

Solving “Easy” Multi-objective Combinatorial Optimisation Problems

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Outline

Easy Problems: Extending Existing Algorithms

Example: Multi-objective Shortest Path Problem

Multi-objective Labelling Algorithms

Two Phase Method for Bi-objective Problems

Example: Bi-objective Integer Minimum Cost Flow Problem

Phase 1: Supported Solutions

Phase 2: Remaining (Non-supported) Solutions

Strategy: Extend Existing Algorithms

Straight-Forward Extension of the Single-Objective Algorithm Possible for Simple Problems

- Multi-objective Shortest Path
- Multi-objective Spanning Tree

Multi-objective Shortest Path Problems

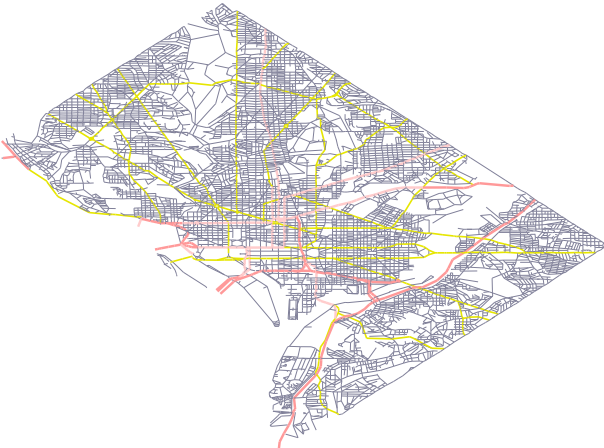
Definition

- $G = (N, A)$ a *directed network* with nodes $N = \{1, \dots, n\}$ and arcs $A \subseteq N \times N$
- Pos. costs $c_{ij} = (c_{ij}^1, \dots, c_{ij}^q) \in \mathbb{N}^q$ for each $(i, j) \in A$, $q \geq 2$
- *Path* in G from node $s \in N$ to node $t \in N$ is sequence $\{(s = i_0, i_1), (i_1, i_2), \dots, (i_{l-1}, i_l = t)\}$ of arcs in A
- \mathcal{P}_{st} : Set of paths connecting s, t

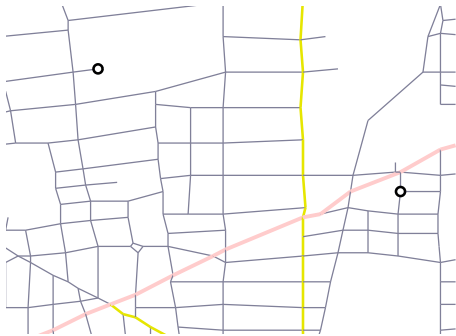
Multi-objective Shortest Path Problem

$$\begin{array}{ll} \min & z(p) = \begin{cases} z_1(p) = \sum_{(i,j) \in p} c_{ij}^1 \\ \dots \\ z_q(p) = \sum_{(i,j) \in p} c_{ij}^q \end{cases} \\ \text{s.t.} & p \in \mathcal{P}_{st} \end{array}$$

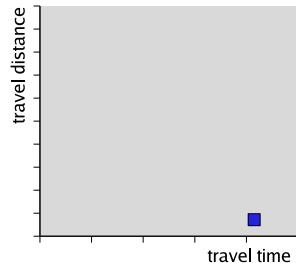
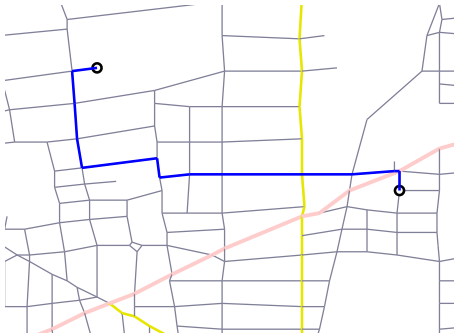
An Example in a Road Network of Washington DC



