

Middle East Technical University



# **Multiple Criteria Decision Making: Interactive Approaches**

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# Outline

- Problem Definition
- Classification
- Choice (Discrete alternative) problem
- Design (Continuous) problem
- MOCO
- Resources

# Problem Definition

(P) "*Min*"  $\{z_1(x), \dots, z_p(x)\}$

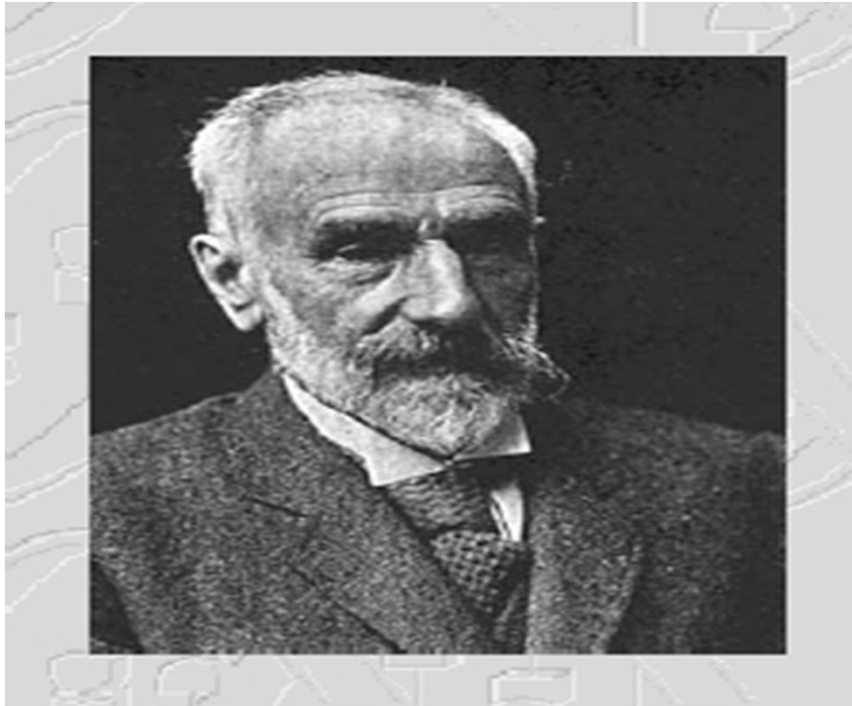
$x \in X$

*where*

$x$  : *decision vector*

$X$  : *solution space*

$z_i$  : *ith objective function*



Francis Ysidro Edgeworth  
1881



Vilfredo Pareto  
1896

Notion of Edgeworth-Pareto Optimal

# Efficient solution

- $\mathbf{x}$  is an efficient solution if there exists no  $\mathbf{x}'$  such that

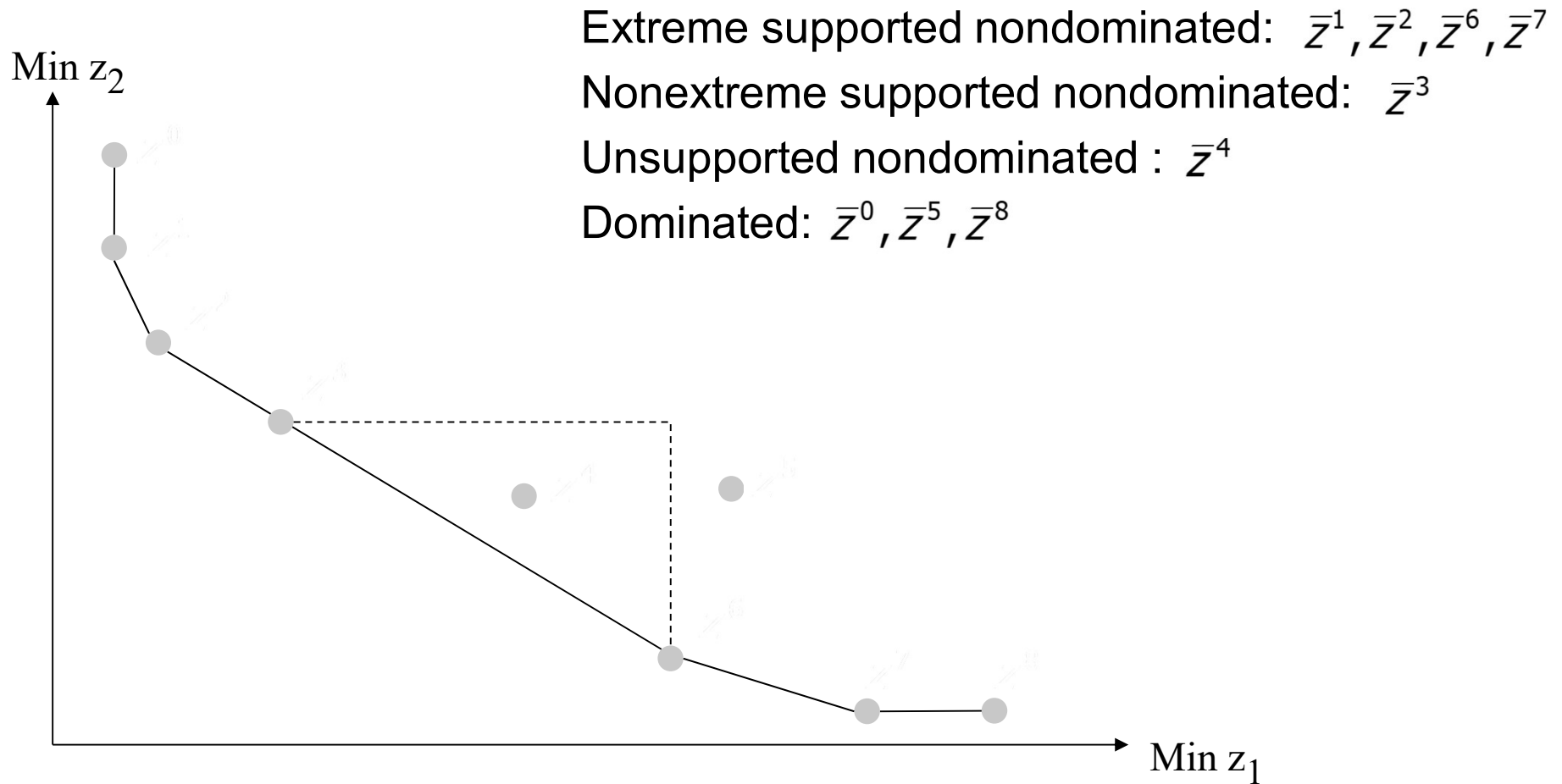
$$z_i(\mathbf{x}') \leq z_i(\mathbf{x}) \quad i=1, \dots, p \text{ and}$$
$$z_i(\mathbf{x}') < z_i(\mathbf{x}) \text{ for at least one } i.$$

- If  $\mathbf{x}$  is efficient then  $(z_1(\mathbf{x}), \dots, z_p(\mathbf{x}))$  is said to be nondominated.
- Remark: “Best” solution is an efficient solution.

# **Efficient set / frontier**

- The set of all efficient solutions form the efficient set / frontier
- The set of all nondominated points form the nondominated set / frontier

# Solution Types



# Classification

- If  $X = \{X_1, \dots, X_n\}$  then  
Choice (*Discrete Alternative*) Problem  
where  $X_i = (x_{i1}, \dots, x_{ip})$
- If  $X = \{\mathbf{x} : g_j(\mathbf{x}) \leq b_j \text{ } j=1, \dots, m\}$  then Design  
(*Continuous Solution Space*) Problem
- If  $X$  is discrete and “large” then  
*Combinatorial Problem*

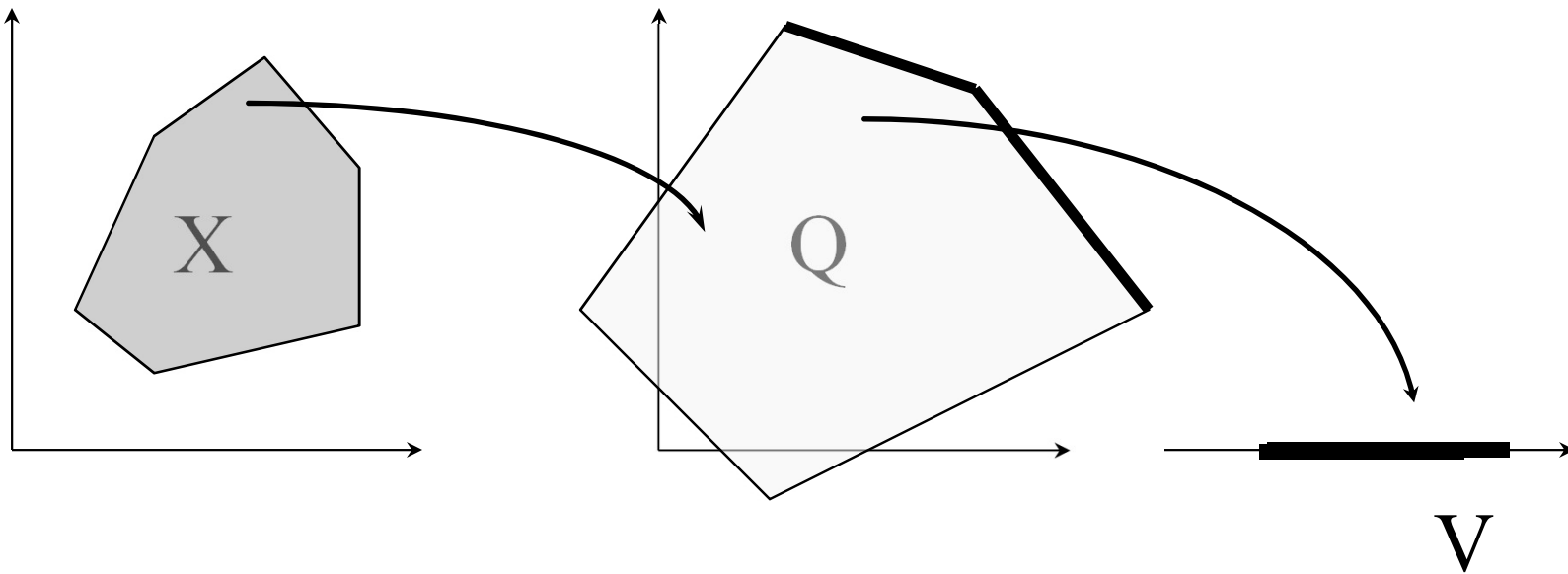


# MOCO

- $X$  is discrete and “large”
- Grows fast with problem size
- Hope of solving to optimality reduces as fast with problem size

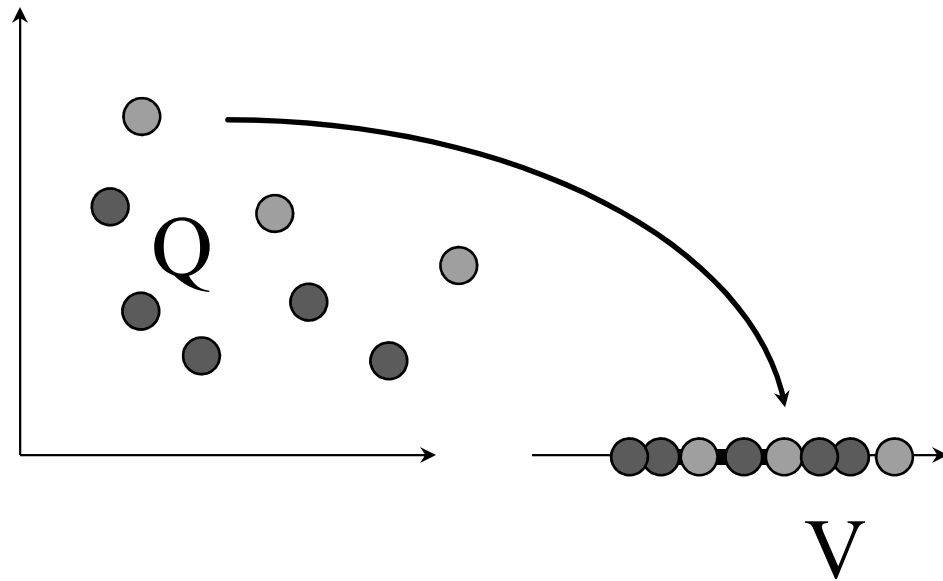
# Basic Concepts: Variable, Criterion and Value Space

Continuous Solution Space



# Basic Concepts: Variable, Criterion and Value Space

Discrete Alternative



## Illustration: An MOLP-Problem

$$\text{Max } f_1 = -x_1 + 2x_2$$

$$\text{Max } f_2 = 2x_1 - x_2$$

Subject to:

$$x_1 \leq 4$$

$$x_2 \leq 4$$

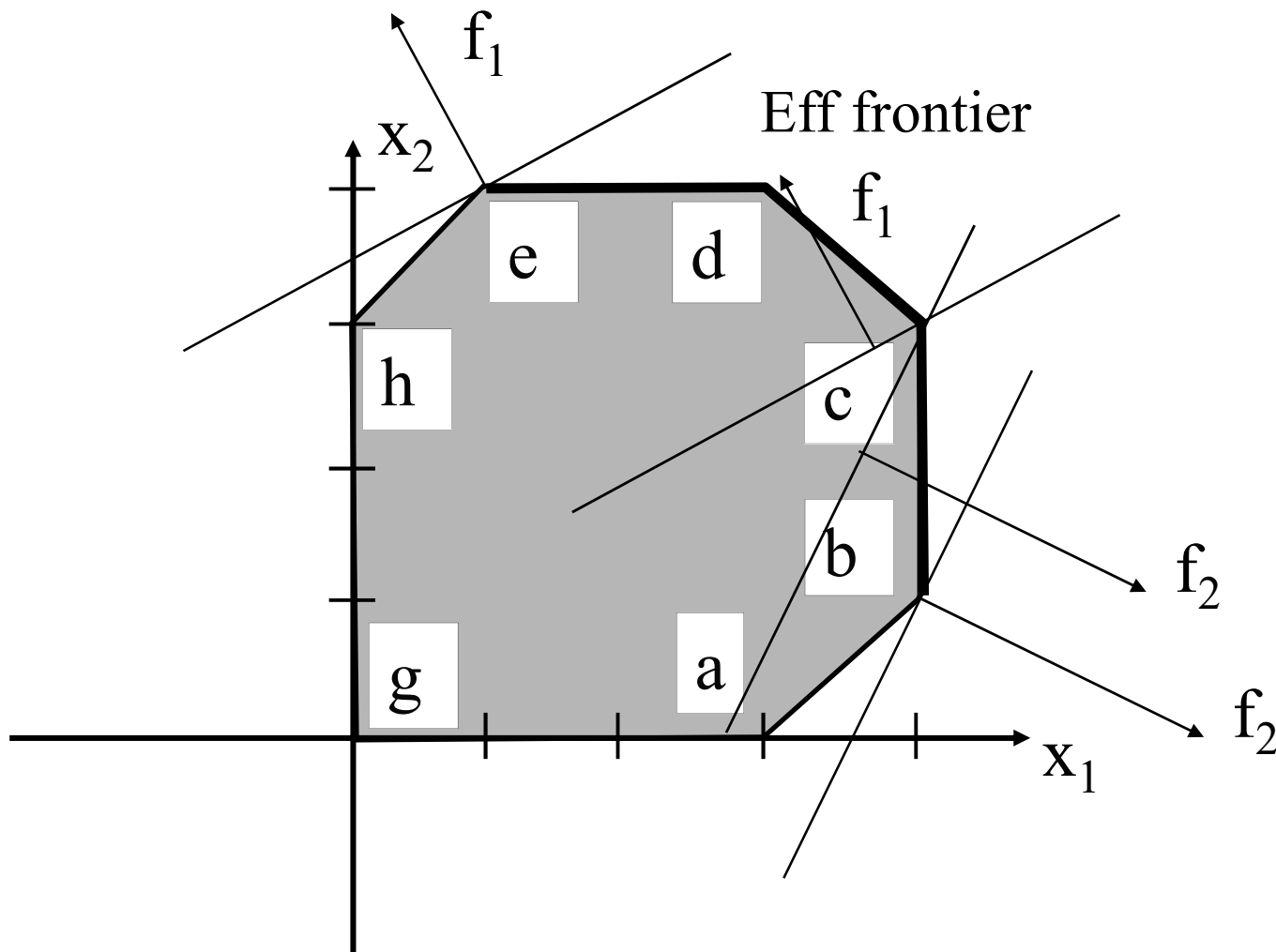
$$x_1 + x_2 \leq 7$$

$$-x_1 + x_2 \leq 3$$

$$x_1 - x_2 \leq 3$$

$$x_1, x_2 \geq 0$$

# MOLP-Example: In Decision Space



# **MOLP-Problem: In Criterion Space**

The MOLP-Problem in Criterion Space

$$\max f_1$$

$$\max f_2$$

Subject to:

$$f_1 + 2f_2 \leq 12$$

$$2f_1 + f_2 \leq 12$$

$$f_1 + f_2 \leq 7$$

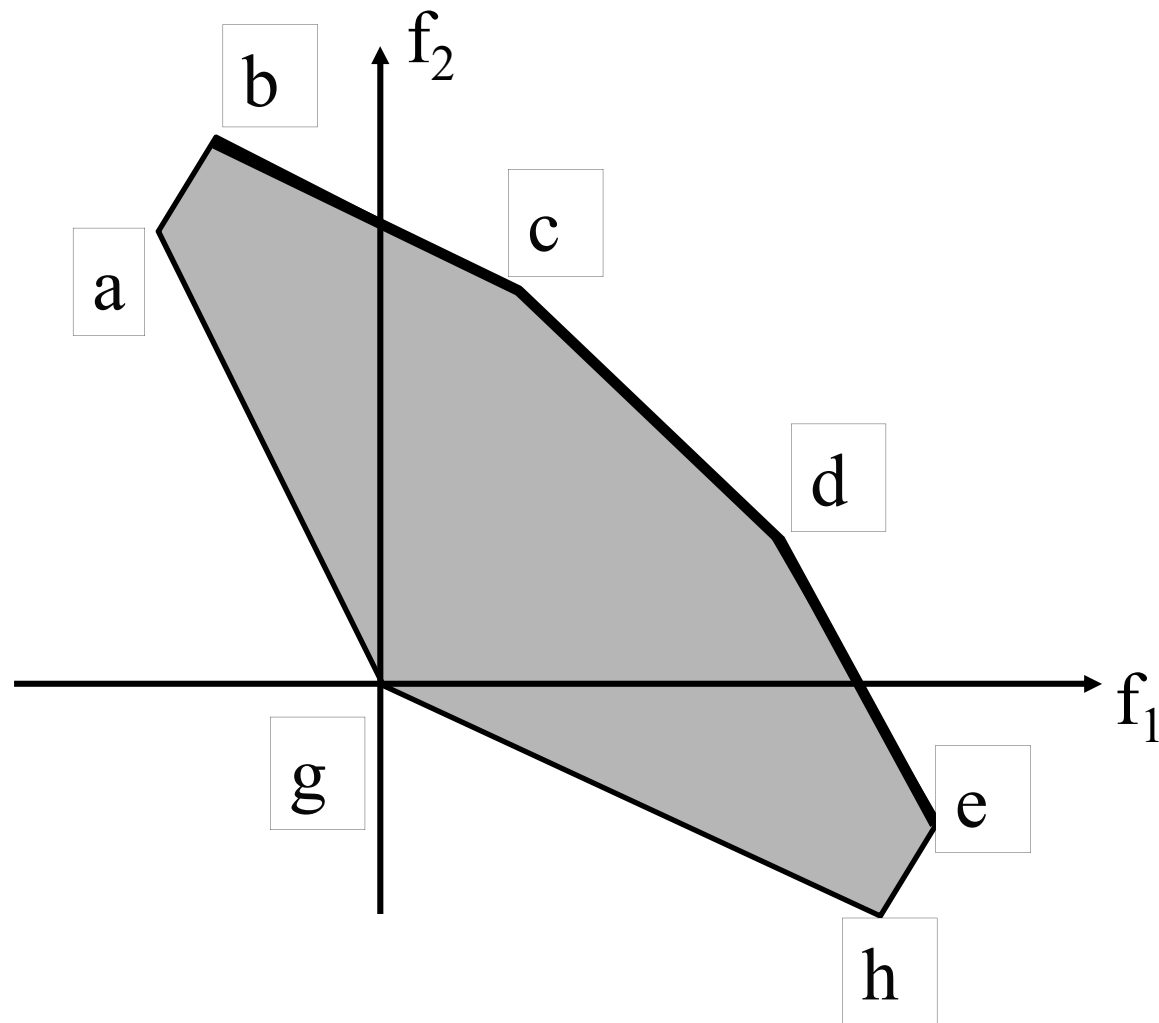
$$f_1 - f_2 \leq 9$$

$$-f_1 + f_2 \leq 9$$

$$f_1 + 2f_2 \geq 0$$

$$2f_1 + f_2 \geq 0$$

# MOLP-Problem: In Criterion Space



# Theorem

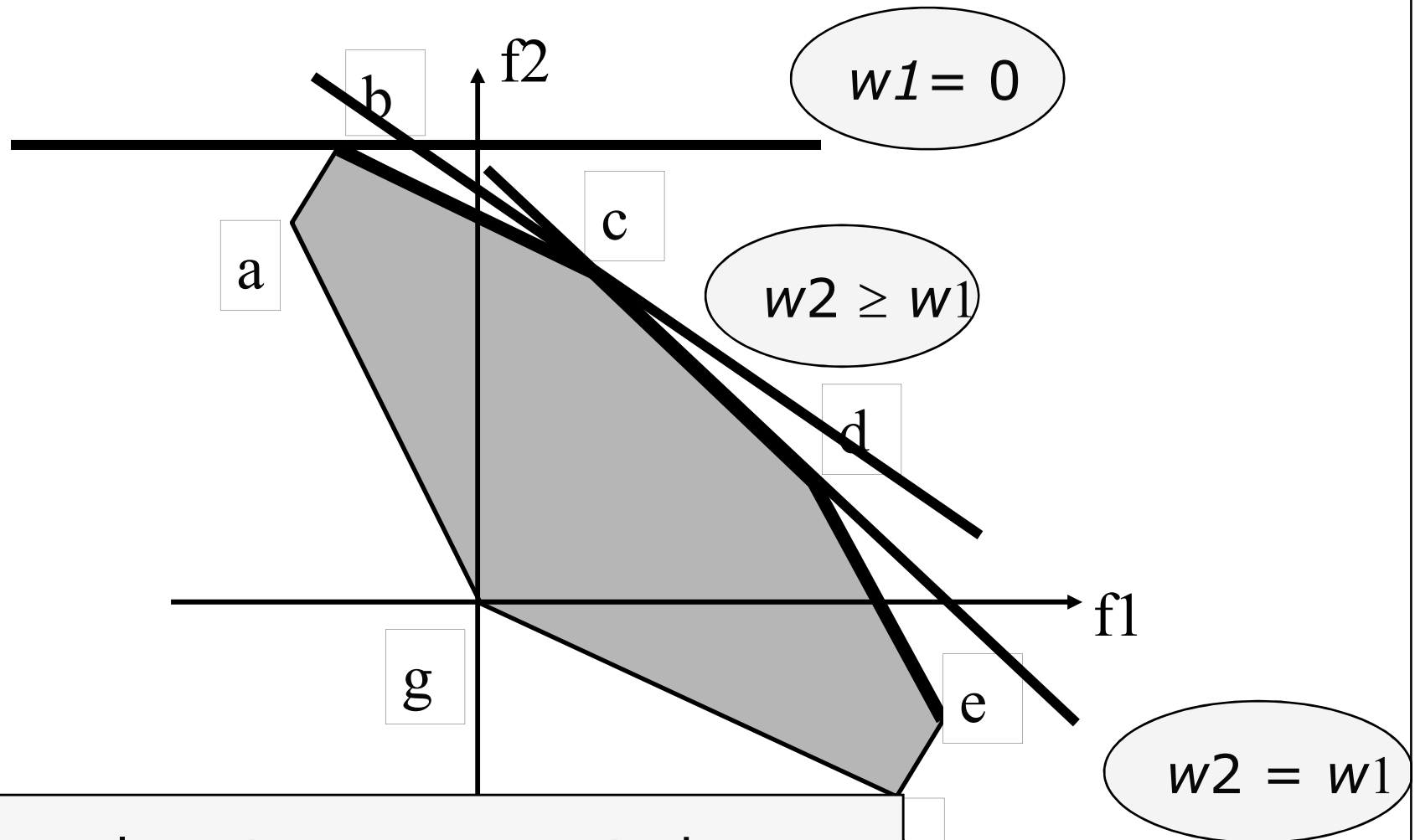
$$\begin{array}{l} \text{Max } \sum w_i z_i(x) \\ \text{st } \quad x \in X \end{array}$$

yields a (supported) efficient solution for any set of weights satisfying  $w_i > 0 \ i=1, \dots, p$

Remark: Changing  $w_i$ 's systematically, different (supported) efficient solutions can be obtained

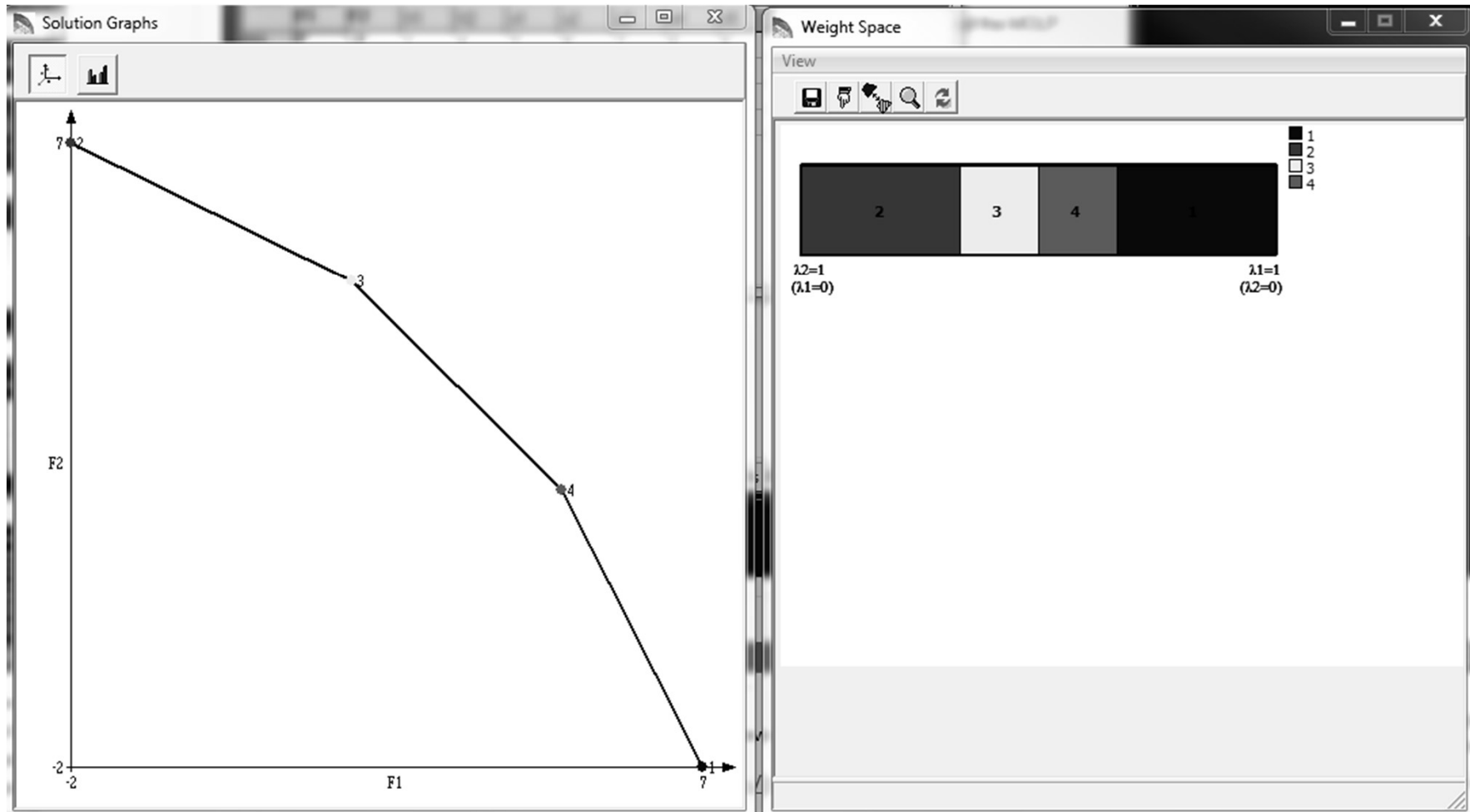


# Weighted Sums: MOLP



Usually, only extreme supported nondominated solutions are obtained!!

# Criteria and weight space

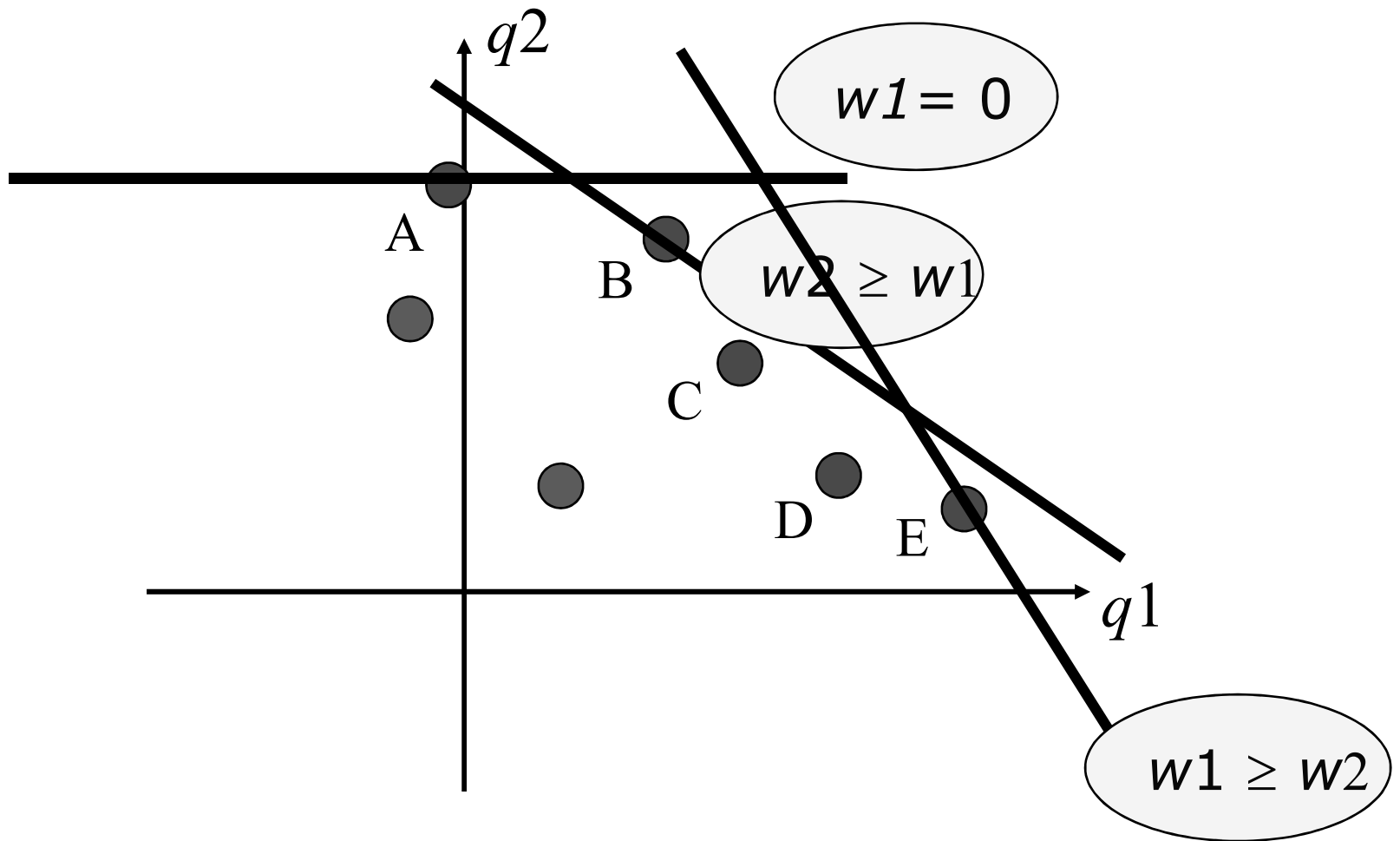


Source: Antunes et al. MOLP software

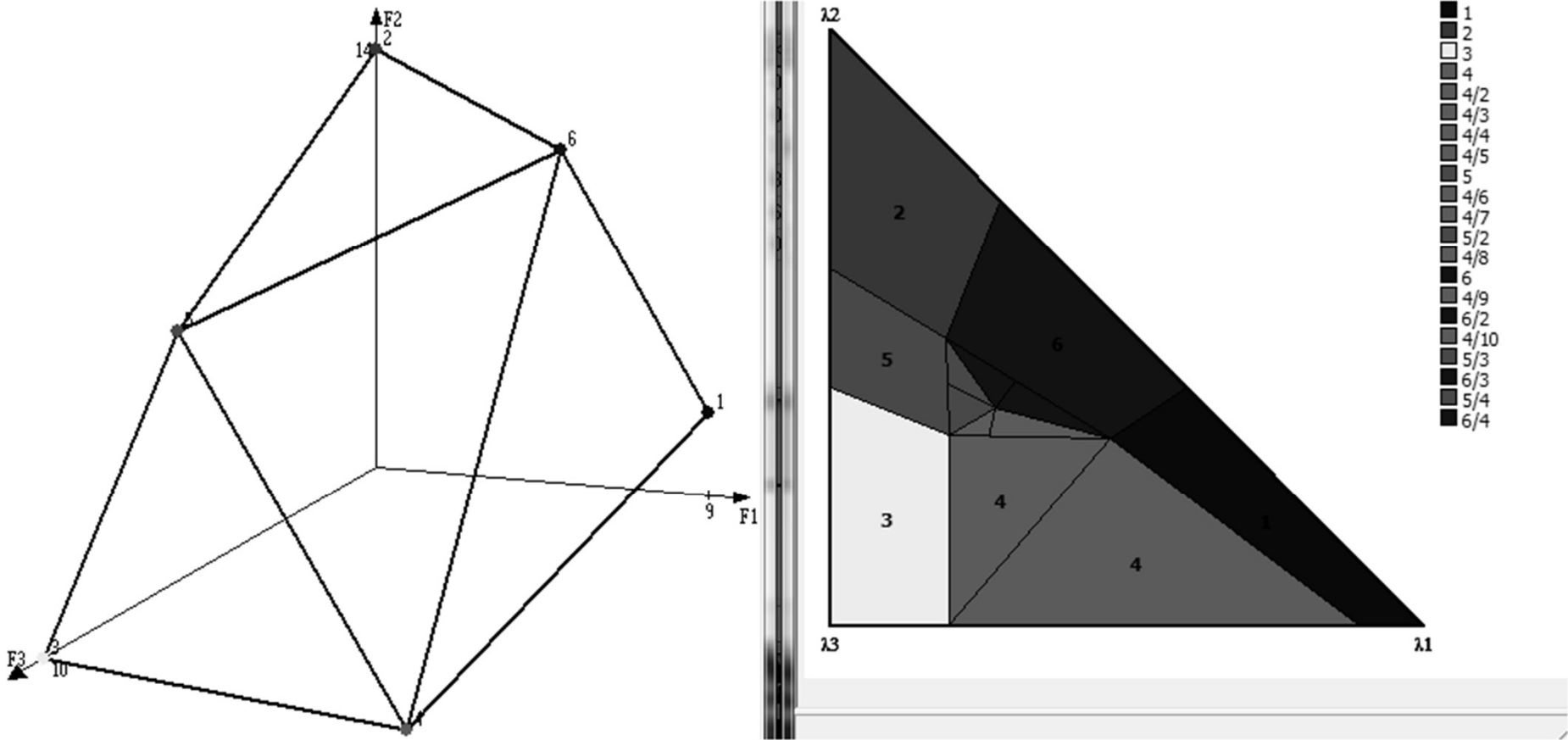


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# Weighted Sums: Discrete Alternative Problem



# Weight Set - Linear

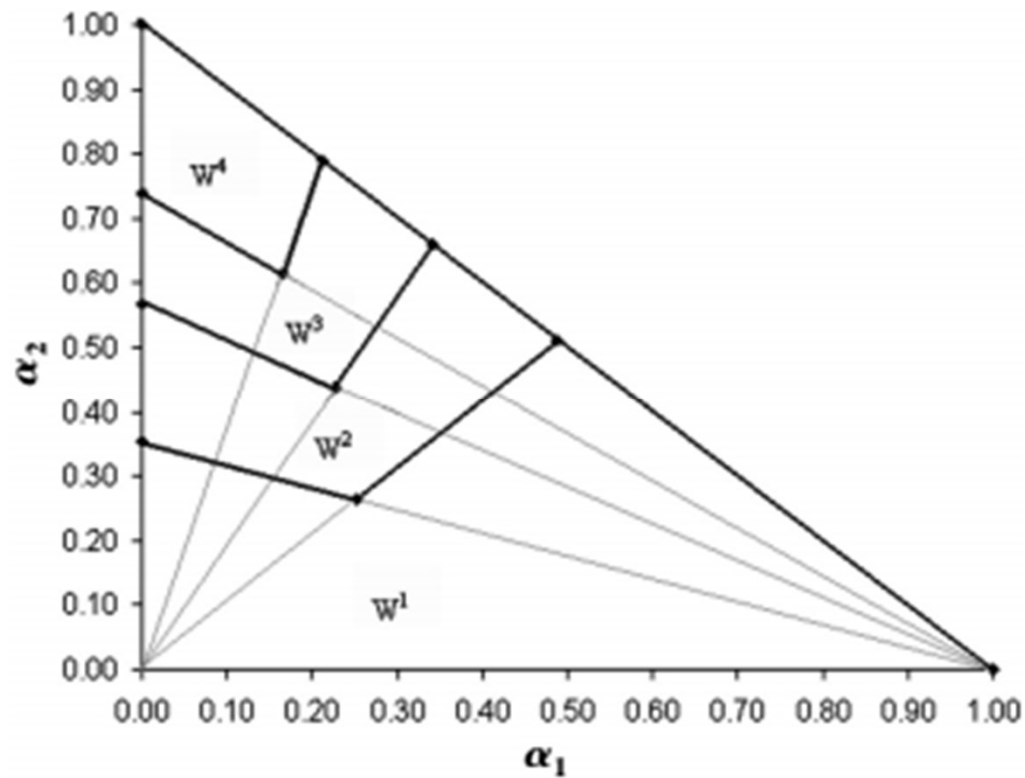


Source: Antunes et al. MOLP software



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# Weight Set - Tchebycheff



Source: Bozkurt et al. (2010) Oper. Res.



# The $\varepsilon$ -constraint approach

- Idea: Write “min. acceptable level” constraints on all but one objective

$$\text{Max } z_k(x)$$

$$z_i(x) \geq \varepsilon_i \quad \forall i \neq k$$

$$x \in X$$

does not guarantee  
an efficient solution

- The solution may be weakly efficient but inefficient

## $\varepsilon$ -constraint (cont.)

- To guarantee an efficient solution, solve

$$\begin{aligned} \text{Max } z_k(\mathbf{x}) + \sum_{i \neq k} \rho_i z_i(\mathbf{x}) \\ z_i(\mathbf{x}) \geq \varepsilon_i \quad \forall i \neq k \\ \mathbf{x} \in X \end{aligned}$$

where  $\rho_i > 0$  and arbitrarily small

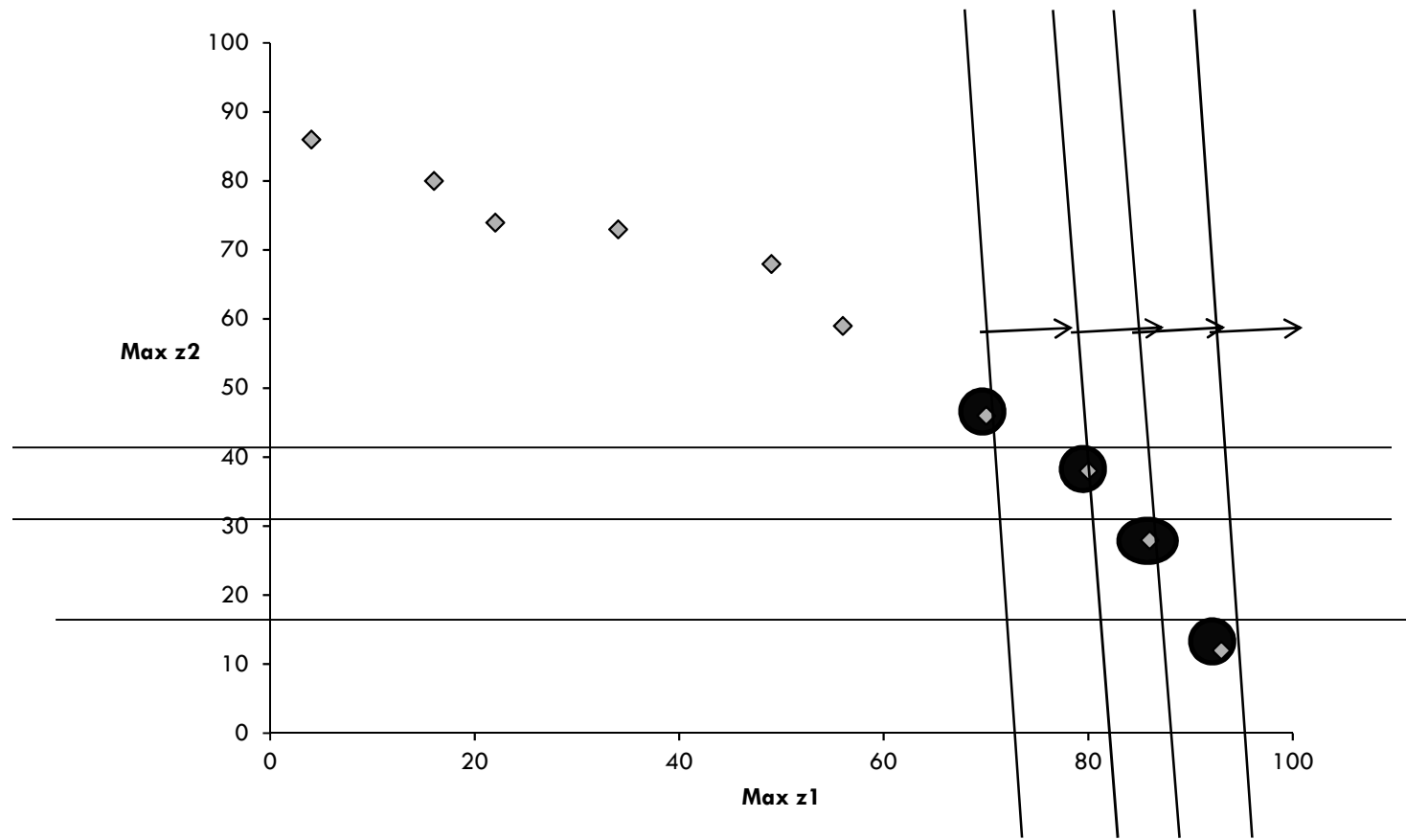
## $\varepsilon$ -constraint (cont.)

