Main research activities

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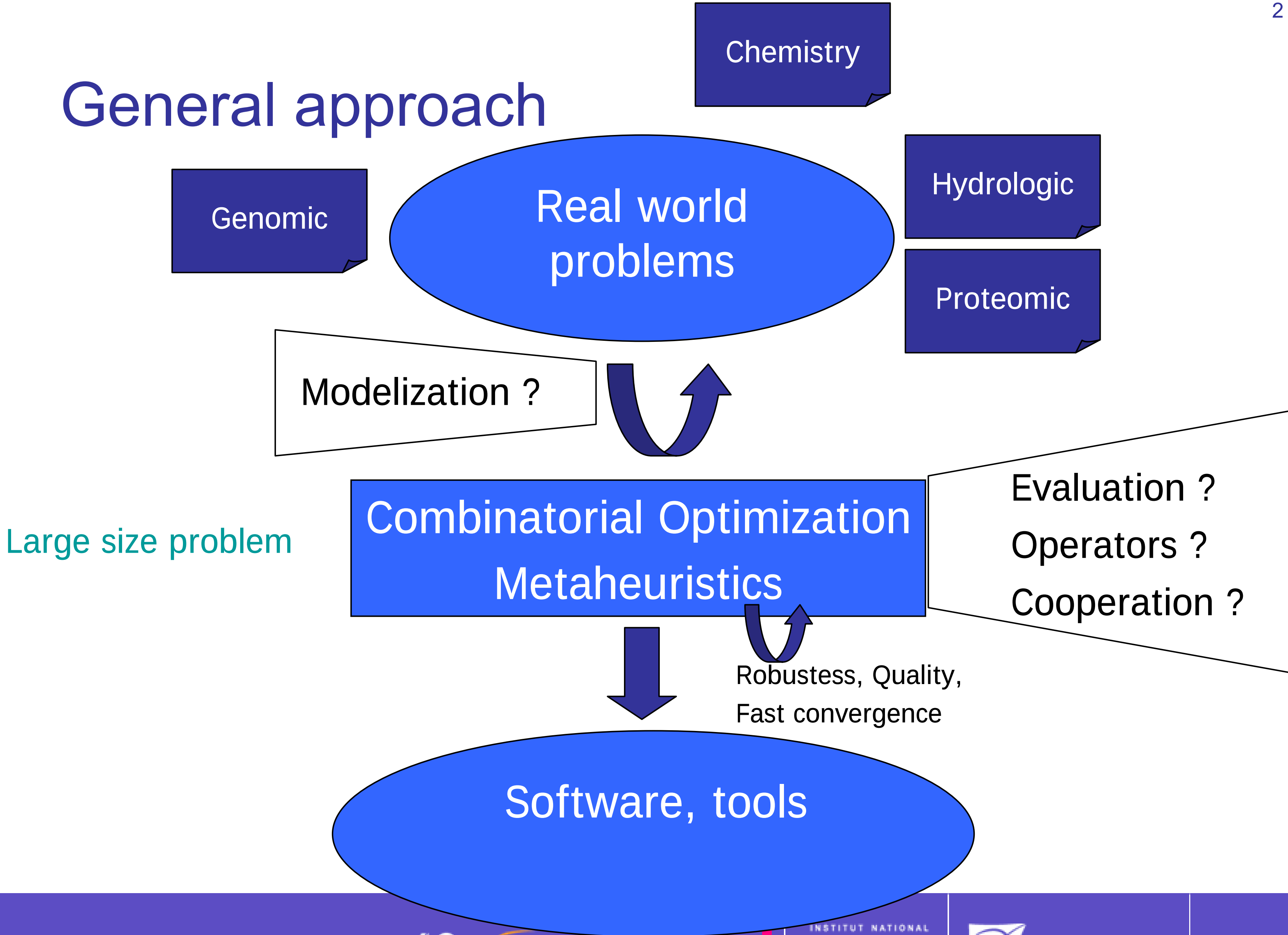
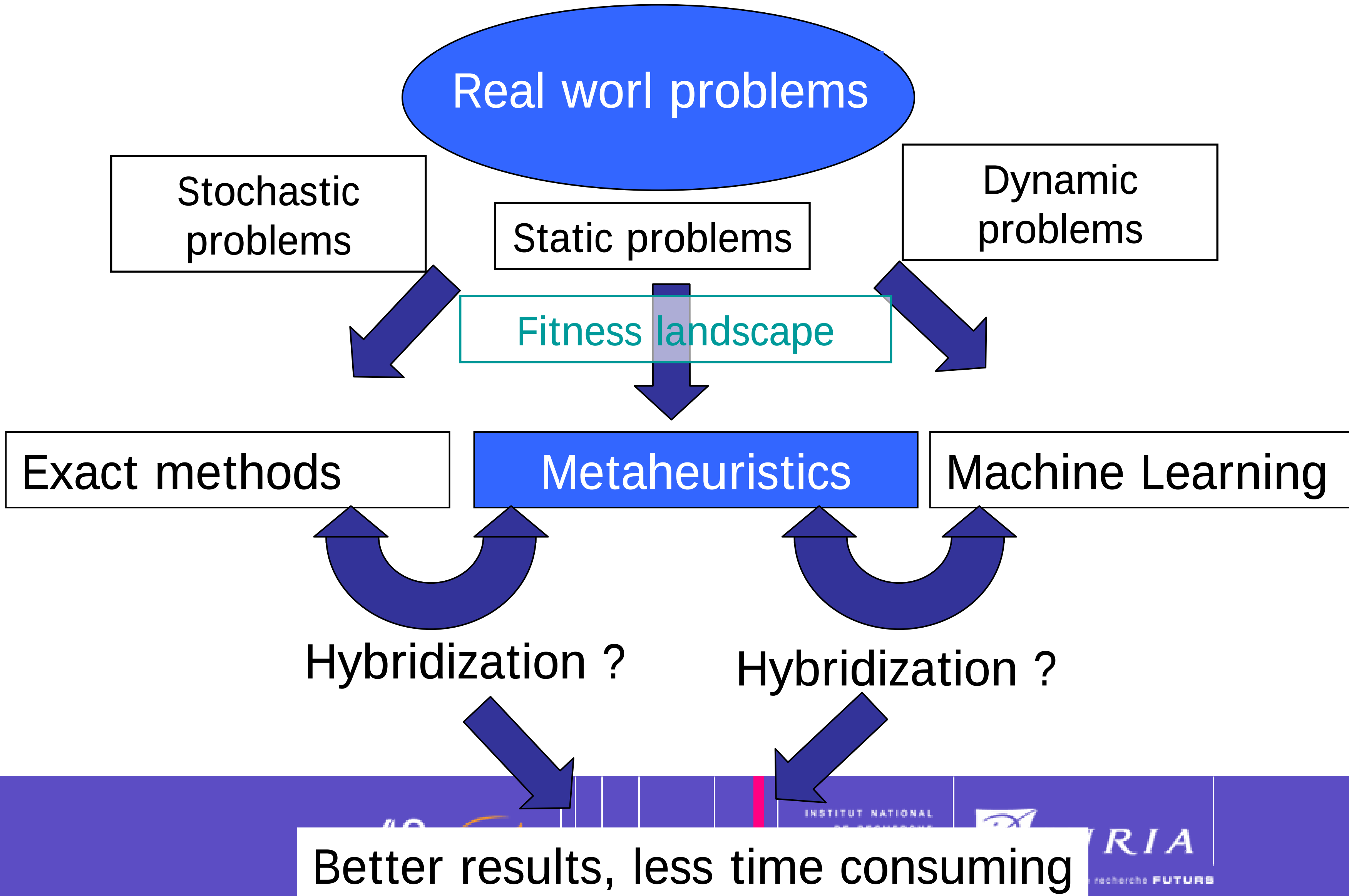
General approach



Cooperative metaheuristics

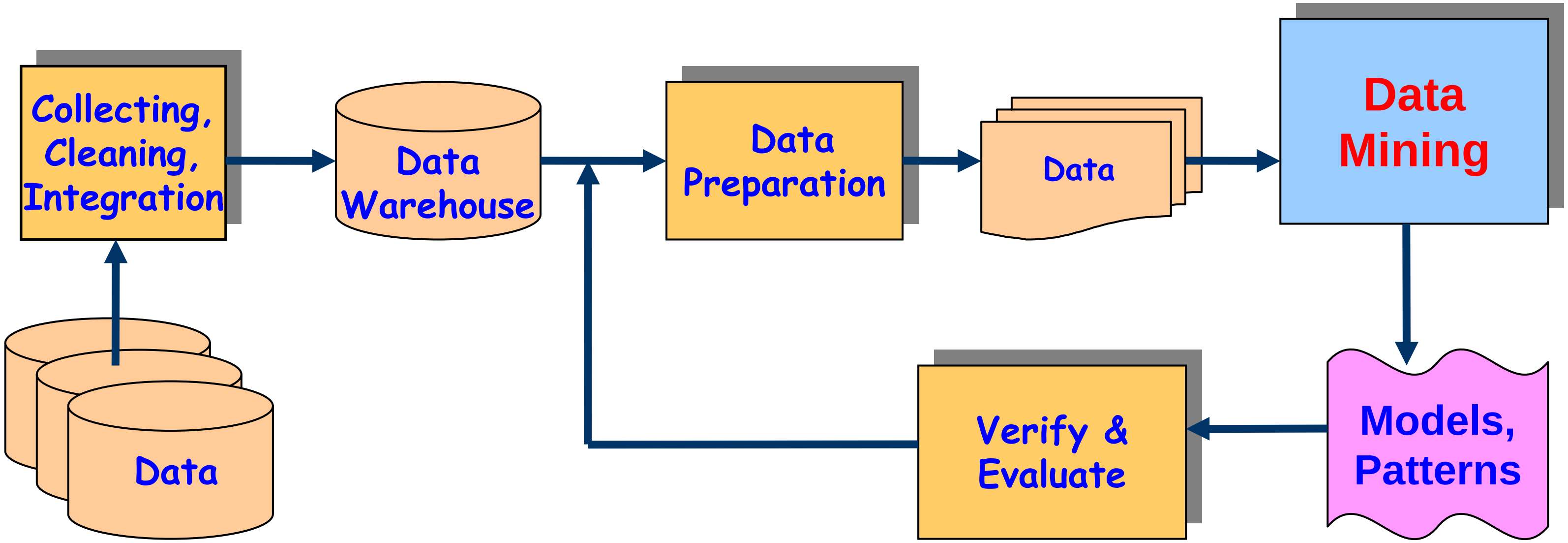


Hybridization of machine learning and metaheuristics

- L. Jourdan, C. Dhaenens and E-G. Talbi, "Using datamining techniques to help metaheuristics: a short survey", HM 2006, LNCS Vol. 4030, pp. 57-69.
- L. Jourdan, D.W. Corne, D. Savic and G.A. Walters, "Preliminary Investigation of the `Learnable Evolution Model' for Faster/Better Multiobjective Water Systems Design", EMO 2005. LNCS 3410, pp. 841-855
- L. Jourdan, D.W. Corne, D. Savic and G.A. Walters, "Hybridising Rule Induction and Multi-Objective Evolutionary Search for Optimising Water Distribution Systems", In Proceeding of Fourth International Conference on Hybrid Intelligent Systems , IEEE HIS 2004, Kita Kyushu, Japan, 5-8 Dec 2004, pp. 435-439

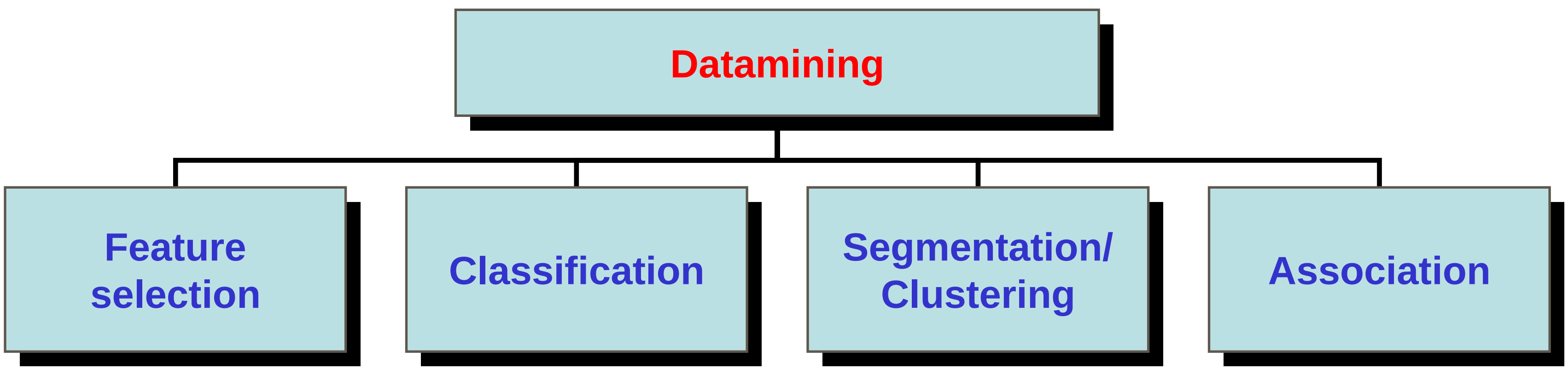
Datamining/machine learning

One step of the complex Knowledge Dicovery in Databases (KDD) process



Datamining

- Several classical tasks:
  - Feature selection
  - Classification
  - Clustering (unsupervised classification)
  - Association discovery



Taxonomy

May use several characteristics.

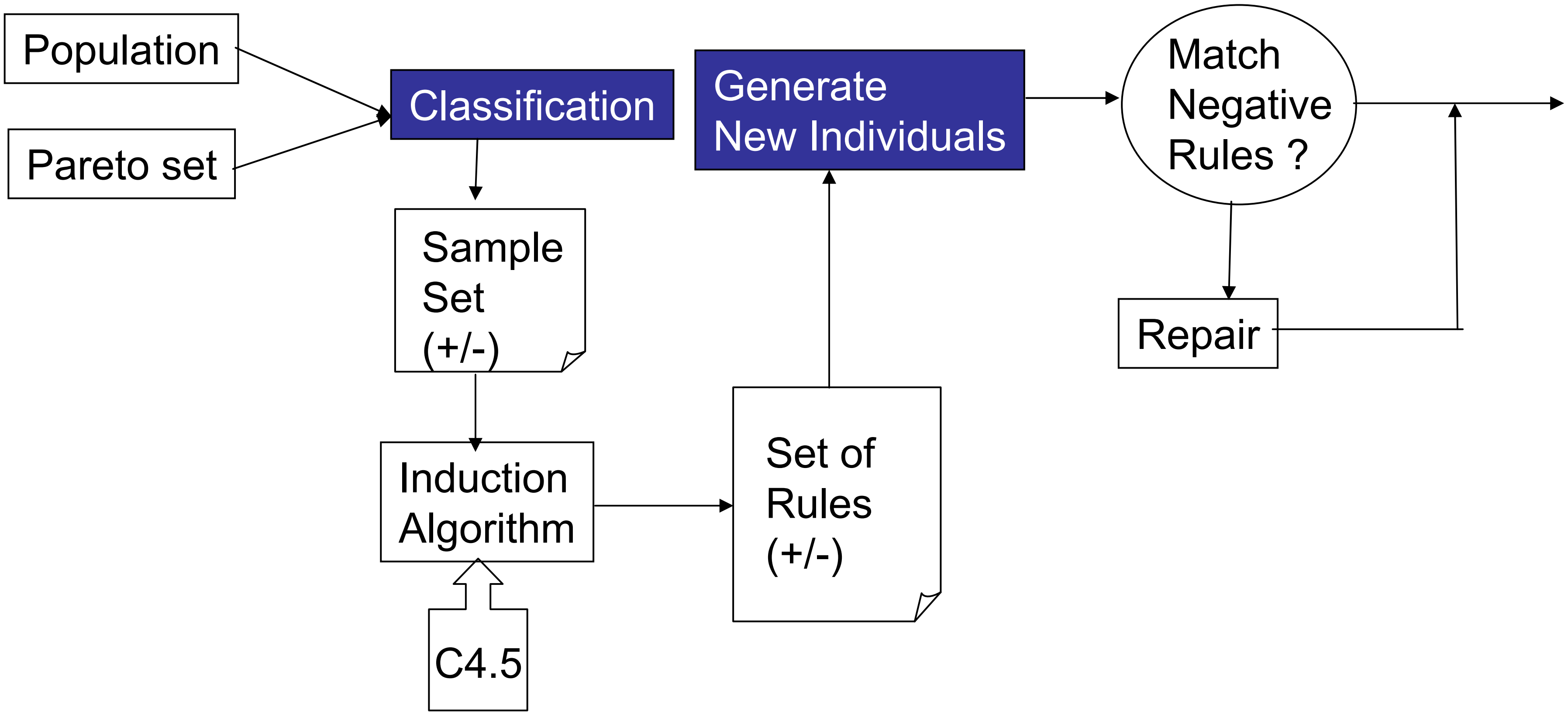
Kind of Knowledge:
- Apriori knowledge
- Dynamic knowledge

Aim:
- Speeding-up
- Quality improvement

Localization:
- Evaluation
- Parameters
- Encoding
- Initialization
- Operators
- Population management
- Local Search

