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Jednociljna i višeciljna optimizacija korištenjem HUMANT algoritma

(Single-Objective and Multi-Objective Optimization using HUMANT Algorithm)

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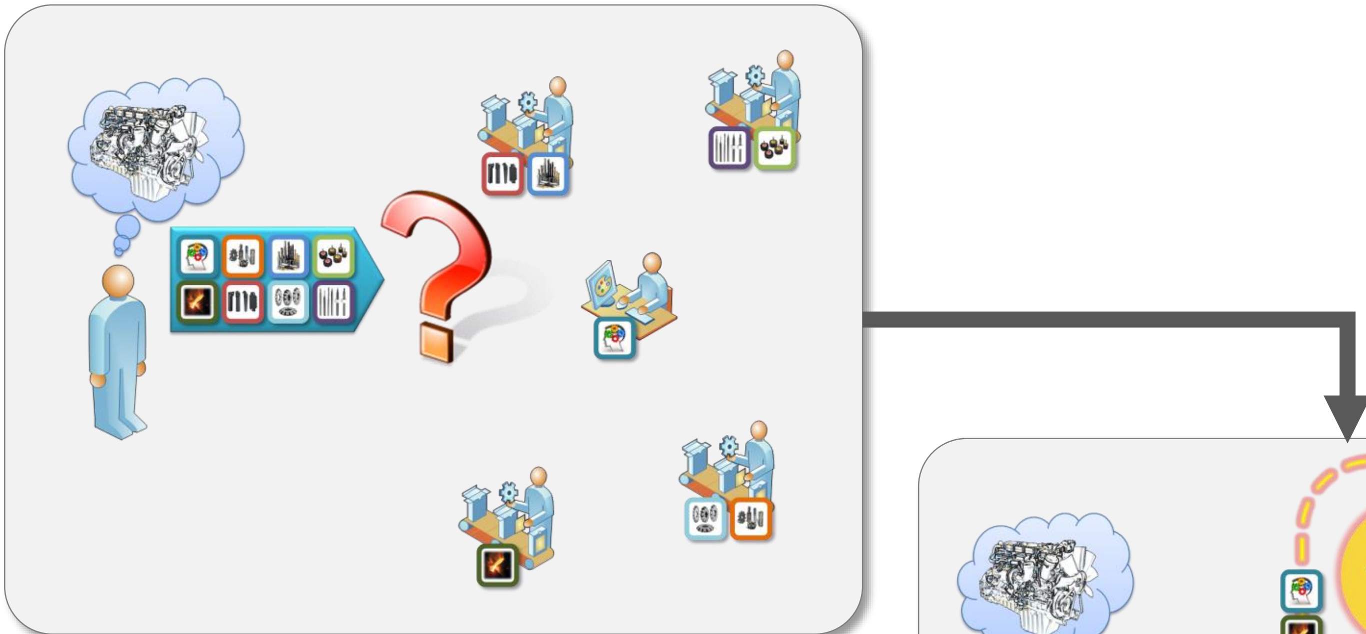
In medias res

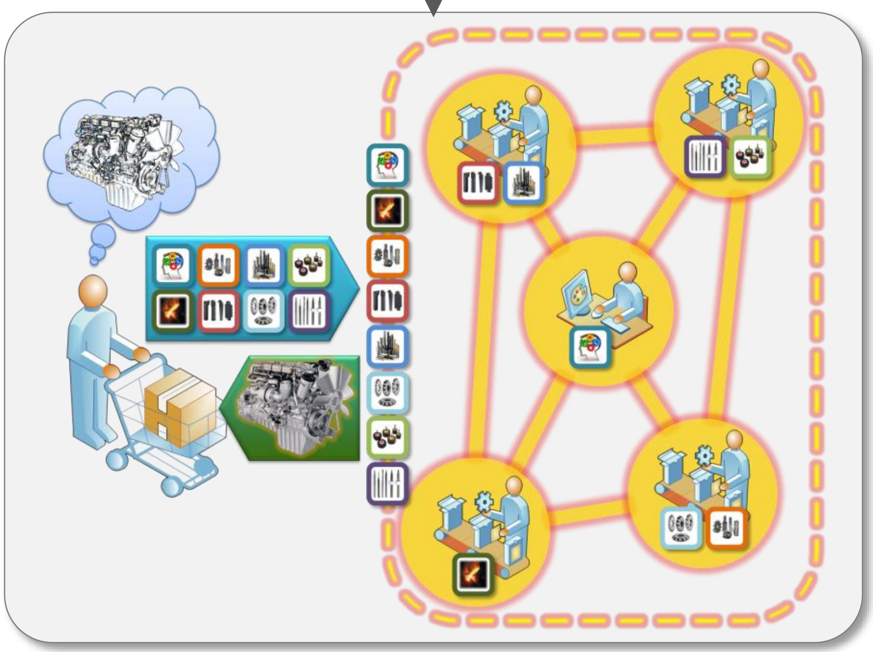
HUMANT algorithm

HUMANT = *HUManoid ANT*

Originally designed to **solve Partner Selection Problem** (PSP)

Regional production networks





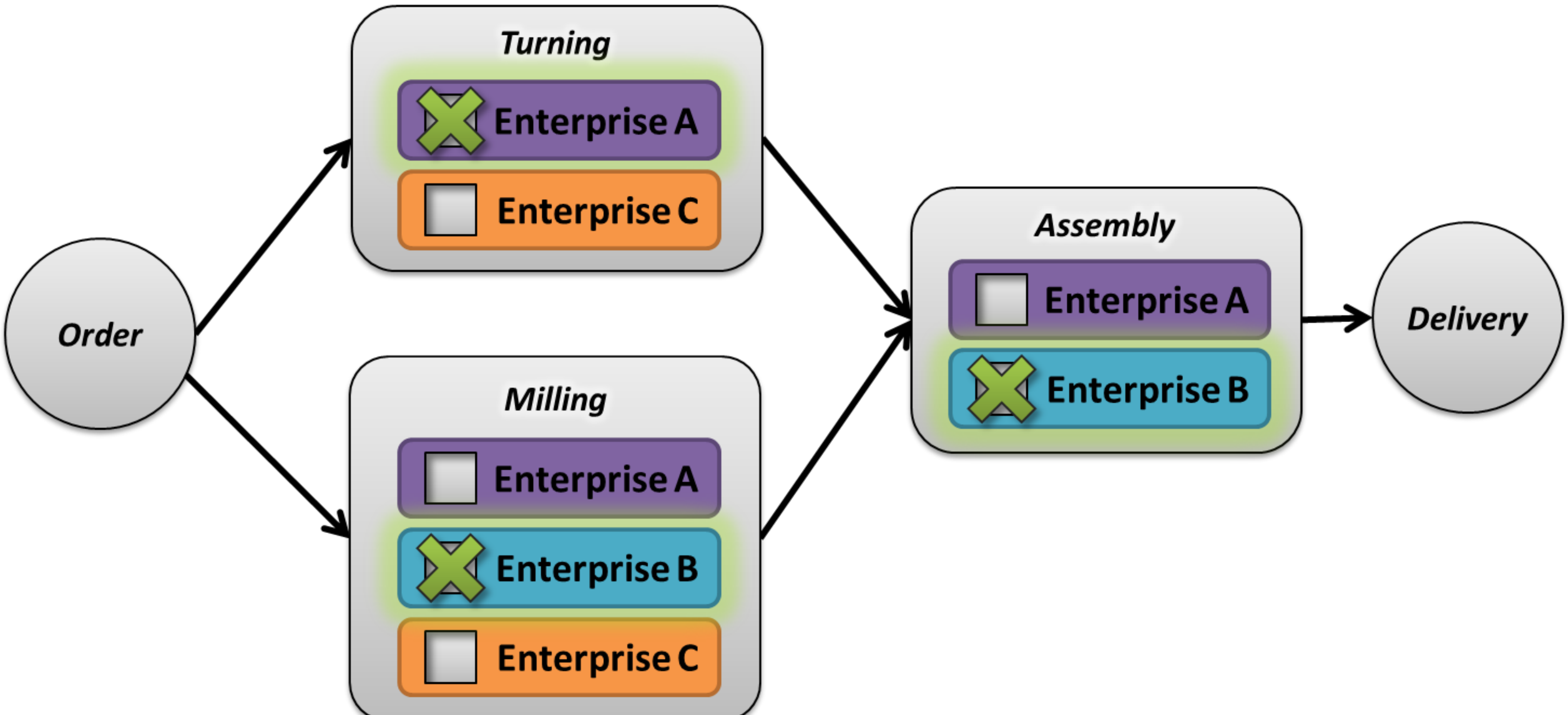
Aim:

