

Maximizing Expectation on Vertex-disjoint Cycle Packing

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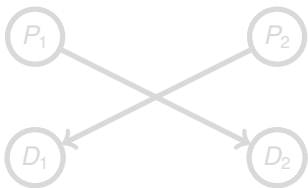
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Background: kidney exchange programs

- in many countries, recent legislation allows patients needing a kidney transplant to receive it from a living donor
- what to do when the transplant from that donor is not possible?
 - blood type
 - other incompatibilities
- patient-donor pair may enter a **kidney exchange program (KEP)**

Kidney exchanges

- idea: allow two (or more) patients in incompatible pairs to exchange their donors
- each recipient receives a compatible kidney from the donor of another pair



Incompatible pairs $P_1 - D_1$ and $P_2 - D_2$ exchange donors

- P_1 receives a transplant from D_2 and vice versa

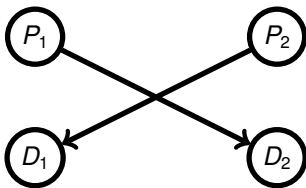


Graph representation:

- vertices are patient-donor pairs
- arcs link a patient to compatible donors

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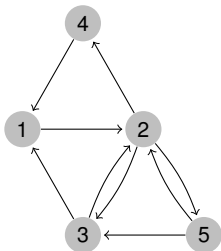
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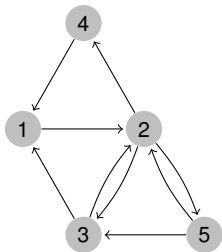
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Kidney exchanges: example



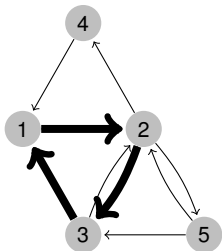
- instance with five pairs
- what is the **maximum number** of transplants?
- what if the allowed number of **simultaneous** transplants is limited?
- how to optimize if there is some **probability** of vertex/arc failure?

Kidney exchanges: example



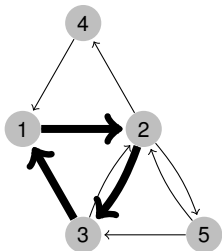
- **feasible exchange**: a set of vertex-disjoint cycles (e.g., $1 - 2 - 3 - 1$)
- size of an exchange: sum of the lengths of its cycles
- maximum exchange in this example: 4 (cycle $1 - 2 - 5 - 3 - 1$)

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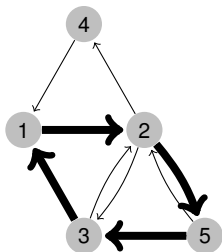
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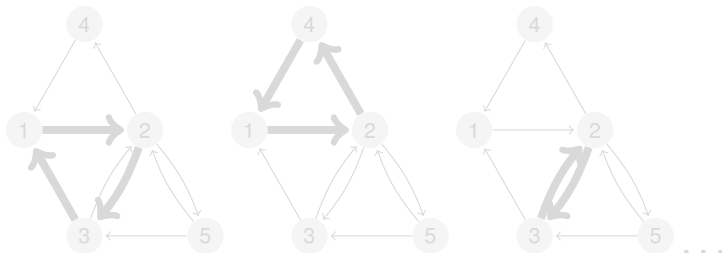
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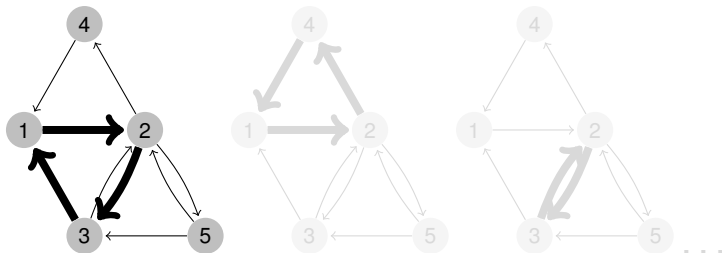
Kidney exchanges: maximum cycle size

- In many situations the **length of each cycle is limited**:
 - limitations in the number of operation rooms
 - number of surgeons available
- If maximum cycle size is $K = 3$, several solutions are possible.