Contributions

LEMMO



Multi-objective water systems optimization

Design/rehabilitation problems

Choose

- Diameter of pipes

Objectives

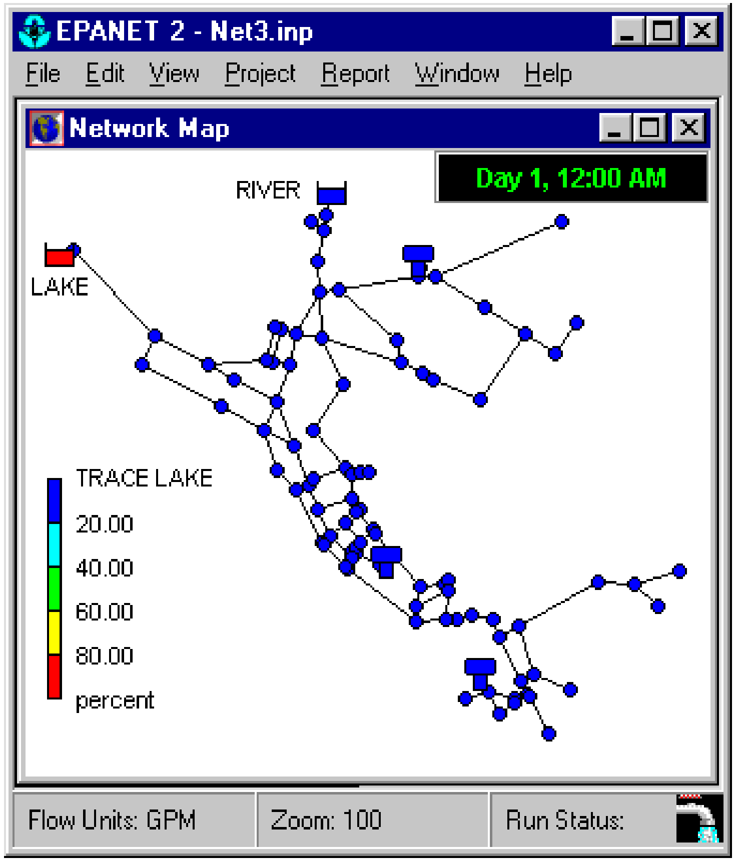
- Minimize the cost of the network
- Minimize the head deficit → EPANET 2

Constraints

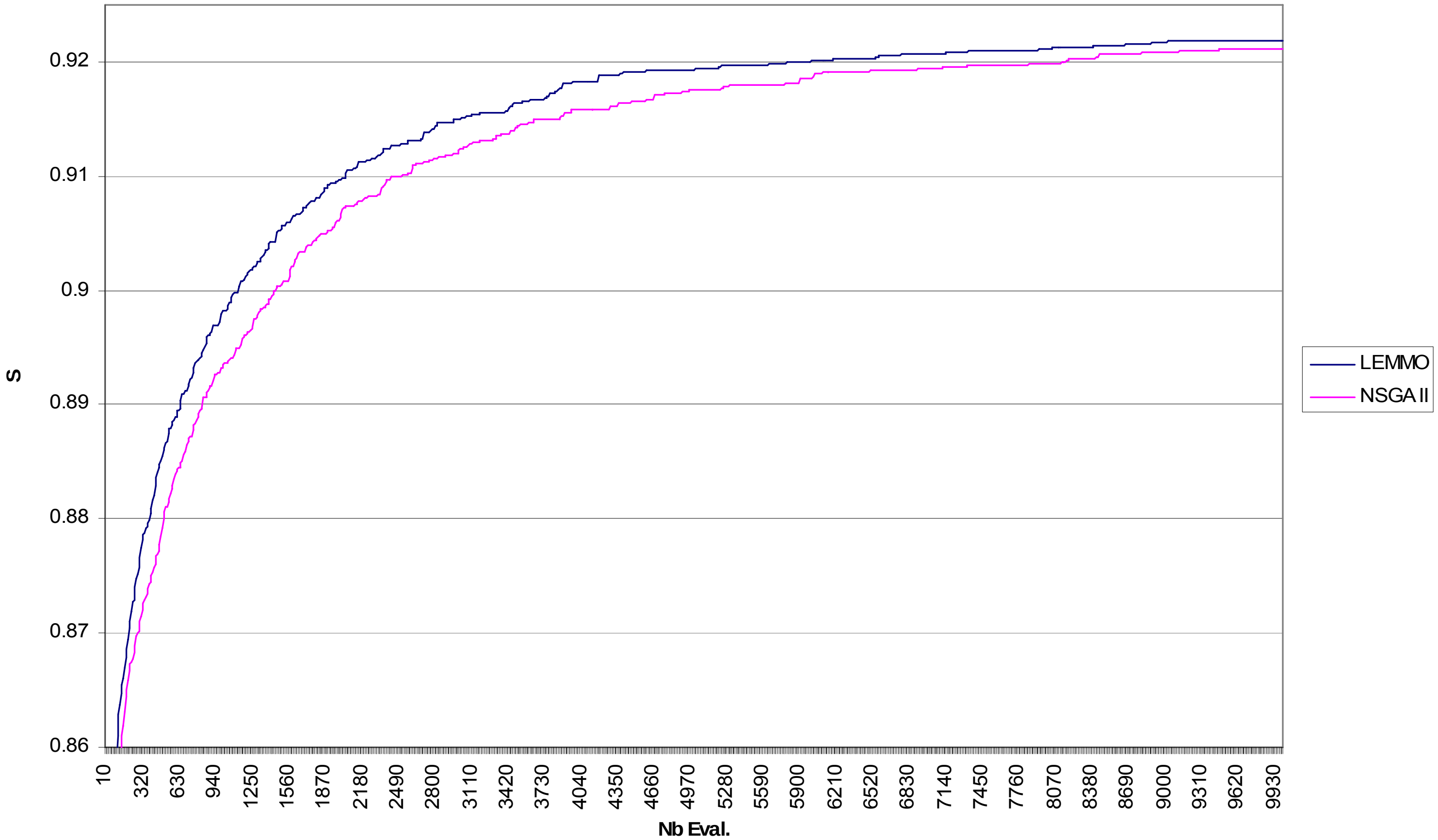
- Minimum pressure on nodes

Evaluation

- Evaluation: time consuming



Example of results



Actually

Using sequence discovery in data to speed up transport problem

- Machine learning algorithms provide sequence of clients that are interesting (eg: C1 then C6 then C15): used algorithm SPADE,
- the order of clients is an information to be use to provide a fixed
- structure is some chromosome of the population of the GA.
- Test bed problems: TSP, VRP mono and multi objective

Hybridization of exact method and metaheuristics

•L. Jourdan, M. Basseur and E-G. Talbi, *Hybridizing Exact Method and Metaheuristics: A Taxonomy*, European Journal of Operational Research, (Available online, 2008).

Proposed grammar

< *hybrid method* > → < ***design-issues*** > < ***implementation-issue*** >

< ***design-issues*** > → < ***hierarchical*** > < ***flat*** >

< ***hierarchical*** > → **< LRH >|< LCH >|< HRH >|< HCH >**

< ***LRH*** > → **LRH (< *method* >(< *method* >))**

< ***LCH*** > → **LCH (< *method* >(< *method* >))**

< ***HRH*** > — **(< *method* >+ < *method* >)**

< ***HCH*** > → **HCH (< *method*>)**

< ***HCH*** > → **HCH (< *method* >,< method >)**

< ***flat*** > → **(< *resolution* >,< *optimization* >,< *function* >)**

< ***resolution*** > → **exact | approached**

< ***optimization*** > — **global | partial**

< ***function*** > → **general | specialist**

< ***implementation-issue*** > → **sequential | parallel < *scheduling* >**

< ***scheduling*** > → **static | dynamic | adaptive**

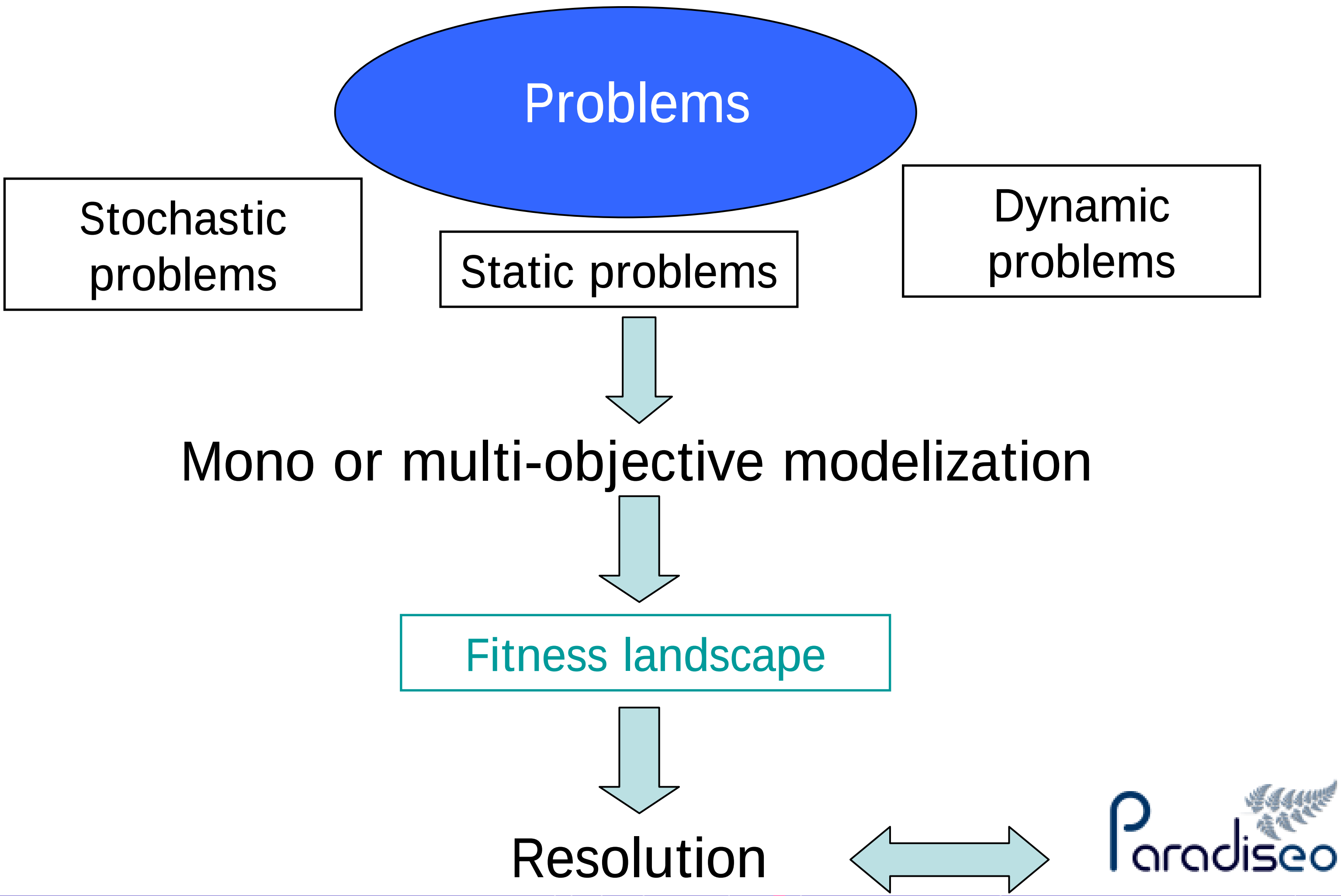
< ***method*** > → **< exact > | < heuristic >**

< ***heuristic*** > → **LS | TS | SA | GA | ES | GP | GH | AC | SS | NM | ... < *hybrid method* >**

< ***exact*** > → **B&B | B&C | B&P | PL | PD | MS | ... < *hybrid method* >**

Hybridization of Metaheuristics

Hybridization of metaheuristics



Static problems

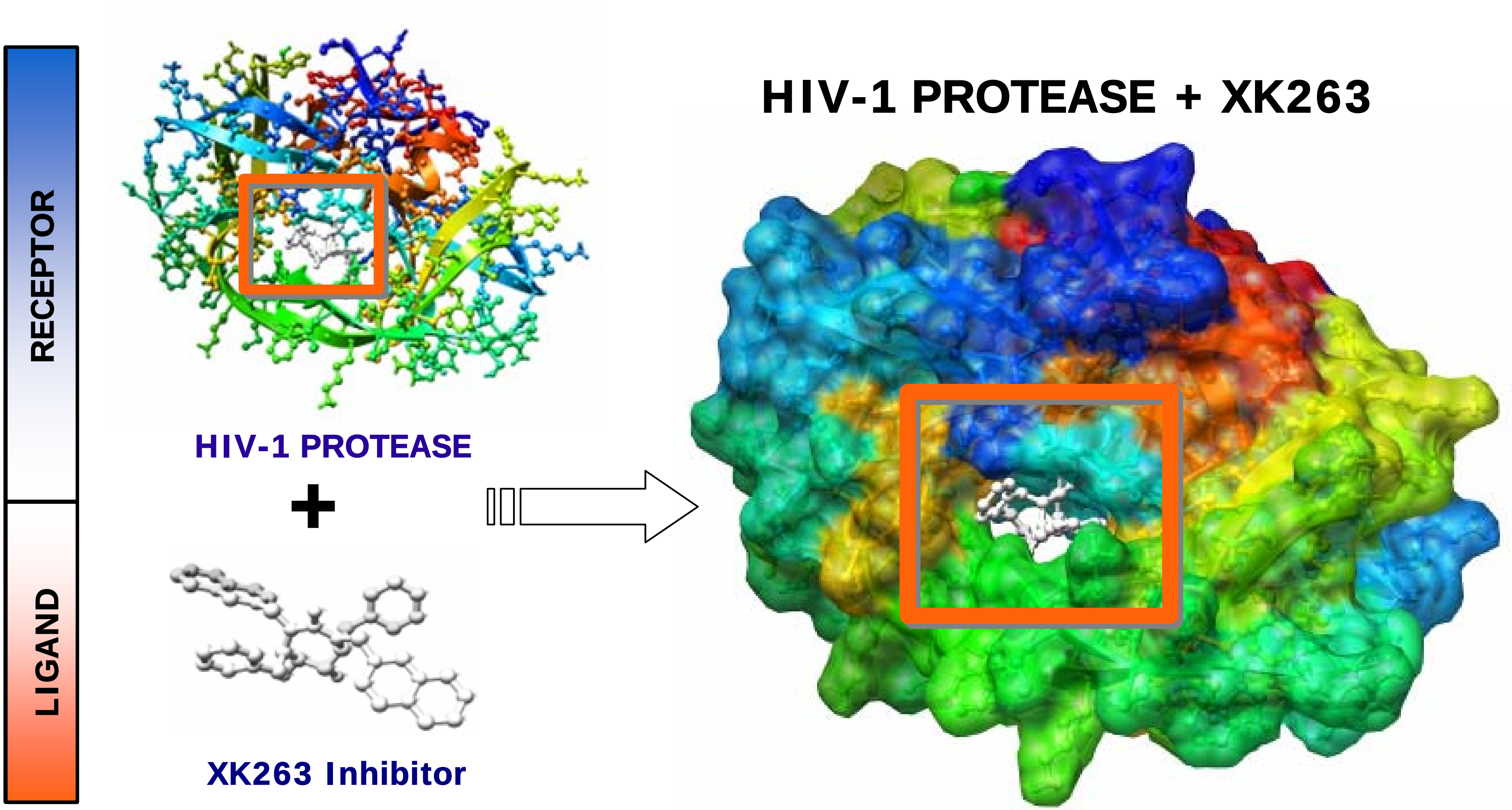
Multi-objective problems

- Difficulties in the problem: Docking
- Difficulties in amelioration of solutions: MORSP, MO Flowshop
  - New multi objective metaheuristics: IBMOLS, SEEA, DMLS …
  - Unification of models: MOGA, MOLS, … available on Paradiseo

Bioinformatics problems

- J-C. Boisson, L. Jourdan, E-G. Talbi et D. Horvath. "Parallel multi-objective algorithms for the molecular docking problem", Conference in Computational Intelligence in Bioinformatics and Bioengineering (CIBCB), 15-17 septembre 2008, Sun Valley Resort, Idaho, USA. (Best student paper).

Molecular docking



Molecular docking ⇔ prediction of the optimal complex receptor/ligand according to chemical and geometric properties.

