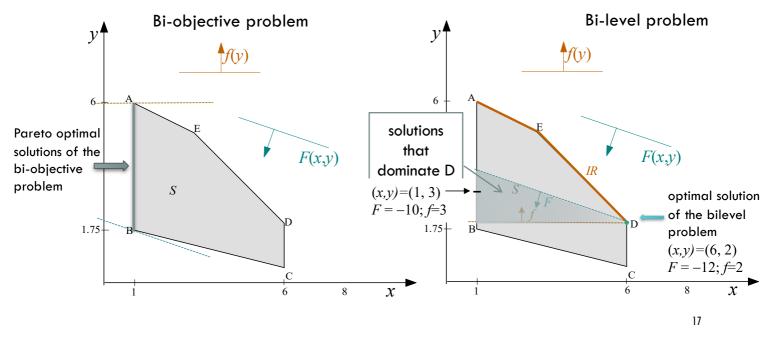
PROPERTIES OF THE (LINEAR) BLP

Bilevel problems are **nonconvex** and **nondifferentiable** optimization problems



BILEVEL VS. BI-OBJECTIVE

 In general, the optimal solution of the bilevel problem is not a Pareto optimal solution of the bi-objective problem.



METHODS FOR THE LINEAR BLP

Main algorithmic approaches:

- 1. Vertex enumeration
- 2. Reformulate the L-BLP as a single-level problem using the Karush-Kuhn-Tucker (KKT) conditions
- 3. Descent algorithms and penalty approaches

2. KKT-BASED APPROACHES

L-BLP:

$$\max_{x} F(x, y) = c_1 x + d_1 y$$

s.t.
$$A_1 x + B_1 y \le b_1$$
$$x \ge 0$$
$$\max_{y} f(y) = d_2 y$$
s.t.
$$A_2 x + B_2 y \le b_2$$
$$y \ge 0$$

Mathematical program with complementarity constraints:

$$\max_{x,y} F(x,y) = c_1 x + d_1 y$$

s.t. $A_1 x + B_1 y \le b_1$
 $A_2 x + B_2 y \le b_2$
 $\lambda B_2 \ge d_2$
 $\lambda (b_2 - A_2 x - B_2 y) = 0$
 $y (\lambda B_2 - d_2) = 0$
 $x \ge 0, y \ge 0, \lambda \ge 0$

Where $\lambda\!\in\!\Re^{m2}$ are the dual variables of the lower level problem

2. KKT-BASED APPROACHES

Mathematical program with complementarity constraints:

$$\max_{x,y} F(x,y) = c_1 x + d_1 y$$

s.t.
$$A_1 x + B_1 y \le b_1$$
$$A_2 x + B_2 y \le b_2$$
$$\lambda B_2 \ge d_2$$
$$\lambda (b_2 - A_2 x - B_2 y) = 0$$
$$y (\lambda B_2 - d_2) = 0$$
$$x \ge 0, y \ge 0, \lambda \ge 0$$

 Use a branch and bound strategy to deal with the complementarity constraints

 Transform the program into a mixed-integer linear programming (MILP) problem and solve it using a general MILP solver (e.g., cplex)

If it cannot be ensured the uniqueness of optimal solutions for the lower-level problem, the formulation of the BLP is **ambiguous**:

$$\max_{x} F(x, y)$$

s.t. $G(x, y) \le 0$
$$\max_{y} f(x, y)$$

s.t. $g(x, y) \le 0$

0

That is: the follower's rational reaction set

 $\Psi(x) = \arg\max_{y} \{f(y): g(x, y) \le 0\}$

is not single valued for every x

If it cannot be ensured the uniqueness of optimal solutions for the lower-level problem, the formulation of the BLP is **ambiguous**:

$$\max_{x} F(x, y)$$

s.t. $G(x, y) \le 0$
$$\max_{y} f(x, y)$$

s.t. $g(x, y) \le 0$

Two main approaches have been suggested:

> Optimistic approach

Pessimistic approach

which consider the optimistic and the pessimistic reformulations, respectively

- Optimistic formulation: the follower chooses, among his alternative optima, the solution that is the **best** for the leader:
- $\mathsf{BLP}_{o}: \max_{x,G(x,y)\leq 0} \varphi_{o}(x) := \max_{y} \{F(x,y) : y \in \Psi(x)\}$
- Pessimistic formulation: the follower chooses, among his alternative optima, the solution that is the worst for the leader:

$$\mathsf{BLP}_{\mathsf{p}}: \qquad \max_{x, G(x, y) \le 0} \varphi_p(x) := \min_{y} \{F(x, y) : y \in \Psi(x)\}$$