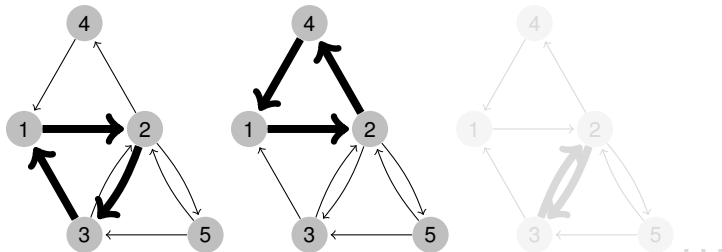
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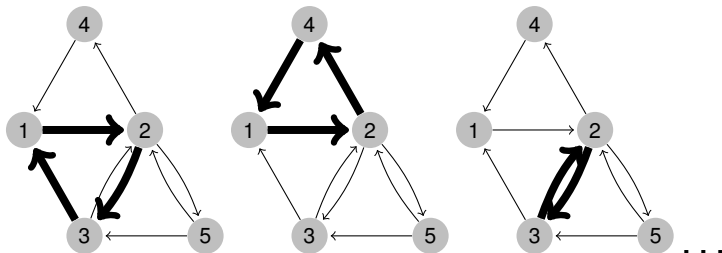
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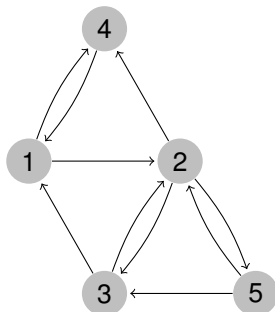


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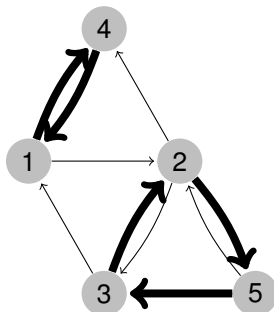
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Another example



Another example



Maximum cycle size and NP-hardness

- In many situations the length of each cycle is limited
- If length is **not limited** \rightarrow *assignment problem*
(polynomial algorithms are known, e.g., hungarian algorithm).
- If length is **limited to 2** \rightarrow *matching problem*
(polynomial algorithms are known: Edmonds algorithm).
- If length is **limited to 3, 4, ...** \rightarrow *problem is NP-hard*
(no polynomial algorithms are known).

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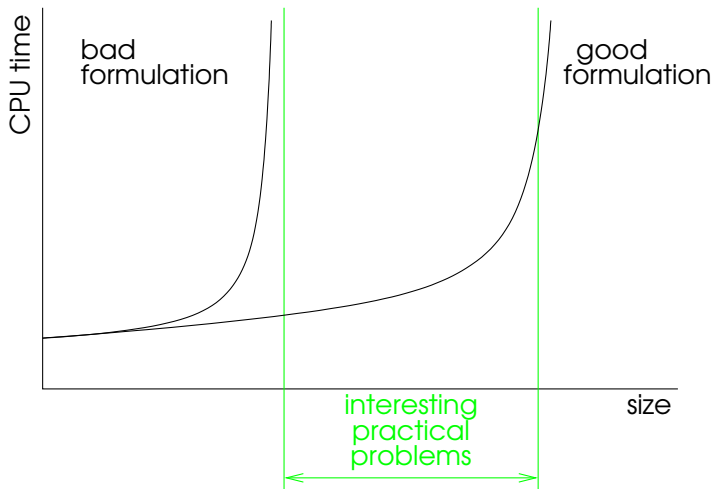
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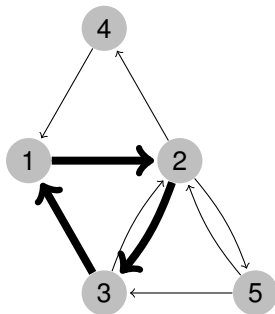
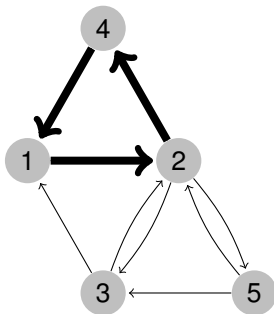
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NP-hard problems