Production of complex products through networked collaboration called **Virtual Enterprise**

Partner Selection Problem (PSP)

Aim:

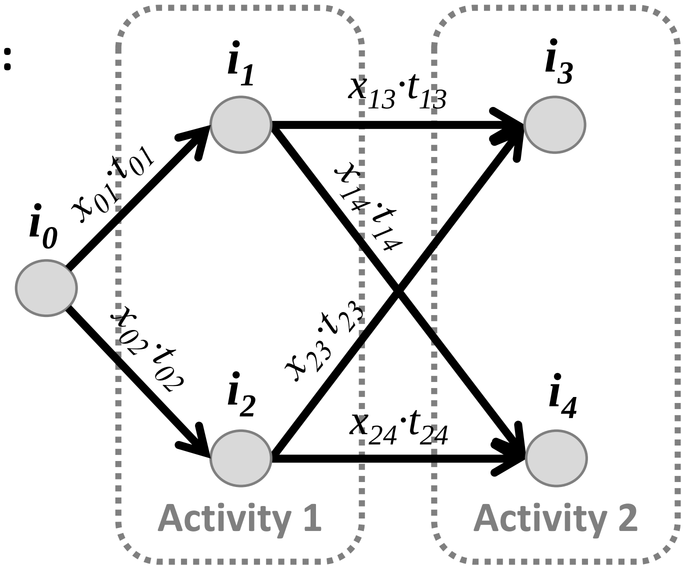
Selection of **optimal agent** (enterprise) **for each activity** (process)



Single-Objective Partner Selection Problem (PSP)

Optimal agent must be assigned to each activity of project. Objective is to **minimize Total time T**:

Problem:



	i_0	i_1	i_2	i_3	i_4
i_0	0	$x_{01}\cdot t_{01}$	$x_{02}\cdot t_{02}$	0	0
i_1	$-x_{01}\cdot t_{01}$	0	0	$x_{13}\cdot t_{13}$	$x_{14}\cdot t_{14}$
i_2	$-x_{02}\cdot t_{02}$	0	0	$x_{23}\cdot t_{23}$	$x_{24}\cdot t_{24}$
i_3	0	$-x_{13}\cdot t_{13}$	$-x_{23}\cdot t_{23}$	0	0
i_4	0	$-x_{14}\cdot t_{14}$	$-x_{24}\cdot t_{24}$	0	0

Fitness function:

$$\boldsymbol{T}(x) = \sum_{i=1}^{m}\sum_{i=1}^{n} x_{ij}\cdot t_{ij} \rightarrow \boldsymbol{Min}$$

Constraints:

$$x_{ij} = 0 \ \ or \ x_{ij} = 1$$

$$\sum_{i=1}^{m} x_{ij}, j = 1,2,\ldots,n$$

$$x_{ij}\cdot t_{ij} \geq 0$$

Multi-Objective Partner Selection Problem (PSP)

Minimization of transport: $$\boldsymbol{S}(x) = \sum_{i=1}^{m} \sum_{i=1}^{n} x_{ij} \cdot s_{ij} \rightarrow \boldsymbol{Min}$$

Minimization of cost: $$\boldsymbol{C}(x) = \sum_{i=1}^{m} \sum_{i=1}^{n} x_{ij} \cdot c_{ij} \rightarrow \boldsymbol{Min}$$

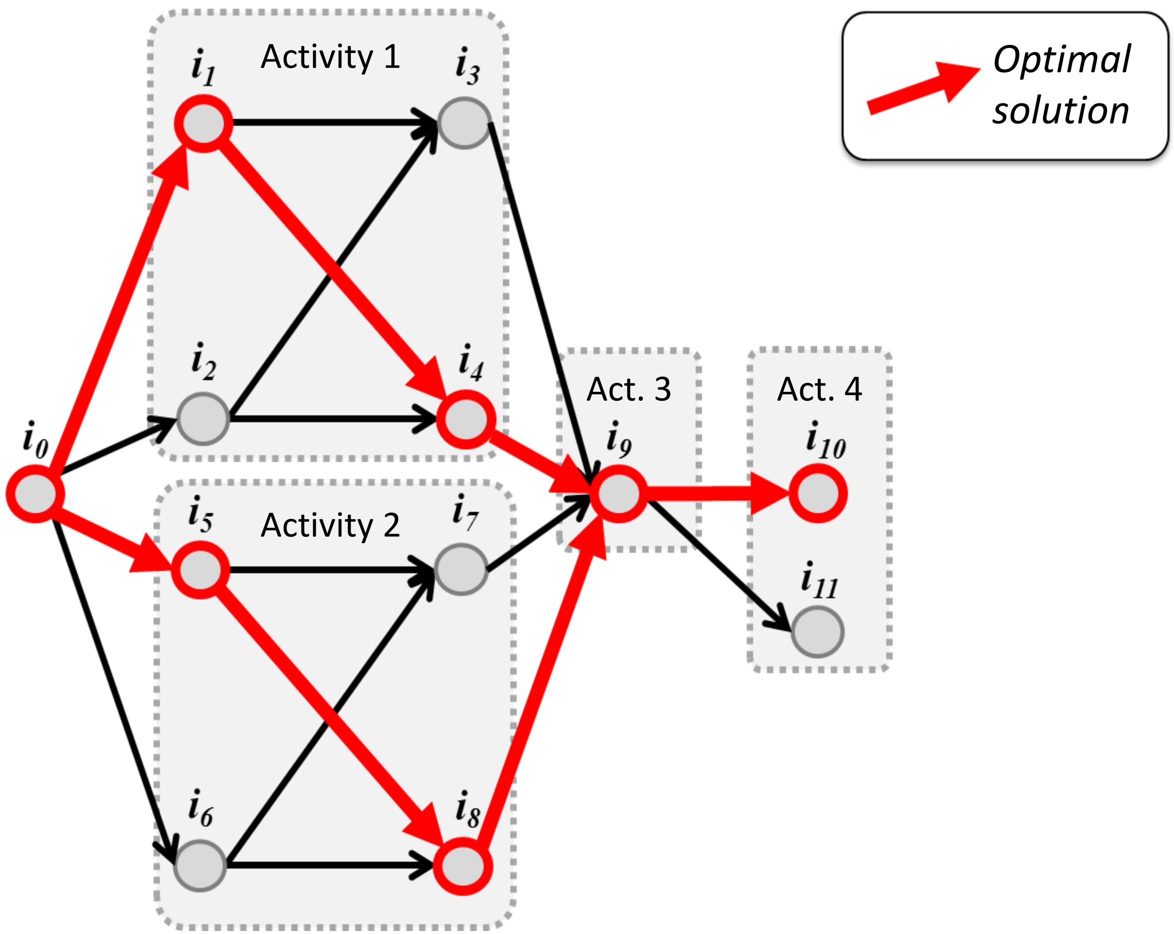
Maximization of quality: $$\boldsymbol{Q}(x) = \sum_{i=1}^{m} \sum_{i=1}^{n} x_{ij} \cdot q_{ij} \rightarrow \boldsymbol{Max}$$