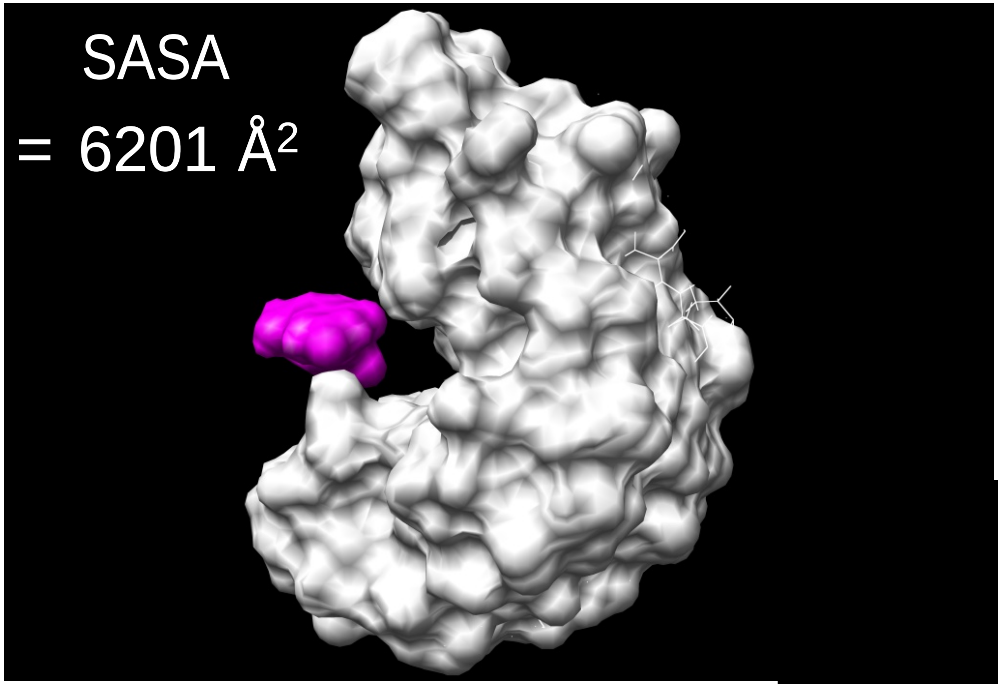
Molecular docking

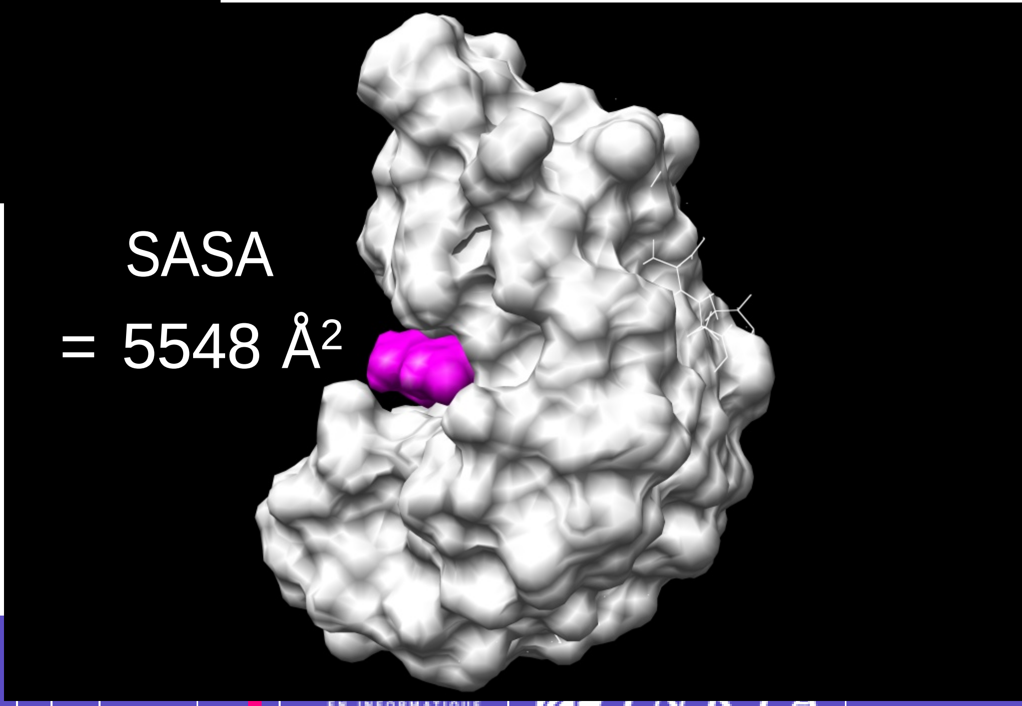
Docking simulation :

- **rigid** ⇔ no conformation modification of the molecules.
- **semi-flexible** ⇔ one of the two molecules may have its conformation modified during the process (generally the ligand).
- **flexible** ⇔ conformational modifications for the both molecules

Several sites can exist for docking the ligand.

Molecular docking





A new bi-objective model (2/4)

1. Energie of the ligand / receptor complex

$$
\begin{aligned}
E = & \sum_{bonds} K_b (b - b_0)^2 \\
+ & \sum_{angle} K_\theta (\theta - \theta_0)^2 \\
+ & \sum_{torsion} K_\phi (1 - \cos n(\phi - \phi_0)) \\
+ & \sum_{Van\ der\ Waals} \frac{K^a_{ij}}{d^{12}_{ij}} - \frac{K^b_{ij}}{d^6_{ij}} \\
+ & \sum_{Coulomb} \frac{q_i q_j}{4\pi\varepsilon d_{ij}} \\
+ & \sum_{desolvation} \frac{K q_i^2 V_j + q_j^2 V_i}{d^4_{ij}}
\end{aligned}
$$

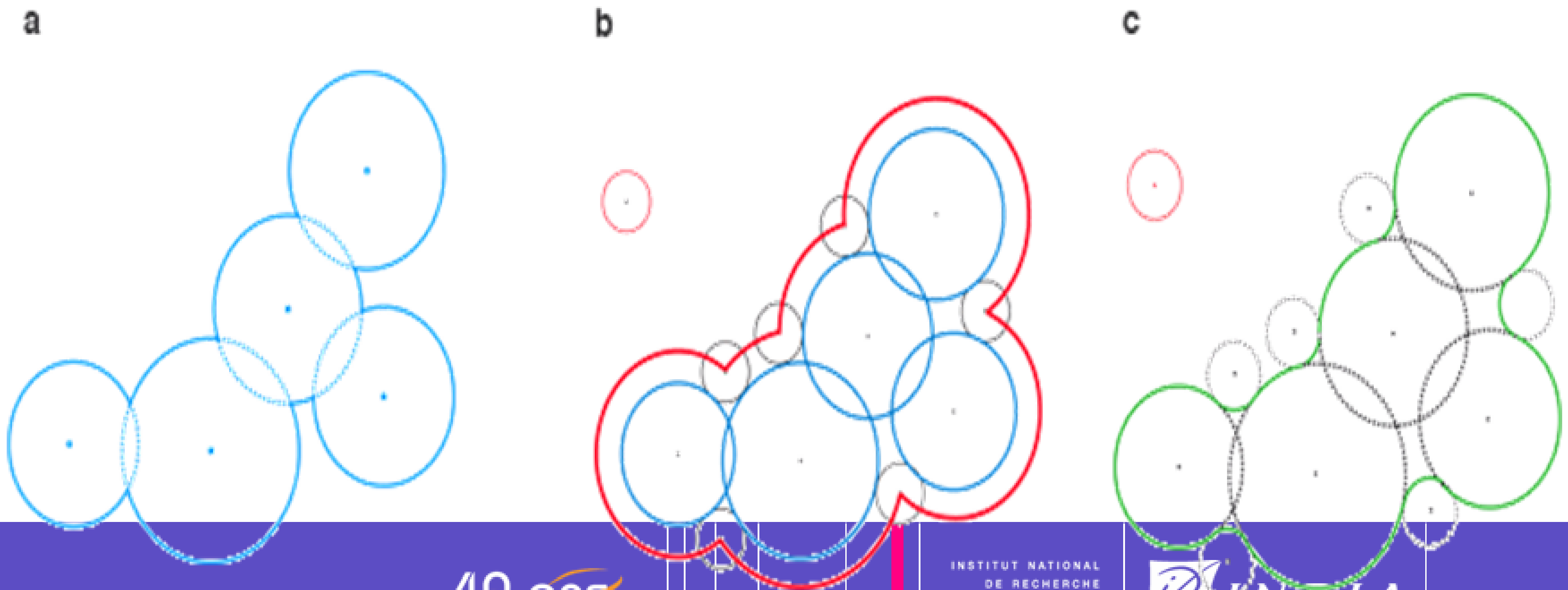
Force field = Consistent Valence Force Field (CVFF)

A new bi-objective model (3/4)

2. Complex surface

Available surfaces :

- ➔ Van Der Waals surface (*a: blue*),
- ➔ Solvent accessible surface (*b: red*),
- ➔ Connoly surface (*c: green*).



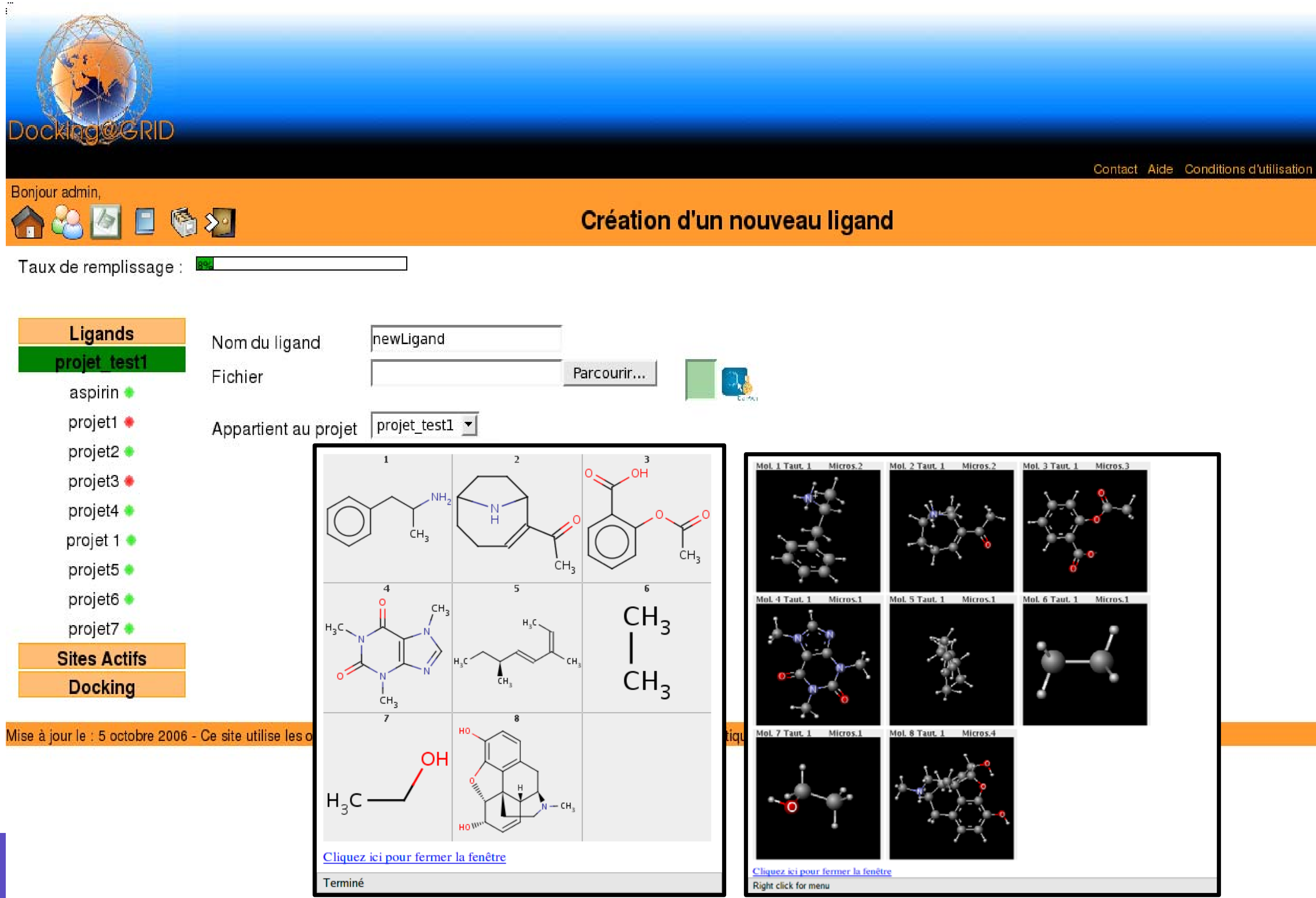
Comparison results (2/2)

Instances from the ccdc astex set

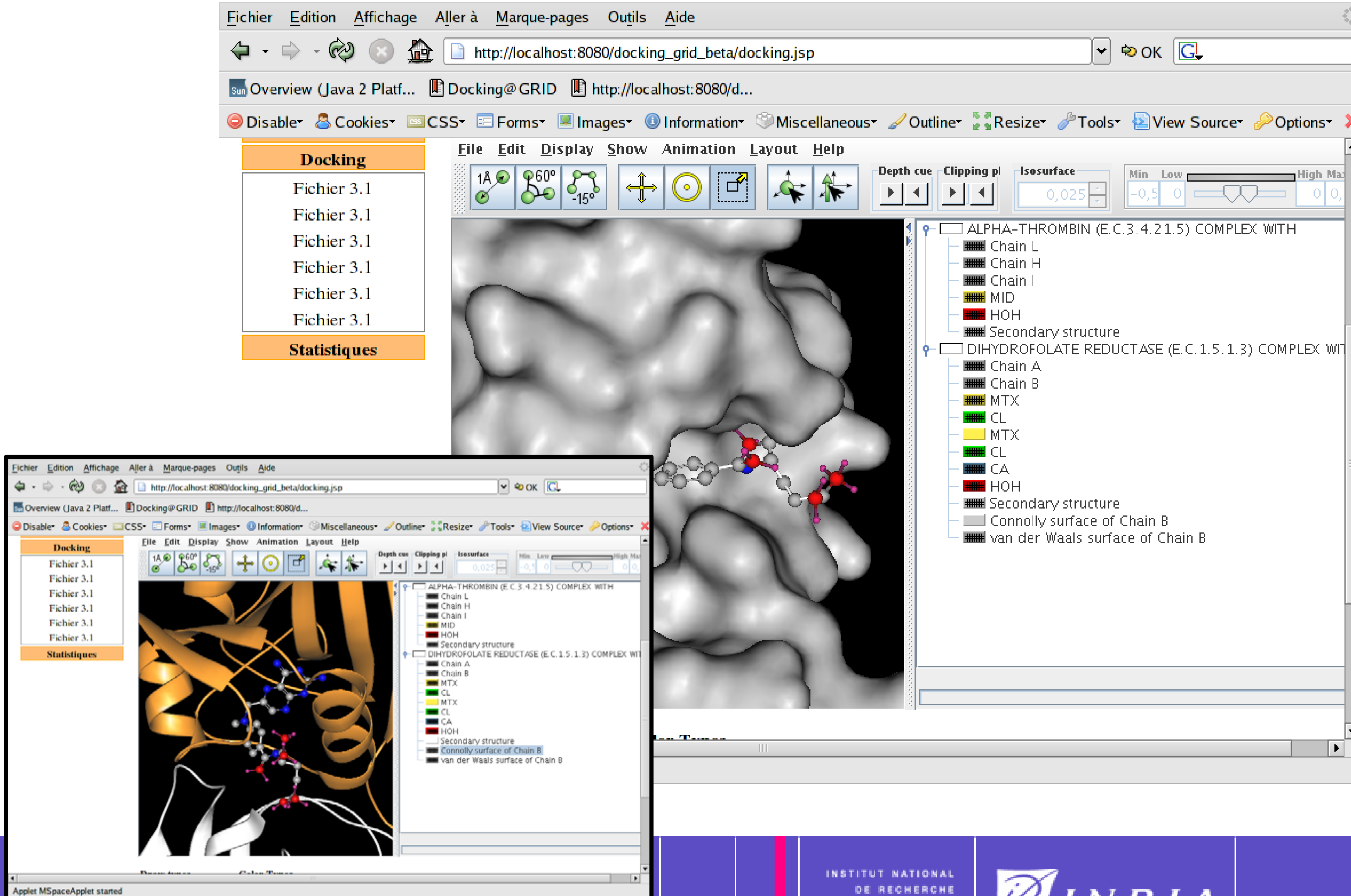
	NSGA-II		IBEA	
Instance	**RMSD (Å)**	**std**	**RMSA (Å)**	**std**
6rsa	1.66	**1.04**	**1.32**	1.3
1mbi	5.2	**0.4**	**4.16**	0.8
2tsc	**2.19**	2.75	**2.19**	**2.68**
1htf	2.88	2.64	**2.59**	**1.33**
1dog	4.38	0.99	**2.44**	**0.56**

Å ⇔ Angström   std ⇔ standard deviation

Docking@GRID



Docking@GRID



Chemistry problems

•L. Jourdan, O. Schütze, T. Legrand, E-G. Talbi, and J-L. Wojkiewicz. *An Analysis of the Effect of Multiple Layers in the Multi-objective Design of Conducting Polymer Composites*. Materials and Manufacturing Processes, Volume 24, Issue 3 March 2009 , pages 350 - 357.

•O. Schuetze, L. Jourdan, T. Legrand, E-G. Talbi, J-L. Wojkiewicz, *New Analysis of the Optimization of Electromagnetic Shielding Properties Using Conducting Polymers and a Multi-Objective Approach*, Volume 19 Issue 7, Pages 762 - 769, Polymers for Advanced Technologies (Available online, 2008).