Mathematical programming formulations

- There are several possibilities for modeling the problem in mathematical programming
- One of the most successful is the *cycle formulation*:
 - enumerate all cycles in the graph with length at most K
 - for each cycle c , let variable x_c be 1 if c is chosen, 0 otherwise
 - every feasible solution corresponds to a set of vertex-disjoint cycles



Cycle formulation

$$\text{maximize } \sum_c w_c x_c \quad (1a)$$

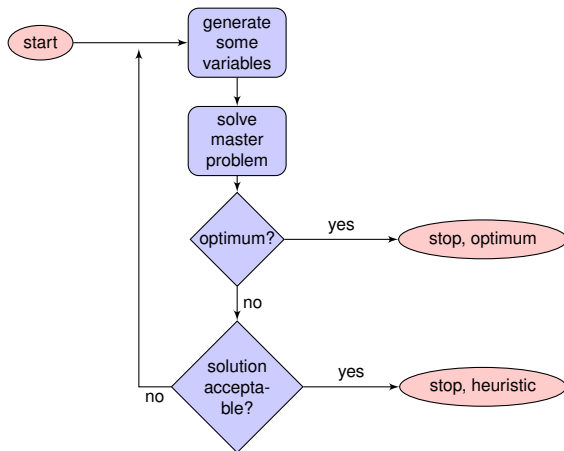
$$\text{subject to } \sum_{c:i \in c} x_c \leq 1 \quad \forall i \quad (1b)$$
$$x_c \in \{0, 1\} \quad \forall c$$

- case of 0 – 1 weights: $w_c = |c|$, (length of cycle c)
- objective: maximize the weight of the exchange
- constraints: every vertex is at most in one cycle (*i.e.*, donate/receive at most one kidney)
- difficulty: number of variables

Cycle formulation

- Exponential number of variables
- Not all are needed for solving the problem
- Use only those necessary → **column generation**

Column generation



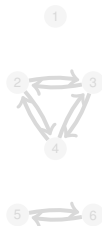
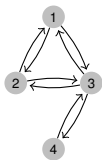
Previous results

- Cycle formulation seems to be more than able to process foreseen number of patient-donor pairs in the KEP in Portugal
- Besides, it may allow to treat slightly different objectives:
 - produce robust solutions
 - maximize **expectation** of the number of transplants
- What if the “*market*” becomes the European Union?

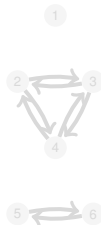
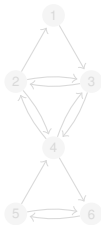
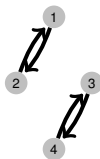
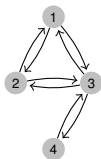
Maximizing expectation

- Basis: cycle formulation
- On standard approach: cycle evaluation is the **number of arcs** in the cycle (*i.e.*, the *number of transplants*)
- Our proposal: use the **expectation** of the number of transplants instead
- Problem: not straightforward to tackle. . .
 - 1 computation of the expectation is heavy, even for small cycles
 - 2 optimization is just a small part in the solution process. . .