- Changing  $\varepsilon_i$  values systematically, we can find many (sometimes all) efficient solutions and approximate the efficient frontier
- We can explore different (desirable) parts of the efficient frontier
- In integer programs, we may be able to find all efficient solutions



# Example

$z_1$	$z_2$
4	86
16	80
22	74
34	73
49	68
56	59
70	46
80	38
86	28
93	12



# **Choice (Discrete) Problem: Further Outline**

- Prior articulation of preferences
  - Estimating a value function
  - Outranking relations
  - AHP
- Progressive articulation of preferences
  - Interactive approaches-implicit value fn.
    - linear
    - quasiconcave
    - general monotone
  - Estimation of the form of value fn.
- Visual Interactive Approaches
  - VIMDA, VISA, ...
- Classification and Sorting Problems

# Progressive articulation of preferences- Interactive approaches

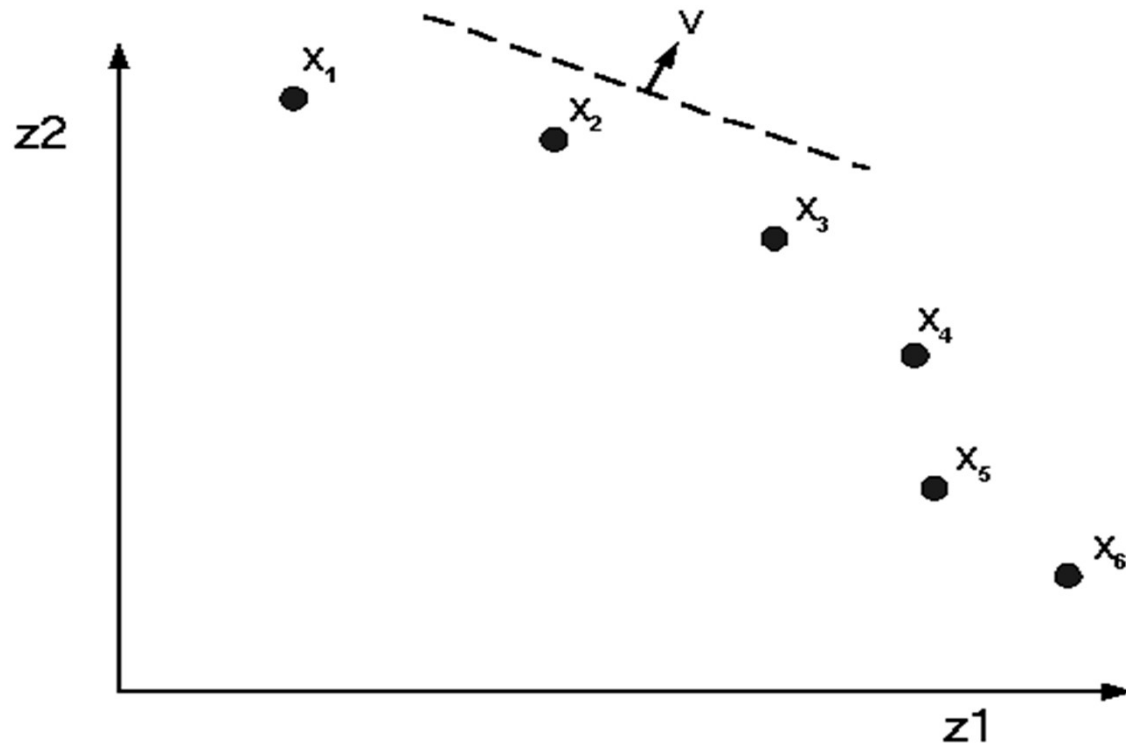
- Suitable for:
  - large # of alts
  - several criteria (say 2-7).
- Aim: converge to “best” alternative quickly.
- Assume
  - the DM can compare pairs of alternatives
  - there exists an implicit value fn,  $v$ , consistent with DM’s preferences
  - the general form of  $v$  (linear or quasiconcave or general monotone) is known.

## **Structure of the approach**

- The DM compares provided pairs of alternatives.
- Set of alternatives is reduced (based on DM's response and known form of  $v$ ).
- Repeat until only “best” alternative is left.

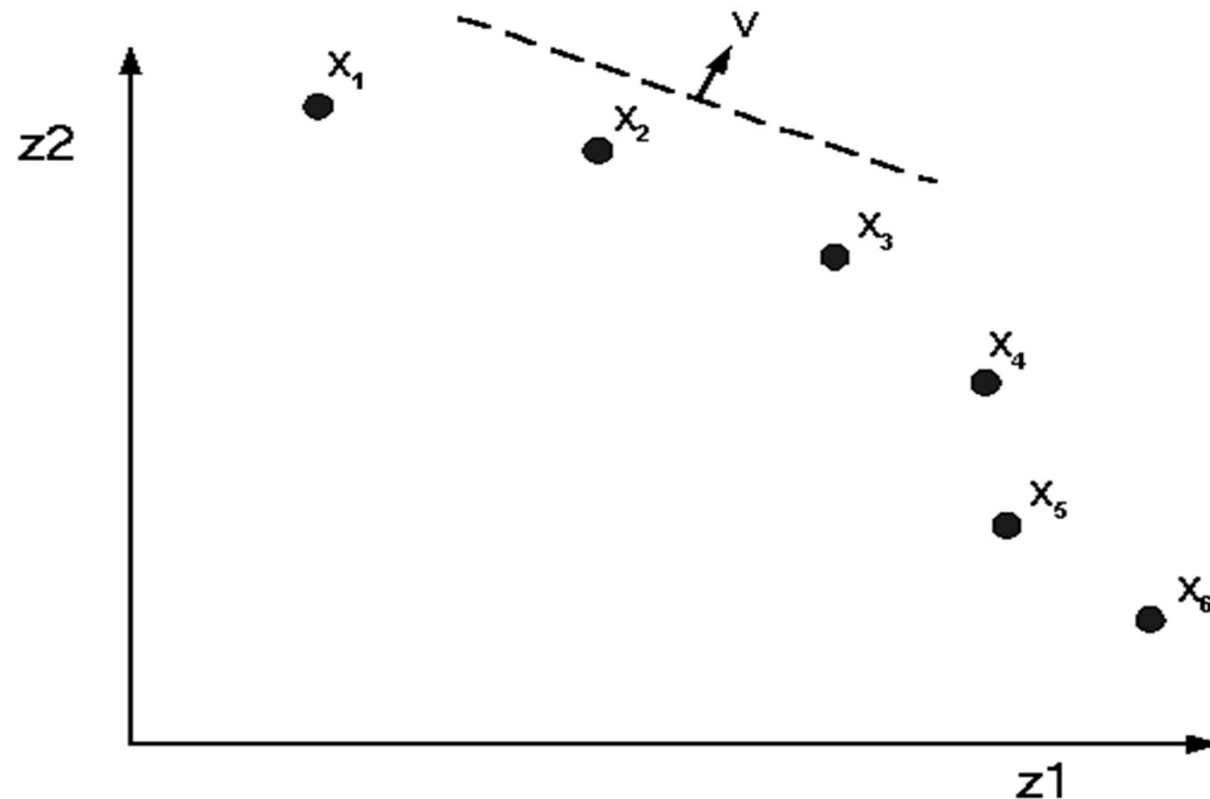
# Linear $v$

- A pair of alts. are adjacent efficient if their convex combinations are not convex dominated



# Linear $v$ (Zionts, *EJOR* 1981)

- Theorem: An alt. preferred to all its adj. eff. alts. is “best.”



# Approach

- Find  $x^*$  maximizing a linear estimated  $v$
- Ask DM to compare  $x^*$  with its adjacent efficient solutions
  - If an adjacent eff. solution is preferred update  $v$  and start again
- If  $x^*$  is preferred to all adjacent eff. solutions, Stop.



Stanley Zionts



## **Quasiconcave v (Korhonen et al, *Mgmt. Sci.* 1984)**

- Property of v: decreasing marginal rate of substitution.
- **Thm:** If  $v(X_k) = \text{Min}_{i \in S} v(X_i)$  then for all Y satisfying

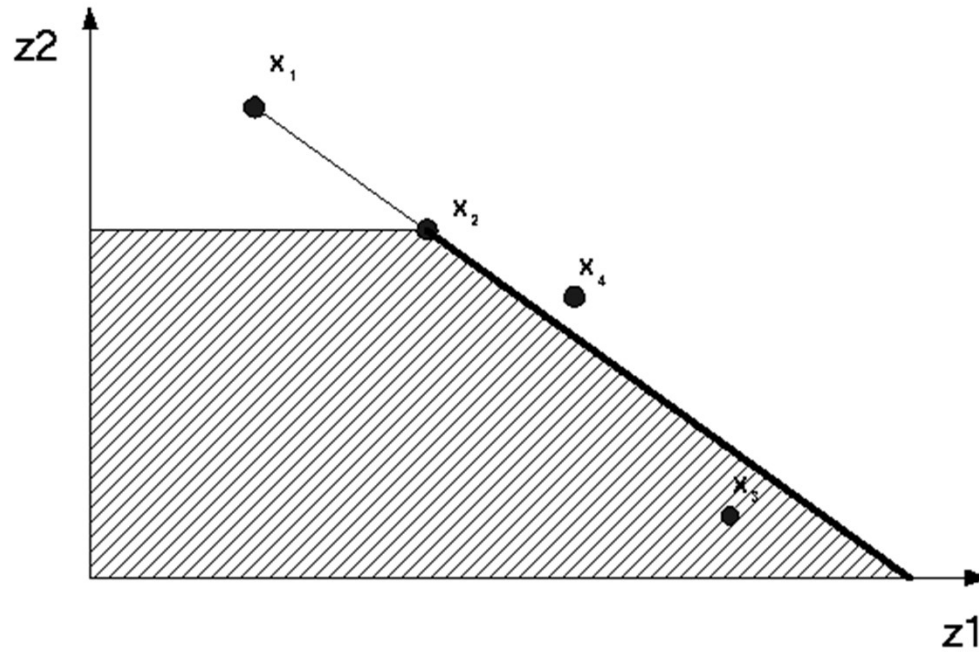
$$C = X_k + \sum_{i \in S} \mu_i (X_k - X_i) \geq Y \quad \mu_i \geq 0$$

we have

$$v(X_k) \geq v(Y).$$

# Demonstration

Assume  $v(X_1) > v(X_2)$



# To solve for $Y_t$

(P) Min 0

$$\text{st } \sum_{i \neq k} \mu_i (X_k - X_i) \geq (Y_t - X_k)$$

$$\mu_i \geq 0 \quad i \neq k$$

If (P) is feasible then  $v(X_k) \geq v(Y_t)$

If (P) is infeasible then no info.

(D) Max  $\lambda(Y_t - X_k)$

$$\text{st } \lambda(X_k - X_i) \leq 0$$

$$\lambda \geq 0$$

- If (D) has 0 obj. at optimal:  
then (P) is feasible and  
 $v(X_k) \geq v(Y_t)$

- If (D) is positive then (P) is  
infeasible and  $v(X_k) ? v(Y_t)$

# Approach

- Ask the DM to compare some pairs of alts.
- Define all cones, and eliminate alts. that fall into any cone,  $C$ .
- Continue until a single alt. is left.



Pekka Korhonen



Jyrki Wallenius

# Variations

- Köksalan, Karwan and Zionts (*IEEE SMC* 1984) and Köksalan and Taner (*EJOR* 1992) make modifications to improve the convergence

**v** :  $L_{\alpha}^{\mathbf{w}}$  (Karakaya et al., EJOR 2018)

$$L_{\alpha}^{\mathbf{w}}(|\mathbf{q} - \mathbf{r}|) = \begin{cases} (\sum_{j=1}^p (w_j |q_j - r_j|)^{\alpha})^{1/\alpha}, & \text{if } 1 \leq \alpha < \infty, \\ \max_{j=1, \dots, p} \{w_j |q_j - r_j|\}, & \text{if } \alpha = \infty, \end{cases}$$

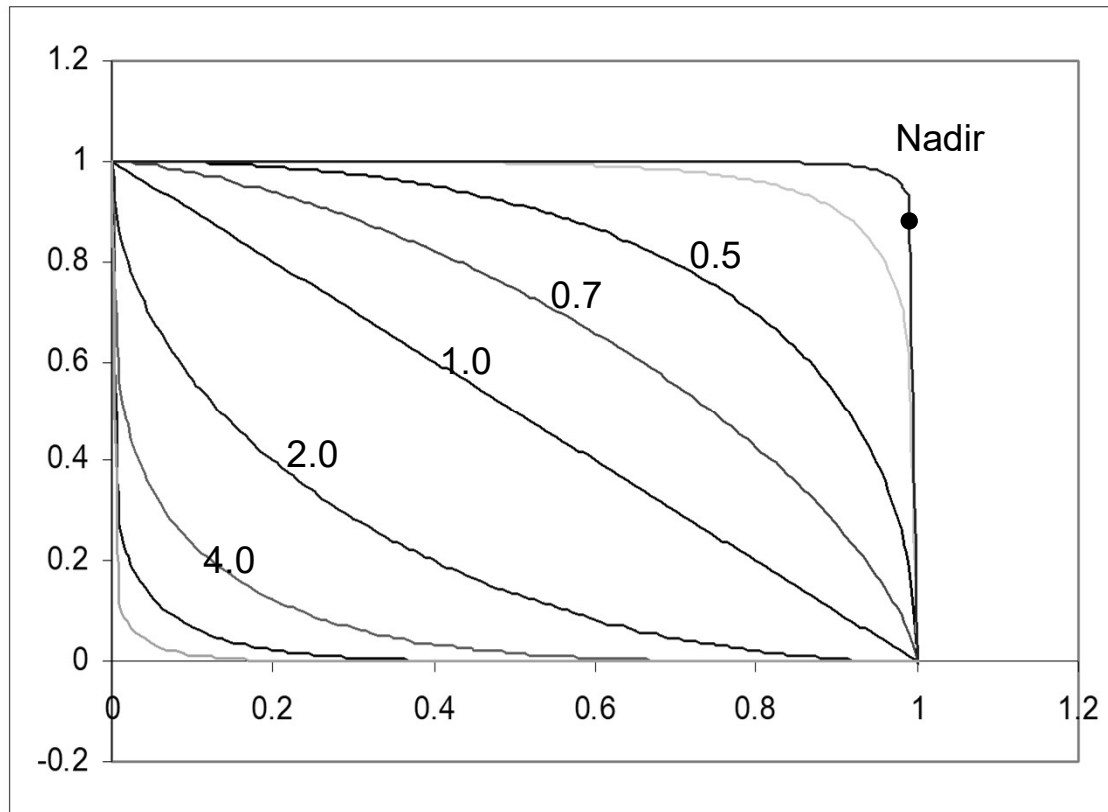


● Property of v:

- approximates quasiconcave/quasiconvex functions well
- takes a variety of forms based on  $\alpha$  and  $\mathbf{w}$



$$(1-u')^\alpha + (1-v')^\alpha = 1 \quad \alpha > 0$$

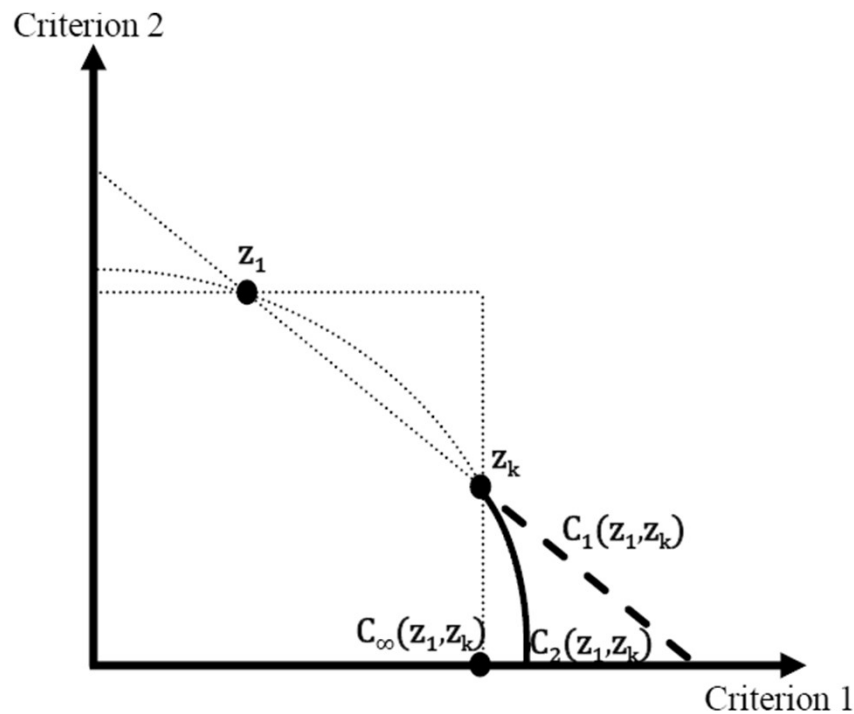


We consider weighted version and  $\alpha \geq 1$



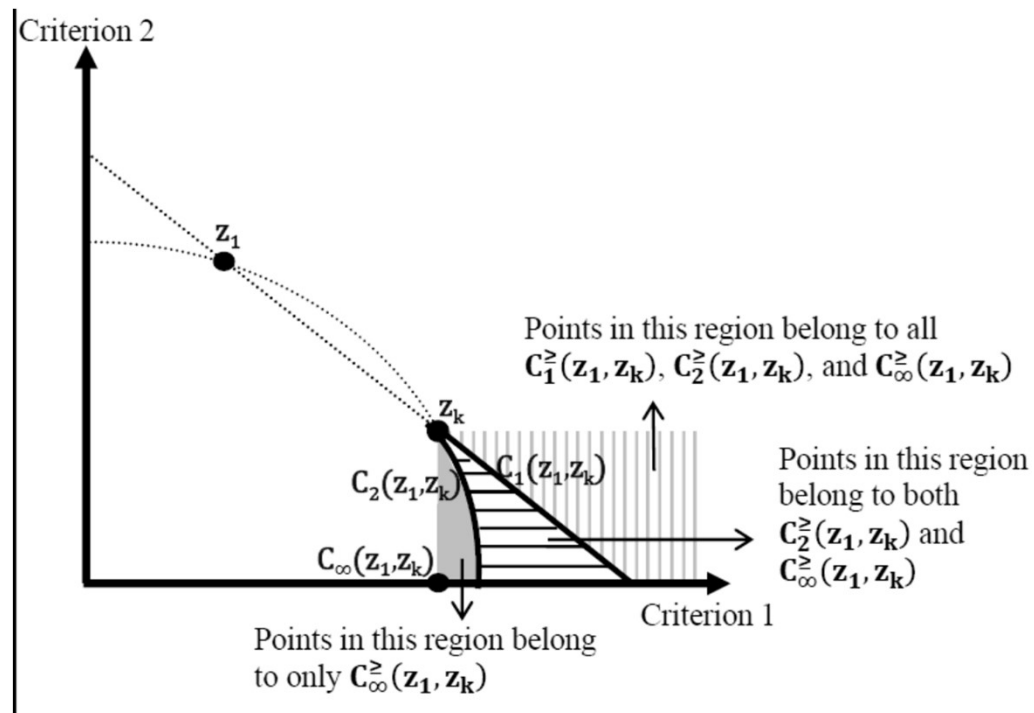
# Inferior Alternatives

Assume that  $z_1$  is preferred to  $z_k$ , i.e.  $v(z_1) < v(z_k)$



# Inferior Alternatives

Assume that  $z_1$  is preferred to  $z_k$ , i.e.  $v(z_1) < v(z_k)$



# Approach

- Start with linear  $v$ .
- Ask the DM to compare some pairs of alts.
- Eliminate inferior alts. that fall into any  $C_\alpha(z_i, z_k)$
- Update parameters of  $v$ . If necessary, increase  $\alpha$
- Continue until a single alt. is left
  
- If  $\alpha$  is known, continue until an alt. is preferred to all its “ $\alpha$ -adjacent” alts.