... **...**

Partner Selection Problem with parallel activities

In practice:

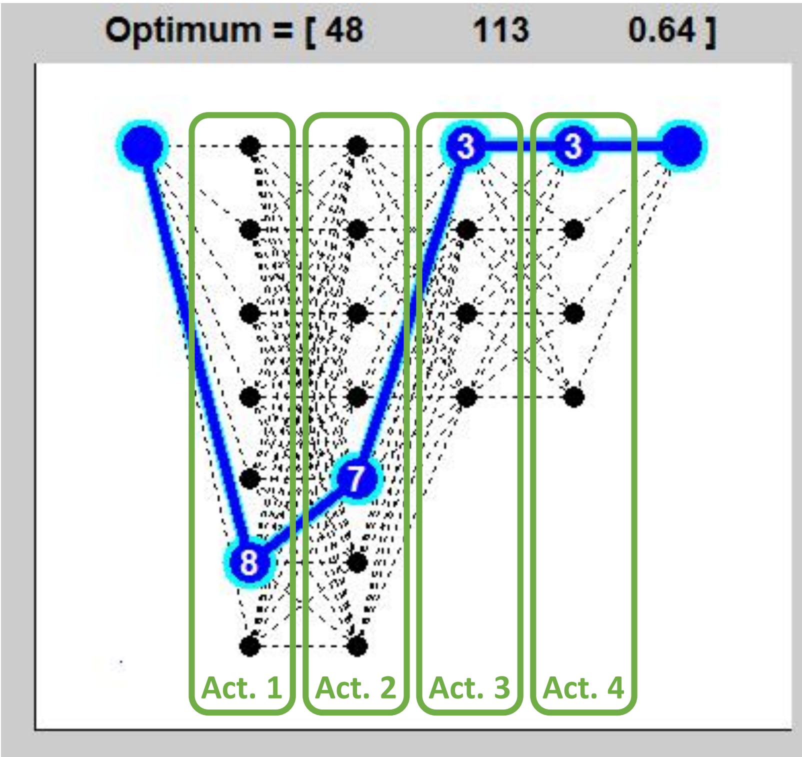
Problem instances **usually have parallel activities**



Example of PSP instance and its optimal solution

PSP instance with **4 activities**, **10 enterprises** and **3 criteria** (S, Q, C)

Graph represents manufacturing process:



Geographic location of enterprises:

Metaheuristic algorithms and MCDM methods

Agorithms for metaheuristic optimization:

- deterministic vs. stochastic
- nature inspired vs. non-nature inspired
- using memory vs. no memory
- based on single solution vs. based on population of solutions
- iterative vs. greedy

Multi-Criteria Decision-Making (MCDM) methods:

- based on utility functions
- outranking methods
- interactive methods

Metaheuristic algorithms and MCDM methods

Agorithms for metaheuristic optimization:

- Ant Colony Optimization (ACO)
- Firefly Algorithm (FA)
- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Simulated Annealing (SA)
- Cuckoo Search (CS)

Multi-Criteria Decision-Making (MCDM) methods:

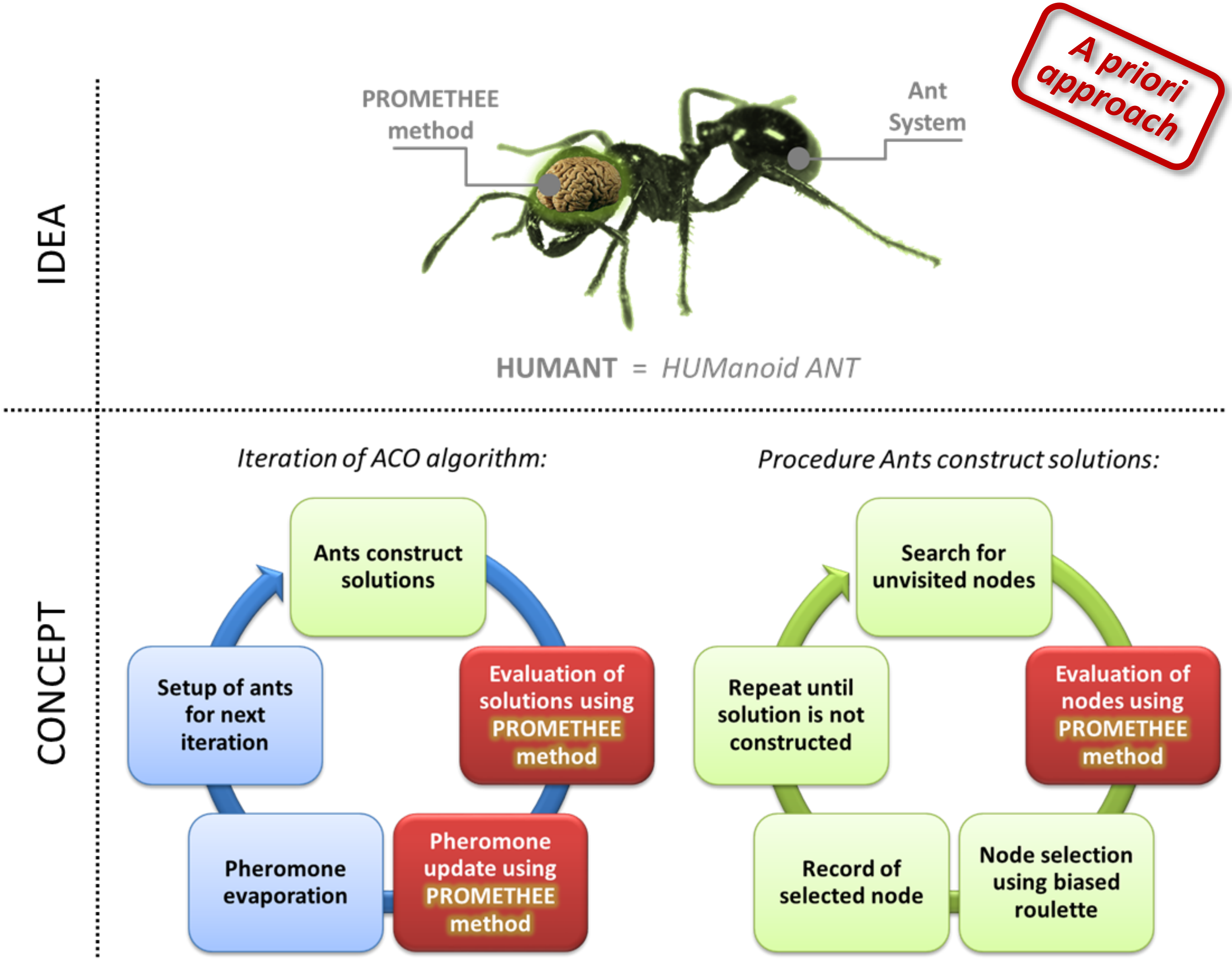
- MAUT
- AHP
- ELECTRE
- PROMETHEE
- TOPSIS
- VIMDA