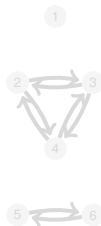
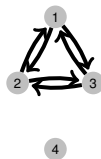
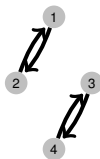
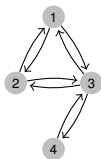
Unreliable vertices



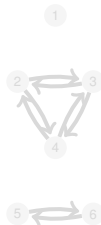
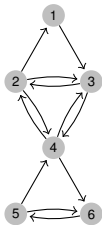
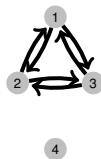
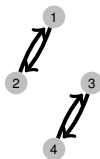
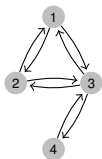
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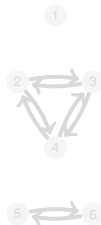
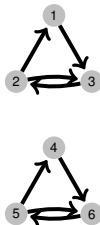
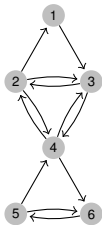
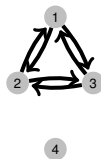
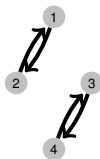
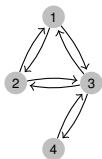
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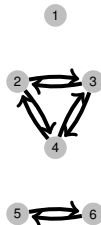
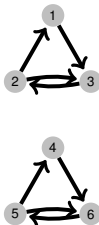
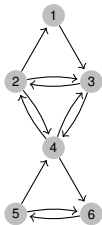
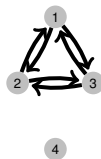
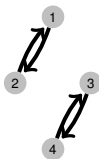
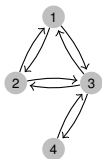
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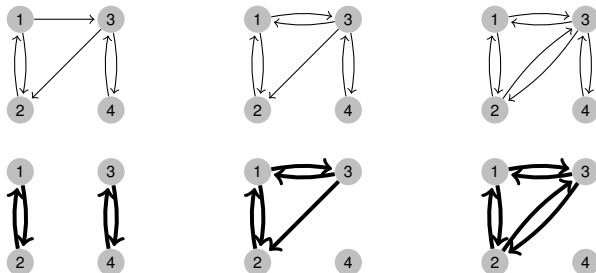
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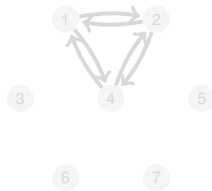
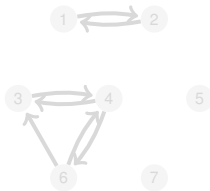
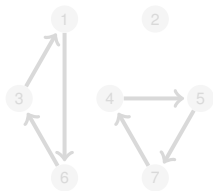
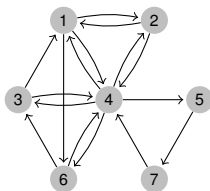
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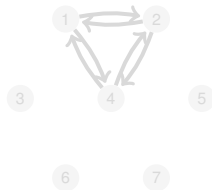
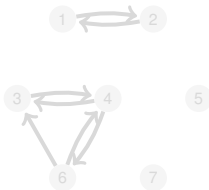
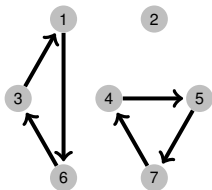
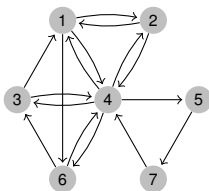
Unreliable arcs



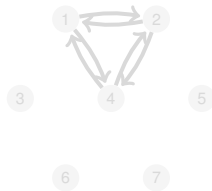
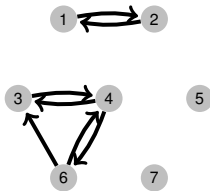
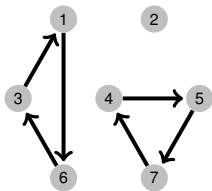
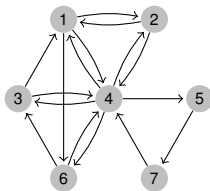
Arc withdrawal



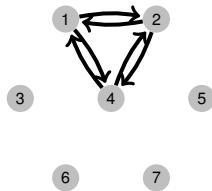
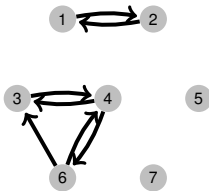
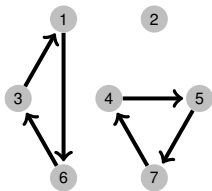
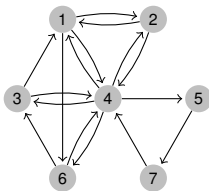
Arc withdrawal