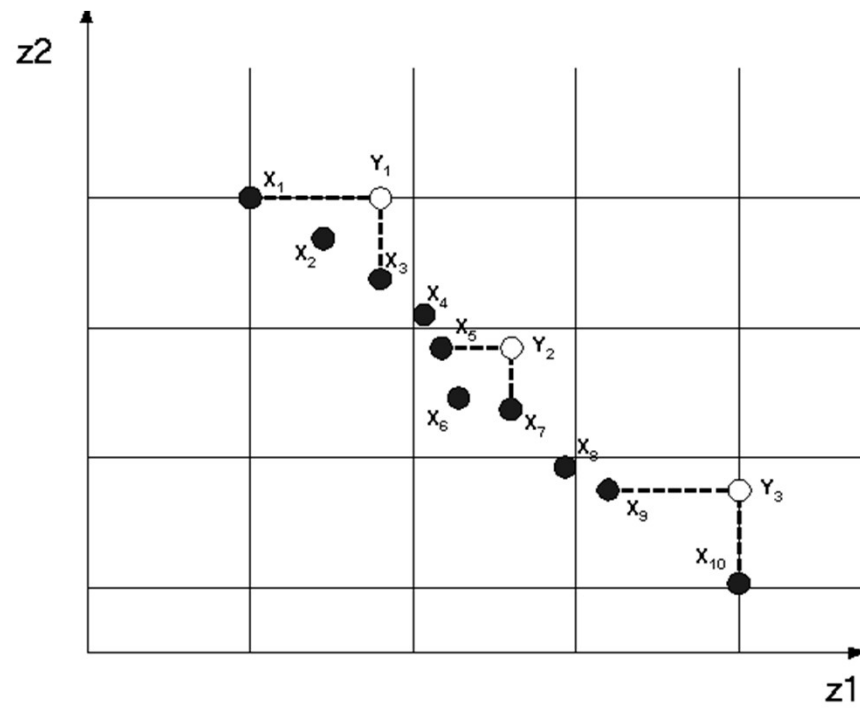


# **General monotone v**

**(Köksalan and Sagala 1995, *Man Sci*)**

- Assume only “more is better”
- Eliminate only based on dominance

# Demonstration



# Approach

- Group alts into partitions & find PIs
- If DM prefers an alt to a PI, delete whole partition
- If necessary, reduce group sizes and redefine PIs
- Repeat until a single alt is left



# Estimate form of $v$

- Korhonen et al (1986, 1993), Salminen et al (1989)
  - Solve various LPs to test violations of linearity and quasiconcavity
- Köksalan & Sagala (1995)
  - Use convex combinations of alts to quickly identify violations of linearity and quasiconcavity
- A General Approach
  - Estimate form of  $v$
  - Use most efficient algorithm available for identified form

# Visual Interactive Approaches

- VIMDA (Korhonen '88 *EJOR*)
- AIM (Lotfi et. al. '92 *C&OR*)
- ...



# Classification and Sorting

- Place alternatives in different classes (based on similarity-classification) or preference-ordered classes (sorting)
- Examples
  - Patients into disease groups based on symptoms
  - Country risk assessment, credit risk assessment
  - Selecting applicants for different scholarships/graduate programs
  - Selecting projects for different kinds of funding policies

# An Approach (Köksalan and Ulu, *EJOR* 2003)



- Linear Utility Function-not explicitly known

$$u(X_i) = \sum_j \lambda_j x_{ij}$$

Preference classes are well defined

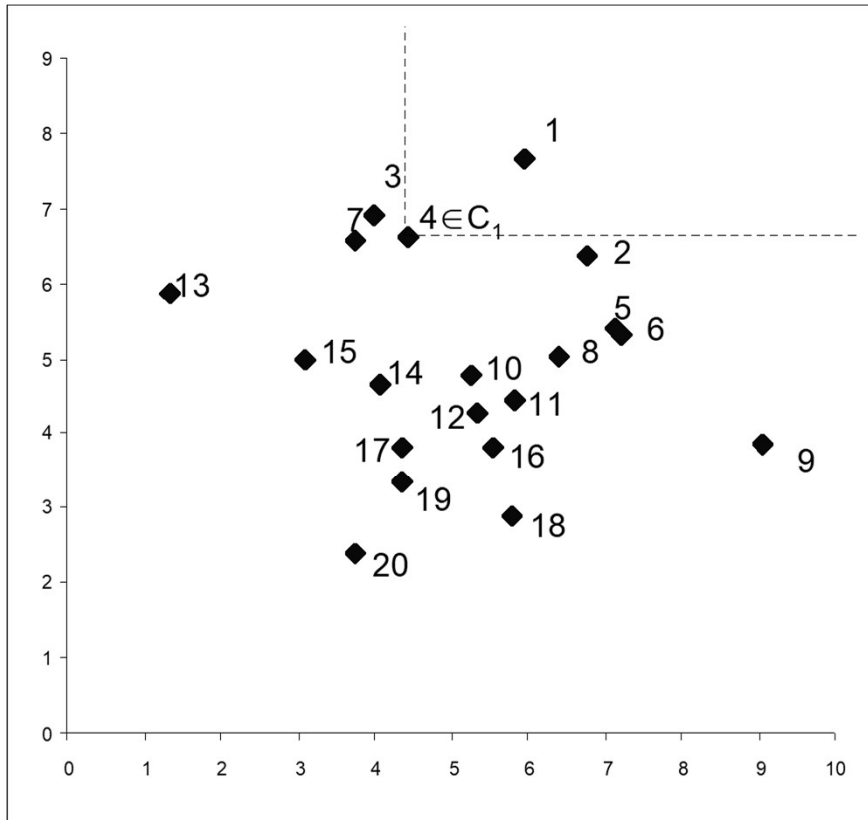
$$X_i \in C \Leftrightarrow LB(C) \leq u(X_i) \leq UB(C) \quad (\text{unknown to us})$$

- DM can correctly place alternatives in preference classes consistent with his/her underlying utility function and the bounds

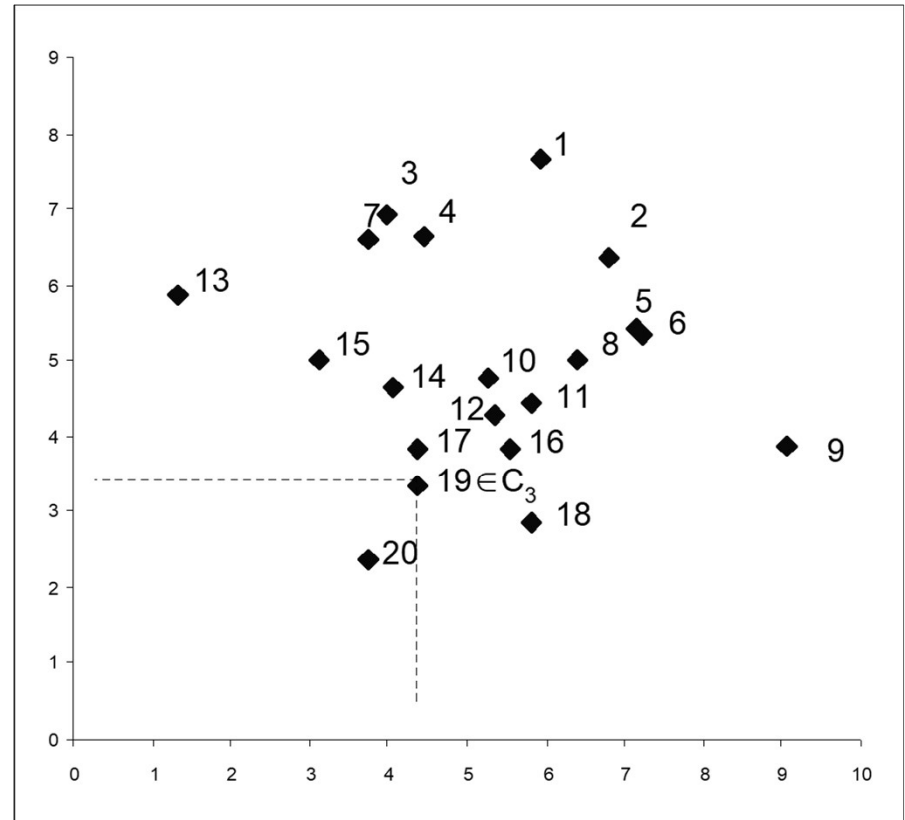
# Algorithm

- Ask DM to place alternatives in a preference class;  $C_i$
- To place alternatives in implied preference classes,  $C_i'$ , use:
  - Dominance
  - Convex combinations
  - Weight space reduction

# Dominance

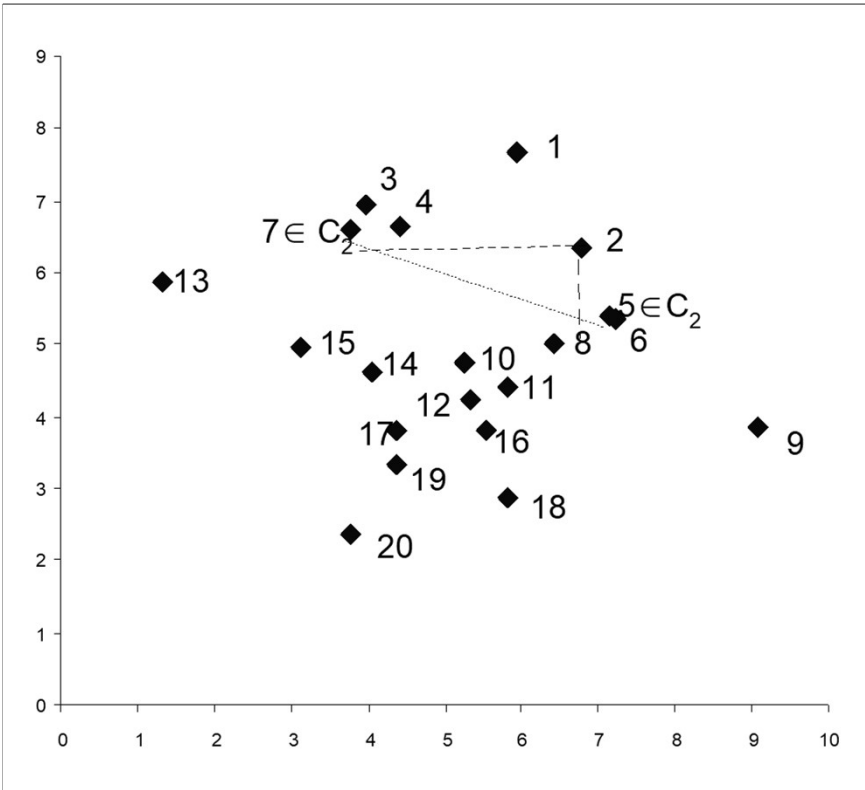


Placing an alternative in  $C_1$  utilizing dominance

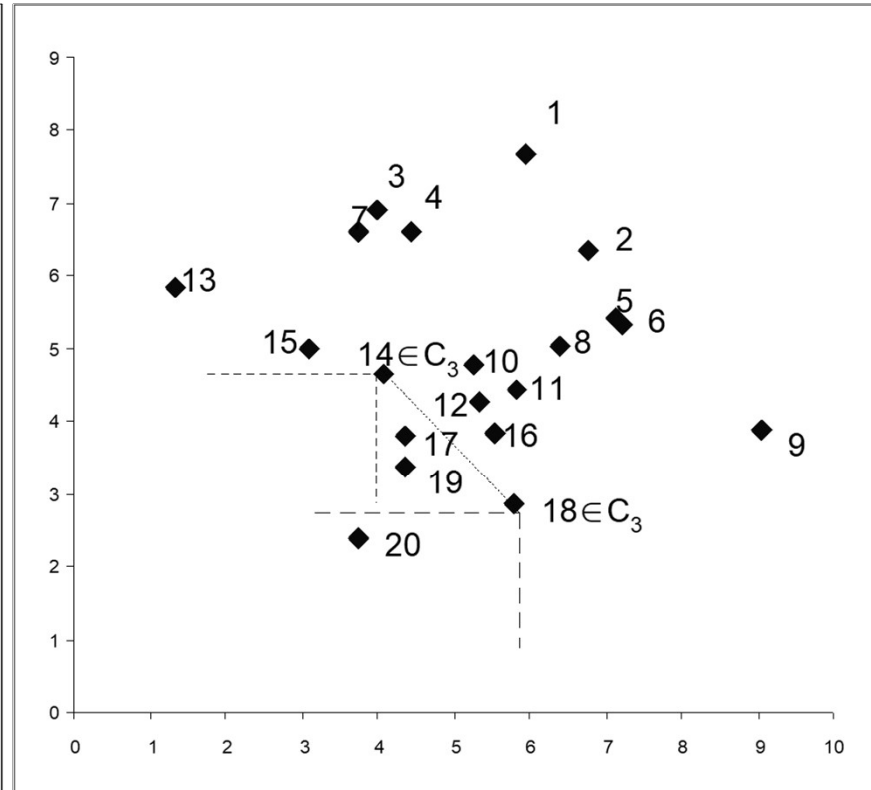


Placing an alternative in  $C_3$  utilizing dominance

# Convex Combinations

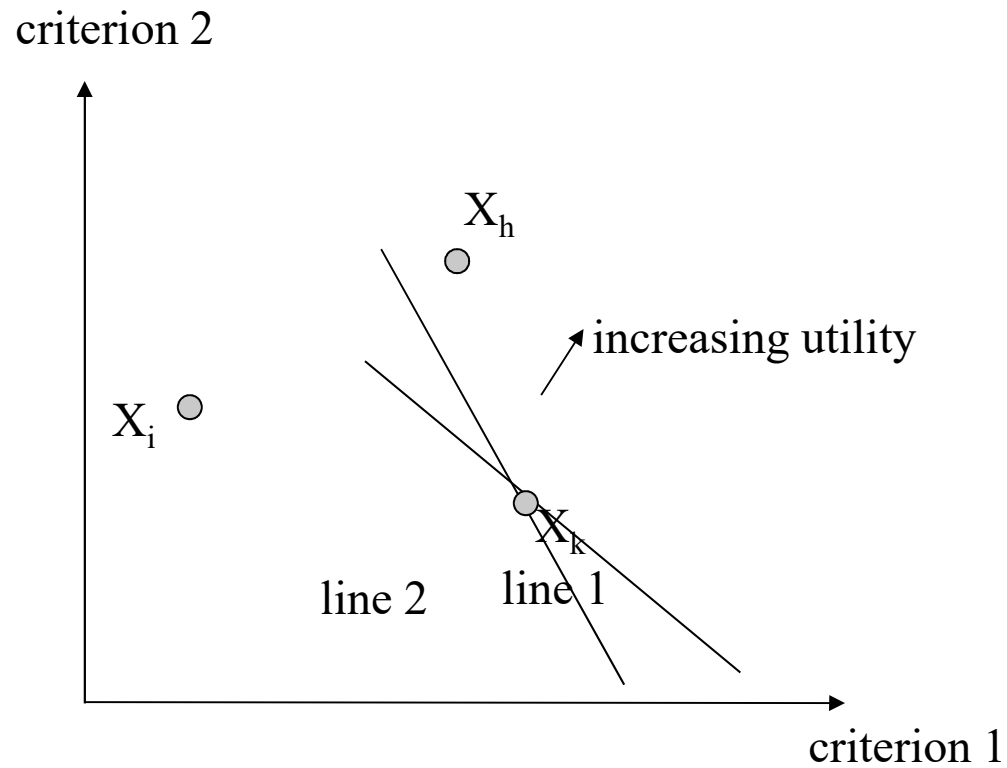


Using convex dominance to detect the worst possible class of an alternative



Using convex dominance to detect the best possible class of an alternative

# Weight Space Reduction



# Variations

- An Interactive sorting method for an additive  $v$  (Koksalan and Ozpeynirci, *COR* 2009)
- An Interactive probabilistic sorting method for an additive  $v$  (Bugdaci, Koksalan, Ozpeynirci, Serin, *IIE Transactions* 2013)
- An Interactive sorting method for quasiconcave  $v$  (Ulu & Koksalan, *NRL* 2014)



# **Design (Continuous Solution Space) Problem**

- Steuer, Multiple Criteria Optimization, Wiley 1986
- Miettinen, Nonlinear Multiobjective Opt, Kluwer 1999

## Further Outline

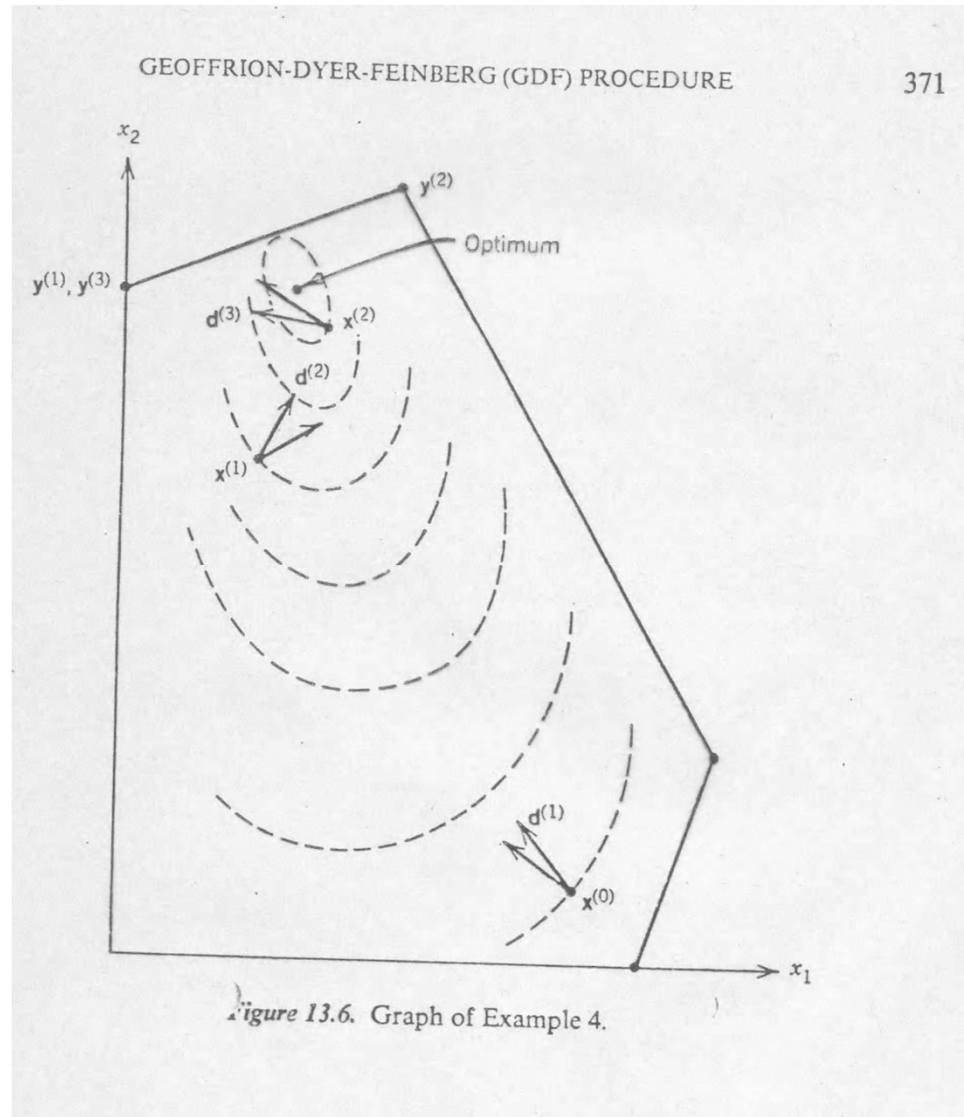
- Prior articulation of preferences
  - GP
- Progressive articulation of preferences
  - Interactive approaches-implicit value fn.
- Posterior articulation of preferences



# Progressive Articulation of Preferences

- Geoffrion, Dyer, and Feinberg (GDF) '72 *Man. Sci.*
  - Benayoun et al. (STEM) '71 *Math. Prog.*
  - Zionts & Wallenius (Z-W) '76 *Man. Sci.*
  - Steuer & Choo '83 *Math. Prog.*
  - Köksalan & Karasakal '06 *JORS*
  - Miettinen et al. '10 *EJOR*
  - \* Visual Aids
  - Korhonen & Laakso '86 *EJOR*
  - Korhonen & Wallenius '88 *NRL*
- and many others

# Frank-Wolfe (F-W) NLP (known v)



Source:  
Steuer (1986)

# Example

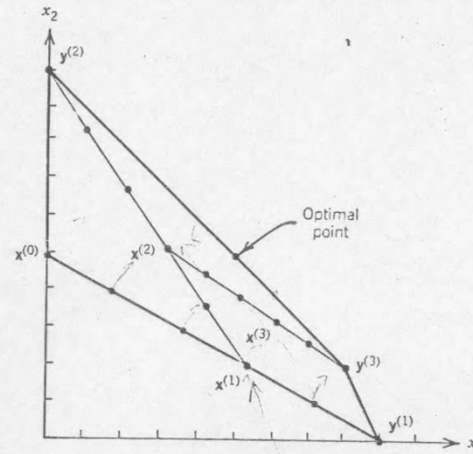


Figure 13.10. Graph of GDF example.