 The optimistic formulation is much simpler to handle and has been mostly investigated, mainly for its simplified version:

$$\max_{\substack{x,y \\ s.t.}} F(x,y)$$

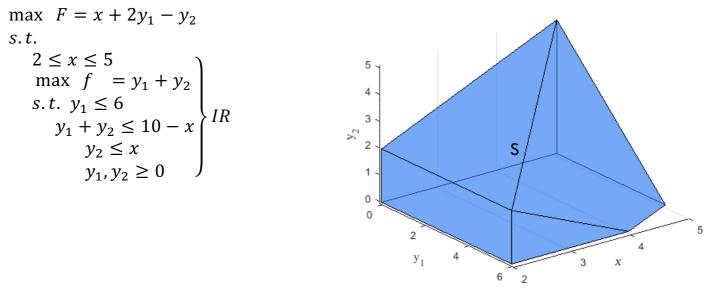
S.t. $G(x,y) \le 0$
$$\max_{y} f(x,y)$$

S.t. $g(x,y) \le 0$

upper-level optimization is taken with respect to x and y



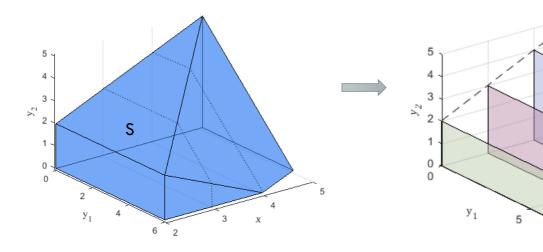
KKT conditions ightarrow only valid in the optimistic case



S≡ constraint region

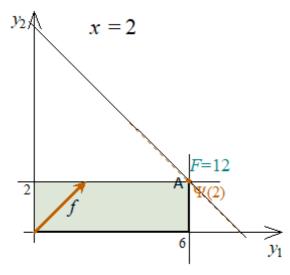
x is the upper level variable and y_1 , y_2 are the lower level variables

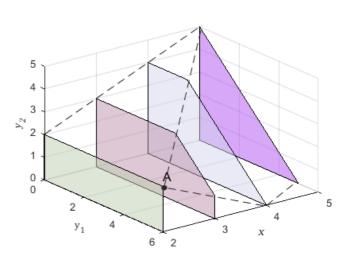
Let us analyze the behavior of F and f for some discrete values of x:



Х

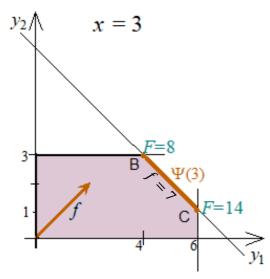
 $\max F = x + 2y_1 - y_2$ $\max f = y_1 + y_2$

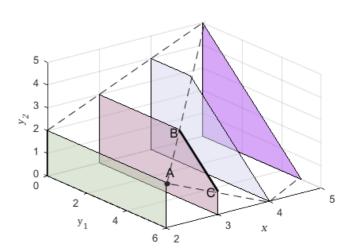




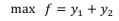
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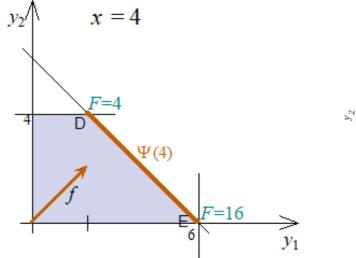
 $\max f = y_1 + y_2$