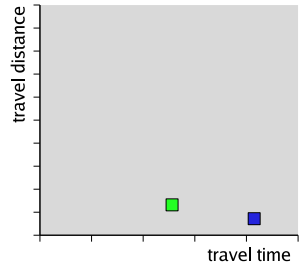
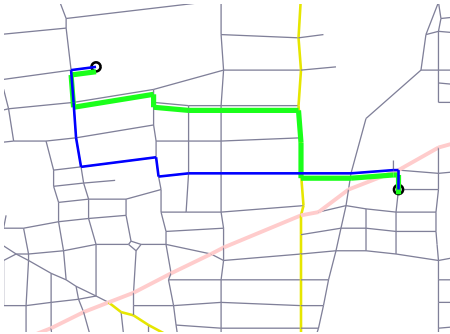
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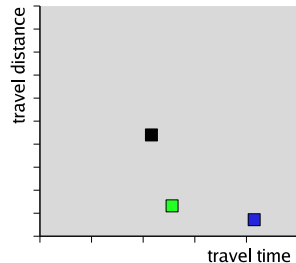
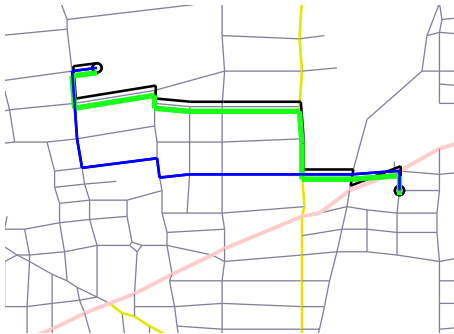
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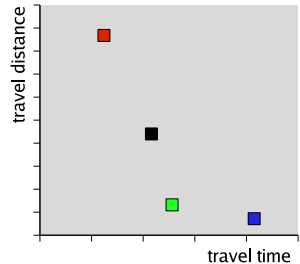
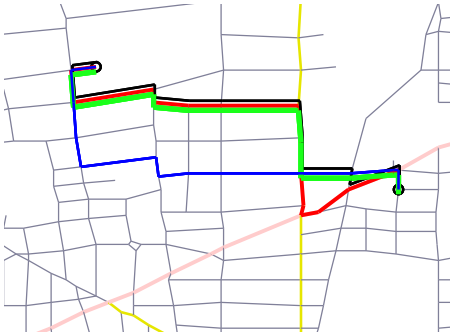
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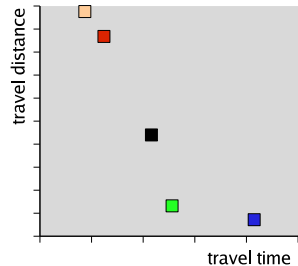
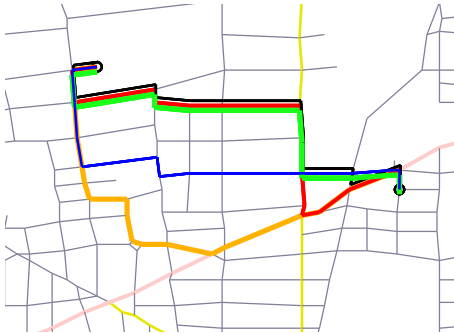
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Examples of Multi-objective Shortest Path Problems

- Shipping of hazardous materials
- Routing airplanes through convective weather
- Scheduling of earth-observing satellites
- Public transport journey planner

Solving Shortest Path Problems: Label Setting

Label Setting Algorithm (Dijkstra)

- 1: {Find shortest path from s to t in G with cost c .}
- 2: label $l_s = (0)$ at s , other nodes un-labeled.
- 3: $L = \{s\}$ {nodes with tent. labels}, $M = \emptyset$ {fixed nodes}
- 4: **while** $L \neq \emptyset$ and $t \notin M$ **do**
- 5: Select $i \in L$ with $l_i = \min\{l_j : j \in L\}$
- 6: **for all** $(i, j) \in \mathcal{A}$ **do**
- 7: **if** $j \notin L \cup M$ **then**
- 8: create $l_j = l_i + c_{ij}$ and $L = L \cup \{j\}$
- 9: **else if** $l_i + c_{ij} < l_j$ **then**
- 10: set $l_j = l_i + c_{ij}$ {Shorter path s to j via i }
- 11: **end if**
- 12: **end for**
- 13: $L = L \setminus \{i\}, M = M \cup \{i\}$ {move i from L to M }
- 14: **end while**

Label Setting for Multi-objective Shortest Path Problems

Main Differences

single-objective	multi-objective
One path s to i , i.e. one label per node	multiple efficient paths from s to each i .
Selection of min cost unmarked label	selection of label that cannot be dominated, e.g. lex-min, min sum.
Comparison of pairs of labels $l_i + c_{ij} < l_j$	Merging of extended label $l_i + c_{ij}$ into set of labels at node j .
Can stop algorithm once $t \in M$	Can only stop when $L = \emptyset$

Solving Multi-objective Shortest Path Problems

Multi-objective Label Setting Algorithm [e.g. 9; 10; 17; 18]