TABLE 13.1  
Iteration Data for the GDF Example

	$h = 1$		$h = 2$		$h = 3$	
$x^{(h-1)}$	(0, 5)		(5.4, 2)		(3.24, 5.2)	
$g$	(72, 12)		(115.2, 245.8)		(326, 223)	
$y^{(h)}$	(9, 0)		(0, 10)		(8, 2)	
$d^{(h)}$	(9, -5)		(-5.4, 8)		(4.76, -3.2)	
	<i>Stepwise Criterion Vectors</i>		<i>Stepwise Criterion Vectors</i>		<i>Stepwise Criterion Vectors</i>	
		$U$		$U$		$U$
	(0, 5)	36.0	(5.4, 2)	368.6	(3.24, 5.2)	691.1
	(1.8, 4)	196.0	(4.32, 3.6)	598.9	(4.192, 4.56)	833.3
	(3.6, 3)	338.6	(3.24, 5.2)	691.1	(5.144, 3.92)	913.8
	(5.4, 2)	368.6	(2.16, 6.8)	607.5	(6.096, 3.28)	922.4
	(7.2, 1)	269.0	(1.08, 3.4)	382.3	(7.048, 2.64)	858.2
	(9, 0)	100.0	(0, 10)	121.0	(8, 2)	729.0
$z^{(h)}$	(5.4, 2)		(3.24, 5.2)		(6.096, 3.28)	
$U(z^{(h)})$	368.6		691.1		922.4	

# **GDF (*Man. Sci.* 1972)**

- There are two problems when  $v$  is not known:
  1. We don't know the gradient (steepest ascent direction)
  2. We cannot find the best point along that direction

# GDF (cont.)

To obtain preference info:

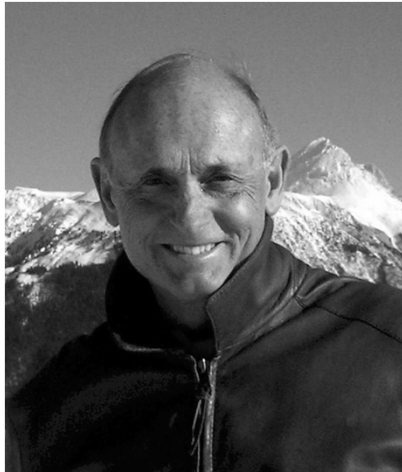
1. Locally approximate  $v$  by

$$F(x) = \sum w_i z_i(x)$$

Let  $w_1=1$ . Estimate  $w_i$  asking the DM local tradeoffs between  $z_1$  and  $z_i$ . *Let  $w_i = \frac{\Delta x_1}{\Delta x_i}$*

Find gradient of  $F(x)$  at the current  $x$ .

2. Ask the DM the best of several discrete points along the direction



Art Geoffrion



Jim Dyer

# The Step Method (STEM) Benayoun, deMontgolfier, Tergny, and Larichev (*Math. Prog.* 1971)



Oleg Larichev

In each iteration, solve (P):

*Min*  $\alpha$

*st*  $\alpha \geq \lambda_i(z_i^* - z_i(\mathbf{x})) \quad i \notin J^*$

$z_i(\mathbf{x}) \geq z_i(\mathbf{x}^{current}) - \Delta_i \quad i \in J^*$

$\mathbf{x} \in X$

Minimizes a weighted  
Tchebycheff distance  
from the ideal point

Parameters

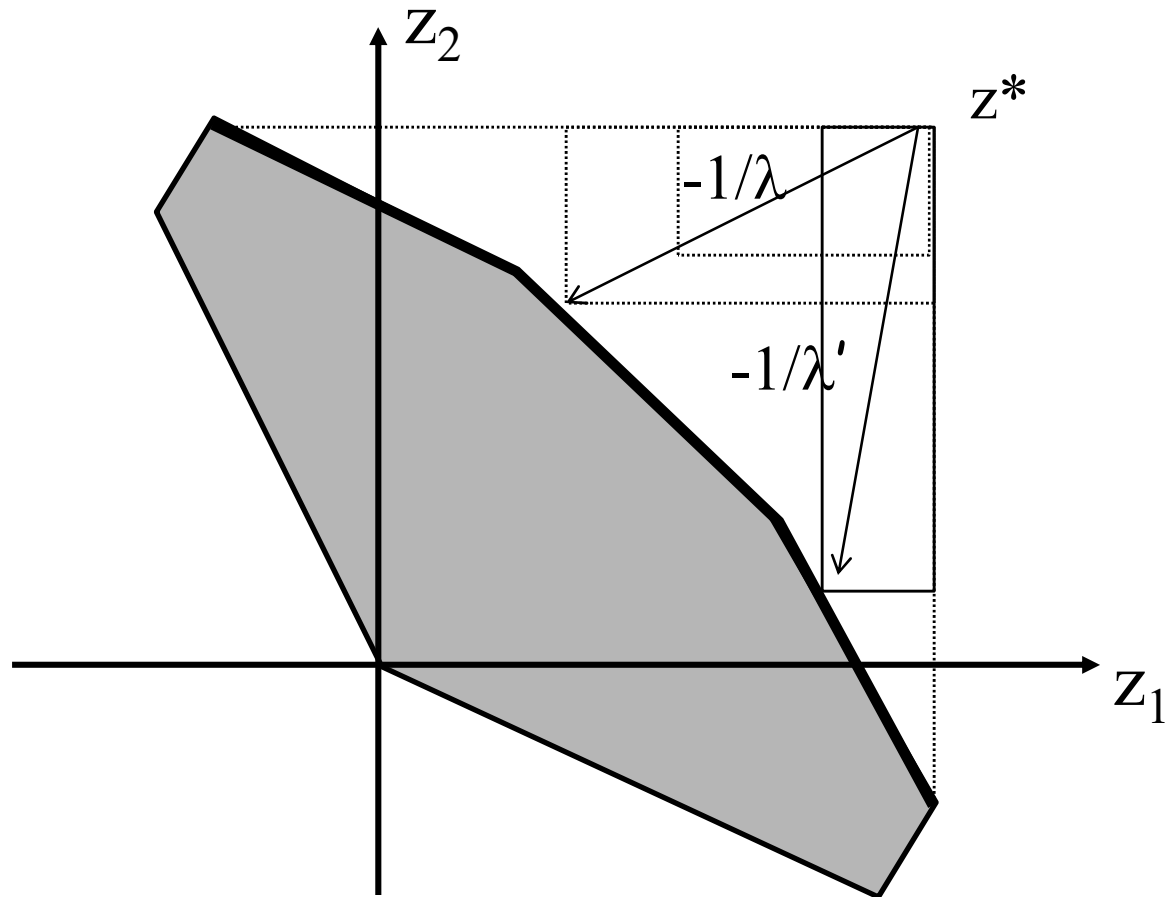
$\lambda_i$ : a weight for obj.  $i$

$\Delta_i$ : amount DM is willing to sacrifice in obj.  $i$

$z^*$ : is the ideal point

$J^*$ : Set of objectives DM is willing to sacrifice from

# In Criterion Space





# **Z-W Method (*Man. Sci.* 1976)**

- Assume
  - $v$  is linear
  - $z_i$  is linear for all  $i$
  - $X$  is a polytope

## **Z-W (cont.)**

1. Find an efficient extreme point solution maximizing an estimated linear  $v$
2. Find its adjacent efficient solutions
3. Ask the DM if he/she likes tradeoffs towards any adjacent eff solutions
  - If not; stop.
  - If yes; update the estimated  $v$  and go to 1.

# Augmented w. Tchebycheff function

Source: Steuer (1986)

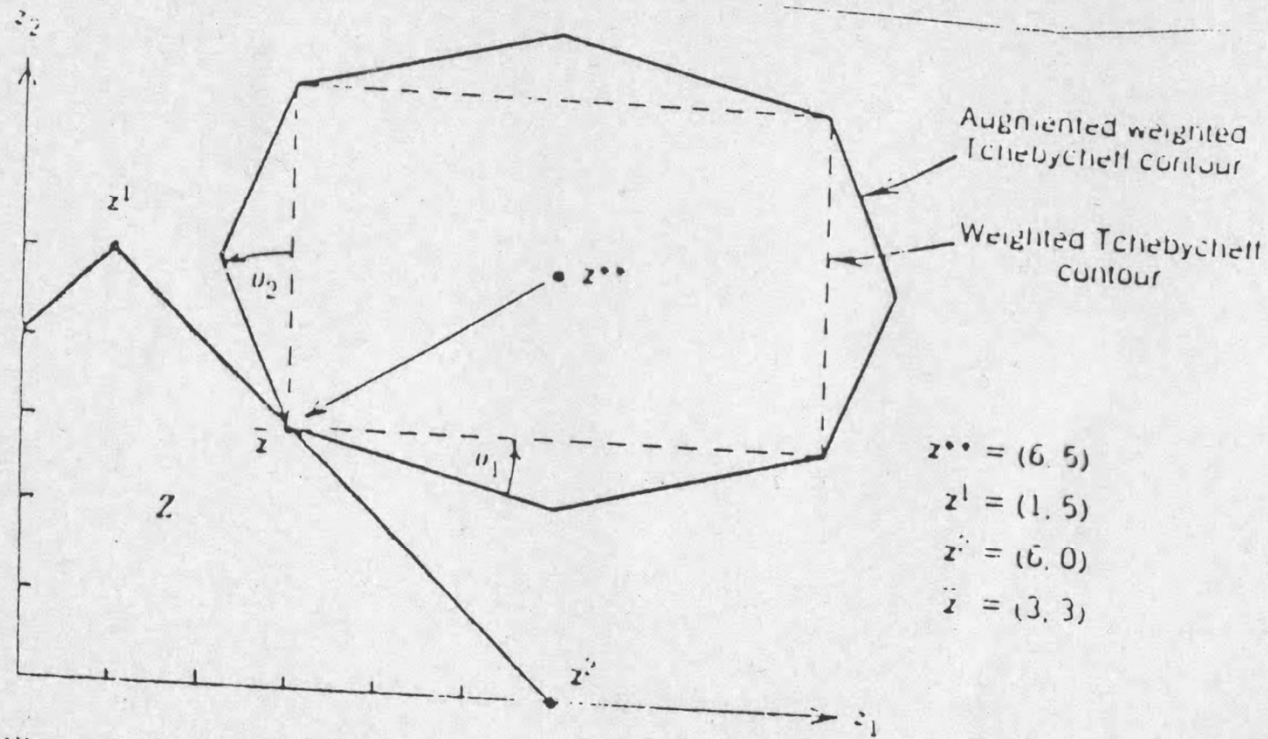


Figure 14.4. Contours of the  $\|z - z^{**}\|_{\infty}$  and  $\|z - \bar{z}\|_{\infty}$  metrics intersecting  $Z$

## Augmented w. Tchebycheff program

$$(TP) \quad \textit{Min} \alpha + \rho \sum (z_i^* - z_i(\mathbf{x}))$$

$$\alpha \geq \lambda_i (z_i^* - z_i(\mathbf{x}))$$

$$\mathbf{x} \in X$$

# Examples

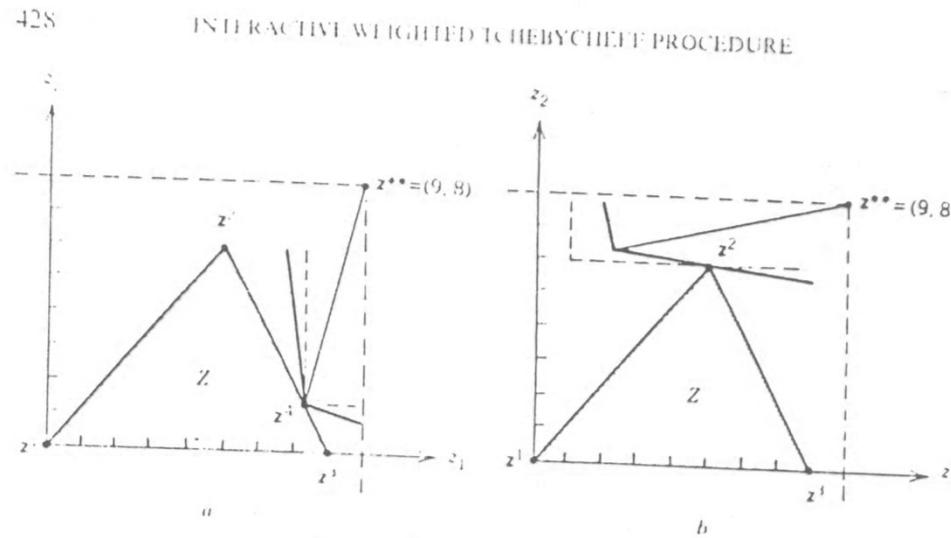


Figure 14.7. Graphs of Example 6.

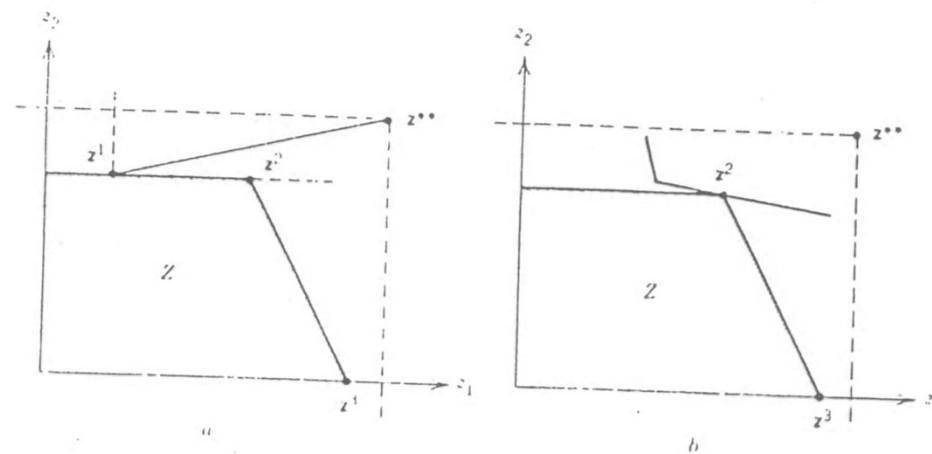
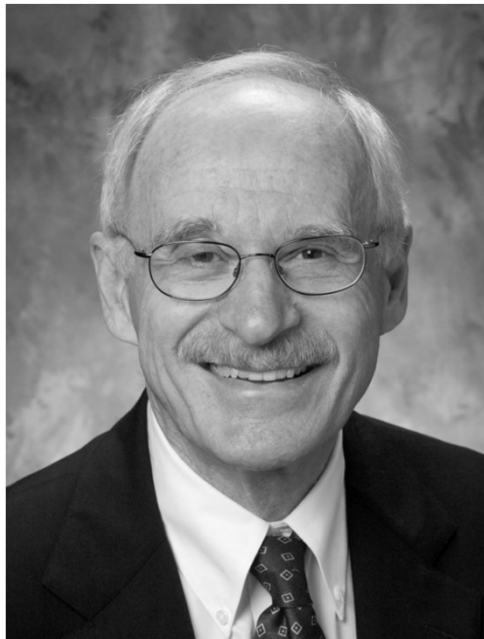


Figure 14.8. Graphs of Example 7.

Source: Steuer (1986)

## **Interactive w. Tch. Approach** **Steuer and Choo (*Math. Prog.* 1983)**

- Randomly generate weights
- With each weight set solve (TP) to find a set of eff solns
- Ask the DM best of a representative (small) set of eff solns
- Shrink the weight set around the weights favoring chosen solution
- Repeat several iterations



Ralph Steuer

# Achievement Scalarizing Program (ASP)

$$\text{Minimize } \alpha - \varepsilon \sum_{i=1}^m z_i(x)$$

$$\text{subject to : } \alpha \geq \lambda_i (q_i - z_i(x)) \quad \forall i$$

$$x \in X$$

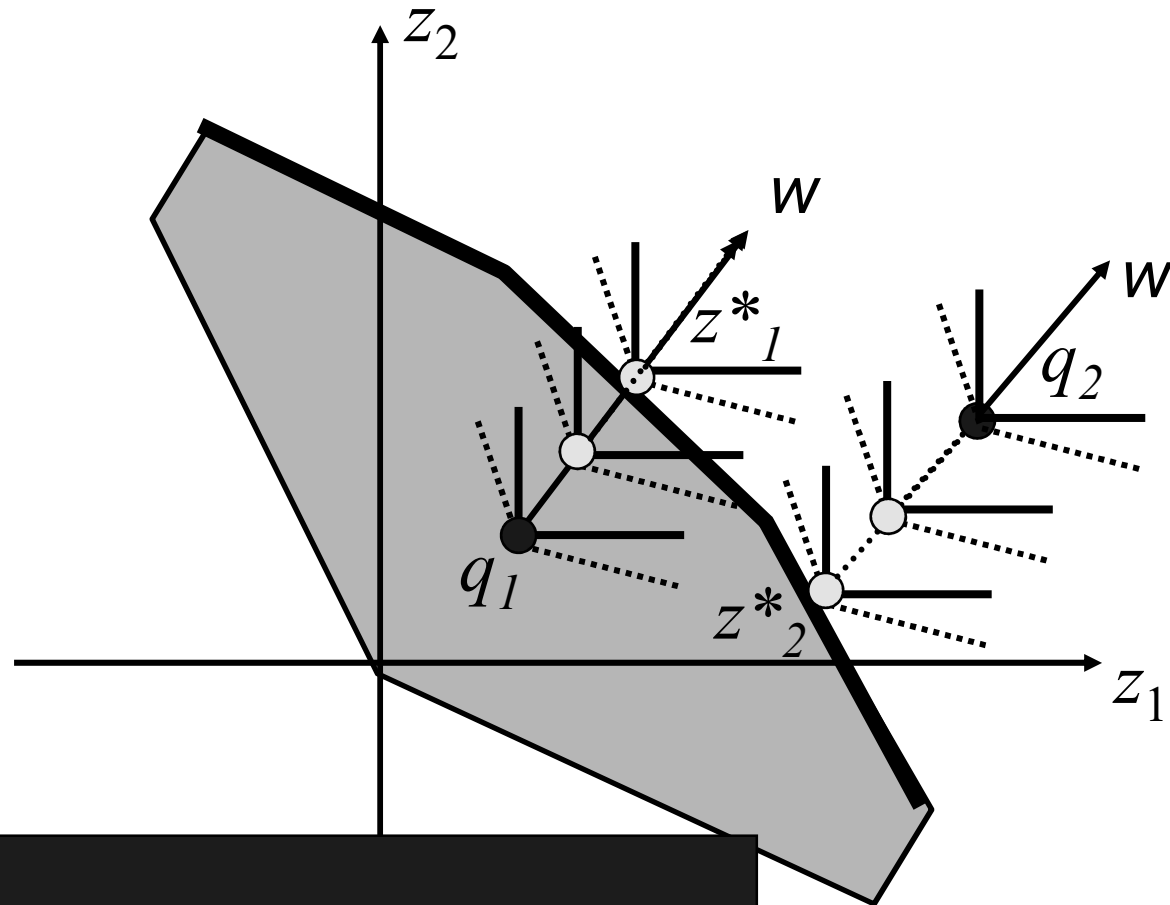
ASP projects  $q$  onto the efficient frontier in the direction  $1/\lambda$  (or  $-1/\lambda$ ).





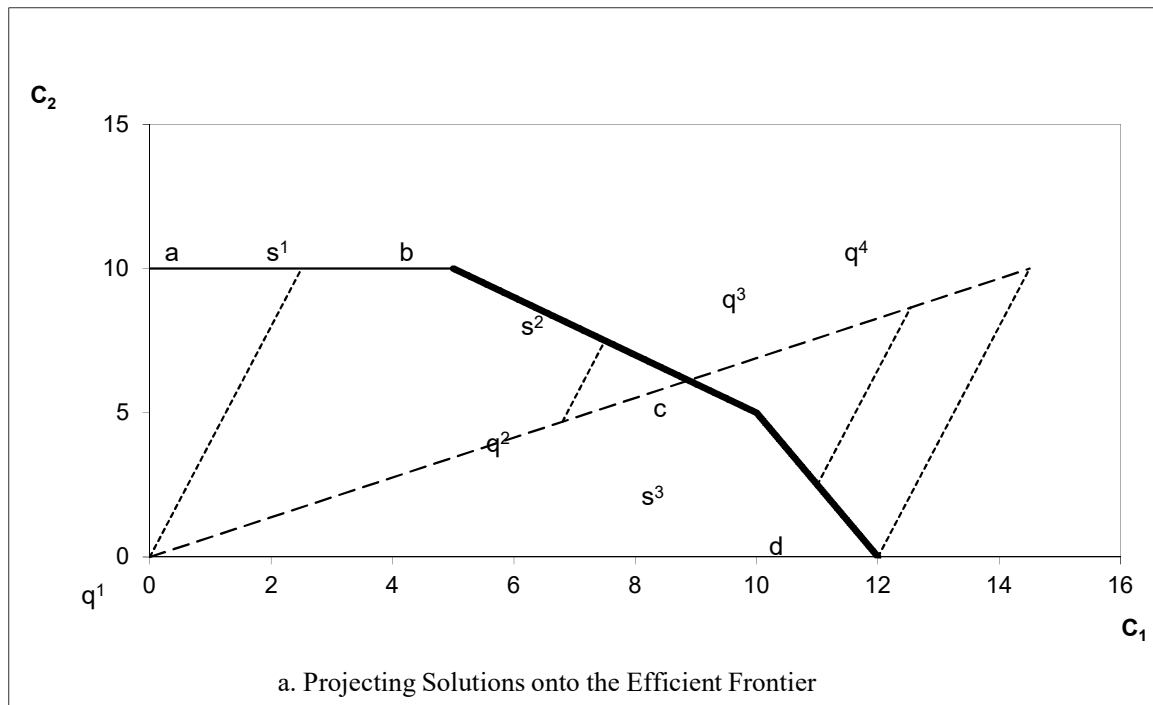
Andrzej Wierzbicki

# ASP



Any nondominated point  
can be reached!!