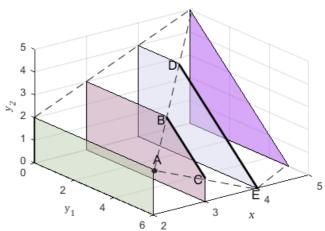




 $\max F = x + 2y_1 - y_2$

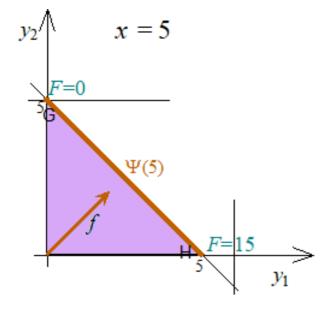


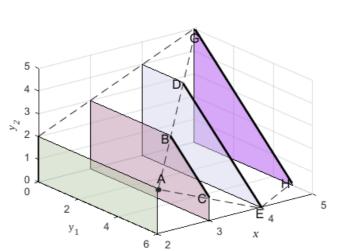


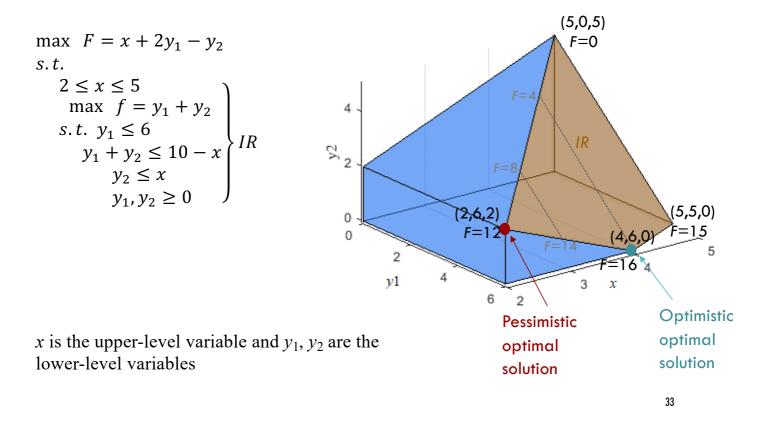


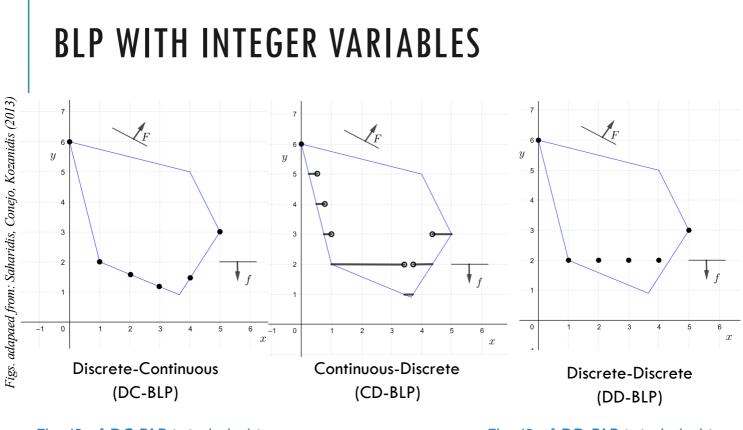
 $\max F = x + 2y_1 - y_2$

 $\max f = y_1 + y_2$





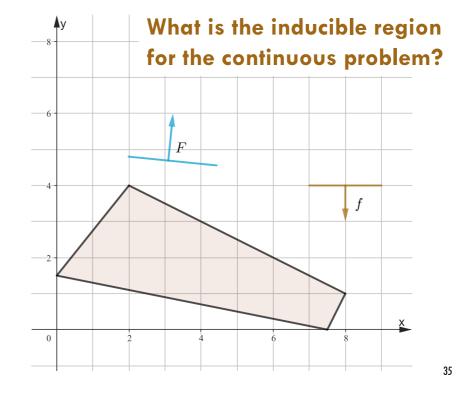






The *IR* of **DD-BLP** is included in the *IR* of **CD-BLP**

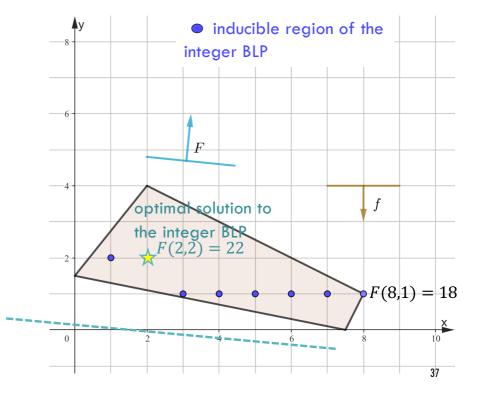
In: Bard and Moore (1990)



Maximize F(x, y) = x + 10ywhere y solves $\max_{y} f(x, y) = -y$ subject to $-25x + 20y \le 30$ $x + 2y \le 10$ $2x - y \le 15$ $2x + 10y \ge 15$ $x, y \ge 0$..., y integer.

In: Bard and Moore (1990)

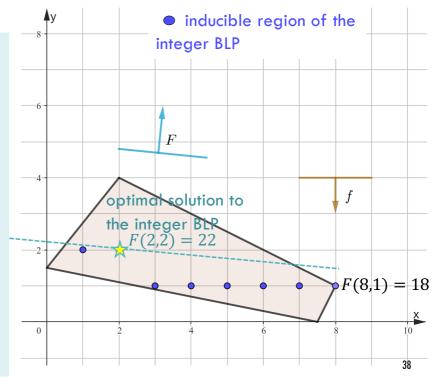
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In: Bard and Moore (1990)

It may happen:

- the optimal solution to the relaxed BLP (continuous BLP) is integer and it is not the optimal solution to the integer BLP
- the optimal F to the relaxed BLP (continuous BLP) does not provide a valid bound to the optimal F for the integer BLP.



Part II Multi-objective Bilevel Optimization

MULTI-OBJECTIVE BILEVEL PROGRAMMING

 $\max_{x} (F_{1}(x, y), \dots, F_{k}(x, y))$ s.t. $G(x, y) \leq 0$ $y \in \arg \max_{y} \{(f_{1}(x, y), \dots, f_{m}(x, y)): g(x, y) \leq 0\}$

 $x \in \mathbb{R}^{n_1}$ – variables controlled by the leader $y \in \mathbb{R}^{n_2}$ – variables controlled by the follower

MULTI-OBJECTIVE BILEVEL PROBLEMS: CASES

- Multiple objective functions at the upper-level, single-objective function at the lower-level
- Single-objective function at the upper-level, multiple objective functions at the lower-level (also known as semi-vectorial BL problem):

$$\max_{x} F(x, y)$$

)

- (SVBLP)
- s.t. $G(x, y) \le 0$ $y \in \arg \max_{y} \{(f_1(x, y), \dots, f_m(x, y)) : g(x, y) \le 0\}$

• Multiple objective functions at both levels

SEMI-VECTORIAL BILEVEL PROBLEM (SVBLP)

(SVBLP)

 $\max_{x} F(x, y)$ s.t. $G(x) \le 0$ $\max_{y} (f_1(x, y), f_2(x, y), \dots, f_m(x, y))$ s.t. $g(x, y) \le 0$

• Only **efficient** solutions to the lower-level problem for each x -vector are feasible to the SVBLP.