Arc withdrawal



Arc withdrawal



Solution procedure

- Preprocessing
- Solution optimization
- Implementation

Solution procedure: preprocessing

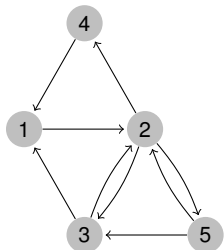
- **Preprocessing**
 - 1 prepare a **database** of cycle configurations for the relevant sizes
 - 2 precompute formulas for expectations for these configurations
HARD
 - 3 store this information in a database
- Example:
 - Use the expectation as objective coefficient for each cycle

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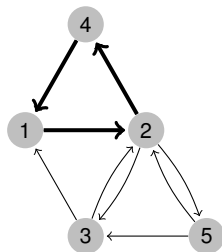
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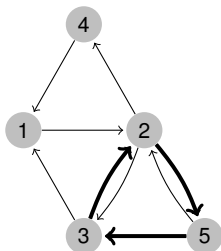
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Solution procedure: cycle configuration database

- **Two-vertex graphs** (1 graph)

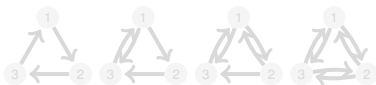


vertices: $2(1 - p_1)(1 - p_2)$

arcs: $2(1 - p_{12})(1 - p_{21})$

both: $2(1 - p_1)(1 - p_2)(1 - p_{12})(1 - p_{21})$

- **Three-vertex graphs** (4 graphs)



- **Four-vertex graphs** (61 graphs)

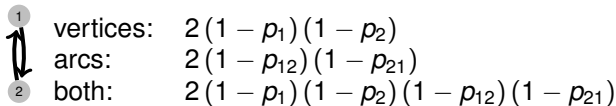


- **Five-vertex graphs** (3725 graphs)

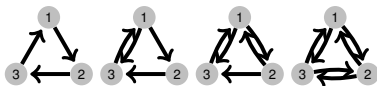


Solution procedure: cycle configuration database

- **Two-vertex graphs** (1 graph)



- **Three-vertex graphs** (4 graphs)



- **Four-vertex graphs** (61 graphs)




- **Five-vertex graphs** (3725 graphs)



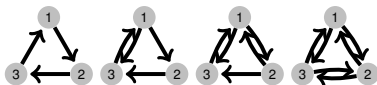
Solution procedure: cycle configuration database

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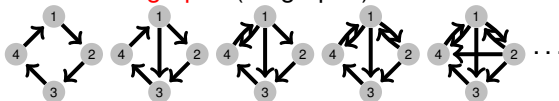


vertices: $2(1 - p_1)(1 - p_2)$
arcs: $2(1 - p_{12})(1 - p_{21})$
both: $2(1 - p_1)(1 - p_2)(1 - p_{12})(1 - p_{21})$

- **Three-vertex graphs** (4 graphs)



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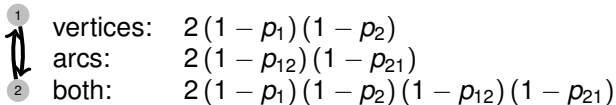


- **Five-vertex graphs** (3725 graphs)

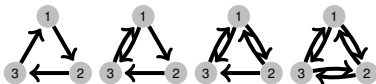


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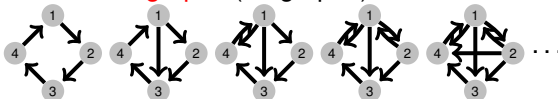
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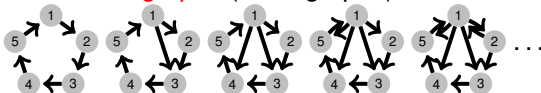
- **Three-vertex graphs** (4 graphs)