# Example: $\lambda_1 = .8, \lambda_2 = .2$

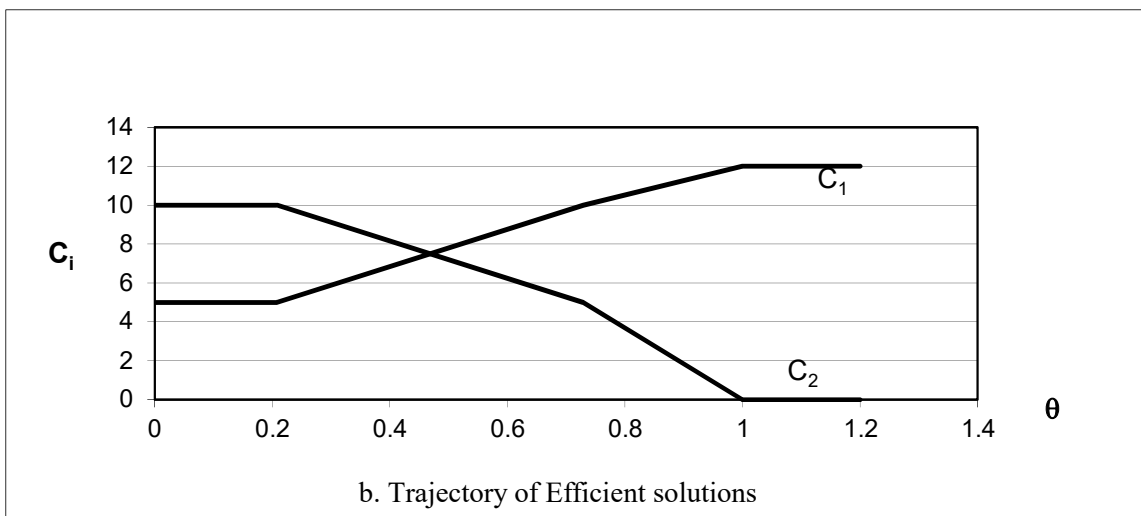
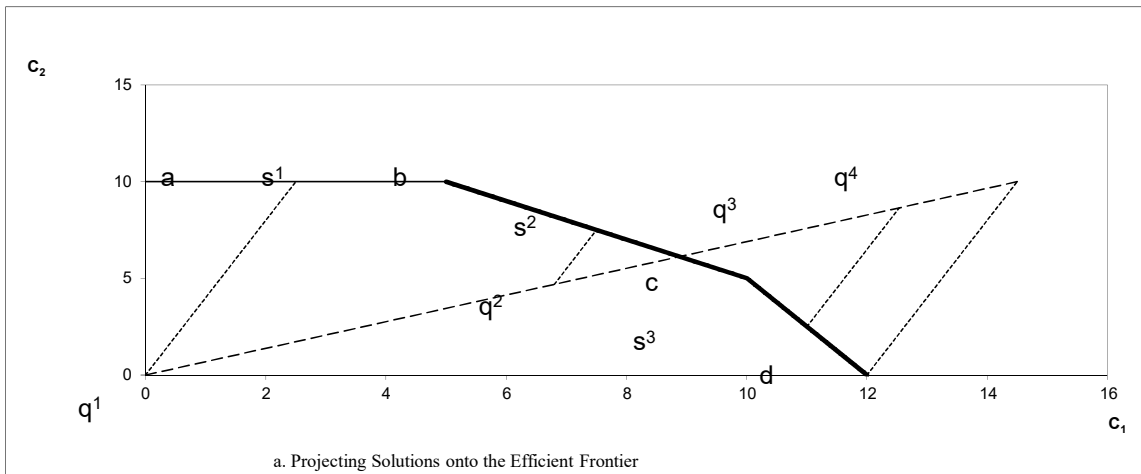


# Parametric ASP (Korhonen and Laakso *EJOR* '86)

$$\text{Minimize } \alpha - \varepsilon \sum_{i=1}^m z_i(x)$$

$$\text{s.t. } \alpha \geq \lambda_i (q_i + \theta_i d_i - z_i(x)) \quad \forall i$$

$$x \in X$$

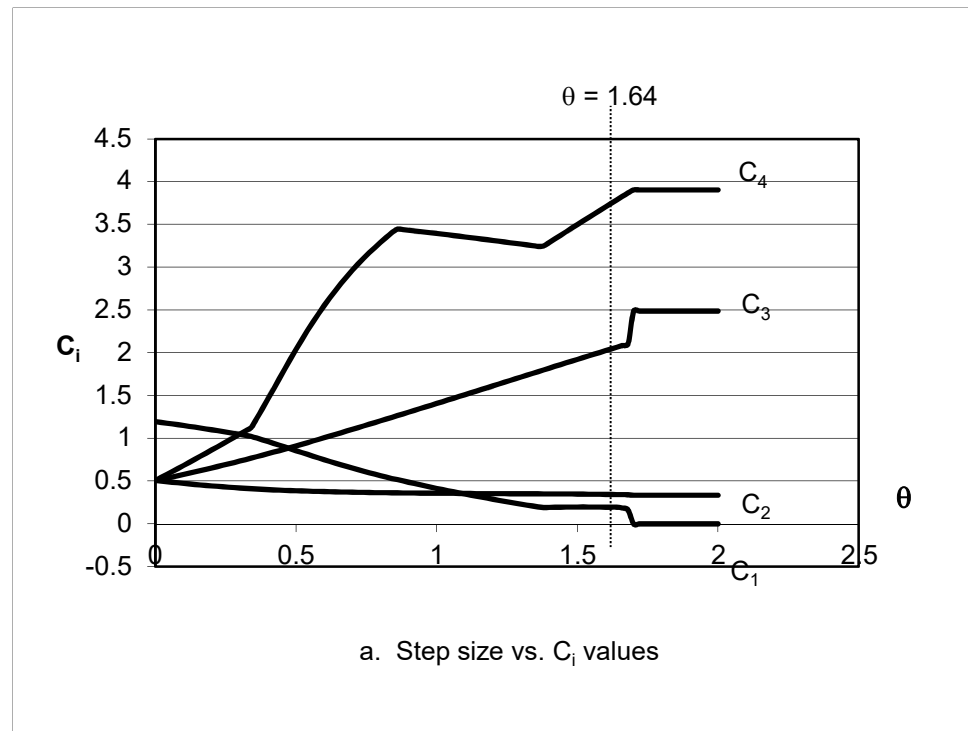


Example Influence of Design Parameters on Performance  
 Optimization and Param.  $\theta \in [0, 1.4]$   

$$Y_i = A_{ij} \sum_{j=1}^n X_j + \sum_{k=1}^m \frac{A_{ik} X_k^2}{2000}$$

$$A_{ij} = \text{Performance Matrix}$$

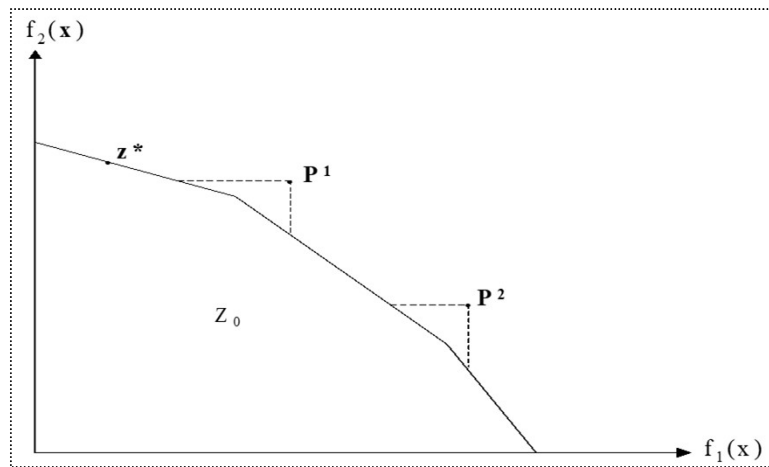
$$A_{ik} = \text{Design Parameter}$$



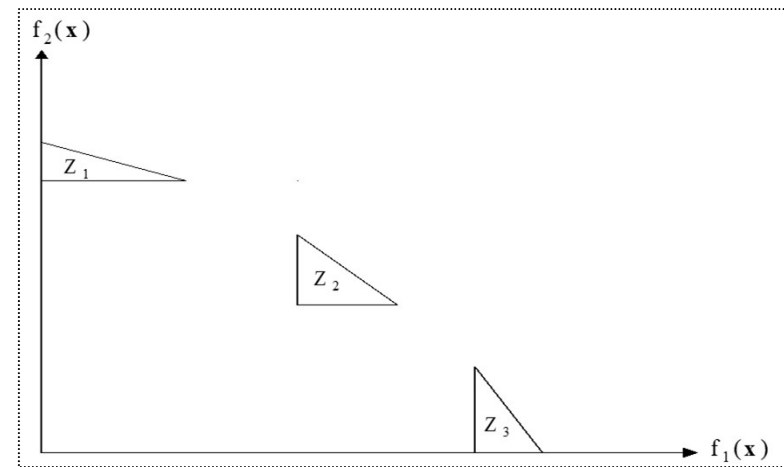
## An Iteration for a Nonlinear Product Design Problem

# General Monotone $v$ (Köksalan and Karasakal *JORS* '06)

Assume  $z^*$  is preferred to  $P^1$  and  $P^2$

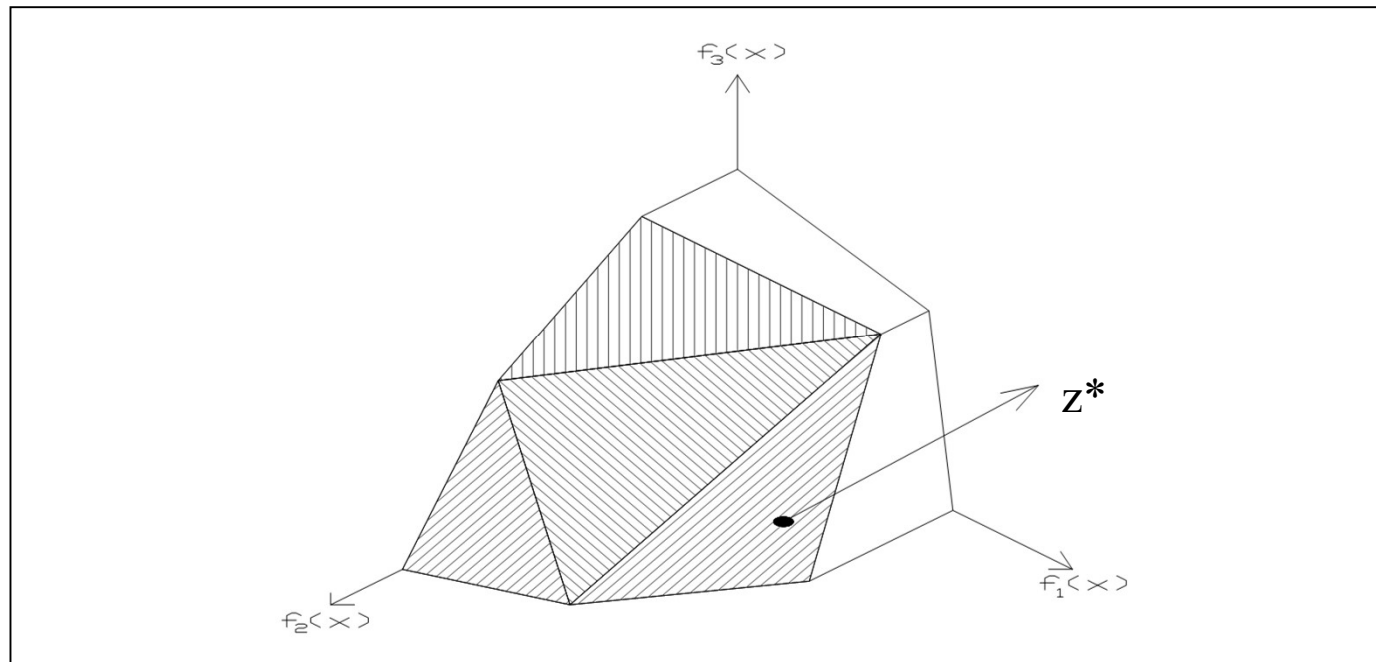


Original space



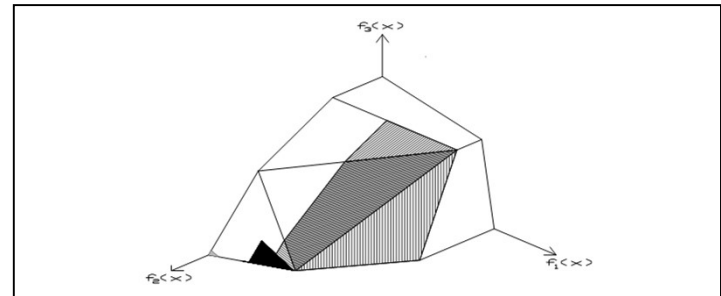
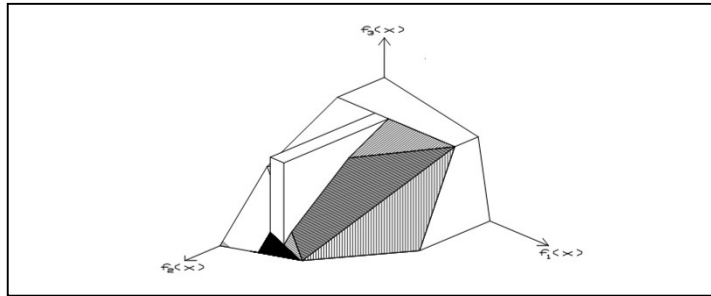
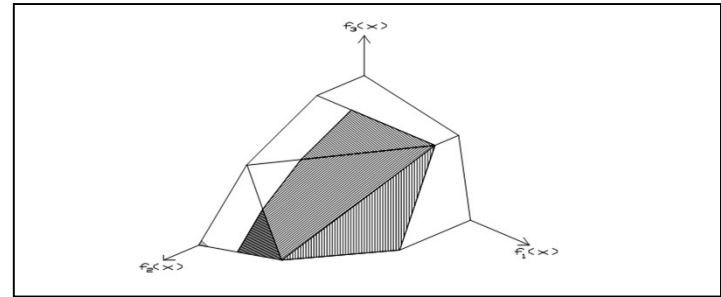
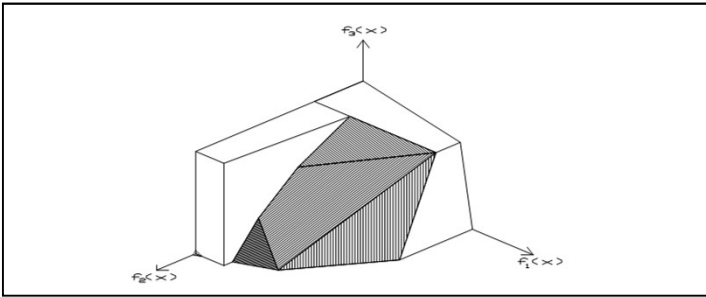
Reduced space

# Example

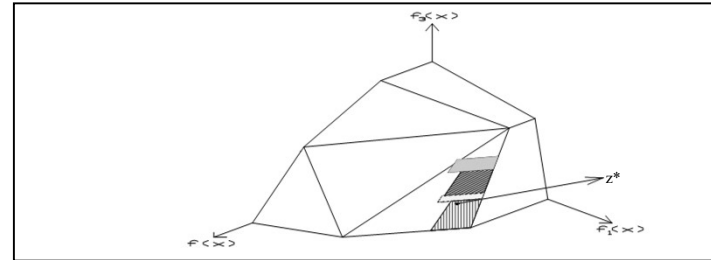
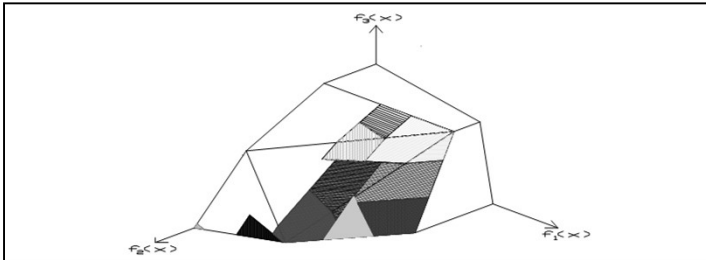
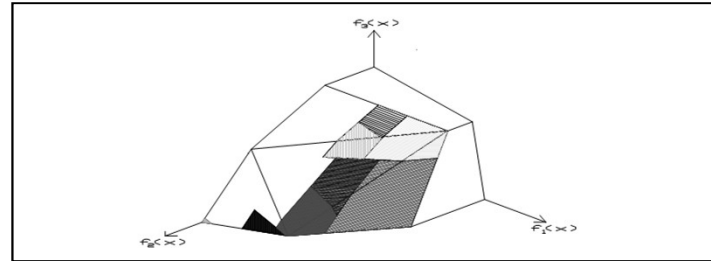
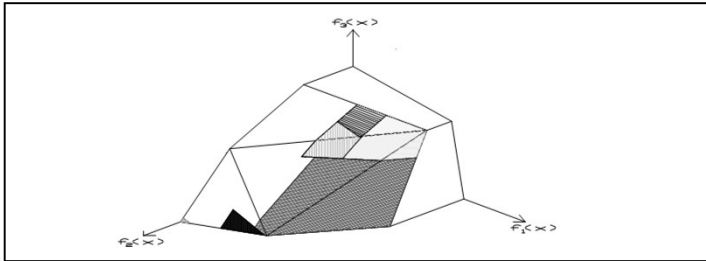
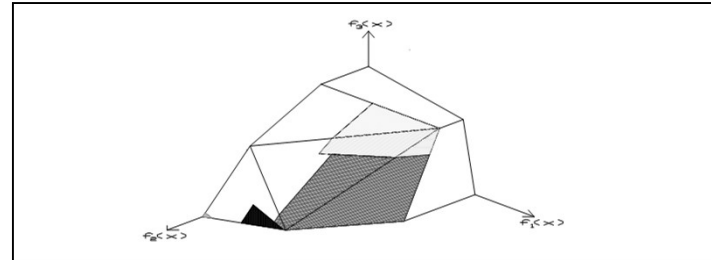
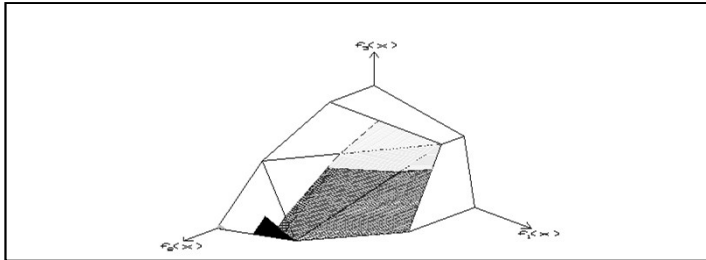




# Example (cont.)



# Example (cont.)



# **Nautilus-** **Miettinen, Eskelinen, Ruiz, Luque,** ***EJOR 2010***

- Starts from the nadir point
- Gets direction information
- Works through dominated solutions to eventually reach the Pareto front