• For each x-vector, there is no best f-value to the follower, but rather a set of lower-level efficient solutions

(For simplicity reasons, we consider that upper-level constraints $G(x) \le 0$ do not include lower-level variables)

SEMI-VECTORIAL BILEVEL PROBLEM (SVBLP)

Let $Y(x') = \{y : g(x', y) \le 0\}$

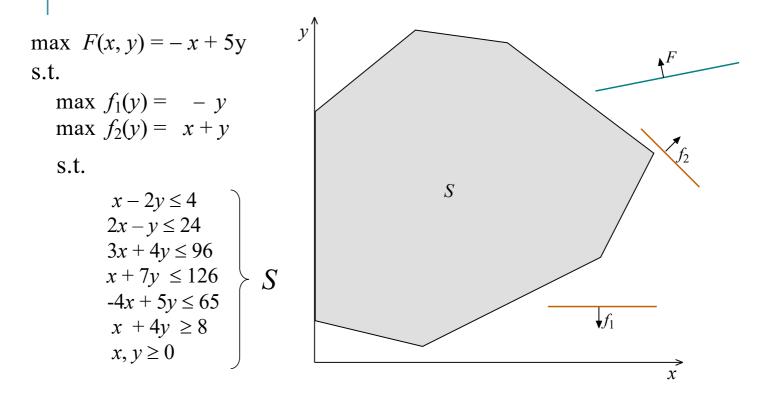
The set of **efficient** solutions to the lower-level problem of the SVBLP for a given x' is:

 $\Psi_{\text{Ef}}(x') = \{y' \in Y(x'): \text{ there is no } y \in Y(x') \text{ such that } f(x', y) > f(x', y')\}$

(where \succ denotes the dominance relation)

The inducible region (feasible region) of the SVBLP is:

 $IR = \left\{ (x, y) \in \mathbb{R}^{n_1} \times \mathbb{R}^{n_2} : G(x) \le 0, \ y \in \Psi_{\text{Ef}}(x) \right\}$



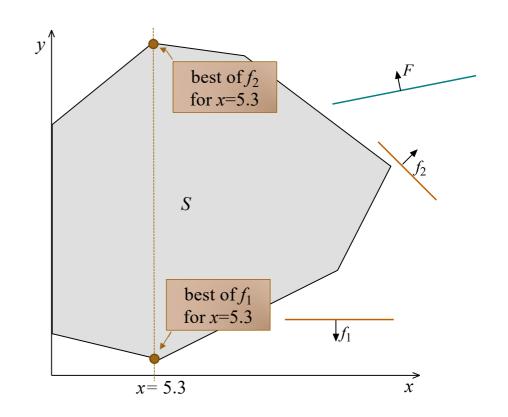
max F(x, y) = -x + 5ys.t. max $f_1(y) = -y$ max $f_2(y) = x + y$ s.t. $(x, y) \in S$ Suppose the leader takes a

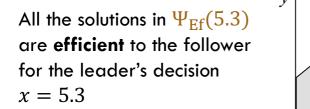
Suppose the leader takes a decision:

e.g. *x*=5.3

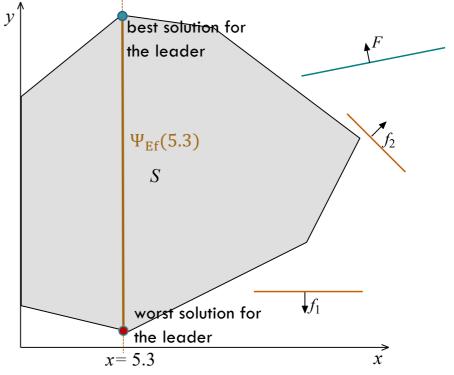
The follower's objectives become:

$$\max f_1 = -y$$
$$\max f_2 = 5.3 + y$$

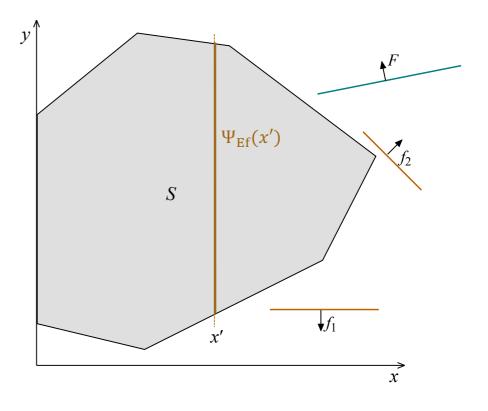




What will be the choice of the follower?



For each leader's decision x' there is a set of efficient solutions $\Psi_{\rm Ef}(x')$ to the follower.