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Label Correcting

Single-objective label correcting

- Nodes *marked* when their labels are created or change
- Keep list of marked nodes, e.g. in FIFO order
- Re-visit marked nodes, extend label along outgoing arcs and un-mark them
- Continue until no more marked labels exist

Multi-objective label correcting [2; 16; 12]

- Similar to the above: node-selection
- Alternative: label-selection (considering individual labels)

Advantages: No need to extract “minimum” label; For node-selection merge sets of labels, which may be faster

Outline

Easy Problems: Extending Existing Algorithms

Example: Multi-objective Shortest Path Problem

Multi-objective Labelling Algorithms

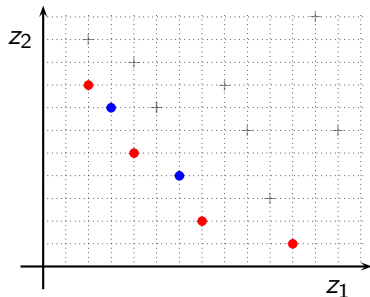
Two Phase Method for Bi-objective Problems

Example: Bi-objective Integer Minimum Cost Flow Problem

Phase 1: Supported Solutions

Phase 2: Remaining (Non-supported) Solutions

Two Phase Method to Identify “Easy” and “Difficult” Solutions Separately

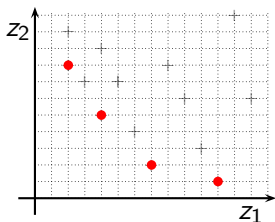


Easy: supported extreme points (red)

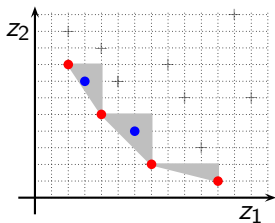
Difficult: non-supported and non-extreme supported points (blue)

The Two Phase Method [19]

In phase 1 all extreme supported solutions are computed



In phase 2 all other solutions are computed



Bi-objective Integer Minimum Cost Flow (BIMFC) Problem

Definition

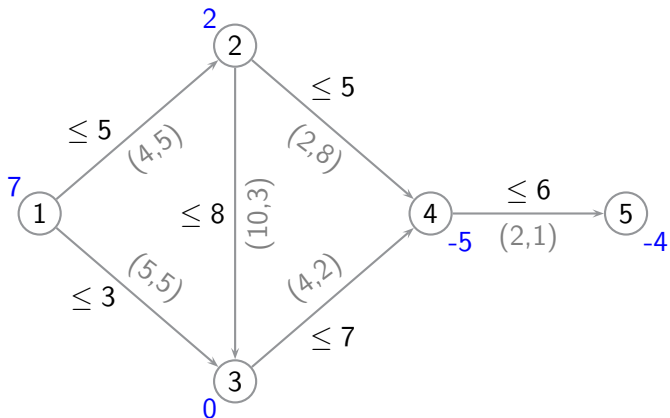
- $G = (N, A)$ with nodes $N = \{1, \dots, n\}$ and arcs $A \subseteq N \times N$
- costs $c_{ij} = (c_{ij}^1, c_{ij}^2) \in \mathbb{Z}^2$ for each $(i, j) \in A$
- lower and upper bounds $l_{ij} = 0$ and $u_{ij} > 0$ for each arc (i, j)
- flow balance b_i for each node i

BIMFC

$$\begin{aligned} \min \quad & z(x) = \begin{cases} z_1(x) = \sum_{(i,j) \in A} c_{ij}^1 x_{ij} \\ z_2(x) = \sum_{(i,j) \in A} c_{ij}^2 x_{ij} \end{cases} \\ \text{s.t.} \quad & \sum_{(i,j) \in A} x_{ij} - \sum_{(j,i) \in A} x_{ij} = b_i, \forall i \in N \\ & 0 \leq x_{ij} \leq u_{ij}, \forall (i, j) \in A \\ & x_{ij} \text{ integer} \end{aligned}$$

Bi-objective Network Flow - Example

Bi-objective network flow problem: Shipping a single commodity through the network



Solving Phase 1

In Phase 1 supported (extreme) solutions need to be computed.