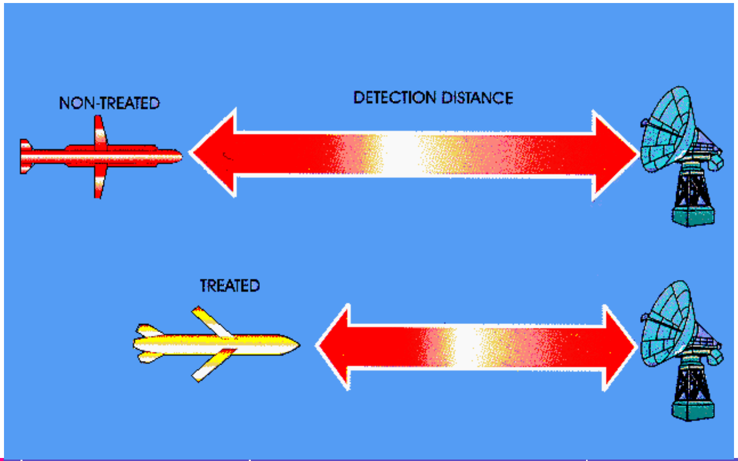
Objective

Cooperative work with Polymer laboratory

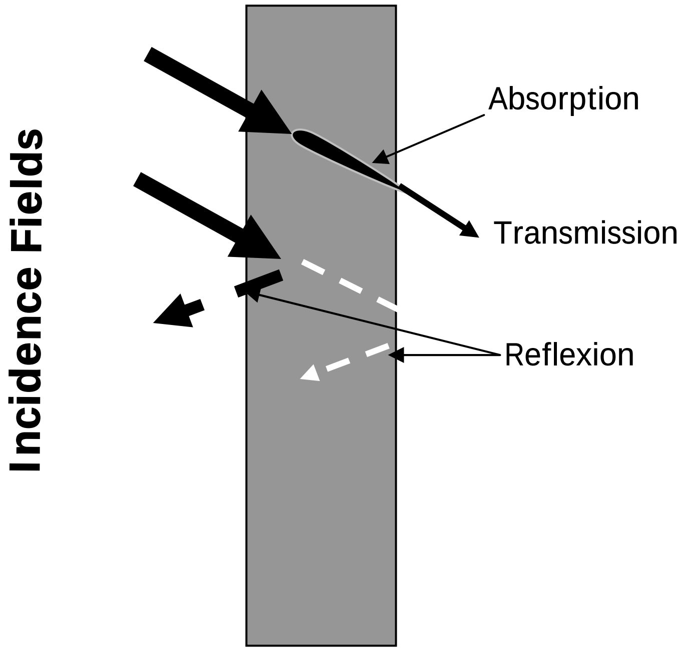
Propose new materials for shielding with specific physical properties

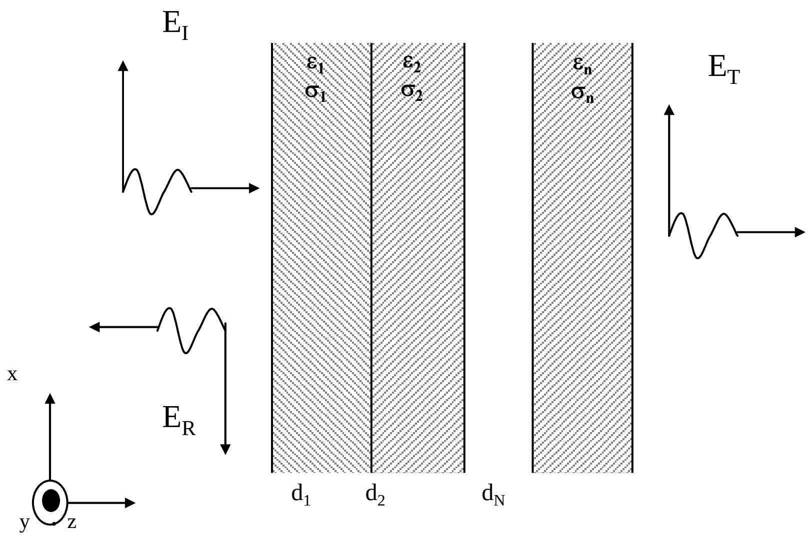
- For military usage:
  - Radar
  - Missiles

- For public usage
  - Car devices: Navigation, DVD, …
  - Cellular phone
  - …

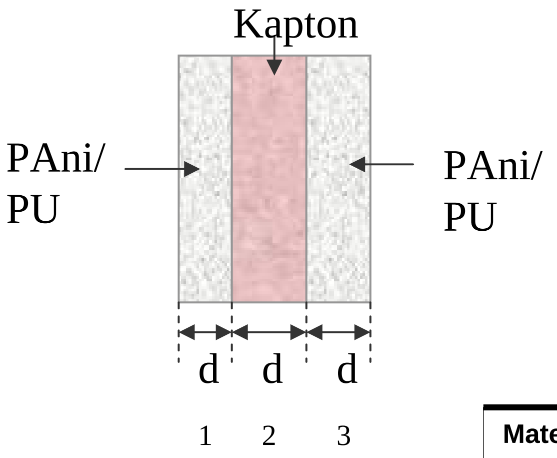


Physical model





Physical model



Polyaniline-polyurethane

Material	ε'	σ (S/m)	d (µm)
1st Layer PAni/PU	-	30 to 6000	de 0 à 300
Kapton (or other material)	3.1	0	0 to 130
3rd Layer PAni/PU	-	de 30 à 6000	de 0 à 300

→ To attenuate the passage of the electromagnetic waves

Modelization

$$\max F_1(X) = -20 * \log(|T|)$$

$$\max F_4(X) = |R|$$

Shielding efficiency

$$\max F_2(X) = -\log\left(\sum_n p_n\right)$$

$$p_n = (sigma_n / sigma_0)^{\frac{1}{t}} + pc$$

$$\max F_3(X) = -\left(\sum_n d_n\right)$$

Cost / Constraints

- R = reflexion coefficient of wave on shielding
- p_n = massic percentage of PAni-PU of the layer n
- d_n = thickness of the layer n

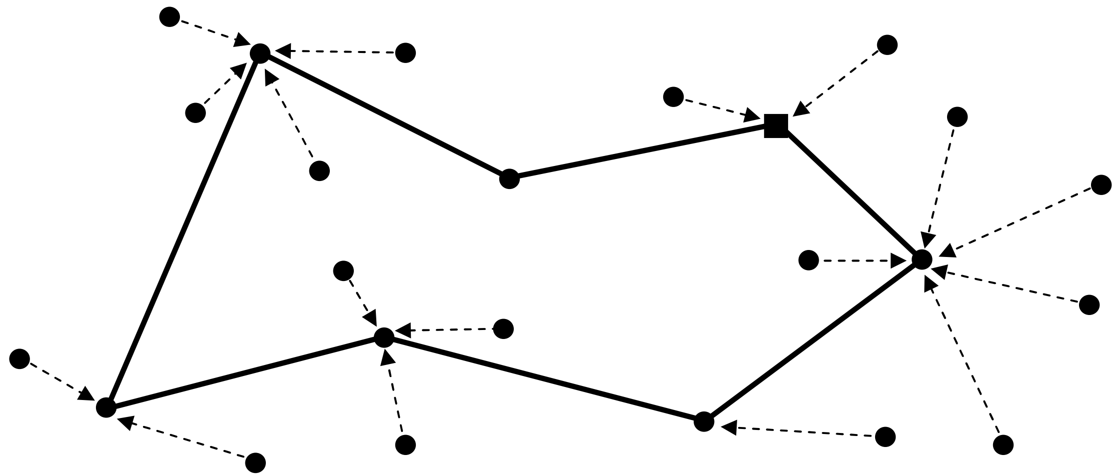
More academic problems

- A. Liefooghe, L. Jourdan, N. Jozefowiez, E-G. Talbi. *On the Integration of a TSP Heuristic into an EA for the Bi-objective Ring Star Problem*. C. Cotta et al. (eds.): International Workshop on Hybrid Metaheuristics (HM 2008), Lecture Notes in Computer Science (LNCS) vol. 5296, pp. 117–130, Malaga, Spain, 2008.
- A. Liefooghe, L. Jourdan, M. Basseur, E-G. Talbi, E.K. Burke. "Metaheuristics for the Bi-objective Ring Star Problem." Eighth European Conference on Evolutionary Computation in Combinatorial Optimisation (EvoCOP 2008), Lecture Notes in Computer Science (LNCS), vol. 4972, pp. 206-217, Napoli, Italy, 2008.

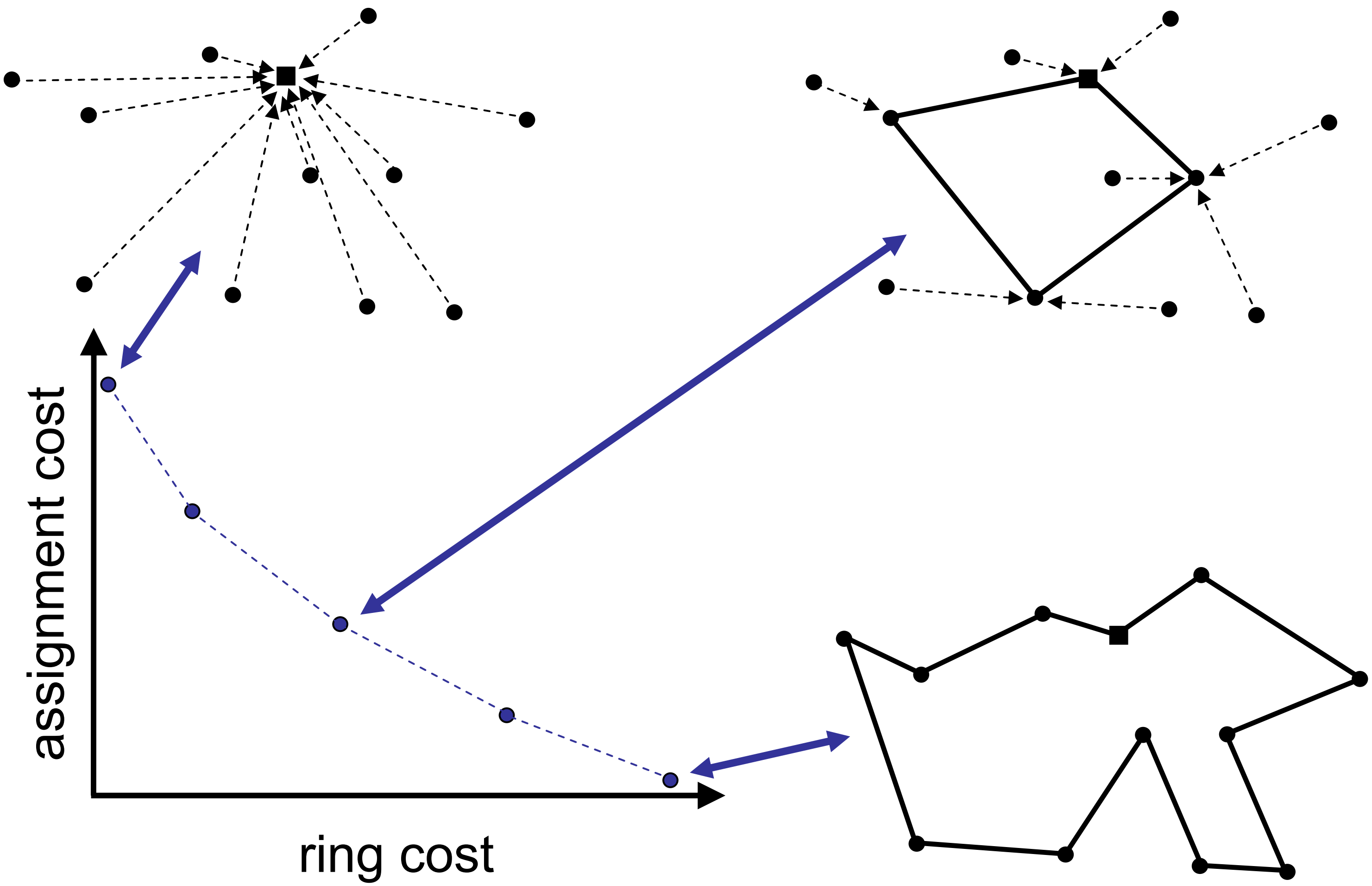
The Bi-objective Ring Star Problem (B-RSP)

The B-RSP aims to locate a simple cycle through a subset of nodes of a graph while:

- Minimizing a ring cost (proportional to the length of the cycle)
- Minimizing an assignment cost (from non-visited nodes to visited nodes)



Justification of the Bi-objective Approach



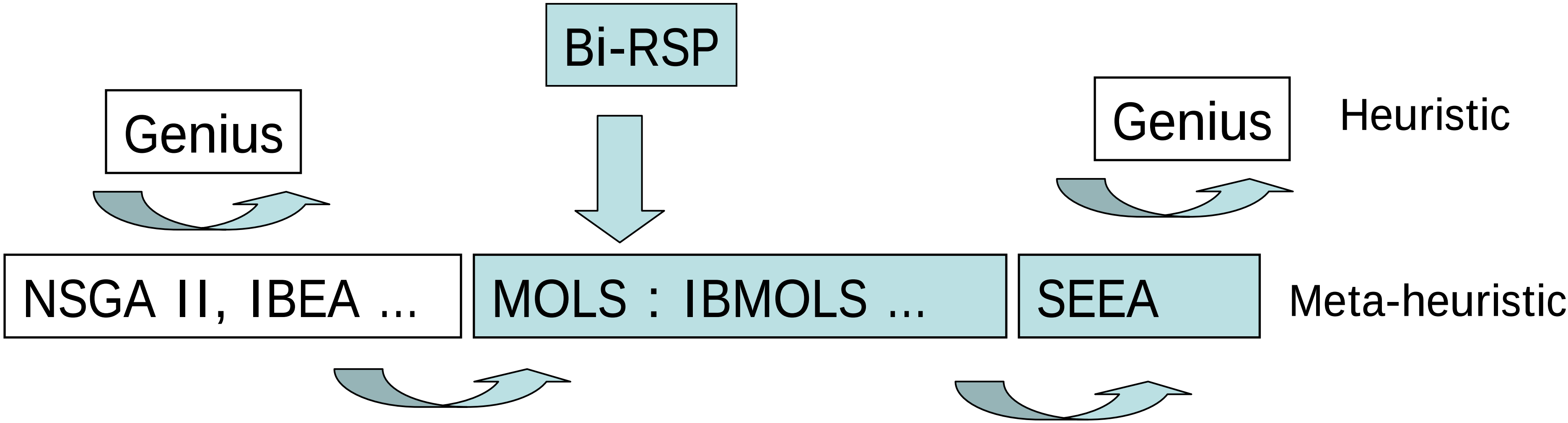
Related Works

- Mono-objective RSP [Labbé et al. 2004, 2005]
  - Minimizing both costs
    - Exact methods and metaheuristics
  - Minimizing the ring cost / constraint on the assignment cost
    - Exact methods and metaheuristics

RSP never explicitly investigated in a multi-objective way

- Median tour problem / Maximum covering tour problem [Current and Schilling 1994]
  - Minimizing the tour length
  - Maximizing the access for non-visited nodes
- Planning for mobile healthcare facilities [Doerner et al. 2007]
  - Non-visited nodes: assigned to the cycle or unable to reach a tour stop

Contributions



Indicator-Based Multi-Objective LS (IBMOLS)

[Basseur et al. 2007]

- Initialization initial population P
- Fitness assignment quality indicator I [Zitzler et al. 2004]
  - Fitness (x) = I (x , P\{x})
- Local search step for all x Є P
  - x* ← one (randomly chosen) neighbor of x
  - Fitness (x) = I (x* , P)
  - Update fitness values: Fitness (z) += I (x* , z), for all z Є P
  - w ← worst solution of P
  - Remove w from P
  - Update fitness values: Fitness (z) -= I (w , z) , for all z Є P
- Output archive A

IBMOLS (2/2)

[Basseur et al. 2007]

- Iterated IBMOLS (I-IBMOLS)
  - Population re-initialization: random noise
  - Multiple mutations applied to randomly chosen archive items
- Quality indicator
  - I (x , x') additive epsilon-indicator ($I_{\varepsilon+}$)
    [Laumanns et al. 2002] [Zitzler et al. 2004]
  - I (x , P\{x}) exponential approach
- Note
  - Extreme points of the trade-off surface
  - Drawback of the epsilon-dominance
    [Hernandez-Diaz et al. 2007]

Indicator-Based EA (IBEA)

[Zitzler et al. 2004]

- Initialization initial population P
- Fitness assignment quality indicator I ($I_{\varepsilon+}$)
  - Fitness (x) = I (x , P\{x})
- Diversity preservation none
- Selection binary tournament
- Variation crossover and mutation
- Replacement remove the worst individual and update fitness values until |P| = N
- Elitism archive A of potentially efficient solutions
- Output archive A

Non-dominated Sorting GA (NSGA-II)

[Deb et al. 2002]

- Initialization initial population P
- Fitness assignment non-dominated sorting
  - Population divided into fronts
  - Fitness (x) = index of the front x belongs to
- Diversity preservation crowding distance (objective space)
- Selection binary tournament
- Variation crossover and mutation
- Replacement N worst individuals are removed
- Elitism archive A of potentially efficient solutions
- Output archive A

Simple Elitist EA (SEEA)

- Initialization initial population P
- Fitness assignment none
- Diversity preservation none
- Selection random individual from A until |P| = N
- Variation crossover and mutation
- Replacement generational
- Elitism archive A of potentially efficient solutions
- Output archive A

Solution Encoding

Random keys [Bean 1994]

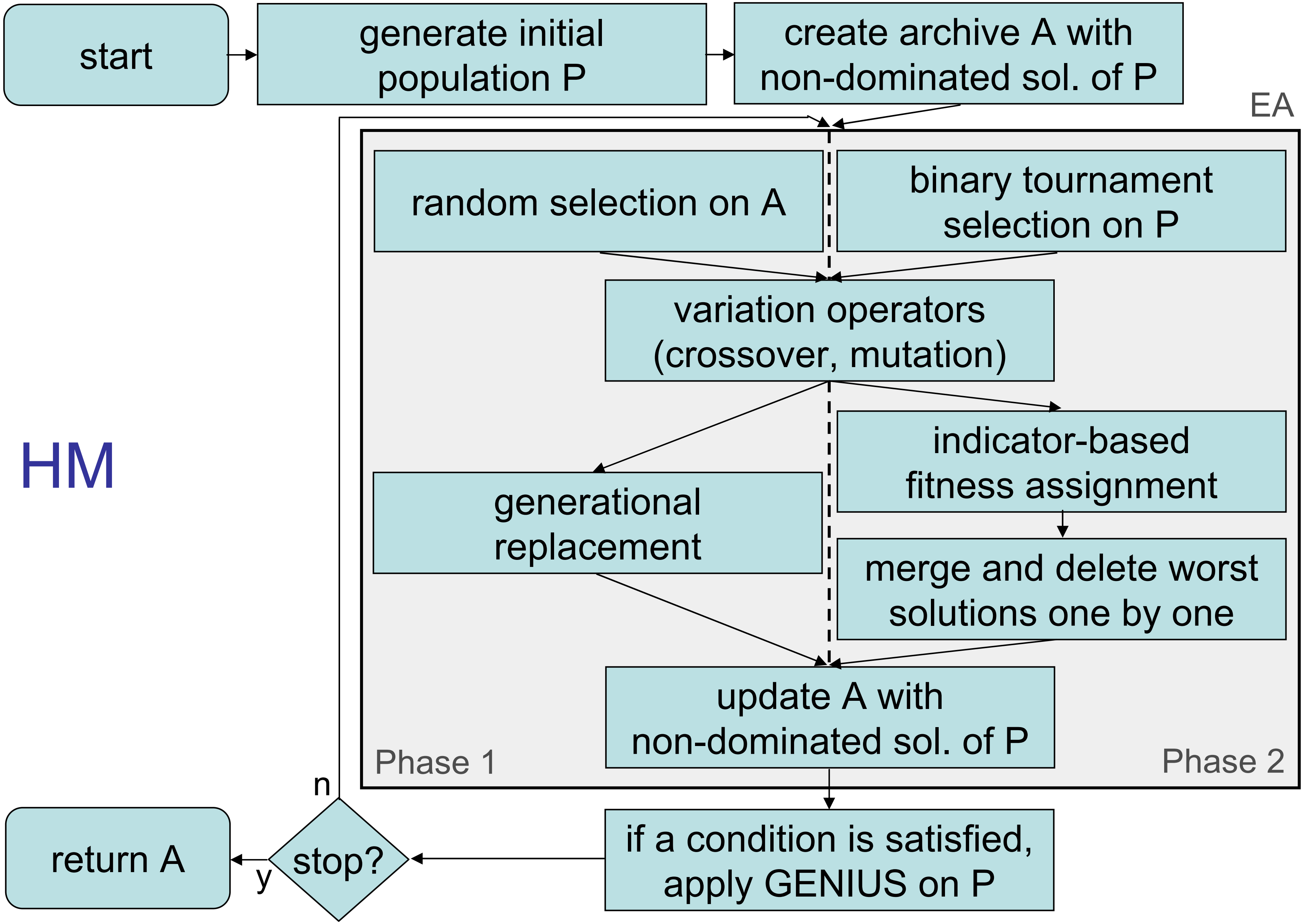
- To each visited node: a random key $x \in [0,1[$
- Random key of v_1 (depot): $x_1 = 0$
- Non-visited node: special value
- If $x_i < x_j$, v_j comes after v_i