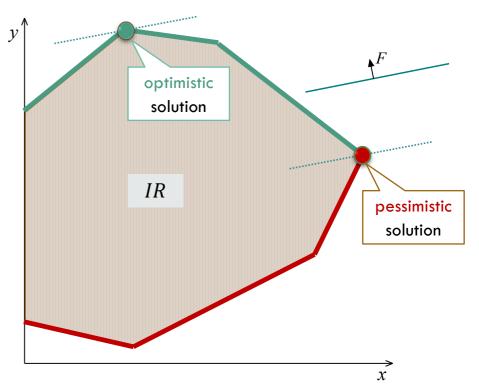


For each leader's decision x' there is a set of efficient solutions $\Psi_{\rm Ef}(x')$ to the follower.

The leader may believe that the follower will choose a solution that most benefits the leader – **optimistic approach**

Or the leader prepares for the worst case – **pessimistic approach**

Intermediate approaches may exist.



DIFFICULTIES FOR THE LEADER IN SVBLP/MOBLP

- The follower's decision may be very difficult to anticipate.
- Almost all literature devoted to SVBLP and MOBLP has adopted the optimistic approach
 - The optimistic approach assumes that the follower is indifferent to all efficient solutions obtained for a given decision of the

However, this assumption is seldom realistic in many practical decision problems

OPTIMISTIC APPROACH: REALISTIC?

Ex: a toll-setting problem

- The owners of a highway system have to set tolls and they want to maximize total revenue; users of highways want to minimize travel costs and minimize travel times.
- For each leader's decision, the follower has a set of efficient solutions:
 - At one extreme, the solution that minimizes cost
 - \rightarrow drivers do not use highways \rightarrow the leader's revenue would be 0.
 - At the other extreme, the solution that **minimizes time**
 - \rightarrow many drivers use highways \rightarrow high revenues for the leader.

The optimistic approach assumes that the follower is indifferent to those two opposite situations, which would lead the leader to set very high prices for tolls.

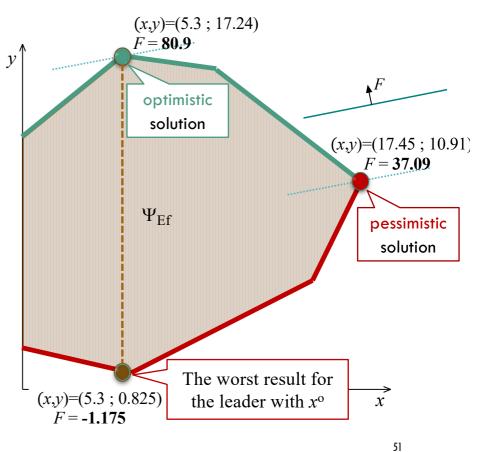


WHAT HAPPENS IF THE OPTIMISTIC APPROACH FAILS?

If the leader takes the best decision according to the **optimistic** approach (x^{o}) , but the follower's choice (y') is the worst for the leader.

The solution obtained (x^{o}, y') may be **significantly worse** than the pessimistic solution.

 \rightarrow this solution will be called deceiving solution



MOST COMMON APPROACHES

Optimistic approach

 assumes that the follower accepts any efficient solution to the lower-level problem and, so, his response is always the most convenient for the leader

o Pessimistic approach

 the leader is risk-averse and prepares for the worst case.

OPTIMISTIC FORMULATION IN SVBLP

 Assumes that the follower's response is always the **best** for the leader

 $\max_{\substack{(x,y)\\ s.t.}} F(x,y) \qquad (optimistic formulation)$ s.t. $G(x) \le 0, y \in \Psi_{\text{Ef}}(x)$

 \rightarrow the optimistic solution, (x°, y°) is a solution that optimizes the optimistic formulation

$$(x^{o}, y^{o}) \leftarrow \max_{x, y} \left\{ F(x, y) : G(x) \le 0, y \in \Psi_{\text{Ef}}(x) \right\}$$

PESSIMISTIC FORMULATION IN SVBLP

- Assumes that the follower's response is always the worst for the leader
 - $\max_{x} \min_{y} F(x, y)$ s.t. $G(x) \le 0, y \in \Psi_{\text{Ef}}(x)$

(pessimistic formulation)

 \rightarrow the **pessimistic solution**, (x^p, y^p) is a solution that optimizes the pessimistic formulation

$$(x^{\mathrm{p}}, y^{\mathrm{p}}) \leftarrow \max_{x} \left\{ \min_{y} \{F(x, y) : y \in \Psi_{\mathrm{Ef}}(x)\} : G(x) \le 0 \right\}$$

OPTIMISTIC VS. PESSIMISTIC APPROACHES

- It is important to acknowledge the risk the leader takes if he adopts an optimistic approach
- The **pessimistic approach** is the most conservative, because it pays attention to the worst choices of the follower for the leader's interests (but it may also offer **opportunities**).
- Other types of solutions can provide useful information to the leader about the risk/opportunity he takes when making a specific decision, in particular:
 - the result of a "failed" optimistic approach:
 deceiving solution
 - the result of a "successful" pessimistic approach: rewarding solution