1. Dichotomic Approach [e.g. 1; 4; 6]:

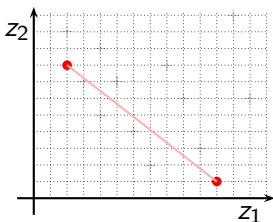
- Supported (extreme) solutions can be obtained by repeatedly solving a single-objective version of the problem at hand with different weighting factors.
- Dichotomic strategy of selecting weighting factors

2. Problem specific approach:

- Modify existing solution algorithm for specific problem to obtain supported (extreme) solutions.
- Example: Network simplex for BIMCF problems [e.g. 12; 13]

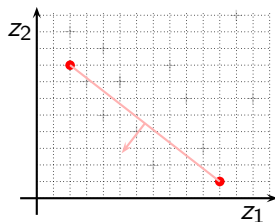
Phase 1 - Dichotomic Approach

- Compute both *lex*(2, 1)- and *lex*(1, 2)-best solutions \bar{x} , \hat{x} and determine weights
 $\lambda^1 = z_2(\hat{x}) - z_2(\bar{x})$ and
 $\lambda^2 = z_1(\bar{x}) - z_1(\hat{x})$



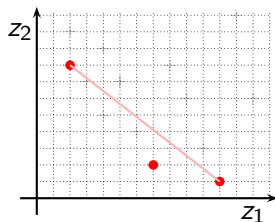
Phase 1 - Dichotomic Approach

- Compute both *lex*(2, 1)- and *lex*(1, 2)-best solutions \bar{x} , \hat{x} and determine weights
 $\lambda^1 = z_2(\hat{x}) - z_2(\bar{x})$ and
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- Determine optimal solution of problem with weighted sum objective $\min \lambda_1 z^1 + \lambda_2 z^2$.



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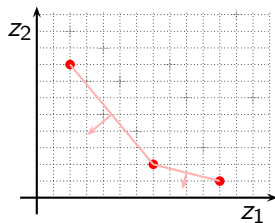
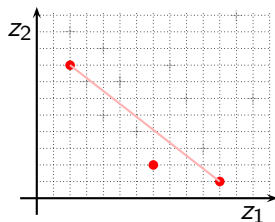
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- Define two subproblems and find optimal solutions in each one.



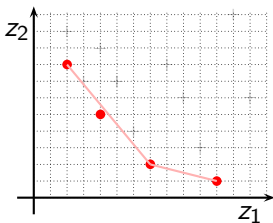
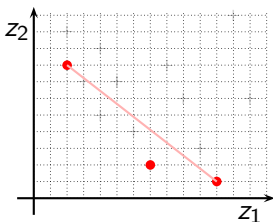
Phase 1 - Dichotomic Approach

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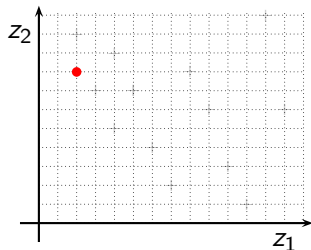
- Determine optimal solution of problem with weighted sum objective $\min \lambda_1 z^1 + \lambda_2 z^2$.
- Define two subproblems and find optimal solutions in each one.
- etc.



Phase 1 - Problem Specific for BIMCF

Adapt network simplex algorithm for BIMCF: Parametric network simplex [13–15].

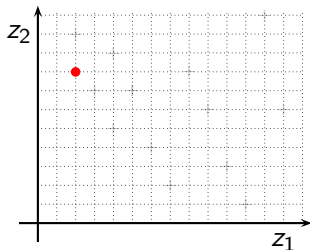
- Compute the $lex(1, 2)$ -best solution



Phase 1 - Problem Specific for BIMCF

Adapt network simplex algorithm for BIMCF: Parametric network simplex [13–15].

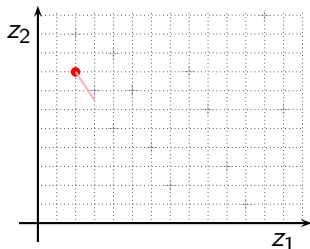
- Compute the $lex(1, 2)$ -best solution
- Run the network simplex algorithm with the objective to find $lex(2, 1)$ -best solution



Phase 1 - Problem Specific for BIMCF

Adapt network simplex algorithm for BIMCF: Parametric network simplex [13–15].

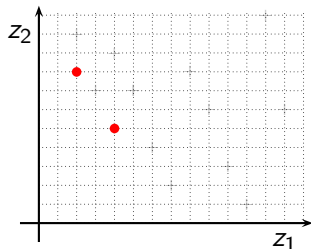
- Compute the $lex(1, 2)$ -best solution
- Run the network simplex algorithm with the objective to find $lex(2, 1)$ -best solution
 - choose basic entering arc with minimum ratio μ of deterioration of z_1 and improvement of z_2 .



Phase 1 - Problem Specific for BIMCF

Adapt network simplex algorithm for BIMCF: Parametric network simplex [13–15].