Example:

Node	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}
Key	0	0.7	-	0.3	-	0.8	0.2	-	0.5	-

➔ Cycle = $(v_1, v_7, v_4, v_9, v_2, v_6)$

➔ v_3, v_5, v_8, v_{10}: assigned to a visited node so that the cost is minimum


start
generate initial population P
create archive A with non-dominated sol. of P
EA
random selection on A
binary tournament selection on P
variation operators (crossover, mutation)
indicator-based fitness assignment
generational replacement
merge and delete worst solutions one by one
update A with non-dominated sol. of P
Phase 1
Phase 2
HM
n
return A
y
stop?
if a condition is satisfied, apply GENIUS on P

Stochastic problems

•A. Liefooghe, M. Basseur, L. Jourdan, E-G. Talbi "Multi-Objective Combinatorial Optimization for Stochastic Problems: an Application to the Flow-Shop Scheduling Problem", EMO 2007, LNCS Vol. 4408, pp. 386-400, Matsushima, Japan
•A. Liefooghe, L. Jourdan, M. Basseur, E-G. Talbi, *Métaheuristiques pour le flow-shop sous incertitude*, Revue d'Intelligence artificielle, Hermès, vol. 22, n°2, pp. 183-208, 2008. ISBN : 0992-499X
•A. Liefooghe, L. Jourdan, E-G. Talbi, «Stochastic multi objective optimization », in preparation

Outlines

• Work on the modelization of the problem: how to have robust solutions for stochastic problems: incorporate the robustness in the model

•Work on the resolution algorithms: make algorithms robust to noise

•Application on flowshop, VRP, …

Evolutionary Optimization in Uncertain Environments

[Jin & Branke 2005]

4 classes:

Noisy objective function

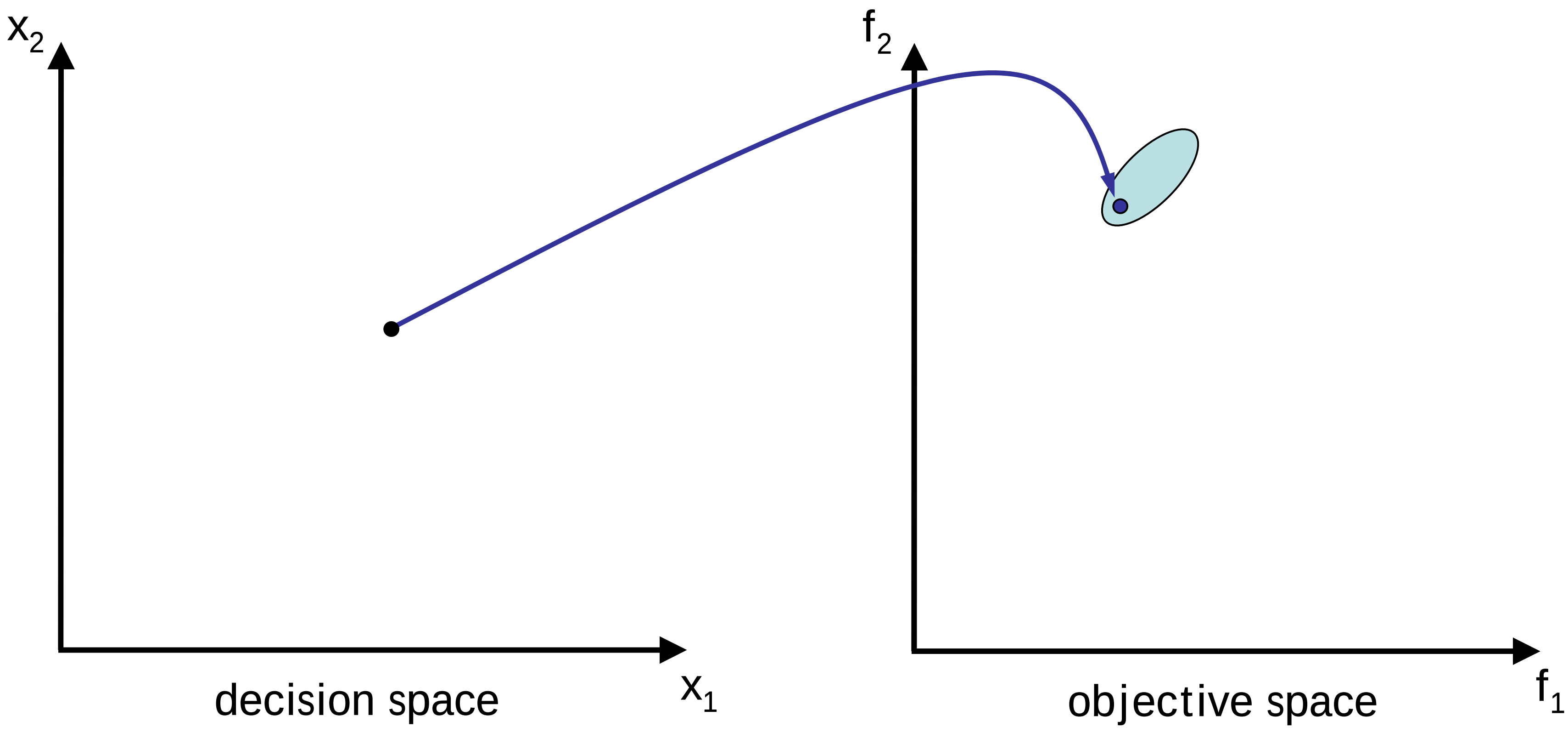
Robustness

- Variation on decision variables
- Variation on environmental parameters

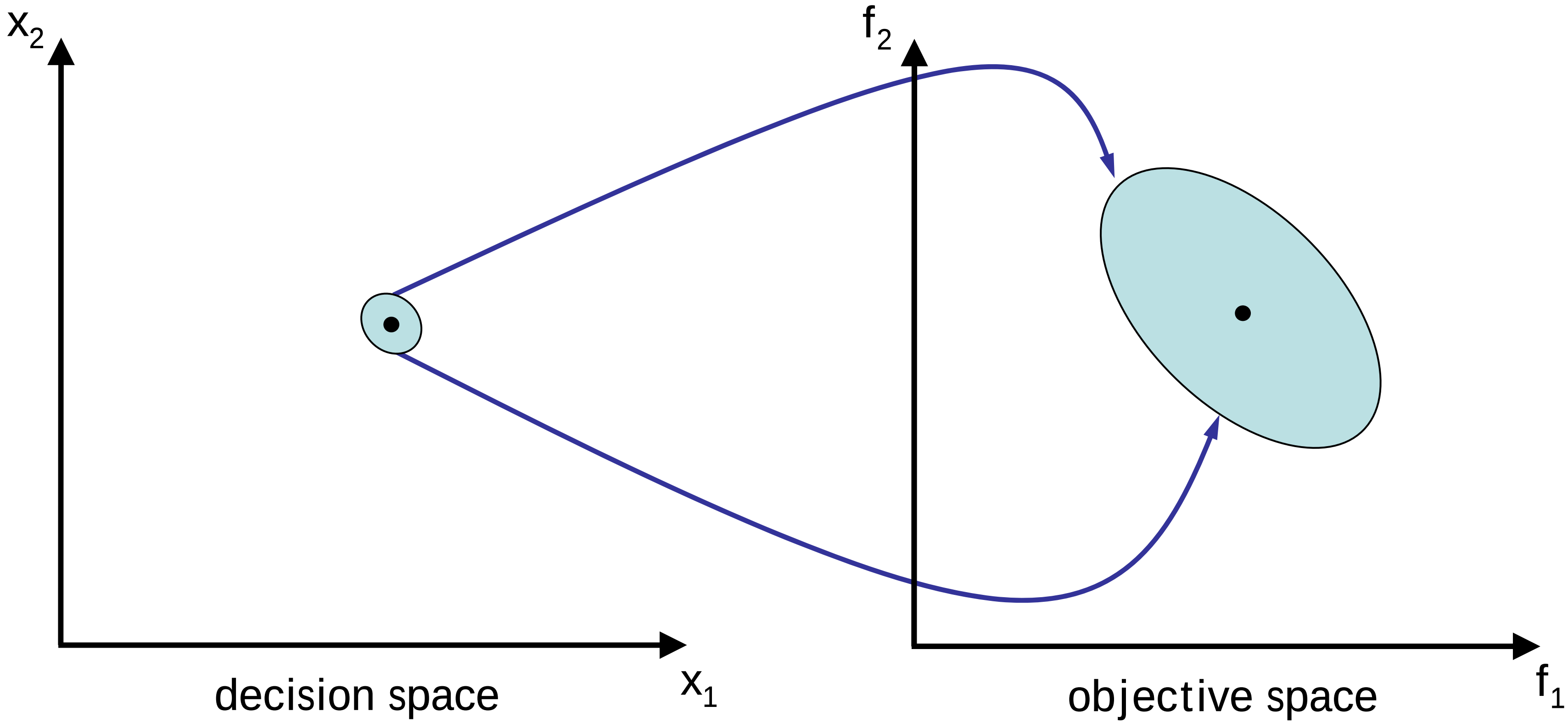
Approximated objective function (costly or unavailable function)

Time-varying objective function (dynamic environments, see next part)

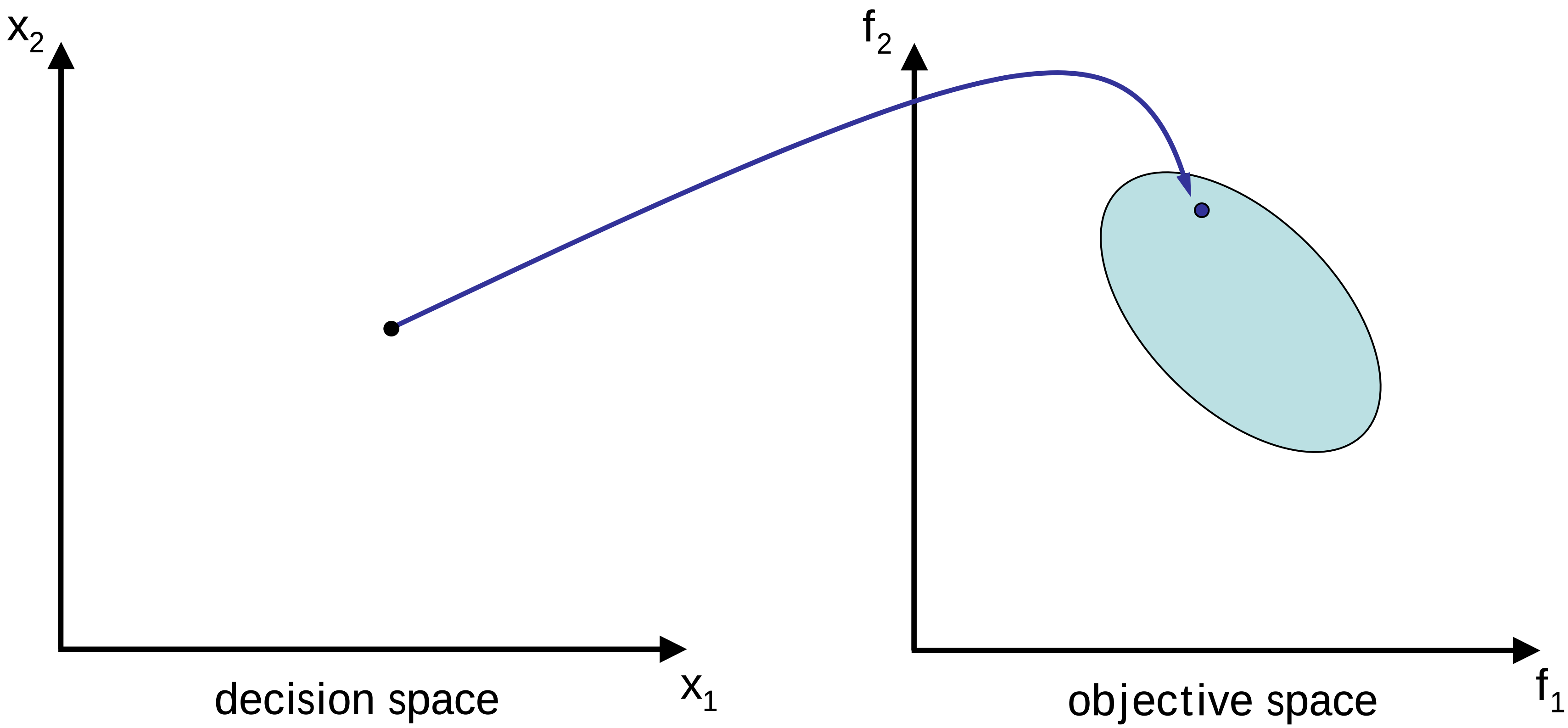
Noisy Objective Function



Variation on Decision Variables



Variation on Environmental Parameters



EMO for Uncertain Single-objective Problems

Searching for robust solutions

A common (single-objective) approach

- Unique objective: expected objective function

Multi-objective approach

- Objective 1: expected value
- Objective 2: variance/Stardand deviation/Entropy

➔ Performance and robustness treated as separate goals

Similar techniques have been applied to solve uncertain MOPs

Stochastic Multi-objective Programming

[Caballero et al. 2003]

Multi-objective approaches

Stochastic multi-objective problem → Deterministic multi-objective problem → Deterministic mono-objective problem

Stochastic approaches

Stochastic multi-objective problem → Stochastic mono-objective problem → Deterministic mono-objective problem

From stochastic to deterministic objective

Expected value [White 1982]

Minimum variance [White 1982]

Both (number of objectives multiplied by 2)

EMO for Uncertain MOPs

Noisy objective function

- Probabilistic Pareto dominance [Teich 2001] [Hughes 2001]
- Modified ranking (average + variance) in NSGA-II [Babbar 2003]
- Epsilon-based approach [Basseur & Zitzler 2006]

Robustness

- Variation on decision variables
  - Average value per objective [Deb & Gupta 2006]
- Variation on environmental parameters
  - none

Existing approaches

- Assumption of specific properties on probability distribution
- Experimented on academic continuous MOPs
- Performance assessment forgets about the uncertainty

Uncertainty Handling

Deterministic case

- A single outcome vector $z \in Z$ per feasible solution $x \in X$
- f represents a deterministic mapping from X to Z
- $z = f(x)$ = 'true' evaluation of x

Stochastic case

- Each time a solution is evaluated, the outcome vector can potentially map to a different point of the objective space
- f does not represent a deterministic mapping from X to Z
- 'true' evaluation of x unknown
- No assumption on any probability distribution associated to the objective functions or the parameters

Scenario-based Uncertainty Handling

Let $S = \{s_1, s_2, \ldots, s_p\}$ be a finite set of independent and equally probable scenarios

To each solution $x \in X$ is now associated a sample of objective vectors $\{z^{(1)}, z^{(2)}, \ldots, z^{(p)}\}$, *where* $z^{(i)}$ represents the outcome vector of x if scenario s_i occurs

Some issues:

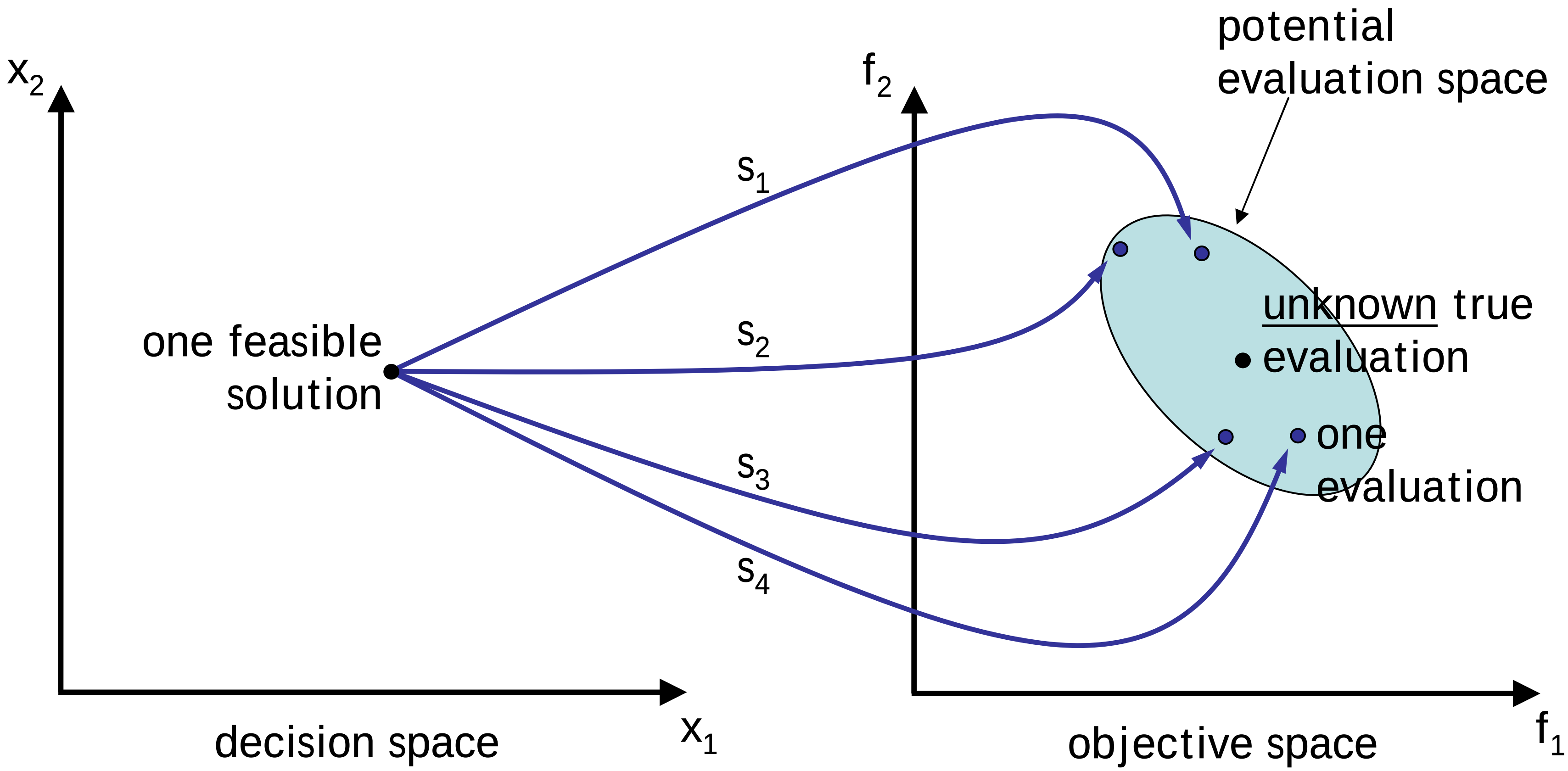
The number of available scenarios is often limited in practice

- Be aware of performance evaluation

Difficult to determine a good sample size

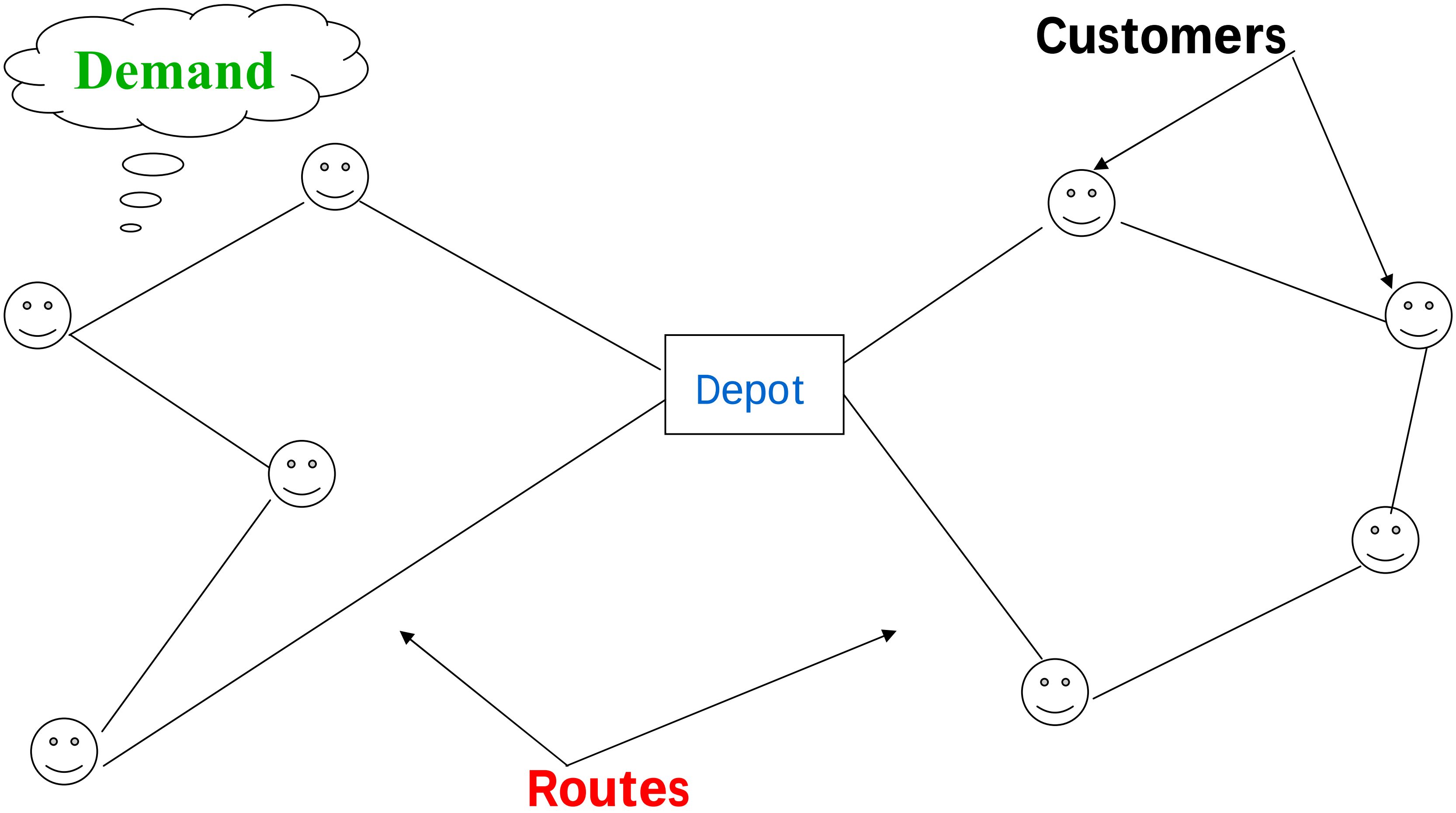
- Trade-off between a fine accuracy and a reasonable time consumption
- Here, we assume a user-given sample size

Scenario-based Uncertainty Handling



VRPSD: search for robust solution

VRP Output

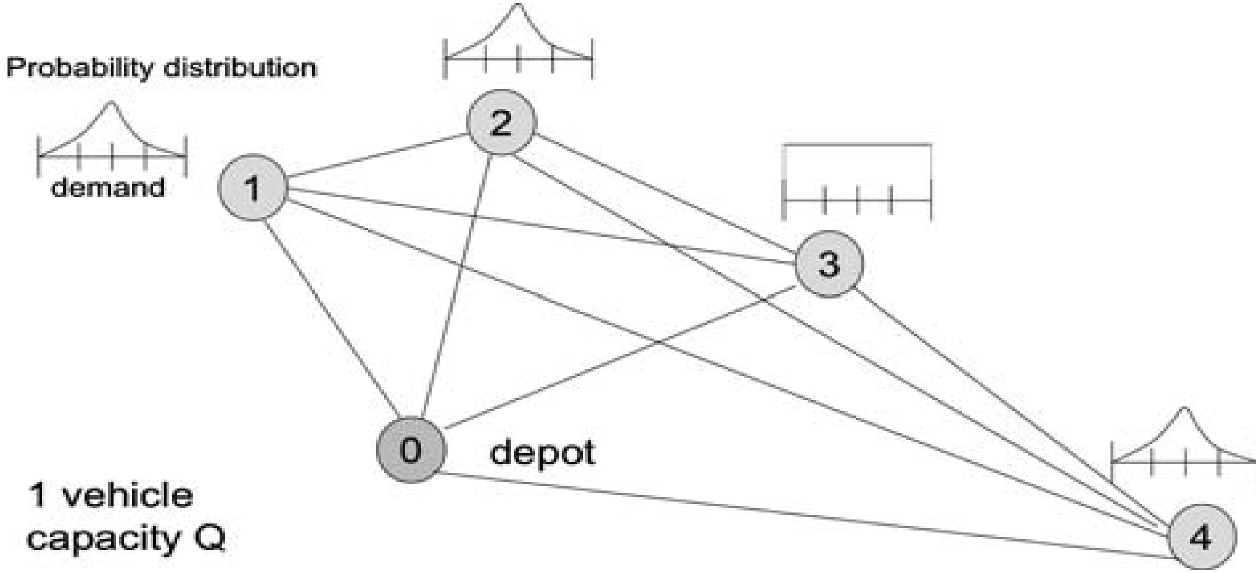


Stochastic VRP

- One or several components of VRP are **random variables and unknown.**
- SVRP Variants
  - Stochastic demands VRPSD: the customer demands are random variables [Taillman 1969].
  - Stochastic customers VRPSC: the presence of the customers has probability [Jézéquel 1985].
  - Stochastic customers and demands VRPSCD: combination between VRPSD and VRPSC [Jézéquel 1985].

Vehicle Routing Problem with stochastic Demands VRPSD

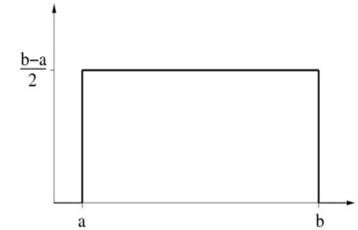
- Customer demands are
  - Uncertain.
  - Random variables.
  - depend on probability distribution Normal distribuion, uniform distribution .....



Uncertainty of Demands in VRPSD

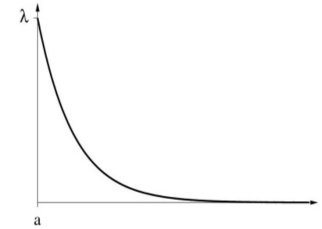
•Uniform distribution:

- p_{ij} is between two values.



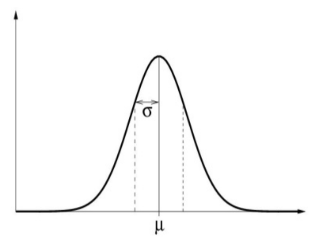
Exponential distribution:

- Break down, repair.....



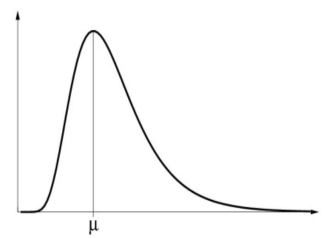
Normal distribution:

- Human factors.
- Unknown or uncontrollable factors.
- Parameters described in a vague.



Long-normal distribution:

- Uncertainties are all taken into account simultaneously .



Real life Examples

- Milk distribution: distributing *uncertain* amount of milk to each customer.
- Waste collection: collecting *uncertain* amount of waste from each waste node.
- Merchandise routing: selling *uncertain* amount of merchandise to each costumer.

Robust Model for VRPSD

Two suggested models:

First Model:

- Minimize the average distance of the route.
- Minimize the Standard Deviation of the distance of the route.

Second Model:

- Minimize the average distance of the route.
- Minimize the Entropy of the distance.
  - Taking into account the probability of the demands.
  - $-\sum p_i * \ln(p_i)$

First results

		Hypervolume indicator I_H IBEA	MOGA	NSGAII	Unary Epsilon indicator I_ϵ IBEA	MOGA	NSGAII
		p-value 0.05	p-value 0.05	p-value 0.05	p-value 0.05	p-value 0.05	p-value 0.05
c101	IBEA	-	$\succeq$ better	$\succeq$ better	-	$\succeq$ better	$\succeq$ better
	MOGA	$\preceq$ worse	-	$\preceq$ worse	$\preceq$ worse	-	$\succeq$ better
	NSGAII	$\preceq$ worse	$\succeq$ better	-	$\preceq$ worse	$\preceq$ worse	-
r101	IBEA	-	$\succeq$ better	$\succeq$ better	-	$\succeq$ better	$\succeq$ better
	MOGA	$\preceq$ worse	-	$\preceq$ worse	$\preceq$ worse	-	$\succeq$ better
	NSGAII	$\preceq$ worse	$\succeq$ better	-	$\preceq$ worse	$\preceq$ worse	-
rc101	IBEA	-	$\succeq$ better	$\succeq$ better	-	$\succeq$ better	$\succeq$ better
	MOGA	$\preceq$ worse	-	$\preceq$ worse	$\preceq$ worse	-	$\equiv$ better
	NSGAII	$\preceq$ worse	$\succeq$ better	-	$\preceq$ worse	$\equiv$ better	-

Table 4.2: Comparison of the quality assessment values obtained by IBEA, MOGA and NSGAII using Mann-Whitney test (H
Epsilon indicator) for the Minimum case of the Stan

		Hypervolume indicator I_H IBEA	MOGA	NSGAII	Unary Epsilon indicator I_ϵ IBEA	MOGA	NSGAII
		p-value 0.05	p-value 0.05	p-value 0.05	p-value 0.05	p-value 0.05	p-value 0.05
c101	IBEA	-	$\succeq$	$\succeq$	-	$\succeq$	$\succeq$
	MOGA	$\preceq$	-	$\equiv$	$\preceq$	-	$\succeq$
	NSGAII	$\preceq$	$\equiv$	-	$\preceq$	$\preceq$	-
r101	IBEA	-	$\succeq$	$\succeq$	-	$\succeq$	$\succeq$
	MOGA	$\preceq$	-	$\preceq$	$\preceq$	-	$\equiv$
	NSGAII	$\preceq$	$\succeq$	-	$\preceq$	$\equiv$	-
rc101	IBEA	-	$\succeq$	$\succeq$	-	$\succeq$	$\succeq$
	MOGA	$\preceq$	-	$\preceq$	$\preceq$	-	$\succeq$
	NSGAII	$\preceq$	$\succeq$	-	$\preceq$	$\preceq$	-

Table 4.3: Comparison of the quality assessment values obtained by IBEA, MOGA and NSGAII using Mann-Whitney test (Hypervolume indicator and Epsilon indicator) for the Maximum case of the Standard Deviation model.

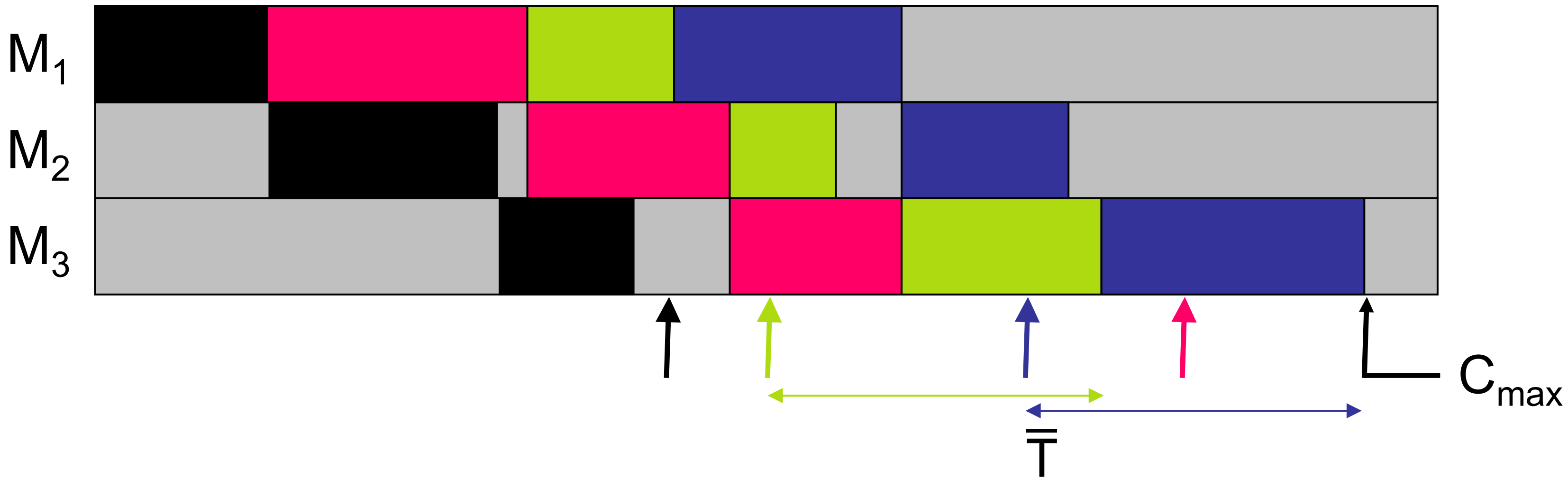
Actually

Definition of a protocole comparison, experiment on larger datasets (grid power ☺)