"FAILED" OPTIMISTIC APPROACH: DECEIVING SOLUTION

- **Deceiving solution,** (*x*^d, *y*^d): if the leader makes an **optimistic decision** and the follower's reaction is the **worst** for the leader.
- It gives an indication of the maximum risk the leader will take if he adopts an optimistic approach.

$$x^{d} = x^{o} \qquad (optimistic x-vector)$$
$$y^{d} \leftarrow \min_{y} \{F(x^{o}, y) : y \in \Psi_{Ef}(x^{o})\}$$

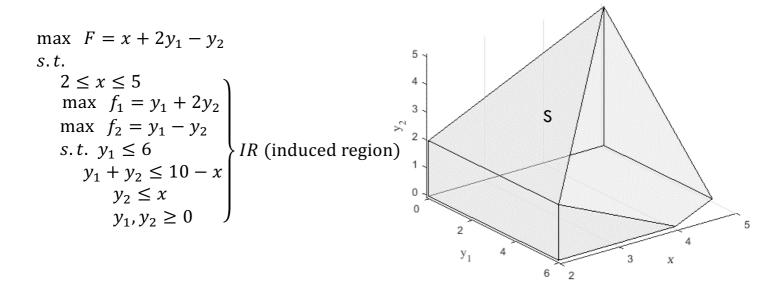
"SUCCESSFUL" PESSIMISTIC APPROACH: REWARDING SOLUTION

- **Rewarding solution,** (x^r, y^r) : if the leader makes a **pessimistic decision** and the follower's reaction is the **best** for the leader.
- It gives an indication of the opportunity the leader will have if he adopts a pessimistic approach.

$$x^{r} = x^{p} \qquad (pessimistic x-vector)$$
$$y^{r} \leftarrow \max_{y} \{F(x^{p}, y) : y \in \Psi_{\text{Ef}}(x^{p})\}$$

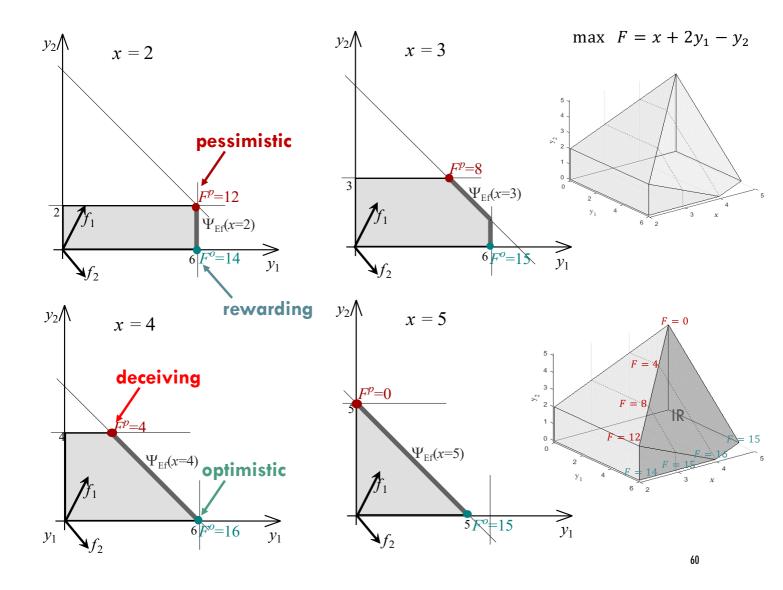
OPTIMISTIC AND DECEIVING PESSIMISTIC AND REWARDING SOLUTIONS

• These four solutions represent "**extreme**" outcomes that can provide the leader important insights about the ranges of possible values for his objective function.

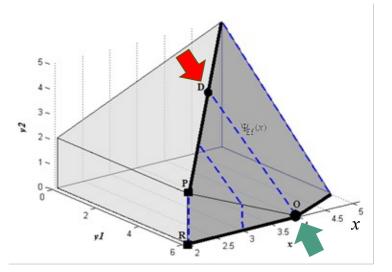


x is the upper level variable y_1, y_2 are the lower level variables

 $S{\equiv} \text{ constraint region}$

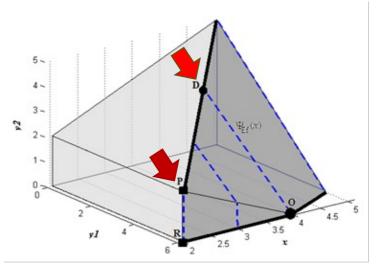


- The leader may take a high risk if he adopts an optimistic approach
 - because there is a large difference in F between the optimistic and the deceiving solutions



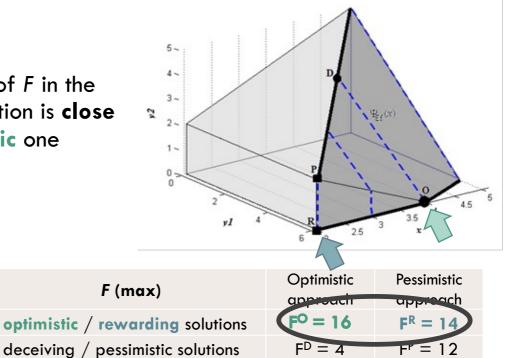


 the deceiving solution is significantly worse than the pessimistic one.