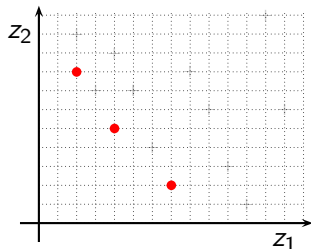
- Compute the $lex(1, 2)$ -best solution
- Run the network simplex algorithm with the objective to find $lex(2, 1)$ -best solution
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 - whenever μ changes, we have an extreme supported solution.



Phase 1 - Problem Specific for BIMCF

Adapt network simplex algorithm for BIMCF: Parametric network simplex [13–15].

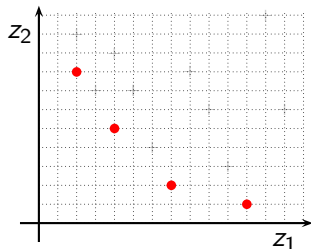
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Phase 1 - Problem Specific for BIMCF

Adapt network simplex algorithm for BIMCF: Parametric network simplex [13–15].

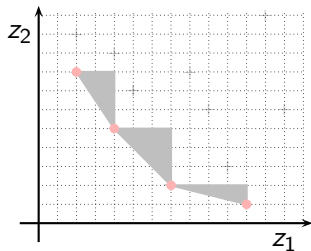
- Compute the $lex(1, 2)$ -best solution
- Run the network simplex algorithm with the objective to find $lex(2, 1)$ -best solution
 - choose basic entering arc with minimum ratio μ of deterioration of z_1 and improvement of z_2 .
 - whenever μ changes, we have an extreme supported solution.
- until $lex(2, 1)$ -best solution is obtained.



Phase 2

Identify Remaining (Non-supported) Solutions

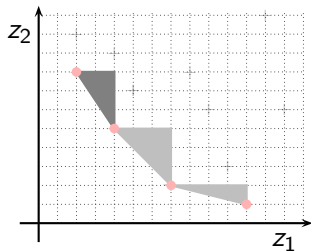
- Need to fill the gaps between solutions found in Phase 1.
- Restrict search to triangles defined by two neighbouring extreme non-dominated points
- Avoid breaking the problem structure, e.g. by introducing additional constraints.



Phase 2

Identify Remaining (Non-supported) Solutions

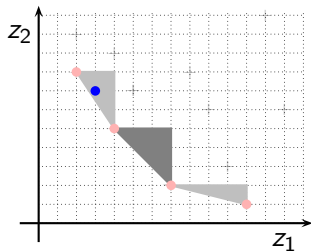
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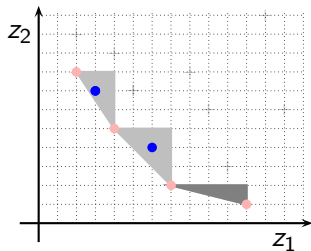
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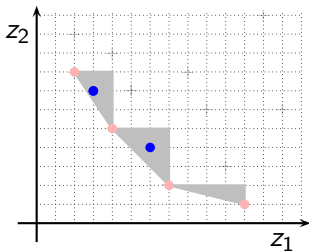
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Phase 2 - Ranking

Ranking

- Consider single objective problem with weighted sum objective

$$\min c_\lambda(x) = \lambda^1 z_1(x) + \lambda^2 z_2(x)$$

- Ranking algorithm computes $x^1, x^2, x^3, \dots, x^k$

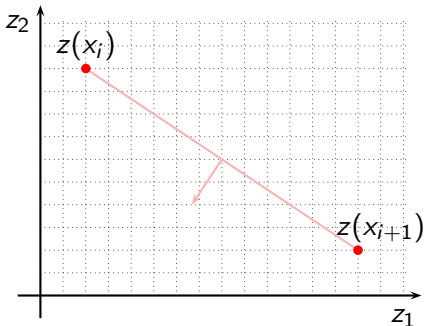
$$\text{with } c_\lambda(x^1) \leq c_\lambda(x^2) \leq c_\lambda(x^3) \leq \dots \leq c_\lambda(x^k).$$

- Continue computing x^{k+1} until it can be guaranteed that all efficient non-supported points are found.