# All “min” type

	Pref.	Visualization	Description																									
(a)		<table border="1"> <thead> <tr> <th></th> <th>min</th> <th>low</th> <th>current</th> <th>max</th> </tr> </thead> <tbody> <tr> <td>f1</td> <td>-6.34</td> <td>-6.34</td> <td>-4.07</td> <td>-4.07</td> </tr> <tr> <td>f2</td> <td>-3.44</td> <td>-3.44</td> <td>-2.83</td> <td>-2.83</td> </tr> <tr> <td>f3</td> <td>-7.50</td> <td>-7.50</td> <td>-0.32</td> <td>-0.32</td> </tr> <tr> <td>f4</td> <td>-0.00</td> <td>-0.00</td> <td>9.71</td> <td>9.71</td> </tr> </tbody> </table>		min	low	current	max	f1	-6.34	-6.34	-4.07	-4.07	f2	-3.44	-3.44	-2.83	-2.83	f3	-7.50	-7.50	-0.32	-0.32	f4	-0.00	-0.00	9.71	9.71	Initial situation
	min	low	current	max																								
f1	-6.34	-6.34	-4.07	-4.07																								
f2	-3.44	-3.44	-2.83	-2.83																								
f3	-7.50	-7.50	-0.32	-0.32																								
f4	-0.00	-0.00	9.71	9.71																								
(b)	2,2,1,1	<table border="1"> <thead> <tr> <th></th> <th>min</th> <th>low</th> <th>current</th> <th>max</th> </tr> </thead> <tbody> <tr> <td>f1</td> <td>-6.34</td> <td>-6.33</td> <td>-4.81</td> <td>-4.07</td> </tr> <tr> <td>f2</td> <td>-3.44</td> <td>-3.42</td> <td>-3.00</td> <td>-2.83</td> </tr> <tr> <td>f3</td> <td>-7.50</td> <td>-7.49</td> <td>-1.32</td> <td>-0.32</td> </tr> <tr> <td>f4</td> <td>-0.00</td> <td>0.65</td> <td>8.35</td> <td>9.71</td> </tr> </tbody> </table>		min	low	current	max	f1	-6.34	-6.33	-4.81	-4.07	f2	-3.44	-3.42	-3.00	-2.83	f3	-7.50	-7.49	-1.32	-0.32	f4	-0.00	0.65	8.35	9.71	Iteration 1
	min	low	current	max																								
f1	-6.34	-6.33	-4.81	-4.07																								
f2	-3.44	-3.42	-3.00	-2.83																								
f3	-7.50	-7.49	-1.32	-0.32																								
f4	-0.00	0.65	8.35	9.71																								
(c)	2,2,1,1	<table border="1"> <thead> <tr> <th></th> <th>min</th> <th>low</th> <th>current</th> <th>max</th> </tr> </thead> <tbody> <tr> <td>f1</td> <td>-6.34</td> <td>-6.31</td> <td>-5.54</td> <td>-4.07</td> </tr> <tr> <td>f2</td> <td>-3.44</td> <td>-3.39</td> <td>-3.17</td> <td>-2.83</td> </tr> <tr> <td>f3</td> <td>-7.50</td> <td>-7.15</td> <td>-2.32</td> <td>-0.32</td> </tr> <tr> <td>f4</td> <td>-0.00</td> <td>2.28</td> <td>7.00</td> <td>9.71</td> </tr> </tbody> </table>		min	low	current	max	f1	-6.34	-6.31	-5.54	-4.07	f2	-3.44	-3.39	-3.17	-2.83	f3	-7.50	-7.15	-2.32	-0.32	f4	-0.00	2.28	7.00	9.71	It. 2. Backward step
	min	low	current	max																								
f1	-6.34	-6.31	-5.54	-4.07																								
f2	-3.44	-3.39	-3.17	-2.83																								
f3	-7.50	-7.15	-2.32	-0.32																								
f4	-0.00	2.28	7.00	9.71																								
(d)	2,3,1,4	<table border="1"> <thead> <tr> <th></th> <th>min</th> <th>low</th> <th>current</th> <th>max</th> </tr> </thead> <tbody> <tr> <td>f1</td> <td>-6.34</td> <td>-6.32</td> <td>-5.56</td> <td>-4.07</td> </tr> <tr> <td>f2</td> <td>-3.44</td> <td>-3.35</td> <td>-3.12</td> <td>-2.83</td> </tr> <tr> <td>f3</td> <td>-7.50</td> <td>-7.14</td> <td>-1.79</td> <td>-0.32</td> </tr> <tr> <td>f4</td> <td>-0.00</td> <td>1.68</td> <td>5.82</td> <td>9.71</td> </tr> </tbody> </table>		min	low	current	max	f1	-6.34	-6.32	-5.56	-4.07	f2	-3.44	-3.35	-3.12	-2.83	f3	-7.50	-7.14	-1.79	-0.32	f4	-0.00	1.68	5.82	9.71	Iteration 3
	min	low	current	max																								
f1	-6.34	-6.32	-5.56	-4.07																								
f2	-3.44	-3.35	-3.12	-2.83																								
f3	-7.50	-7.14	-1.79	-0.32																								
f4	-0.00	1.68	5.82	9.71																								
(e)	1,2,1,2	<table border="1"> <thead> <tr> <th></th> <th>min</th> <th>low</th> <th>current</th> <th>max</th> </tr> </thead> <tbody> <tr> <td>f1</td> <td>-6.34</td> <td>-6.30</td> <td>-6.30</td> <td>-4.07</td> </tr> <tr> <td>f2</td> <td>-3.44</td> <td>-3.26</td> <td>-3.26</td> <td>-2.83</td> </tr> <tr> <td>f3</td> <td>-7.50</td> <td>-2.60</td> <td>-2.60</td> <td>-0.32</td> </tr> <tr> <td>f4</td> <td>-0.00</td> <td>3.63</td> <td>3.63</td> <td>9.71</td> </tr> </tbody> </table>		min	low	current	max	f1	-6.34	-6.30	-6.30	-4.07	f2	-3.44	-3.26	-3.26	-2.83	f3	-7.50	-2.60	-2.60	-0.32	f4	-0.00	3.63	3.63	9.71	It. 4. Final solution
	min	low	current	max																								
f1	-6.34	-6.30	-6.30	-4.07																								
f2	-3.44	-3.26	-3.26	-2.83																								
f3	-7.50	-2.60	-2.60	-0.32																								
f4	-0.00	3.63	3.63	9.71																								

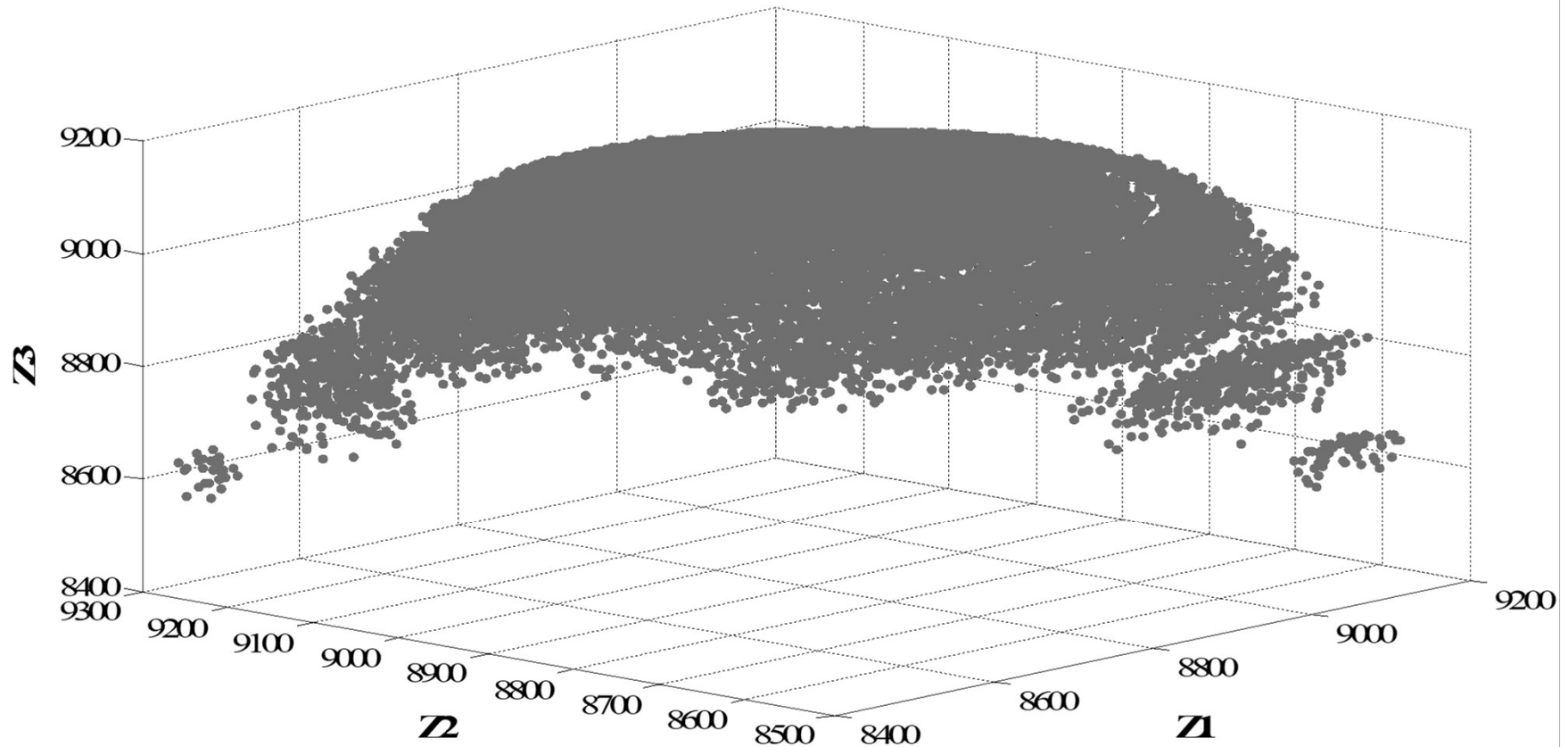
Fig. 3. Some iterations with NAUTILUS.

# Combinatorial problems (MOCO)

- Mostly bicriteria approaches
- Many “optimize” a given  $v$
- Some generate the nondominated set
- Many use modern heuristic search
- Few interactive approaches
- Review article (Ehrgott & Gandibleux '00 *OR Spektrum*)
- Multi-objective Optimization using Evolutionary Algorithms (Deb '01)
- Computationally hard  
(NP-complete, #P-complete)

# INTRODUCTION

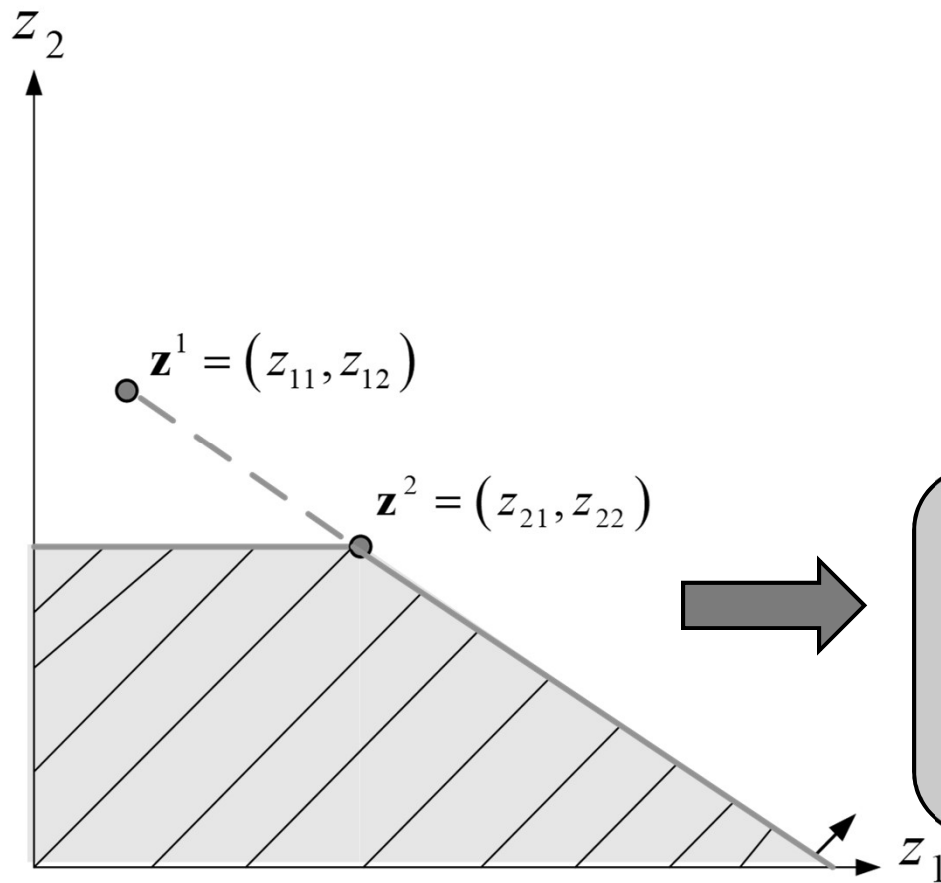
*200-item MOKP with 27260 nondominated points*



# QUASICONCAVE VALUE FUNCTION AND CONES

Lokman, Köksalan, Korhonen, Wallenius (*ANOR* 2016)

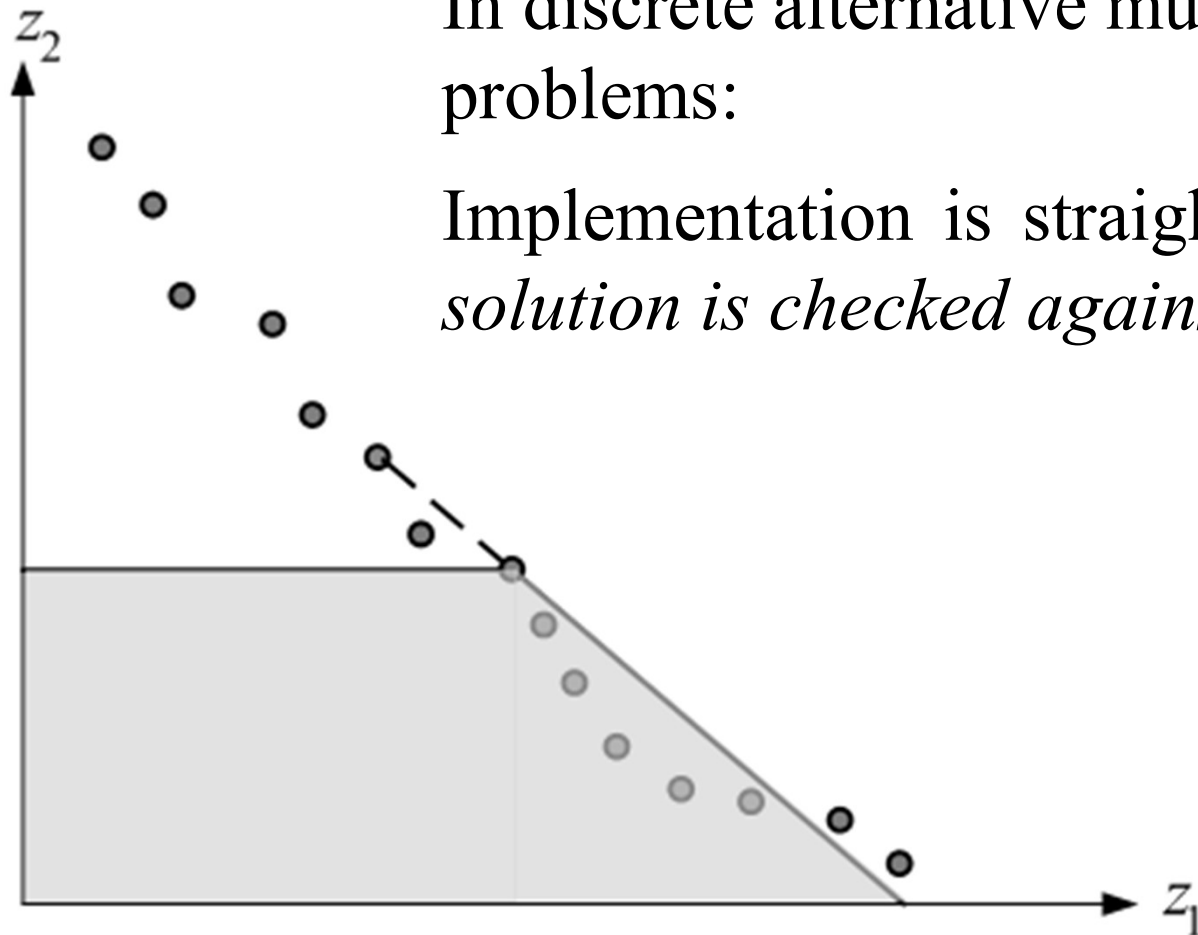
## Demonstration of a 2-point convex cone



Cone dominated region  
If  $\mathbf{z}^1$  is preferred to  $\mathbf{z}^2$ ,  
all points in this region will be  
less preferred than  $\mathbf{z}^1$ .

The region dominated by  $C(\mathbf{z}^1; \mathbf{z}^2)$  – (Korhonen et al. 1984)

# QUASICONCAVE VALUE FUNCTION AND CONES



In discrete alternative multi-objective problems:

Implementation is straight forward: *each solution is checked against each cone.*



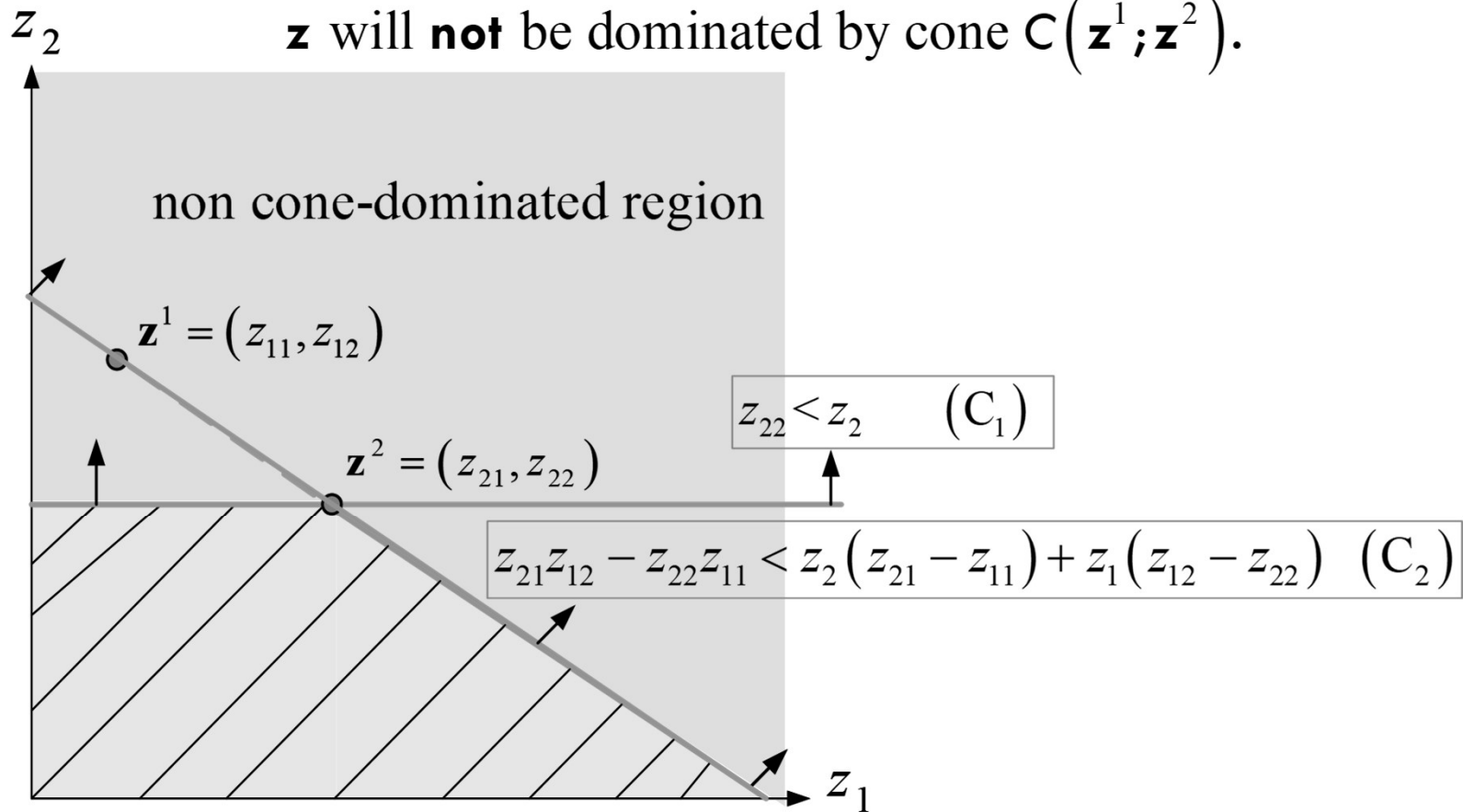
# QUASICONCAVE VALUE FUNCTION AND CONES

In our case:

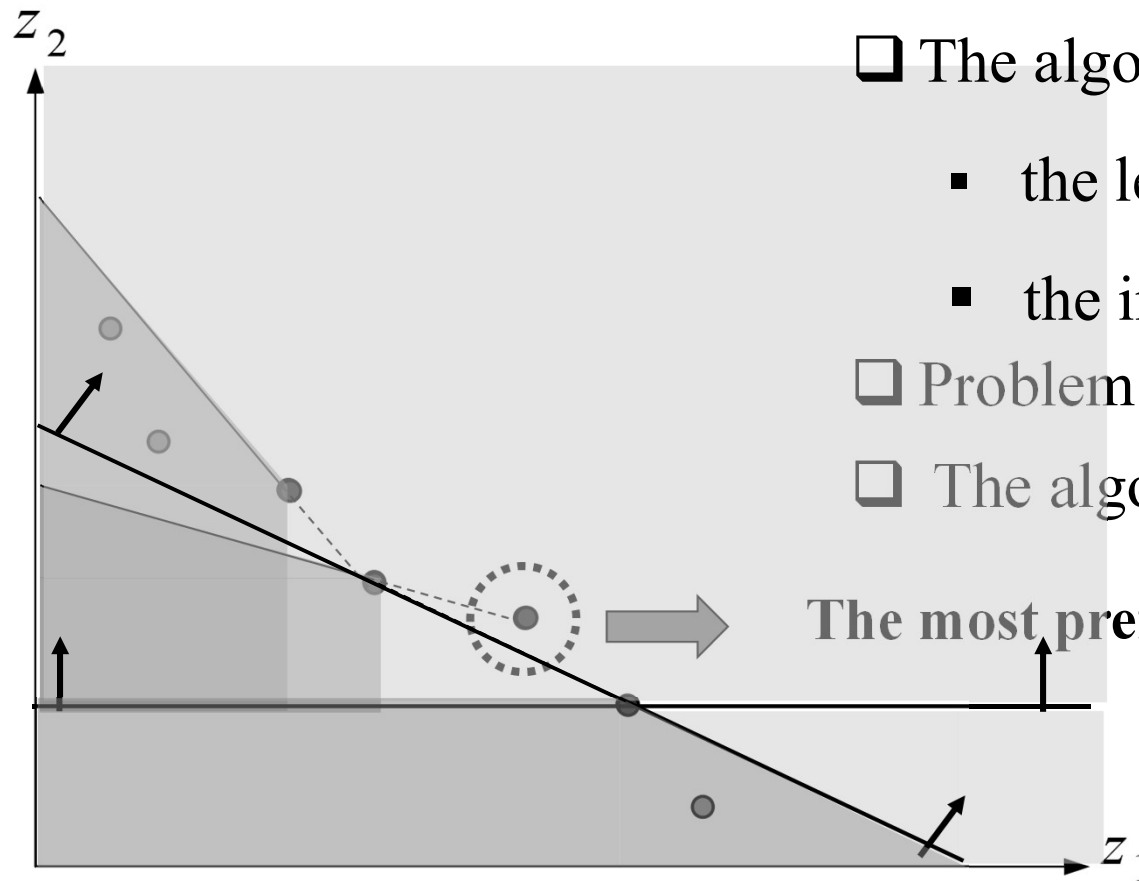
- The solution space is defined by a set of constraints.
- Nondominated points are implicit.
- We need to characterize the admissible solution space: the non cone-dominated region.
- This region is typically nonconvex.
- Representing the admissible region is more manageable with 2-point cones.