Multi-Objective optimization

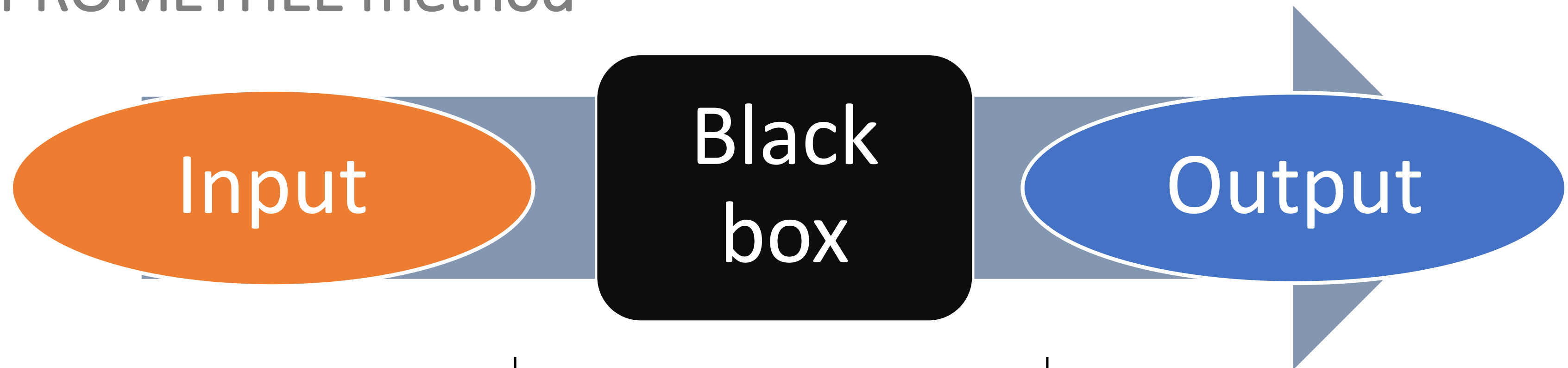
There are three possible approaches:

- ***A priori* approach** – decision-maker provides his preferences before the optimization process.
- ***A posteriori* approach** – the optimization process determines a set of Pareto solutions, and then decision-maker chooses one solution from the set of solutions provided by the algorithm.
- **Interactive approach** – there is a progressive interaction between the decision-maker and the solver, i.e. the knowledge gained during the optimization process helps decision-maker to define his preferences.

Idea and concept of HUMANT algorithm



PROMETHEE method



An input is a matrix consisting of set of **potential alternatives** (enterprises) A, where each a element of A has its *f(a)* which represents evaluation of one criteria:

	$f_1(.)$	$f_2(.)$	......	$f_j(.)$	......	$f_k(.)$
a_1						
a_2						
$\dots$						
a_i				$f_j(a_i)$		
$\dots$						
a_n						

Method **PROMETHEE I** ranks actions by a **partial pre-order**, with the following dominance flows:

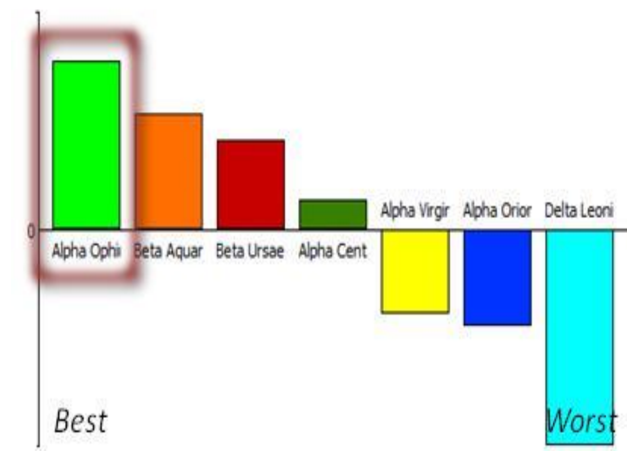
$$\Phi^+(a) = \frac{1}{n-1}\sum_{x\in A}\pi(a,x)$$

$$\Phi^-(a) = \frac{1}{n-1}\sum_{x\in A}\pi(x,a)$$

Method **PROMETHEE II** ranks the actions by **total pre-order**:

$$\Phi\ (a) = \Phi^+(a) - \Phi^-(a)$$

An output is set of **ranked alternatives** (enterprises):



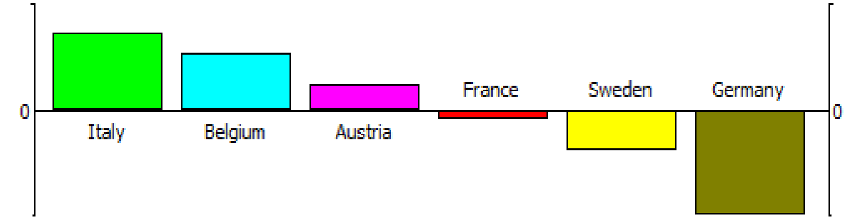
PROMETHEE method

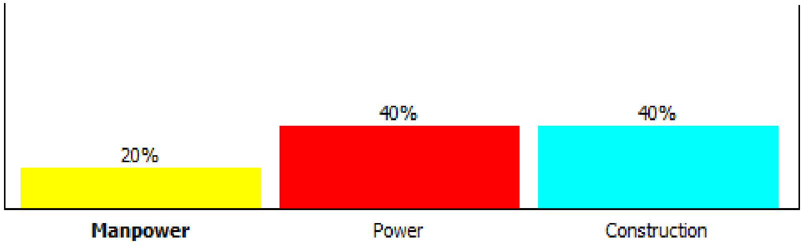
Example of **evaluation of 6 projects using 3 criteria**

INPUT:

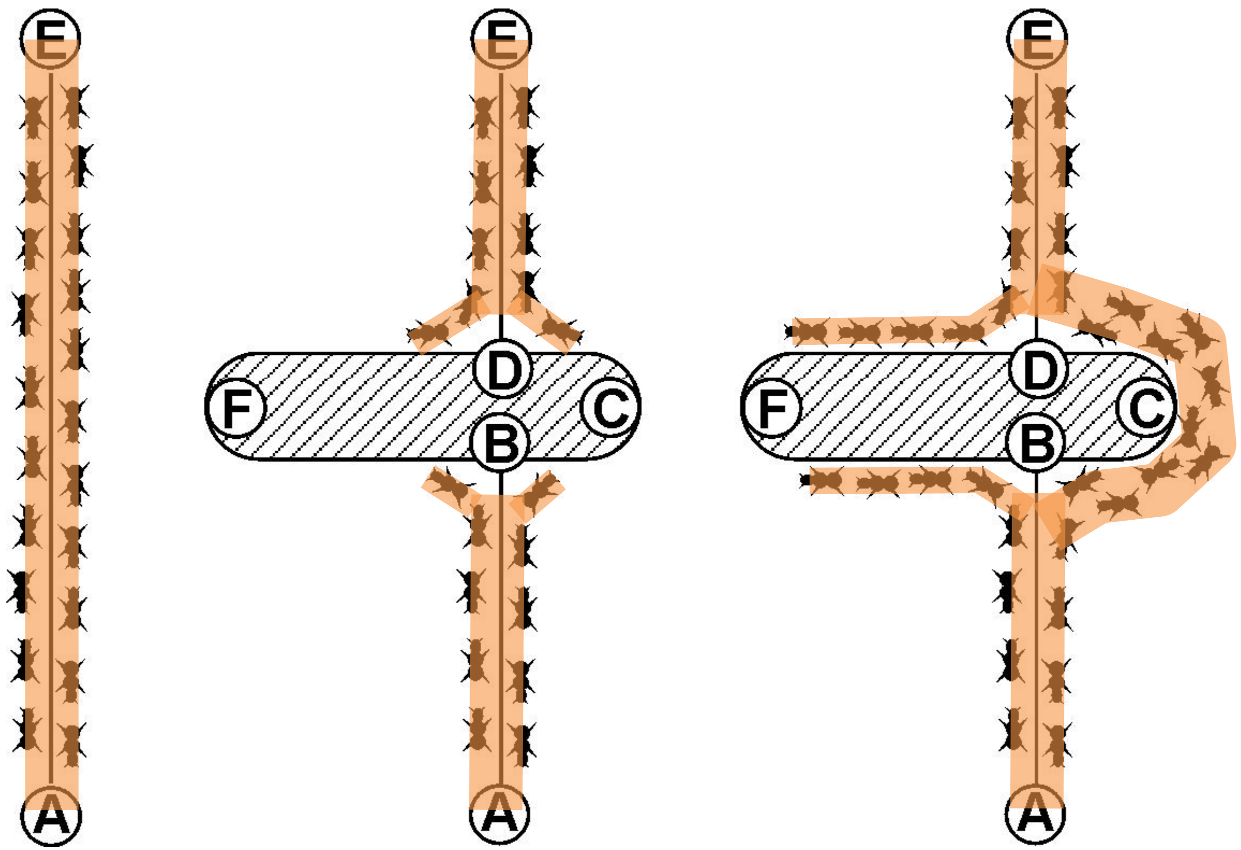
Scenario1	Manpower	Power	Construction
Unit	persons	MW	M€
Cluster/Group			
Preferences			
Min/Max	min	max	min
Weight	0,20	0,40	0,40
Preference Fn.	U-shape	V-shape	Linear
Thresholds	absolute	absolute	absolute
- Q: Indifference	10	n/a	50
- P: Preference	n/a	300	500
- S: Gaussian	n/a	n/a	n/a
Statistics			
Evaluations			
Italy	80	900	600
Belgium	65	580	200
Germany	83	600	400
Sweden	40	800	1000
Austria	52	720	600
France	94	960	700

OUTPUT:





Ant System

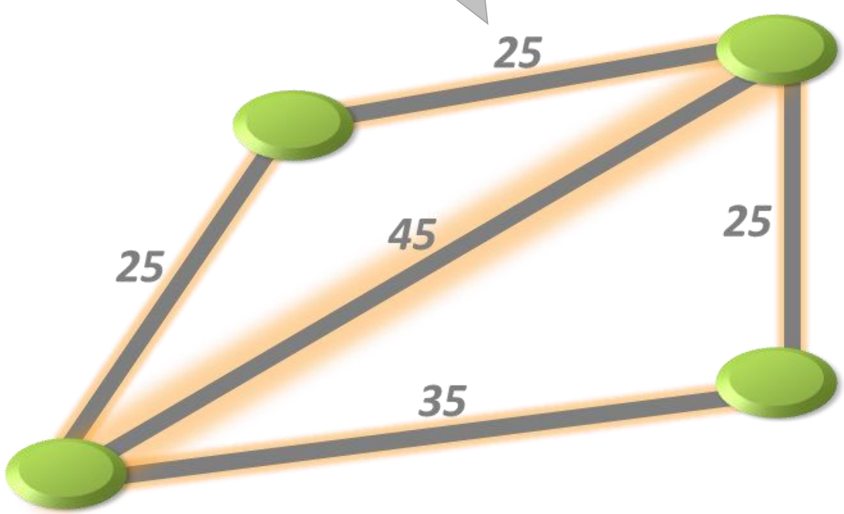


Ants choose their path randomly, but not completely randomly, the criterion is also a **level of pheromone trail on each path**.

Ant System (Ant Colony Optimization)

In 1992 **M. Dorigo presented Ant System** of artificial ants with vision

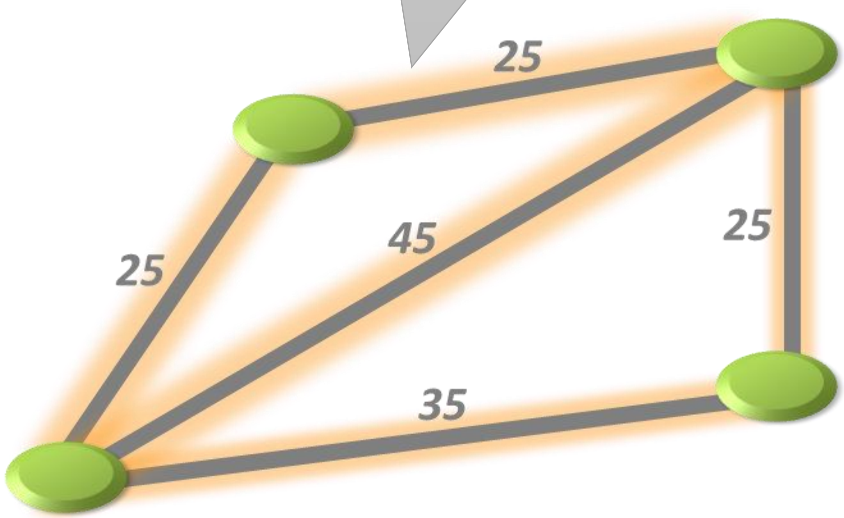
Artificial ants see **paths** in front of them, and **pheromone level**.