Ranking All Solutions in a Triangle: Illustration

In each triangle ... [11–13]

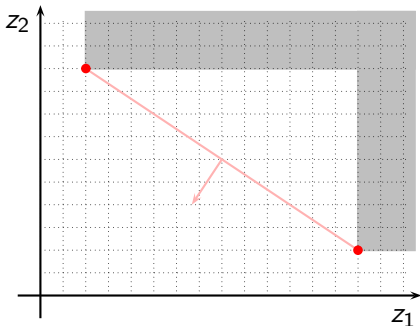
- Solve problem with objective c_λ



Ranking All Solutions in a Triangle: Illustration

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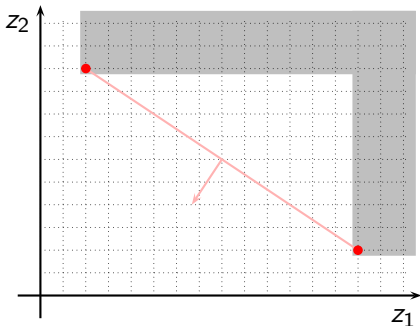
- Solve problem with objective c_λ
- Restrict to triangle



Ranking All Solutions in a Triangle: Illustration

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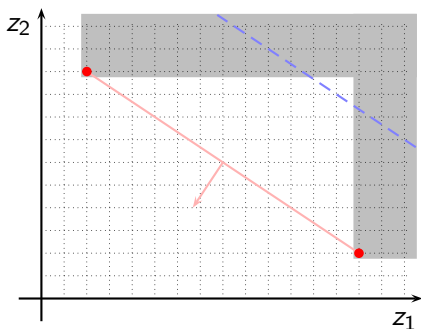
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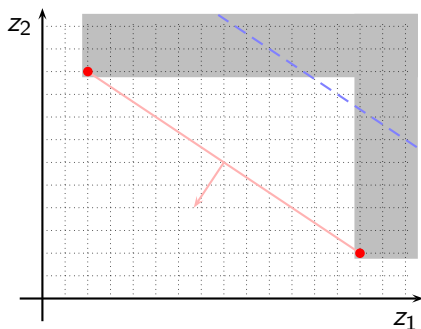
- Solve problem with objective c_λ
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- Find upper bound u_λ on c_λ



Ranking All Solutions in a Triangle: Illustration

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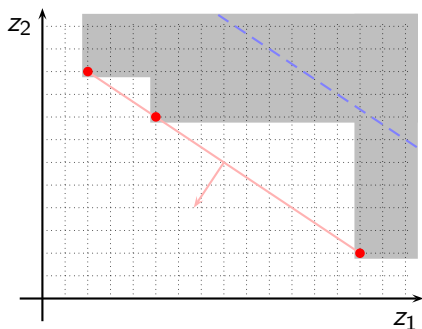
- Solve problem with objective c_λ
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- Find upper bound u_λ on c_λ
- Rank flows x while $c_\lambda(x) \leq u_\lambda$
If x is efficient: save it and update u_λ .



Ranking All Solutions in a Triangle: Illustration

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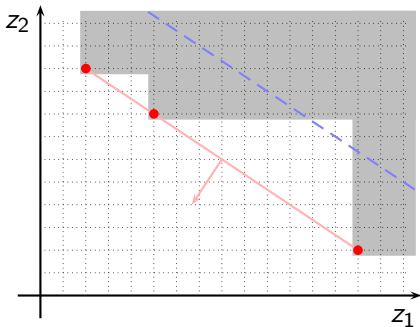
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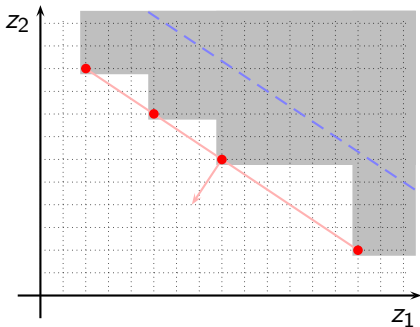
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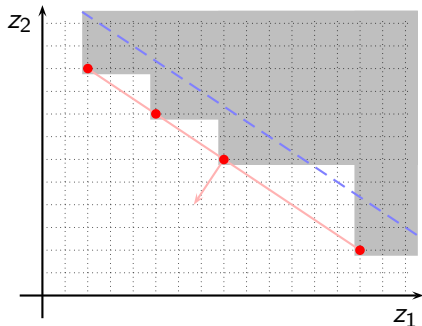
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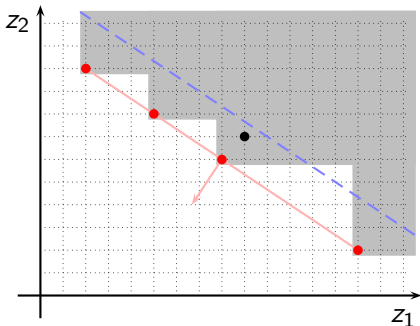
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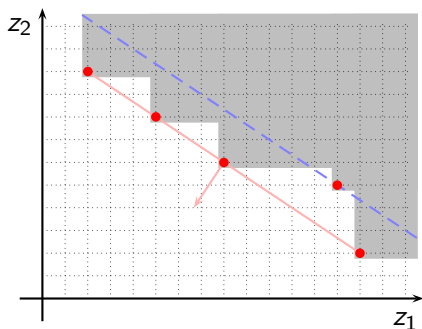
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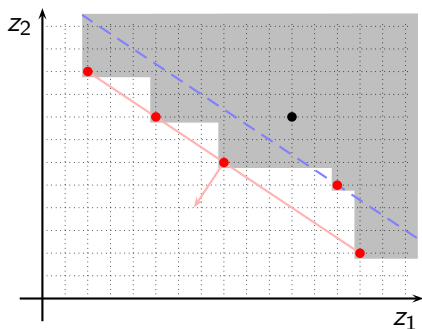
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Ranking All Solutions in a Triangle: Illustration