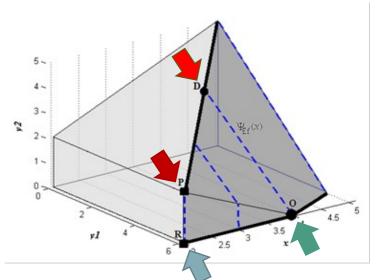






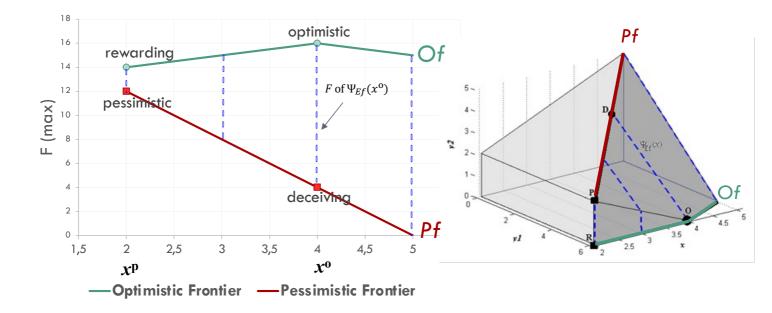


 So, in this problem, a pessimistic approach could be more advisable than an optimistic one, since a high risk is associated with the optimistic approach.



F (max)	Optimistic approach	Pessimistic approach
optimistic / rewarding solutions	F ^O = 16	$F^R = 14$
deceiving / pessimistic solutions	$F^{D} = 4$	$F^{P} = 12$

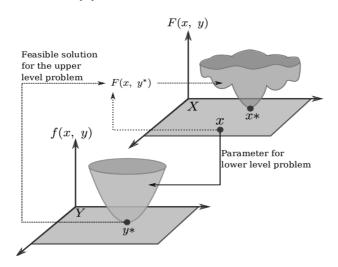
OPTIMISTIC AND PESSIMISTIC FRONTIERS - EXAMPLE 2



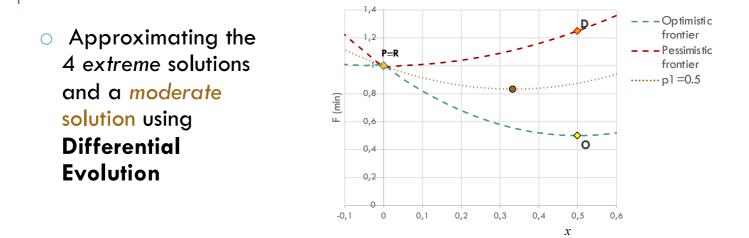
META-HEURISTIC APPROACHES

In particular involving population-based meta-heuristics:

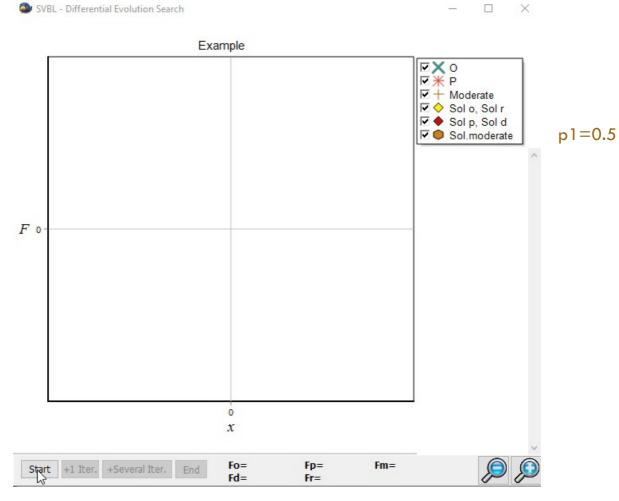
- Meta-heuristics (EA, PSO, DE, etc.) at both levels
- Hybrid algorithms with meta-heuristics at the upper level and NLP/MILP/etc. solver to solve the lower-level problem for each instantiation of the upper-level variables x.



COMPUTING SOLUTIONS FOR A NONLINEAR BLP



moderate solution: optimizes the expected value of the leader's objective function, considering that p1 is the probability of the follower to choose the optimistic solution for a given x, and (1-p1) is the probability to choose the pessimistic solution.



FINAL REMARKS FOR SVBL

Multiple objective functions at the lower level pose additional difficulties for the leader to anticipate the follower's reaction

➔ different types of solutions can provide broader information to the leader

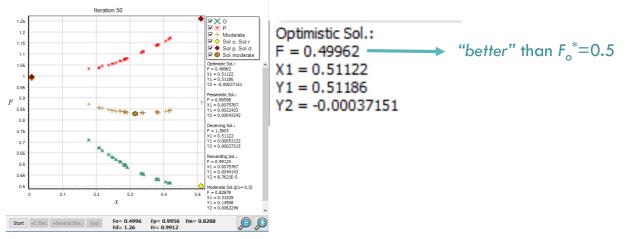
→ the optimistic, pessimistic, deceiving and rewarding solutions delimit ranges of possible values for the leader taking into account follower's extreme decisions

→ moderate solutions may provide further decision support to the leader: optimize the expected value for the leader's objective function considering different probabilities of the follower's decision being in favor or against the interests of the leader.