MAX-MIN Ant System (MMAS)

In 2000 **T. Stützle and H.H. Hoos presented MAX-MIN** Ant System

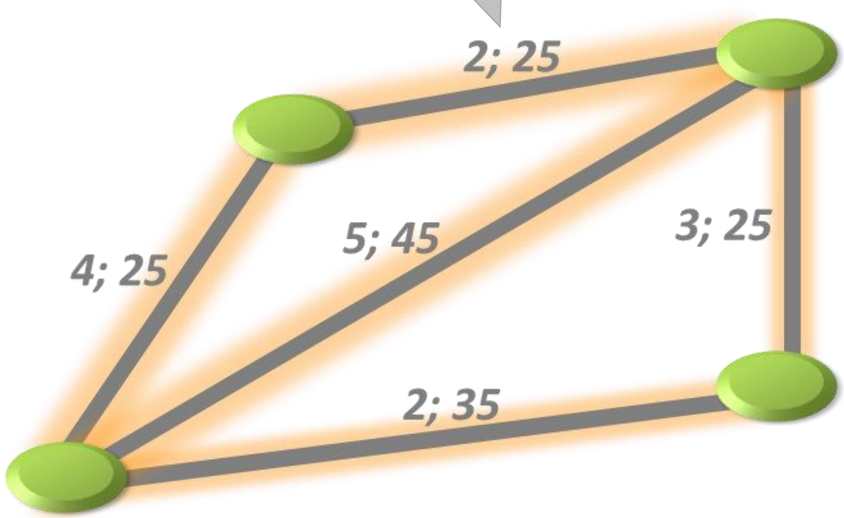
On the beginning, **pheromone level is set to maximum** on each path, and search is based on its evaporation.



Multi-Objective Ant Colony Optimization (MO-ACO)

New generation of intelligent **Multi-Objective Ant Algorithms**

Each path has several values (several criteria), so the **ants need to be more intelligent**.



Similar researches

in short

I am a PhD student working at the Université Libre de Bruxelles (ULB) in Brussels, Belgium, in the Department of Computer & Decision Engineering (CoDE). I have a scholarship funded by the Scientific Research Directorate of the French Community of Belgium in the context of the Meta-X Project. I am working under the supervision of Pr. Yves De Smet and Dr. Thomas Stuetzle.

For some details on what I am working on, please pay a visit to the **research** tab.

Stefan Eppe

research topic

I am working on Metaheuristics for solving MOCOP's. In particular, I am interested in applying ence modelling techniques developed in the MCDA community to the well established ACO metaheuristic.

The goal of my research is to consider how to integrate a decision maker's a priori preference ultiobjective combinatorial optimization heuristics. Currently I am examining possible paths of applying preference modeling techniq oped by the multicriteria decision aid (MCDA) community in a multiobjective ant colony optimization (MO-ACO) algorithm.

Dr. Thomas Stuetzle.

Difference between HUMANT algorithm and ACO

Main ACO equations:

$$(p_{ij})_k = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_k [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}}$$

$$(\Delta\tau_{ij})_k = \frac{Q}{L_k}$$

Main HUMANT equations:

$$p_{ij} = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\Phi'_{ij}]^{\beta}}{\sum_{k=1}^{n} [\tau_{ik}(t)]^{\alpha} \cdot [\Phi'_{ik}]^{\beta}}$$

$$\Phi'_{\mathrm{ij}} = \frac{\frac{1}{n-1} \sum_{k=1}^{n} \left(\Pi\left(X_{ij}, X_{ik}\right) + \left(1 - \Pi\left(X_{ik}, X_{ij}\right)\right)\right)}{2}$$

PROMETHEE method

$$\Delta\tau_{ij} = 2\left(\Phi^{+}(x) - \Phi^{-}(x)\right) = 2\left(\Pi\left(x, s^{id}\right) - \Pi\left(s^{id}, x\right)\right)$$

Solution to the problem of non-dominating alternatives

$$p_{ij} = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\Sigma_k \, [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}}$$

Node number	Pheromone τ_{ij}	Distance $1/\eta_{ij}$	Probability p_{ij} using ACO calculation ($\alpha = 1$, $\beta = 4$)	Probability p_{ij} using PROMETHEE calculation ($\alpha = 1$, $\beta = 4$)	Probability p_{ij} using modified PROMETHEE calculation ($\alpha = 1$, $\beta = 47$)
8	1	**463**	**52,2%**	**5,8%**	**48,1%**
7	1	**563**	**23,9%**	**5,6%**	**27,9%**
21	1	**720**	**8,9%**	**5,2%**	**11,7%**
39	1	**825**	**5,2%**	**4,9%**	**6,5%**
15	1	**1004**	**2,4%**	**4,5%**	**2,3%**
37	1	**1029**	2,1%	4,4%	2,0%
2	1	**1205**	1,1%	4,1%	0,7%
14	1	**1290**	0,9%	3,9%	0,4%
45	1	**1542**	0,4%	3,4%	
30	1	**1574**	0,4%	3,4%	
…	…	…	…	…	…

Solution:
$\beta = n$

HUMANT algorithm parameters

Comparison of parameters of MAX-MIN AS and HUMANT algorithm

Parameter description	MAX-MIN ant system	HUMANT algorithm
Importance of pheromone trail on edge	α	α
Importance of weight (cost) of edge	β	γ
Maximal level of pheromone trail	τ_{max}	τ_{max}
Minimal level of pheromone trail	τ_{min}	τ_{min}
Pheromone evaporation rate	ρ	ρ
Ideal solution	-	s^{id}