In each triangle ... [11–13]

- Solve problem with objective c_λ
- Restrict to triangle
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If x is efficient: save it and update u_λ .



Example: Ranking Solutions for BIMCF

Ranking k best flows by Hamacher [7]

- Identify best x_0 and second best \bar{x}_0 feasible solutions in \mathcal{X}
- Partition \mathcal{X} so that $\mathcal{X} = \mathcal{X}_1 \cup \mathcal{X}_2$, $\mathcal{X}_1 \cap \mathcal{X}_2 = \text{emptyset}$ and x_0 is optimal in \mathcal{X}_1 and $x_0 \notin \mathcal{X}_2$, and \bar{x}_0 is optimal in \mathcal{X}_2 and $\bar{x}_0 \notin \mathcal{X}_1$.
- $x_1 = x_0$ and $x_2 = \bar{x}_0$
- Identify second best solution $\bar{x}_1 \in \mathcal{X}_1$ and $\bar{x}_2 \in \mathcal{X}_2$.
- The third best solution is the one with smaller objective value out of \bar{x}_1 and \bar{x}_2 .
- Split corresponding partition further.

Illustration of Ranking by Hamacher [7]

x_0	
best cost 47	x^1
second best cost 48	x^2

Illustration of Ranking by Hamacher [7]

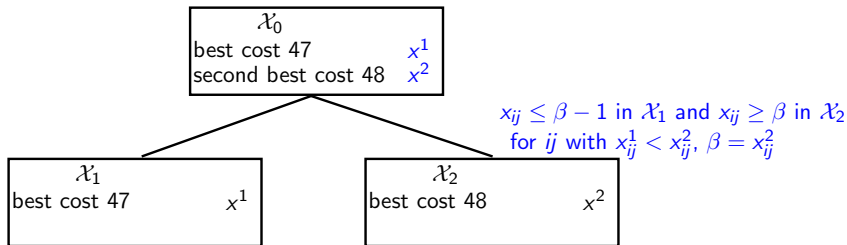


Illustration of Ranking by Hamacher [7]

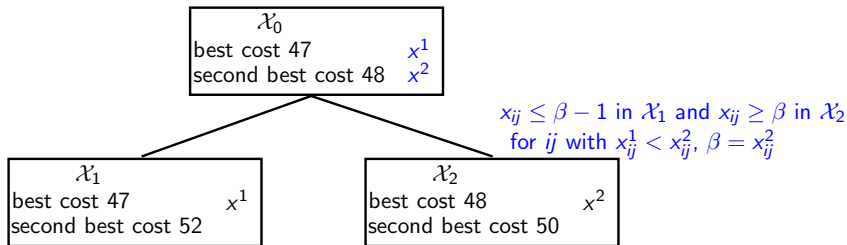


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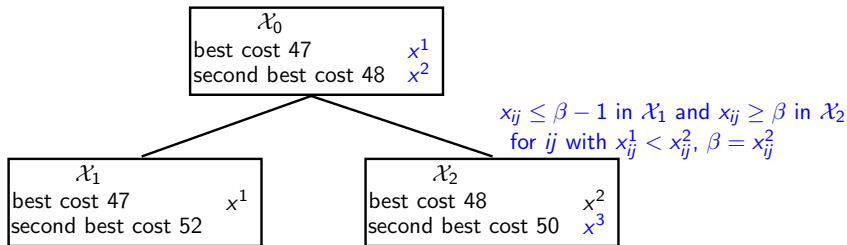