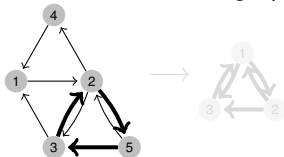
- **Four-vertex graphs** (61 graphs)



- **Five-vertex graphs** (3725 graphs)



1 Match enumerated graph with one in the database



2 Extract expectation formula from the database

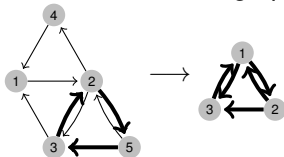
$$\begin{aligned}
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 \end{aligned}$$

3 Map probabilities from original graph to the one stored

$$\begin{array}{lcl}
 p_2 & \leftrightarrow & p_1 \\
 p_5 & \leftrightarrow & p_2 \\
 p_3 & \leftrightarrow & p_3 \\
 p_{25} & \leftrightarrow & p_{12} \\
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 p_{53} & \leftrightarrow & p_{23} \\
 p_{32} & \leftrightarrow & p_{31} \\
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 \end{array}$$

4 Compute expectation for the cycle (2 – 5 – 3); it will be its coefficient at the objective

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2 Extract expectation formula from the database

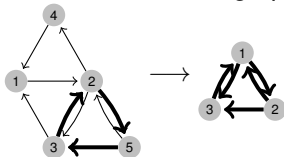
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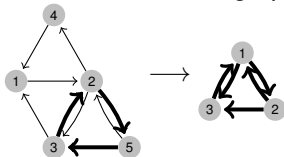
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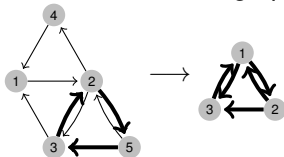
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4 Compute expectation for the cycle (2 – 5 – 3); it will be its coefficient at the objective

Solution procedure: solution optimization

- **Solution optimization**

- 1 read instance: compatibility between pairs, failure probability for vertices/arcs
- 2 prepare compatibility graph
- 3 enumerate cycles of relevant size
- 4 setup optimization model
 - 1 one variable for each cycle
 - 2 constraints: each vertex in at most one cycle
 - 3 objective coefficient: expectation of number of transplants **HARD**
- 5 solve optimization model **easy?!!**

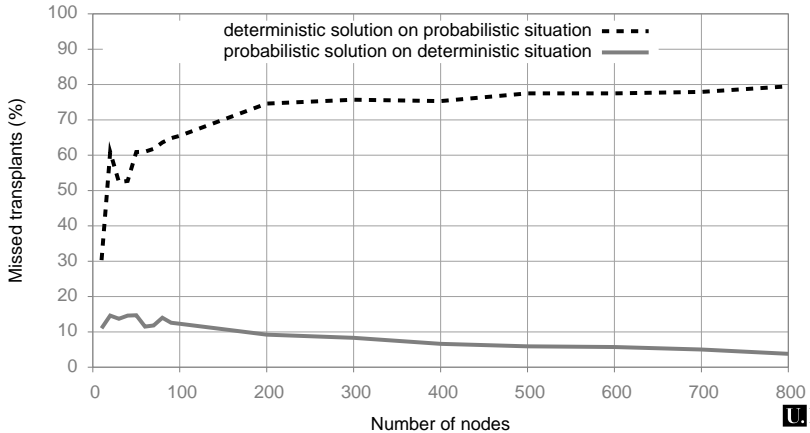
Solution procedure: implementation

- **Implementation**

- 1 contact selected pairs
- 2 verify solution (check back outs)
- 3 make last-minute compatibility check
- 4 make transplants

Results: cross-formulation performance

IMPACT OF SWAPPING SOLUTIONS



Conclusions

- There are many applications of information technologies in health care
- Applications involve many disciplines in computer science and informatics
- KEP: case where welfare of patients can be maximized
 - number of transplants
 - robustness of the solution
 - quality of the solution (maximize patient-donor compatibility)
- Careful implementation of operations research program leads to significant social benefits