HUMANT algorithm

and

Preliminary results of HUMANT algorithm on TSP

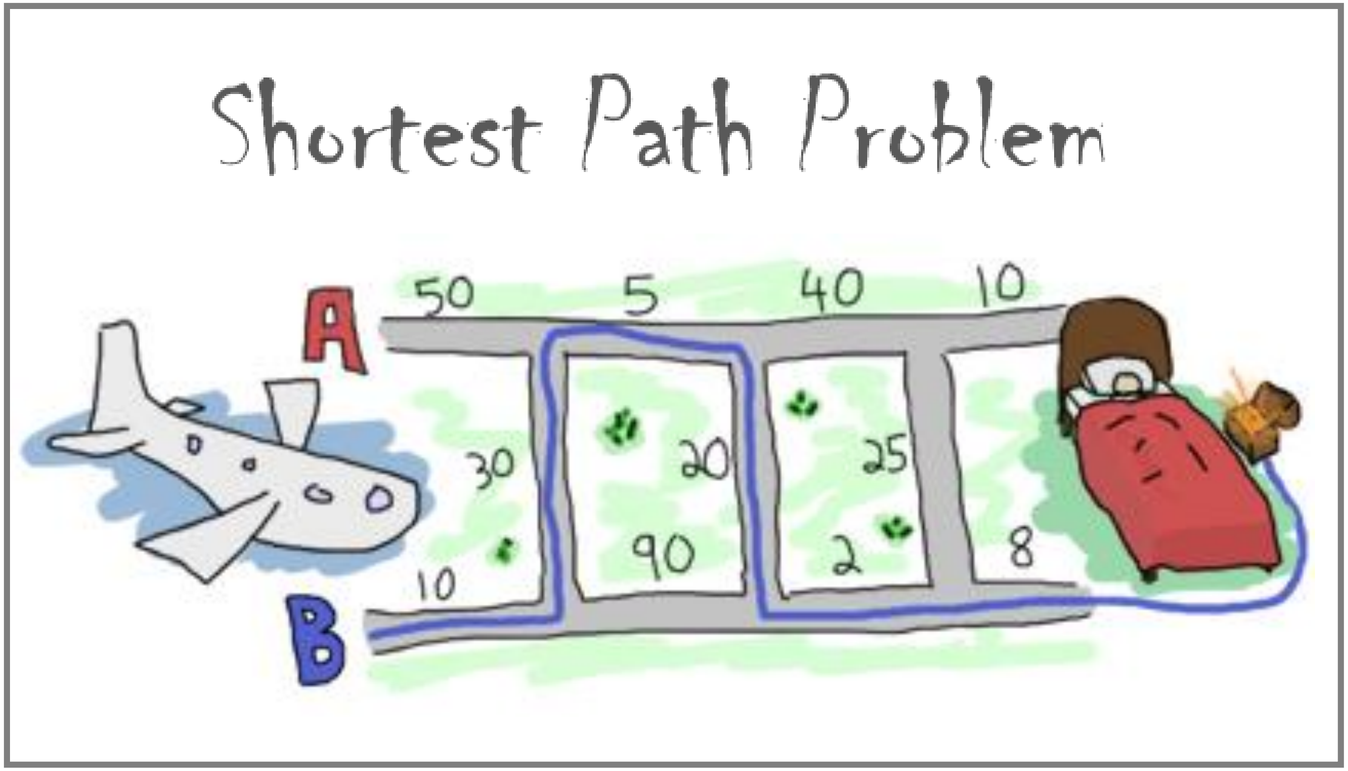
Performance of HUMANT algorithm on TSP instances from *TSPLIB*

Problem instance	**HUMANT algorithm**	**MAX-MIN ant system (MMAS)**	**Ant Colony System (ACS)**	**Ant System (AS)**
48-cities problem (*att48*)	10662 (0.32%)	-	-	-
51-cities problem (*eil51*)	455.1 (6.83%)	427.6 (0.38%)	428.1 (0.49%)	437.3 (2.65%)
100-cities problem (*kroA100*)	21358.3 (0.36%)	21320.3 (0.18%)	21420.0 (0.65%)	22471.4 (5.59%)

HUMANT algorithm is **better on 100-cities problem than 51-cities problem**, it is even better than original ACS and AS. However, *eil51* is a specific problem with many local optima and HUMANT algorithm has **very strong convergence**.