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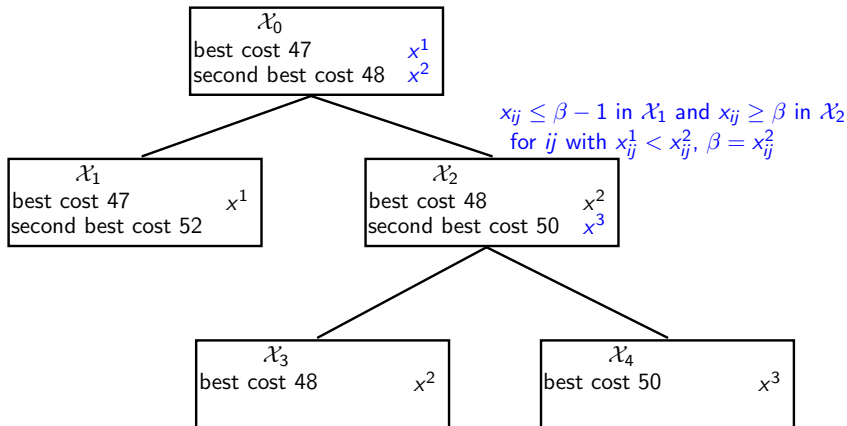


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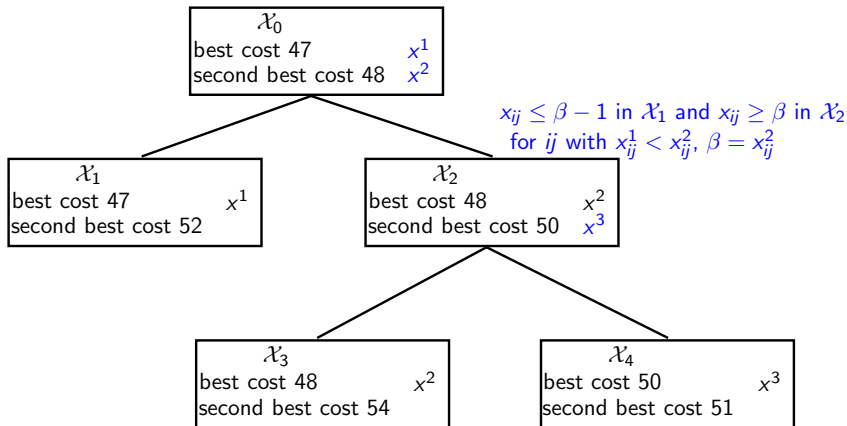
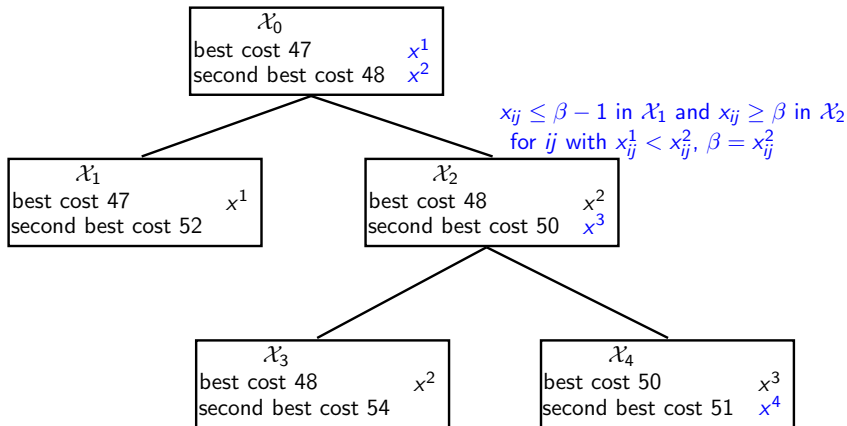


Illustration of Ranking by Hamacher [7]



Summary

- For some easy multi-objective problems it is possible to extend single-objective solution algorithms. Examples are multi-objective shortest path [e.g. 3; 17; 2; 16] and spanning tree problems [e.g. 5; 8].
- The two phase method solves problems when algorithms for the single-objective problem are available and there exists a method of solving phase 2 efficiently, e.g. by ranking. Examples are multi-objective integer minimum cost network flow [13] and assignment problems [11].

Outline

Appendix

- [1] Y.P. Aneja and K.P.K. Nair. Bicriteria transportation problem. *Management Science*, 25:73–78, 1979.
- [2] J. Brumbaugh-Smith and D. Shier. An empirical investigation of some bicriterion shortest path algorithms. *European Journal of Operational Research*, 43(2):216–224, 1989.
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- [15] A. Sedeño-Noda, C. González-Martín, and J. Gutiérrez. The biobjective undirected two-commodity minimum cost flow problem. *European Journal of Operational Research*, 164: 89–103, 2005.
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