# QUASICONCAVE VALUE FUNCTION AND CONES

Idea      If (C1) or (C2) is satisfied, then we guarantee  $\mathbf{z}$  will **not** be dominated by cone  $\mathbf{C}(\mathbf{z}^1; \mathbf{z}^2)$ .



# AN INTERACTIVE ALGORITHM



- The algorithm excludes:
  - the less preferred regions
  - the incumbent point
- Problem becomes infeasible.
- The algorithm stops.

# AN INTERACTIVE ALGORITHM

## Solving MIP Problems Using Convex Preference Cones

Assuming quasiconcavity of DM's value function:

- iteratively generates new nondominated points
- constructs 2-point convex cones based on the preferences of the DM.
- keeps an incumbent point and excludes inferior regions and the incumbent point.
- terminates when problem becomes infeasible since it implies all remaining nondominated points are inferior to the incumbent.
- guarantees finding the most preferred point

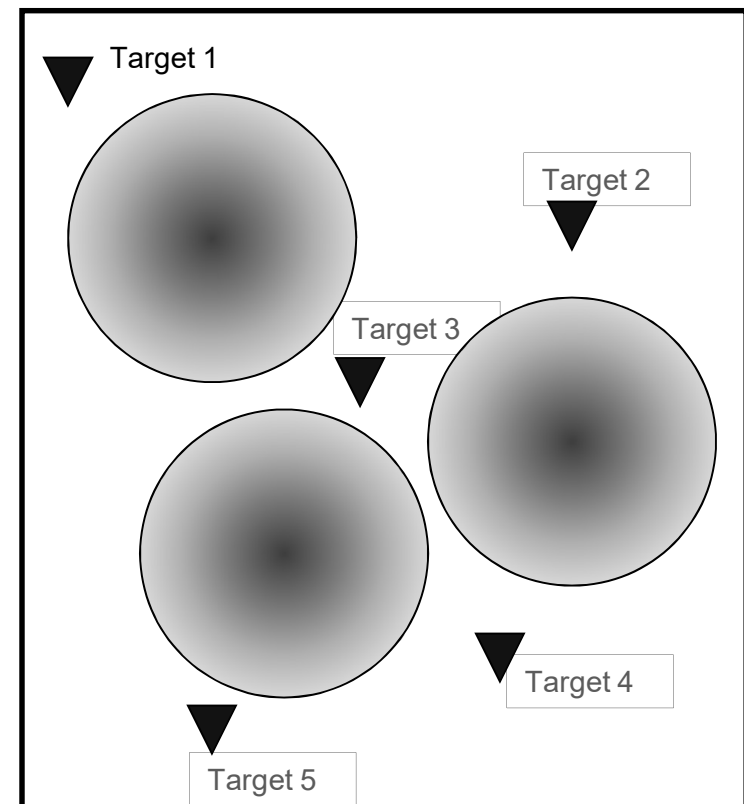


# UAV ROUTE PLANNING

Öztürk Tezcaner D. and M. Köksalan, *ANOR* (2016)

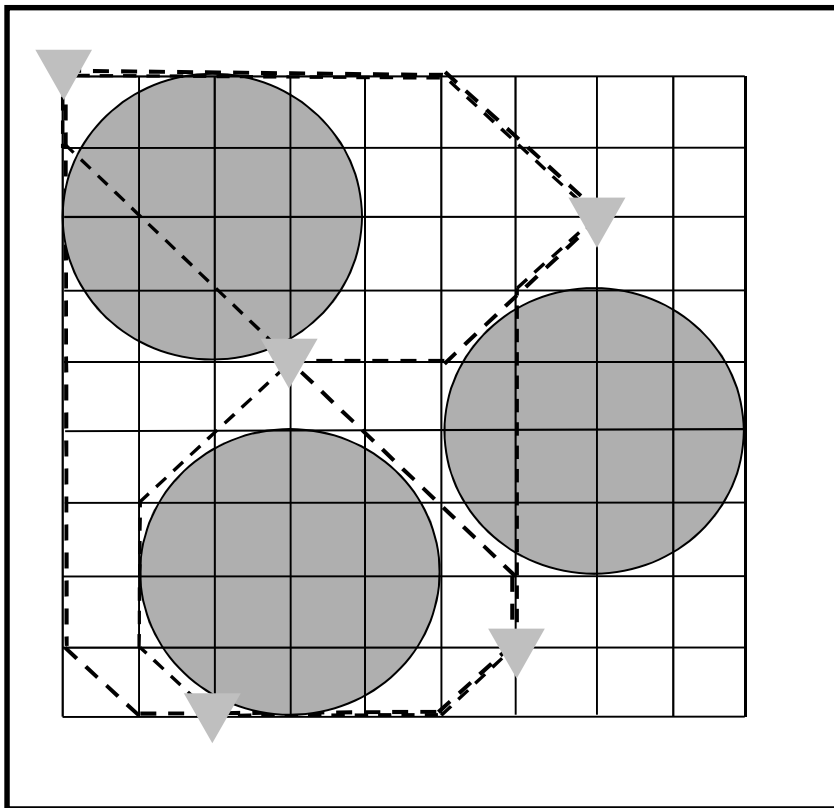
- UAV starts from a base, visits all targets, and returns to the base
- Minimize;
  - distance
  - radar detection threat

→ Biobjective Routing Problem

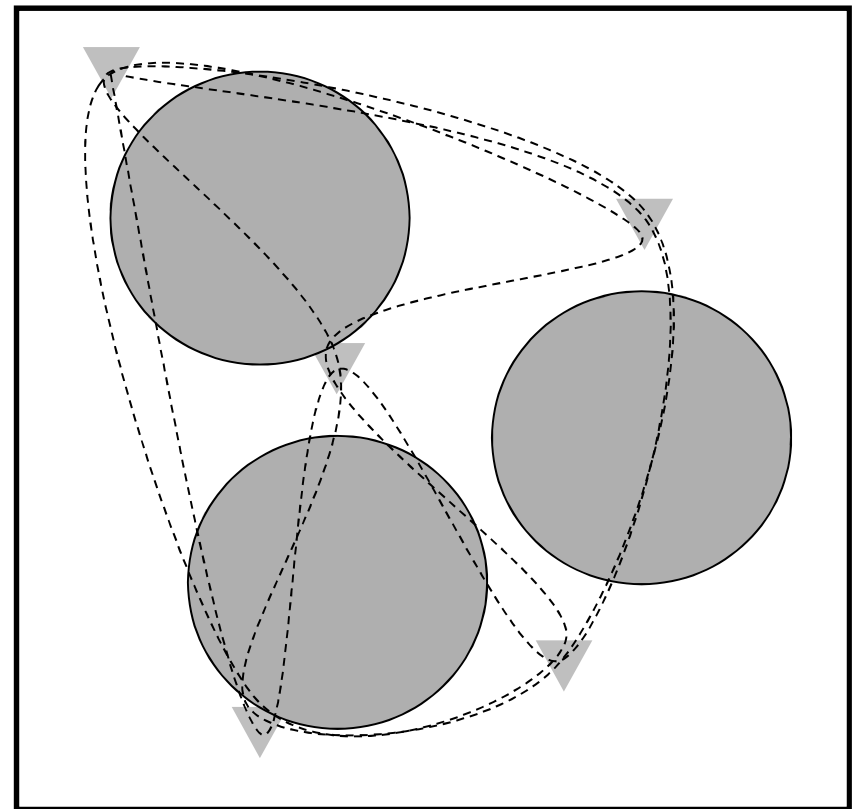


# Terrain Types

## Discretized Terrain



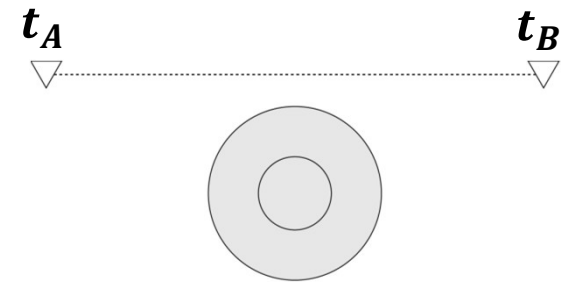
## Continuous Terrain



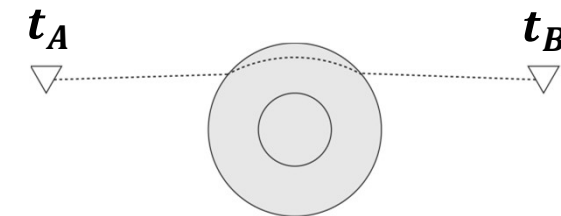
# Movement Between Targets

Three types of moves:

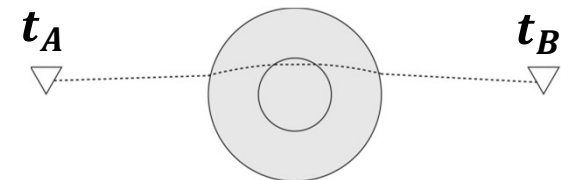
*Type 1:* No intersection with the radar region



*Type 2:* Moves through outer radar region only

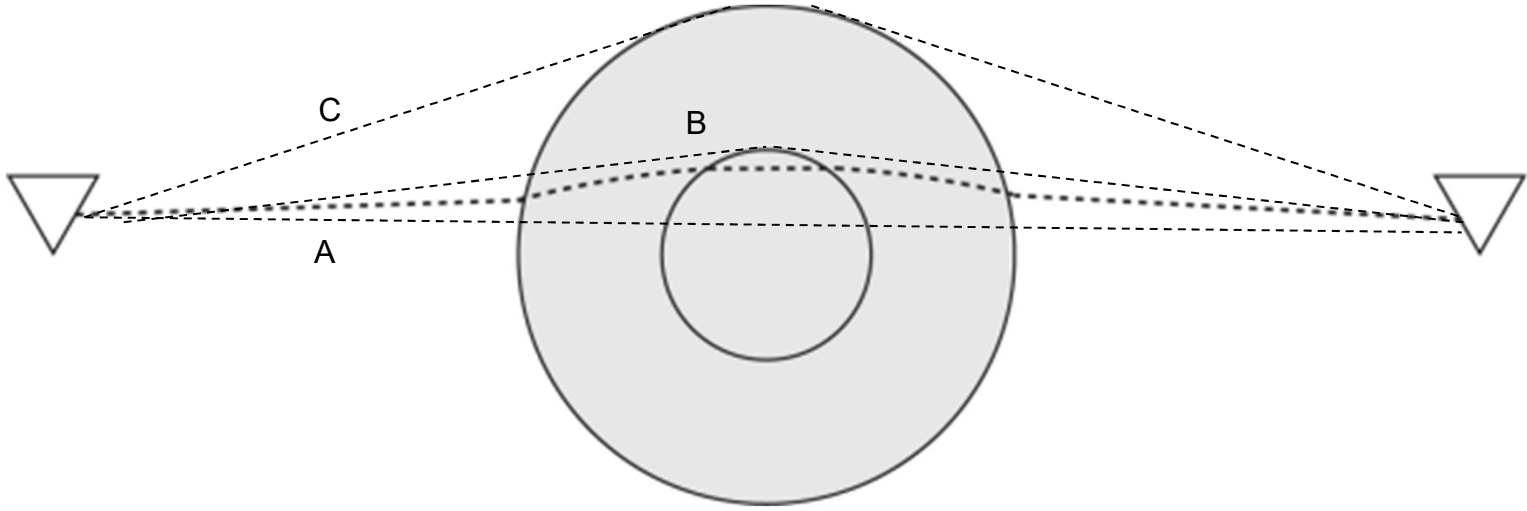


*Type 3:* Moves through both radar regions



$$D = \int_{t_A}^{t_B} ds$$

$$RDT = \int_{t_A}^{t_B} p_d \cdot ds$$

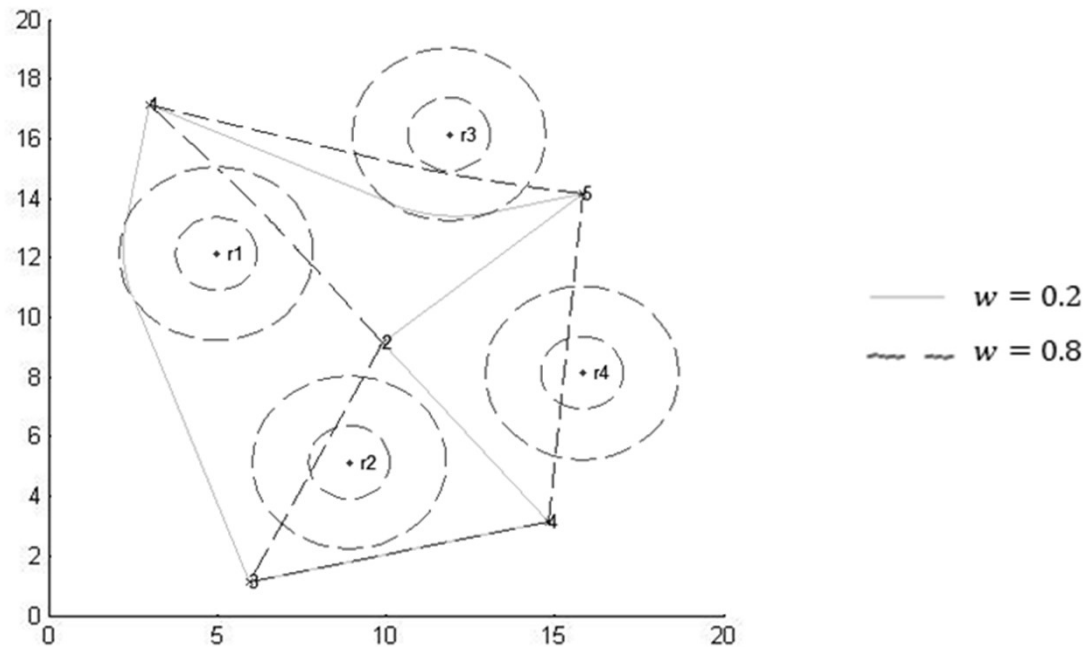




# UAV Routing - Continuous Terrain

- Finding the most preferred solution of a DM with linear preference function

$$U(z) = w \cdot z_1(x) + (1 - w) \cdot z_2(x) \text{ where } 0 < w < 1$$



Routes found for  $w = 0.2$  and  $w = 0.8$

# Recent Software

- iMOLPe - interactive Multi-Objective Linear Programming explorer
- Visualization of results obtained with TRIMAP, STEM, ICW and Pareto Race interactive methods.
- Free download: <http://www.uc.pt/en/org/inescc/software>



# Some References

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Bozkurt, B., Fowler, J. W., Gel, E. S., Kim, B., Köksalan, M., and Wallenius, J. "Quantitative Comparison of Approximate Solution Sets for Multi-Criteria Optimization Problems with Weighted Tchebycheff Preference Function," *Operations Research* 58 (3), 650-659, 2010.

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# Resources

## International Society on MCDM:

<http://www.mcdmsociety.org/> : Free membership thru Web site

## International Conferences

- 25<sup>th</sup> International Conference, Summer 2019, Istanbul, Turkey, Ilker Topcu.
- 24<sup>th</sup> International Conference, July 9-14, 2017, Ottawa, Canada, Sarah Ben Amor.
- 23<sup>rd</sup> International Conference, August 3-7, 2015, Hamburg, Germany, Martin J. Geiger.
- 22<sup>nd</sup> International Conference, June 17-21, 2013, Málaga, Spain, Francisco Ruiz.
- 21<sup>st</sup> International Conference, June 13-17, 2011, Jyväskylä, Finland, Kaisa Miettinen
- 20<sup>th</sup> International Conference, June 22-26, 2009, Chengdu, China, Yong Shi, S. Wang
- 19<sup>th</sup> International Conference, January 7-12, 2008, Auckland, New Zealand, M. Ehrgott
- 18<sup>th</sup> International Conference, June 19-23, 2006, Chania, Greece, C. Zapounidis
- 17<sup>th</sup> International Conference, August 6-11, 2004, Vancouver, Canada, Bill Wedley
- 16<sup>th</sup> International Conference, 2002, Semmering, Austria, M. Luptacik, R. Vetschera
- 15<sup>th</sup> International Conference, July 10-14, 2000, Ankara, Turkey, Murat Köksalan
- ...
- 1<sup>st</sup> International Conference, 1975, Jouy-en-Josas, France, H. Thiriez, S. Zionts



# **Resources (cont.)**

## **Other groups:**

- **INFORMS Section on MCDM**
- **EURO Working Group on MCDA (MCDA '84, Vienna, Austria, September 22-24, 2016)**
- **GP**
- **MOEA**
- **...**



# Publications

- Many books
- Journal of MCDA
- Springer Proceedings
- Regular OR Journals
- Other Specialized Journals





# History of MCDM

Multiple Criteria Decision Making: From Early History to the 21<sup>st</sup> Century by M. Köksalan, J. Wallenius and S. Zionts, World Scientific, 2011.

"Our ability to analyze and resolve complex decision problems is one of the most important developments of the last half of the 20th century. But, like all such endeavors, advances were often based on earlier ideas from a multitude of fields, ideas that encouraged and gave impetus to new generations of researchers. All readers of *Multiple Criteria Decision Making: From Early History to the 21st Century* will find that the authors have woven the early and modern histories of MCDM into a scientific adventure story one that helps us to understand better how advances in a field of research are the result of many, many seemingly unrelated activities."

Saul I. Gass  
Professor Emeritus  
Department of Decision, Operations and Information Technologies  
Robert H. Smith School of Business, University of Maryland, College Park

"Rarely do we get to understand the evolution of a scientific field told with such care and understanding. And a handy guide to the MCDM literature as well! I'll have all of my students read it!"

Mark H. Karwan  
Praxair Professor in Operations Research, SUNY Distinguished Teaching Professor  
Industrial and Systems Engineering at the University at Buffalo (SUNY)

"I really enjoyed reading this book. It was written by three experts who have lived with MCDM and its history for a long time (two of them for over 40 years!). How our community has a useful and valuable book that can be used by students and researchers to learn about MCDM and its history. I particularly like the photos which bring the history and its people to life."

Pekka Korhonen  
Professor of Statistics  
Aalto University, School of Economics

"This book brings to life — contributors, contributions, activities — the evolution, growth, and future directions of MCDM, a multidiscipline that embraces all facets of decision making. Kudos to three highly distinguished MCDM scholars who have written a classic, which should be essential reading and serve as a resource for scholars in all academic and professional disciplines."

Herb Moskowitz  
Purdue University Fellow Professor

Multiple Criteria Decision Making (MCDM) is all about making choices in the presence of multiple conflicting criteria. MCDM has become one of the most important and fastest growing subfields of Operations Research/Management Science. As modern MCDM started to emerge about 50 years ago, it is now a good time to take stock of developments. This book aims to present an informal, non-technical history of MCDM, supplemented with many pictures. It covers the major developments in MCDM, from early history until now. It also covers fascinating discoveries by Nobel Laureates and other prominent scholars.

The book begins with the early history of MCDM, which covers the roots of MCDM through the 1990s. It proceeds to give a decade-by-decade account of major developments in the field starting from the 1970s until now. Written in a simple and accessible manner, this book will be of interest to students, academics, and professionals in the field of decision sciences.



www.worldscientific.com  
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Multiple Criteria Decision Making

Köksalan | Wallenius | Zionts

## Multiple Criteria Decision Making

From Early History to the 21st Century

Murat Köksalan  
Jyrki Wallenius  
Stanley Zionts



World Scientific