MO Flowshop

Flow-shop: deterministic model

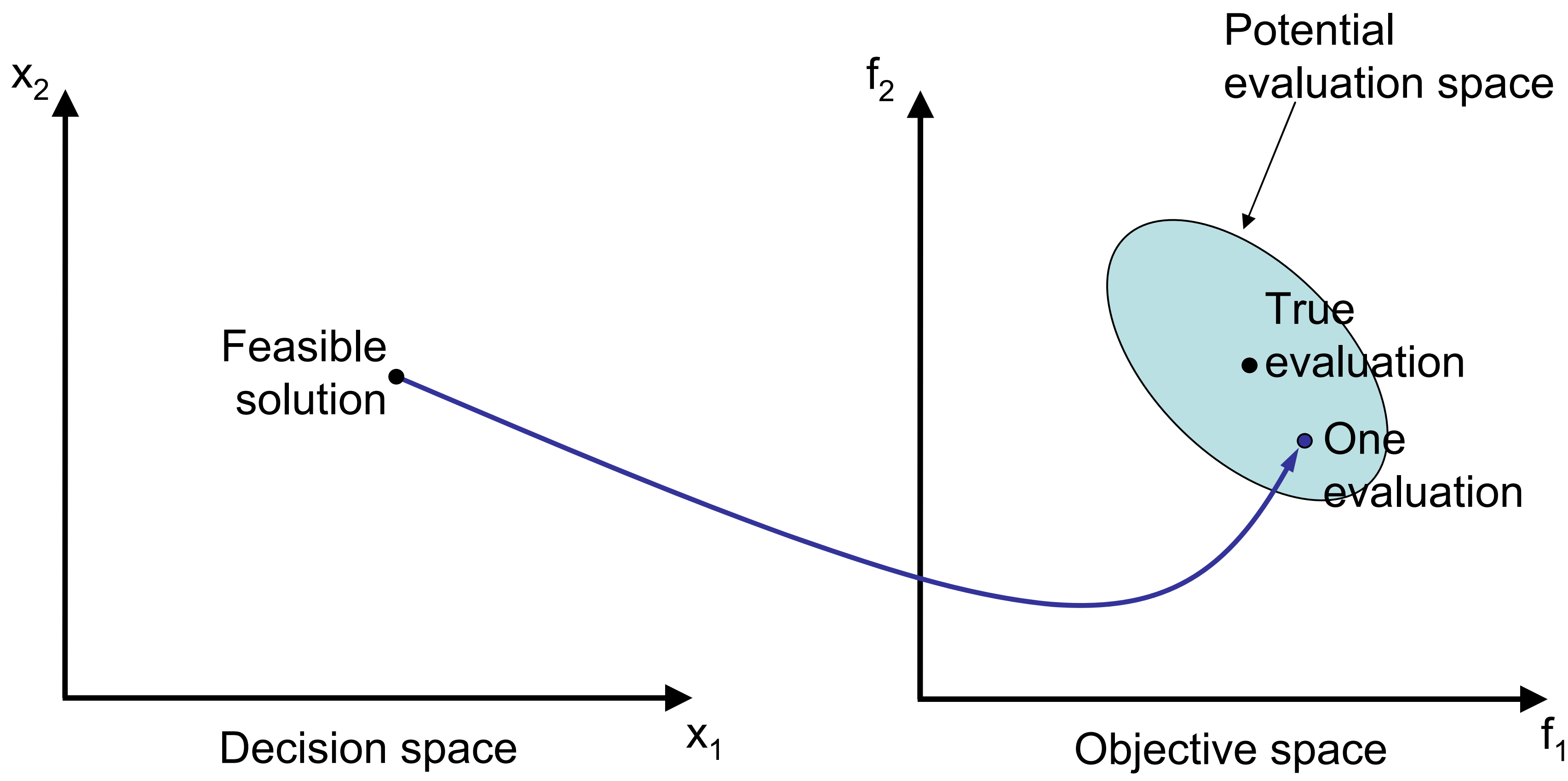
- N jobs to schedule on M machines
- Machines are critical resources
- 2 objectives to optimize (minimize)
  - Makespan (C_{max})
  - Total tardiness ($\bar{T}$)

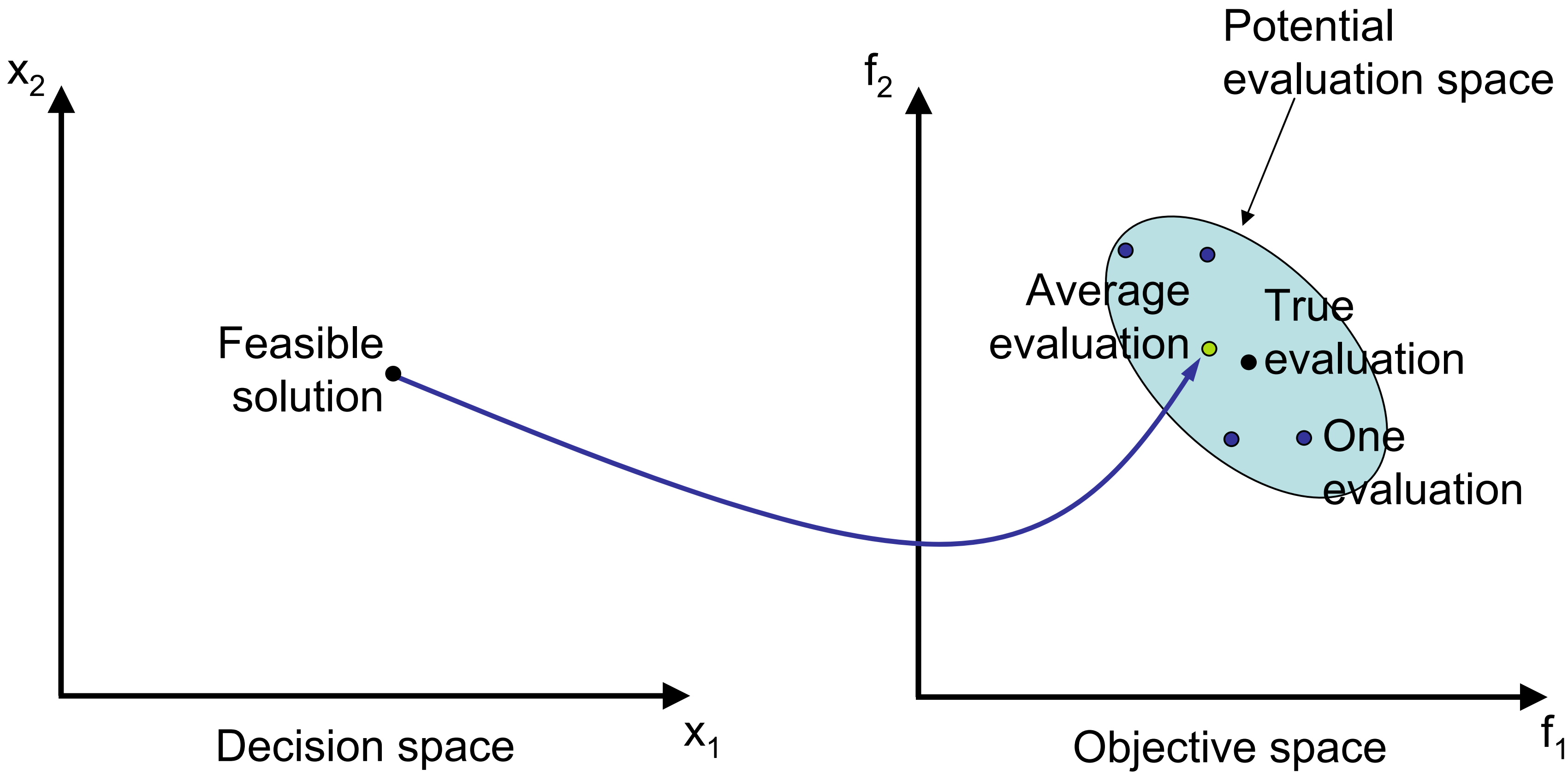


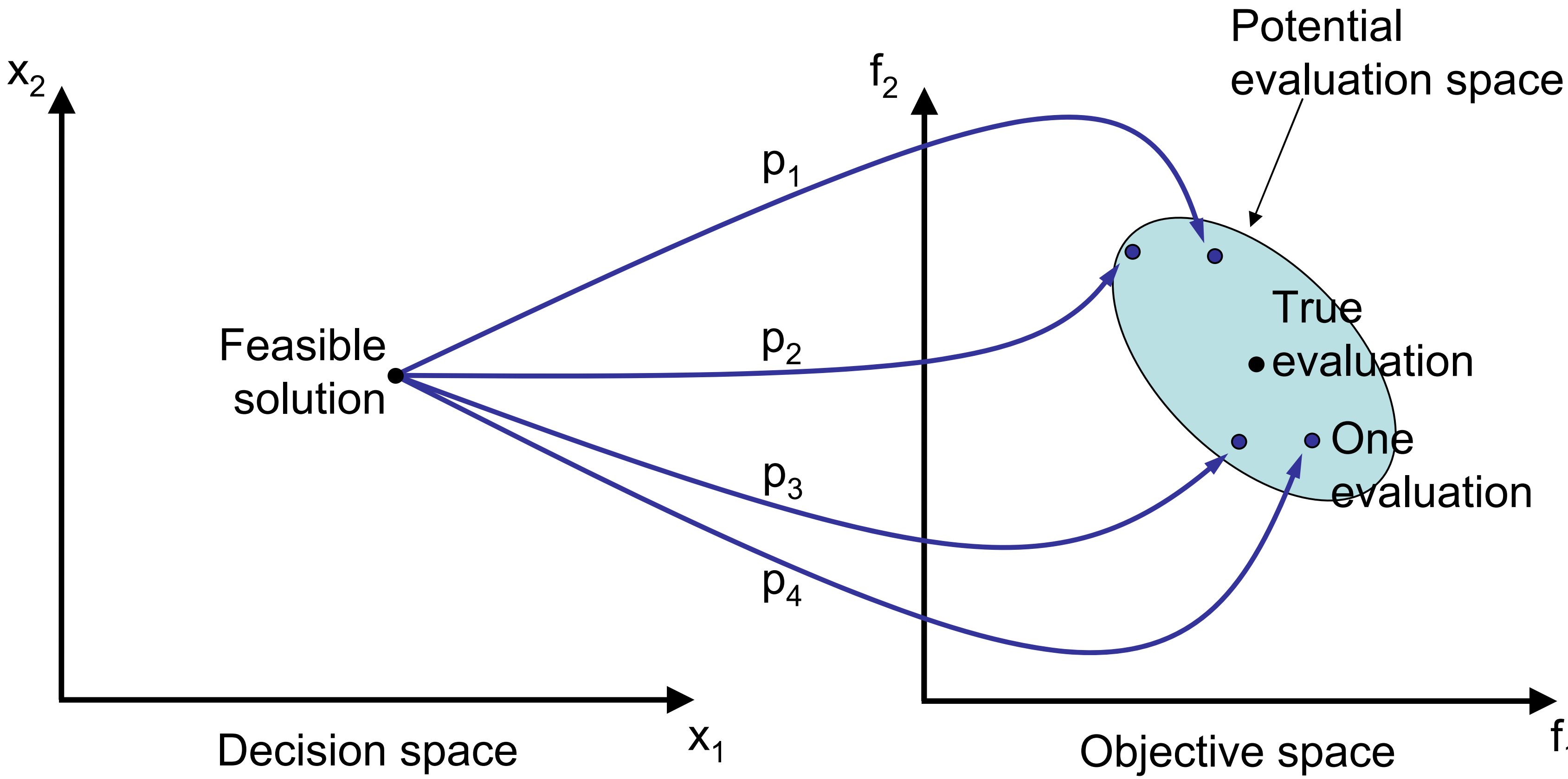
Flow-shop: sources of uncertainty

- Due dates (d_j)
  - Interval $[d_j^1, d_j^2]$
  - Dynamic variations
- Processing times ($p_{i,j}$)
  - Breakdowns
  - Human factors
  - Unknown / uncontrollable parameters
  - …

Proactive stochastic approach where processing times are represented by random variables

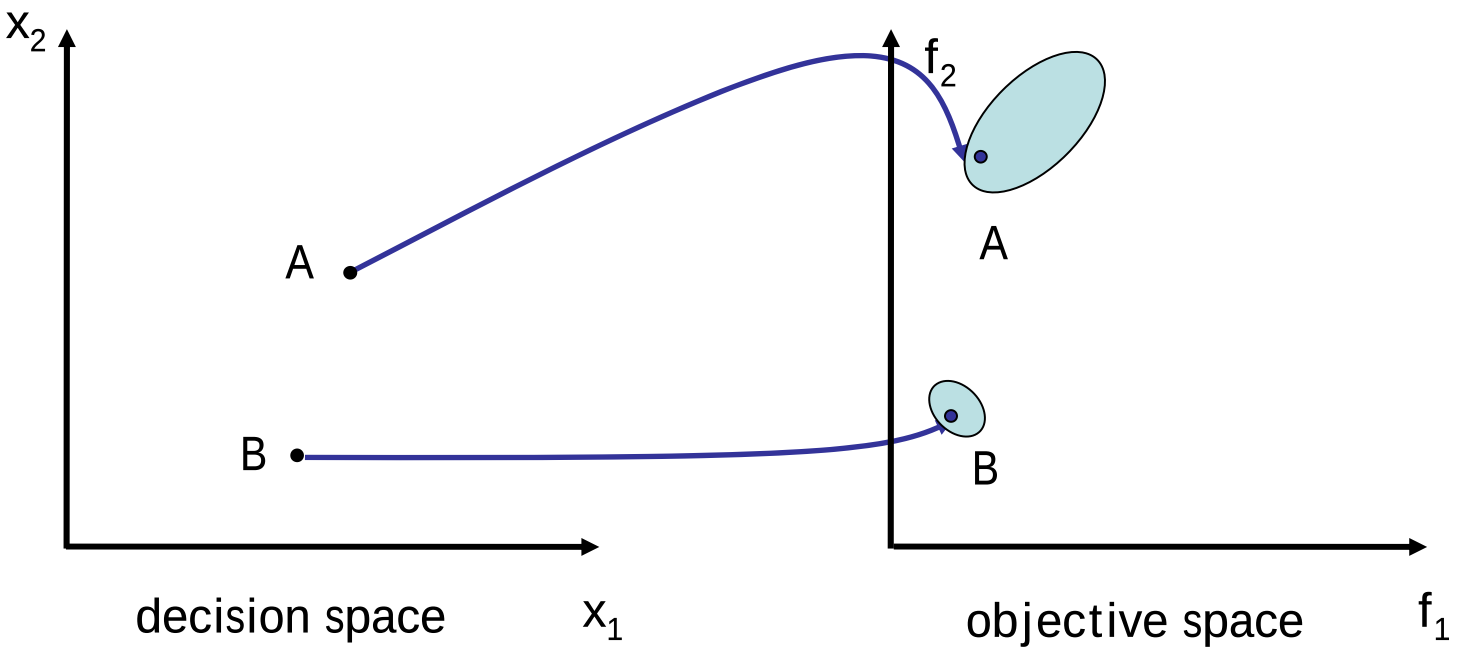

Potential
evaluation space
x2
f2
True
evaluation
Feasible
solution
One
evaluation
Decision space
x1
Objective space
f1


Potential
evaluation space
x_2
f_2
Average
evaluation
True
evaluation
Feasible
solution
One
evaluation
Decision space
x_1
Objective space
f_1


Potential
evaluation space
x_2
f_2
p_1
p_2
p_3
p_4
Feasible
solution
True
evaluation
One
evaluation
Decision space
x_1
Objective space
f_1

The definition of Robust solution

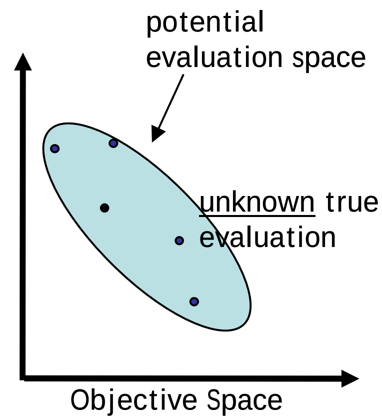
The *Robust solution* is less sensitive to the perturbations at its neighborhood. [Deb & Gupta 2006]



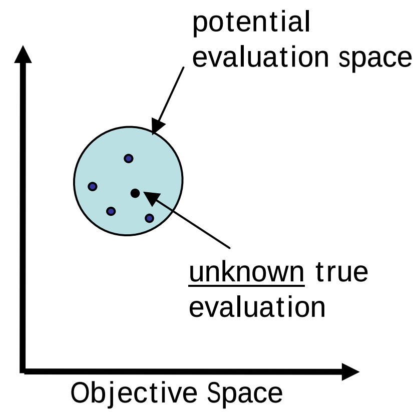
B is more robust than A

Motivation for Robust VRPSD

- Having Robust solution
  - Less randomness and less sensitive to perturbation:
    - smaller potential evaluation space.



- Smaller potential space:
  - Being closer to the unknown true evaluation.