But these problems are very difficult to solve...

FINAL REMARKS FOR SVBL

- Population-based meta-heuristics have been increasingly used to deal with SVBP/MOBLP
- It is very difficult to evaluate results from approximate algorithms, which may lead to misleading results: apparently better solutions may be false if they are not efficient to the lower level



Part III

Bilevel Optimization: An Application in the Energy Sector

DEMAND RESPONSE AS A BILEVEL OPTIMIZATION PROBLEM

- The electricity retailer (leader) determines dynamic time-of-use prices to maximize profit
- The consumer (follower) reacts scheduling load operation to minimize the electricity bill (to profit from periods of low energy prices), subject to comfort requirements (quality of service, associated with appliance operation)

BILEVEL MODEL FOR THE INTERACTION BETWEEN RETAILER AND CONSUMER

- The retailer (*leader*) determines the prices x_i (*i*=1,...,*I*) to be charged to the consumer in each predefined sub-period P_i of the planning period $T=\{1,...,T\} \rightarrow maximize profit$
- Knowing the electricity prices, the consumer (follower) reacts by means of re-scheduling appliance operation → minimize cost
- The consumer's energy decisions affects the retailer's profit

DEMAND RESPONSE

Shiftable loads (operation cycle cannot be interrupted):

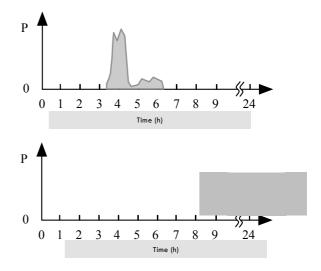
- Dishwasher
- Clothes dryer
- Washing machine

Interruptible loads

- Electric water heater
- Electric vehicle

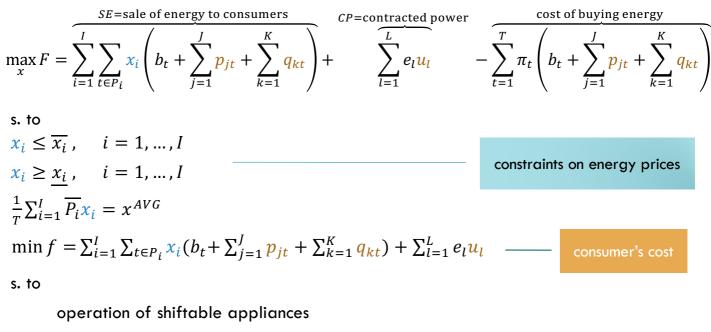
Thermostatic controlled loads

• Air conditioning system



BILEVEL MODEL

retailer's profit



75

operation of shiftable appliances operation of interruptible appliances power component

CASE ANALYSIS: DATA

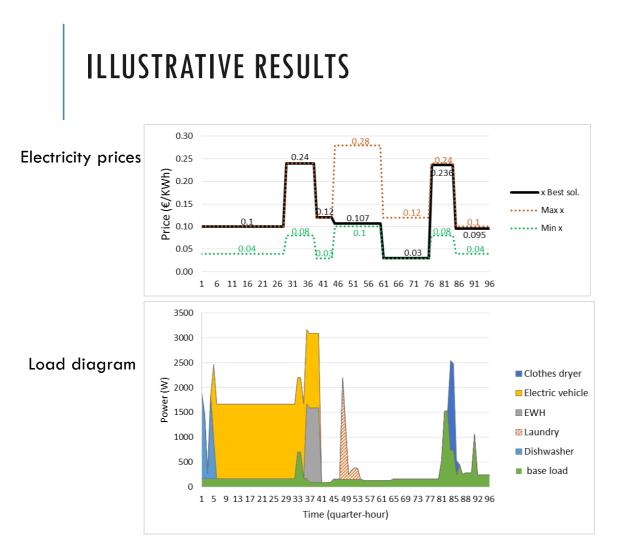
Retailer's (UL) problem

- 6 tariff periods Pi
- 6 continuous variables
- 13 constraints (lower/upper bounds + average price)

Consumer's (LL) problem

- 3 shiftable appliances (J=3) dish + laundry +dryer machines
- 2 interruptible loads (K = 2) EV + EWH
- non-controllable base load

24 h planning horizon discretized in 15 min time intervals For each instantiation of the UL variables, the LL MILP problem has 559 binary variables, 691 continuous variables and 2389 constraints.



CONCLUSIONS

- Main concepts on single-objective bilevel optimization
- Semi-vectorial bilevel optimization optimistic, pessimistic, deceiving, and rewarding solutions
- An overview of an application of bilevel optimization in the design of time-of-use tariffs