HUMANT algorithm

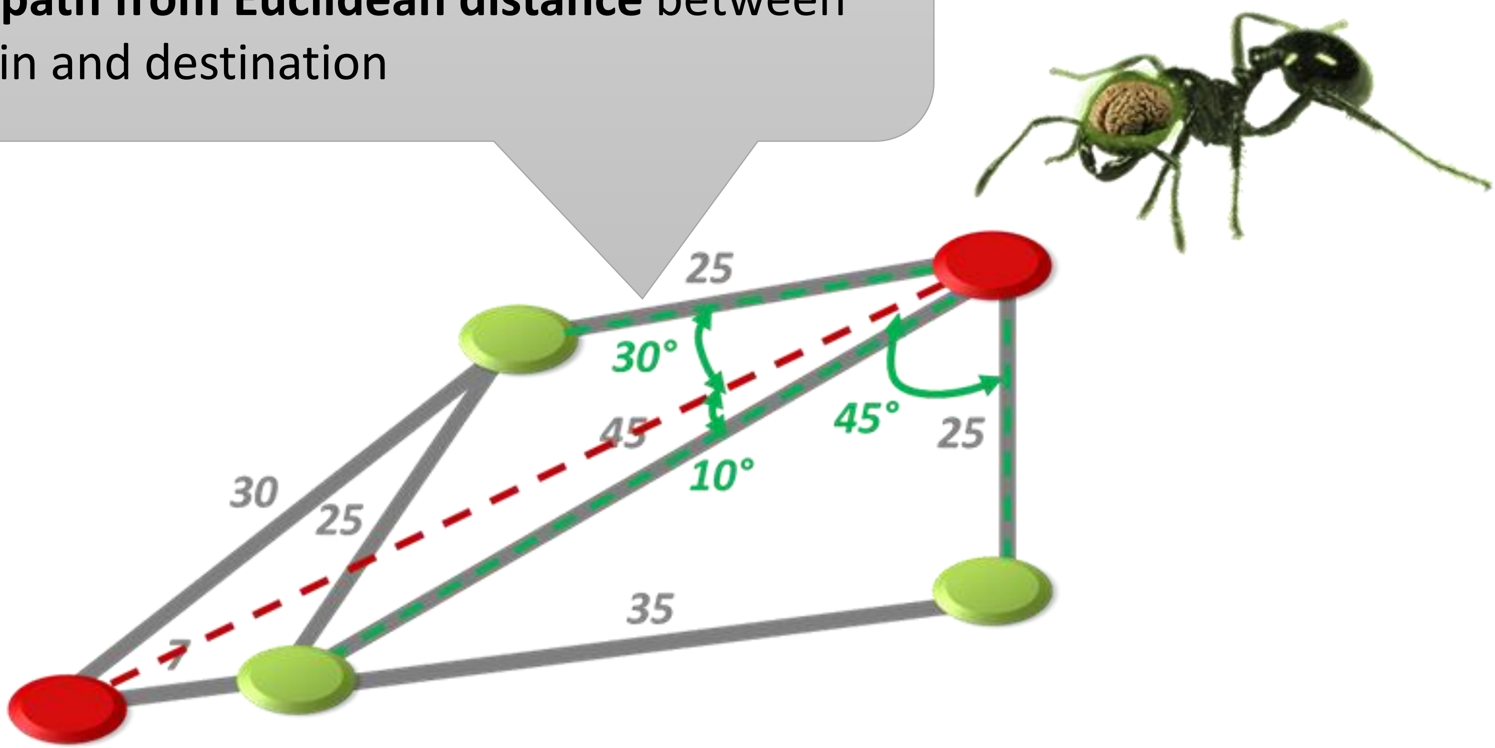
and



Preliminary results of HUMANT algorithm on SPP

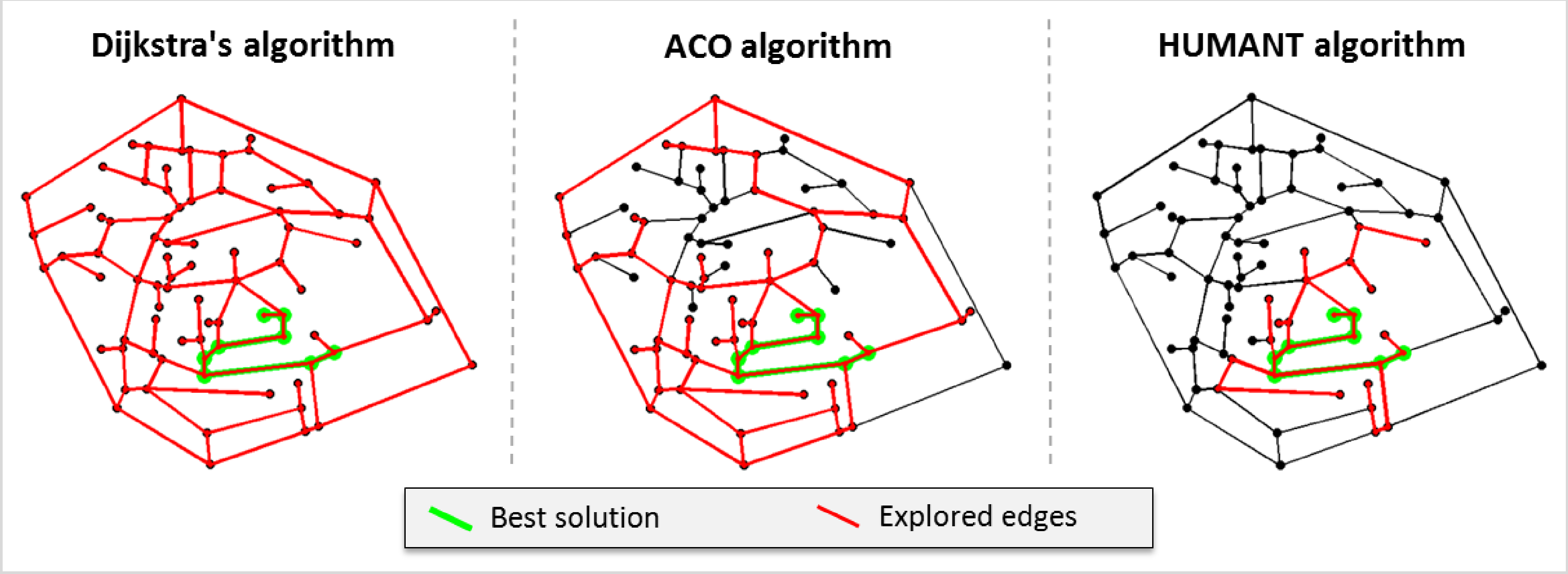
On Shortest Path Problem it is possible to test **Multi-Objective approach** to Single-Objective optimization problems

Multi-objective (bi-criteria) approach to SPP: **distance to the next** node and **deviation of the path from Euclidean distance** between origin and destination



Preliminary results of HUMANT algorithm on SPP

Using no constraints HUMANT algorithm explores only relevant area



HUMANT algorithm

and

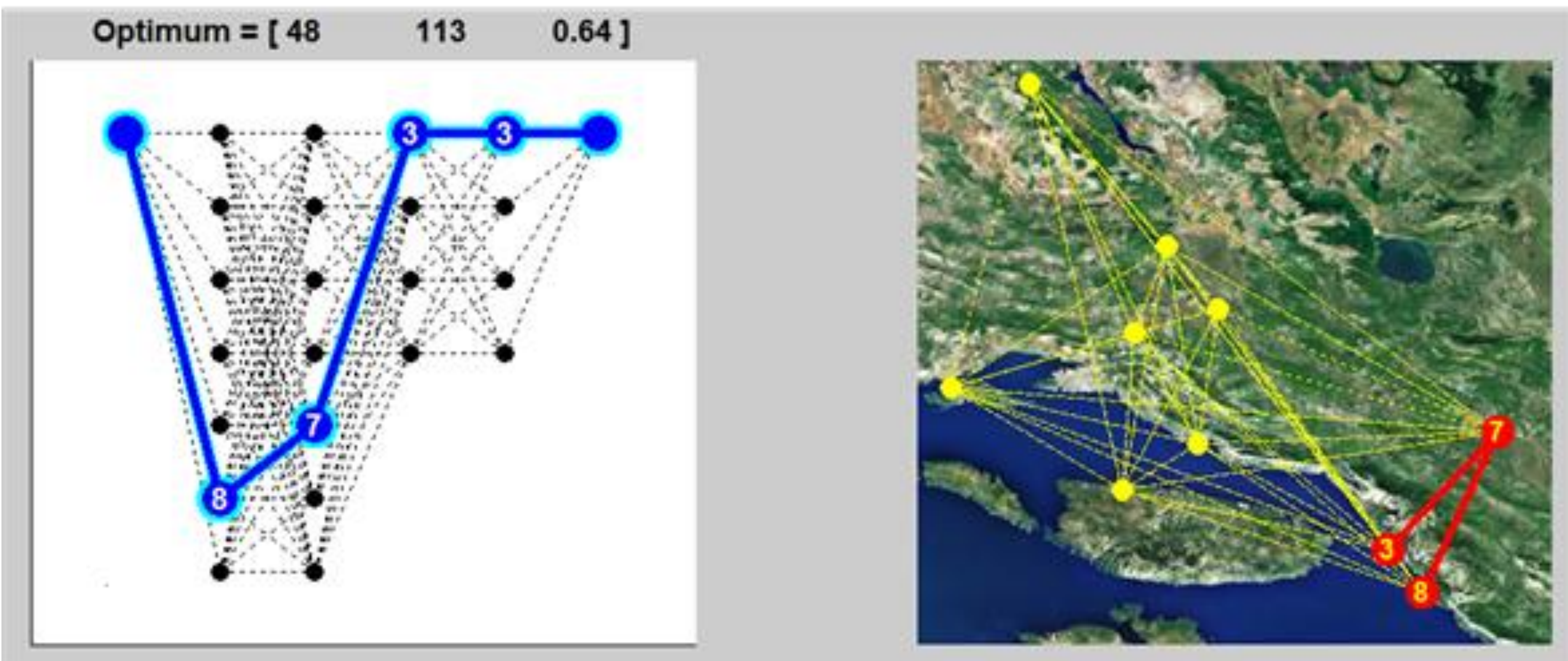
Preliminary results of HUMANT algorithm on PSP

Following parameters were used to solve this problem:

$\boldsymbol{\alpha} = 1, \quad \boldsymbol{\gamma} = 1, \quad \boldsymbol{\rho} = 0.4, \quad \boldsymbol{\tau}_{min} = 0, \quad \boldsymbol{\tau}_{max} = 1$

and following criteria weights:

$\boldsymbol{w}_{cost} = 0.15, \quad \boldsymbol{w}_{transport} = 0.4, \quad \boldsymbol{w}_{quality} = 0.45$



Conclusion

Pros:

- can be applied to single-objective and multi-objective problems
- strong convergence finds optimum very fast
- automatic calculation of PROMETHEE parameters
- multi-objective approach to single-objective optimization problems can be used
- parallelization is possible

Cons:

- strong convergence not suitable for problems with many optima
- more complex calculations, slower than standard ACO
- only for problems that can be expressed as mathematical graph