- One of the common methods to have a robust solution is to Optimize the second order moment or higher order moments of the evaluation function[Jin & Sendhoff 2003]

Proposed Search Methods

A user-given I^Z-indicator is assumed

Nine uncertainty-handling I^X-indicators

- Five general-purpose approaches (can be used outside IBEA)
- Four IBEA-related approaches

These strategies allow the statement of different kinds of DM preferences

➔ Nine uncertainty-handling IBEAs

- Uncertainty-handling I^X-indicators used in the fitness assignment scheme of IBEA

Proposed Search Methods

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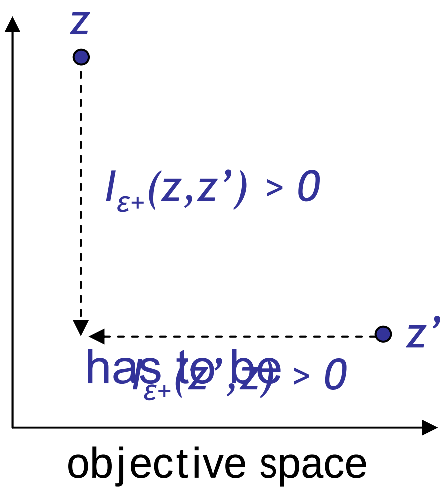
These strategies allow the statement of different kinds of DM preferences

➔ Nine uncertainty-handling IBEAs

- Uncertainty-handling I^X-indicators used in the fitness assignment scheme of IBEA

Uncertainty-handling Indicators



I^Z-indicator

Example: additive ε-indicator [Zitzler et al. 2003]

- $I_{\varepsilon+}(z,z') = max_{i \in \{1,\ldots,n\}} (z_i - z_i')$
- Minimum value by which a point *z* can or translated to weakly dominate *z'*

I^X-indicator

In the deterministic case, it is a commonplace

- $I^X(x,x') = I^Z(f(x),f(x'))$

I^{XN}-indicator (fitness values)

Different techniques exist [Zitzler & Künzli 2004]

Example: summing approach

- $I^{XN}(x,P\backslash\{x\}) = \sum_{x' \in P\backslash\{x\}} I^X(x',x)$ (P: current population)

Solution-level Binary Indicators

➔ convert the objective vector sample set into a single point

Single scenario indicator

$I^{X(1)}(x,x') = I^Z(z^{(1)},z'^{(1)})$

Best-case objective vector indicator

$I^{X(Z\text{-}best)}(x,x') = I^Z(z^{best},z'^{best})$

z_k^{best}: minimum of $\{z_k^{(1)},\ldots,z_k^{(p)}\}$ $\forall k \in \{1,\ldots,n\}$

Worst-case objective vector indicator

$I^{X(Z\text{-}worst)}(x,x') = I^Z(z^{worst},z'^{worst})$

z_k^{worst}: maximum of $\{z_k^{(1)},\ldots,z_k^{(p)}\}$ $\forall k \in \{1,\ldots,n\}$

Average-case objective vector indicator [Babbar et al. 2003][Deb et al. 2006]

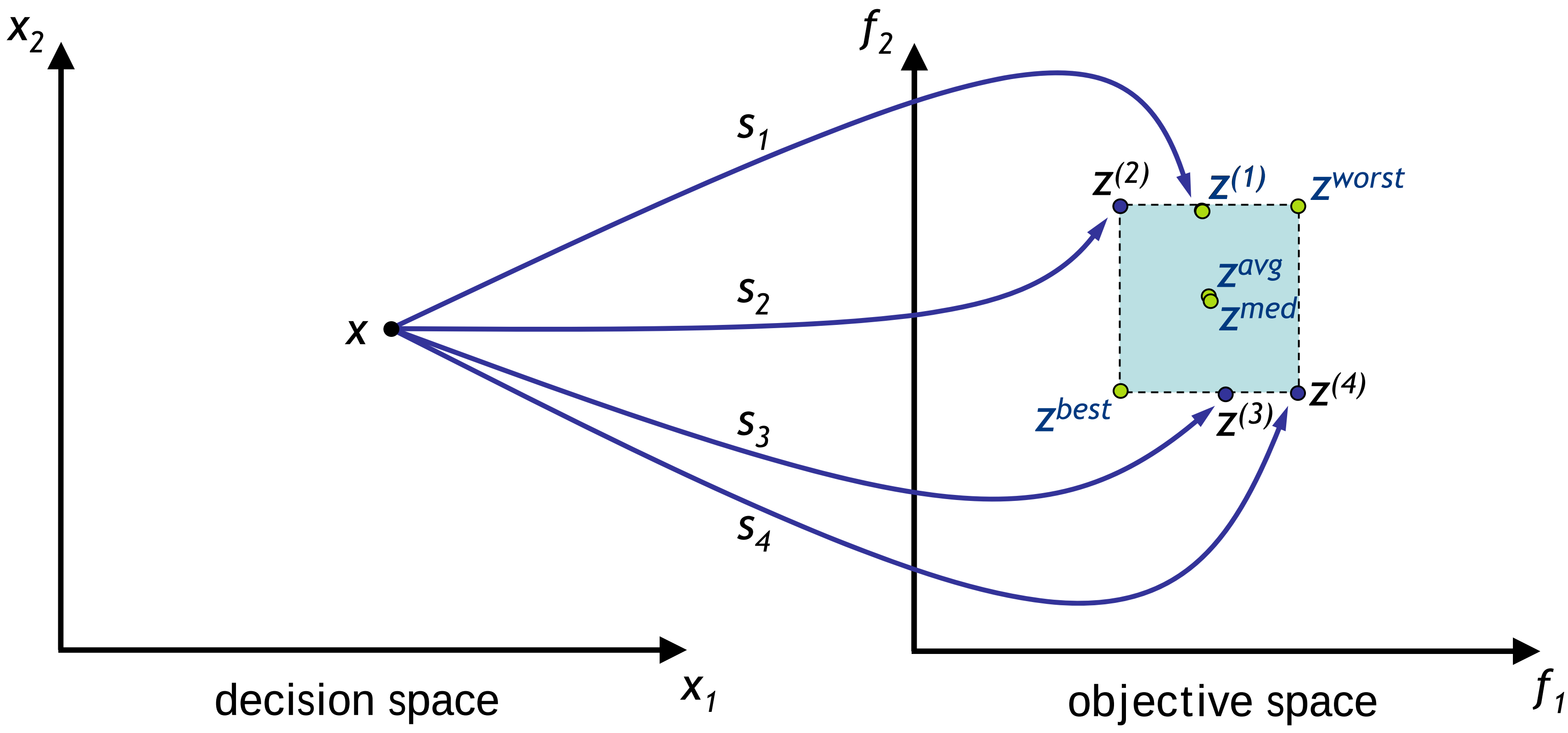
$I^{X(Z\text{-}avg)}(x,x') = I^Z(z^{avg},z'^{avg})$

z_k^{avg}: average of $\{z_k^{(1)},\ldots,z_k^{(p)}\}$ $\forall k \in \{1,\ldots,n\}$

Median-case objective vector indicator

$I^{X(Z\text{-}med)}(x,x') = I^Z(z^{med},z'^{med})$

Solution-level Binary Indicators



Binary Indicators based on I^Z-values

➔ convert the I^Z-values into a single one

Given an I^Z-indicator and two solutions *x* and *x'* Є *P*, let us define the following sample set

$I^Z\text{-set} = \{ I^Z(z^{(1)},z'^{(1)}) , I^Z(z^{(2)},z'^{(2)}) , \ldots , I^Z(z^{(p)},z'^{(p)}) \}$

Best-case Indicator

$I^{X(best)}(x,x')$: minimum value of I^Z-set

Worst-case Indicator

$I^{X(worst)}(x,x')$: maximum value of I^Z-set

Average-case Indicator

$I^{X(avg)}(x,x')$: average value of I^Z-set

Median-case Indicator

$I^{X(med)}(x,x')$: median value of I^Z-set

Performance Assessment

Approximating the efficient set of a deterministic MOP is already bi-objective

- Good convergence and diversity properties
- Large literature: performance metrics…

Uncertain MOP

- Robustness as a third goal?

Performance Assessment

This issue has not been satisfyingly addressed yet

- Uncertainty forgotten ('true' scenario assumed)
- Mean over a sample of objective vectors

Main drawbacks

- In practice, not a unique (deterministic, average-case or random) scenario
- Re-evaluated set may contain both dominating and dominated solutions

➔ Some state-of-the-art performance metrics may be useless

Performance Assessment

<u>A single simulation run per algorithm</u>

Let us define two output sets of two algorithms A and B

$A^i = \{x^1, x^2, \ldots, x^a\}$ $\qquad$ $B^i = \{x'^1, x'^2, \ldots, x'^b\}$

Now, given a x^j and q scenarios

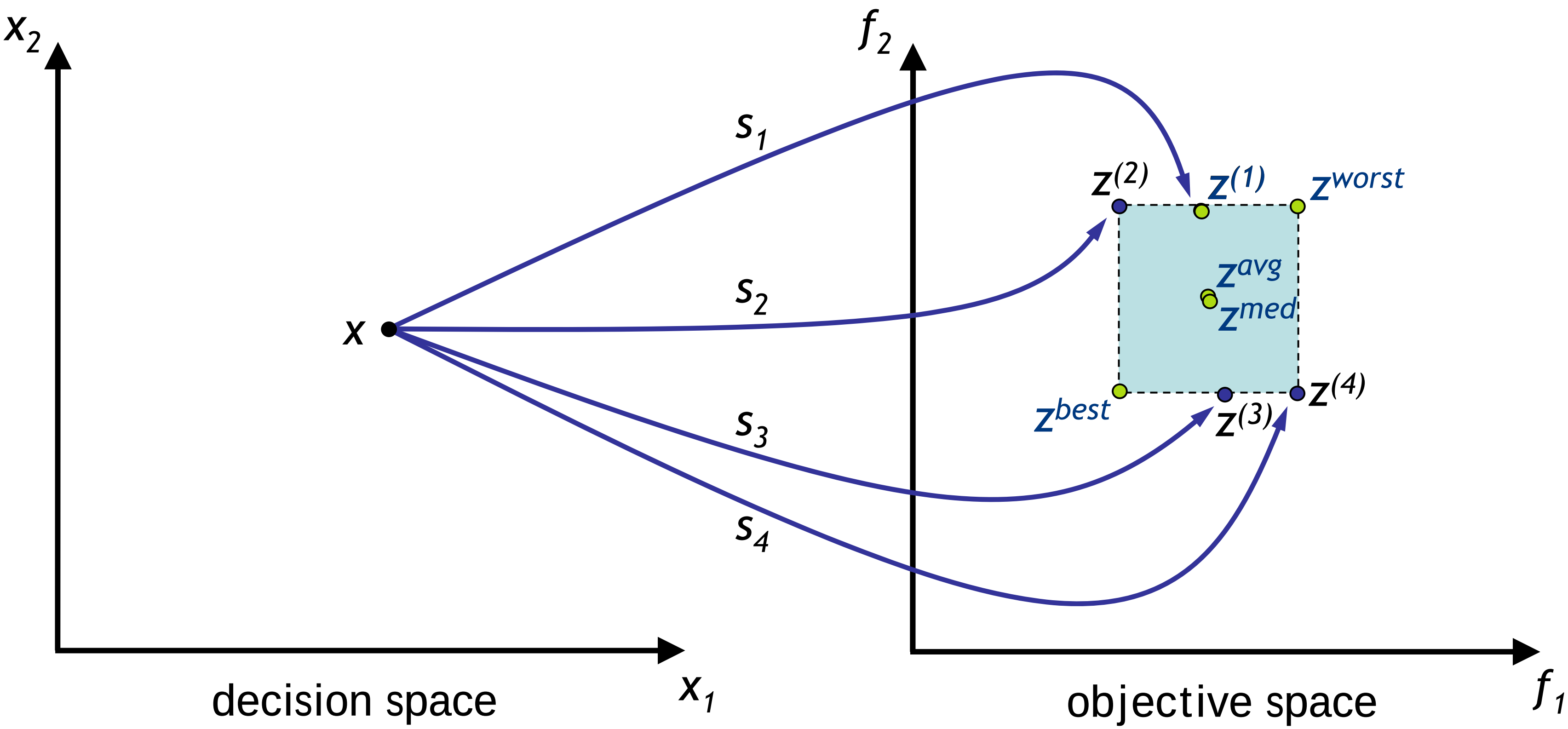
$f(x^j) = \{z^{j(1)}, z^{j(2)}, \ldots, z^{j(q)}\}$ $\qquad$ $f(x'^j) = \{z'^{j(1)}, z'^{j(2)}, \ldots, z'^{j(q)}\}$

Then

$$Z^A = \{z^{1(1)}, z^{1(2)}, \ldots, z^{1(q)}, \; z^{2(1)}, z^{2(2)}, \ldots, z^{2(q)}, \; \ldots \; z^{a(1)}, z^{a(2)}, \ldots, z^{a(q)}\}$$

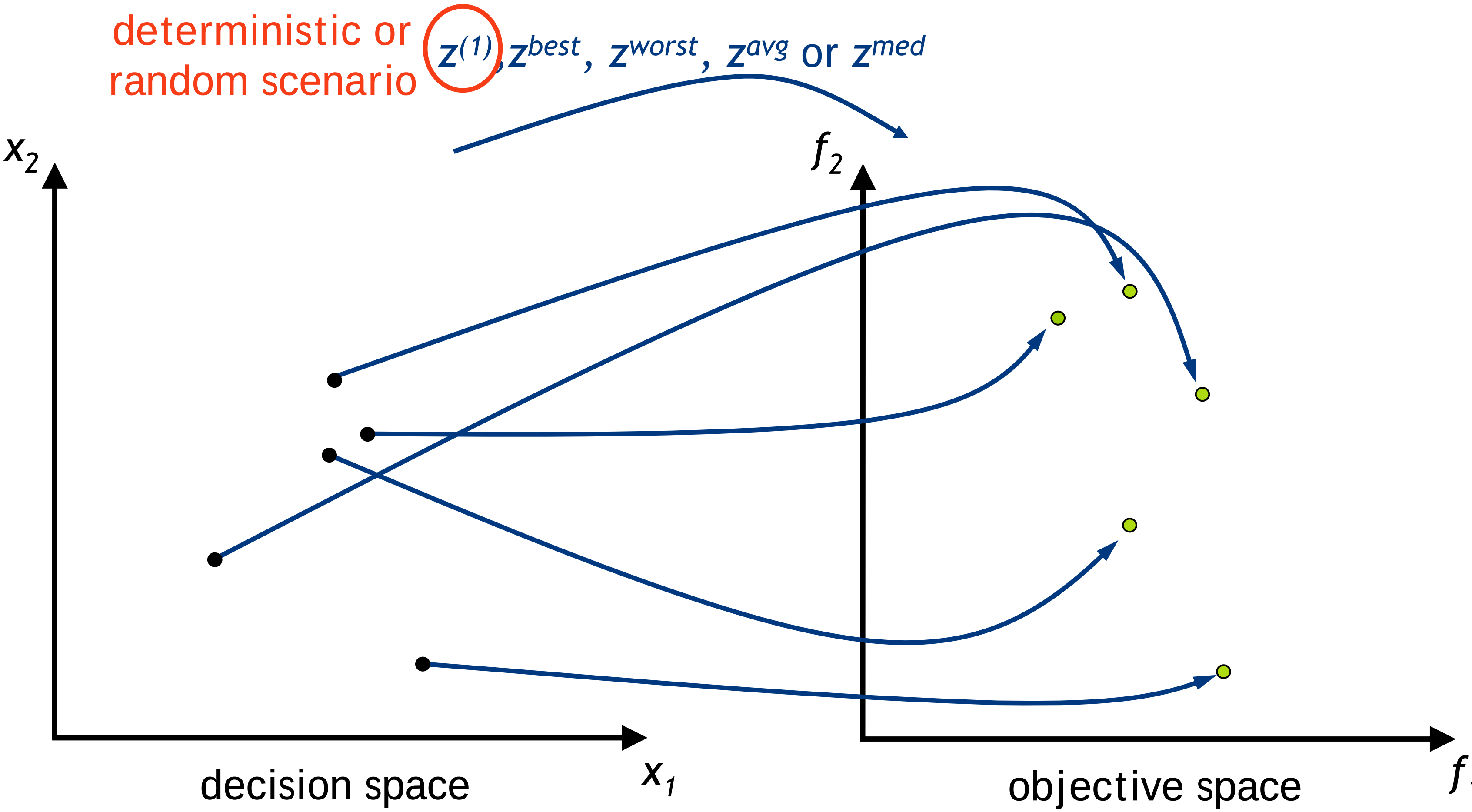
$$Z^B = \{z'^{1(1)}, z'^{1(2)}, \ldots, z'^{1(q)}, \; z'^{2(1)}, z'^{2(2)}, \ldots, z'^{2(q)}, \; \ldots \; z'^{b(1)}, z'^{b(2)}, \ldots, z'^{b(q)}\}$$

Performance Assessment – Protocol 1



Performance Assessment – Protocol 1

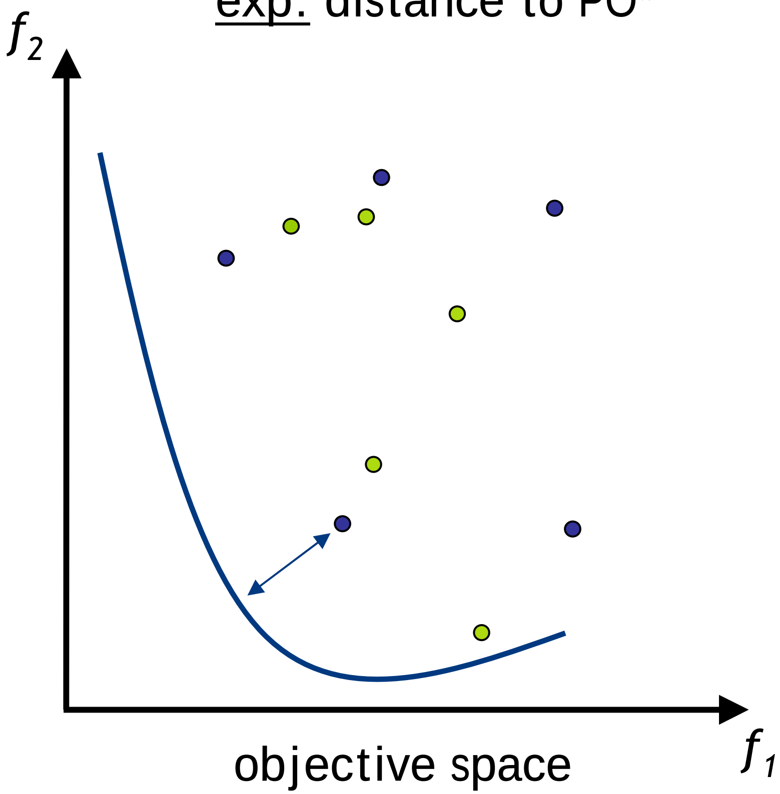
➔ convert the objective vector sample set into a single point



Performance Assessment – Protocol 1

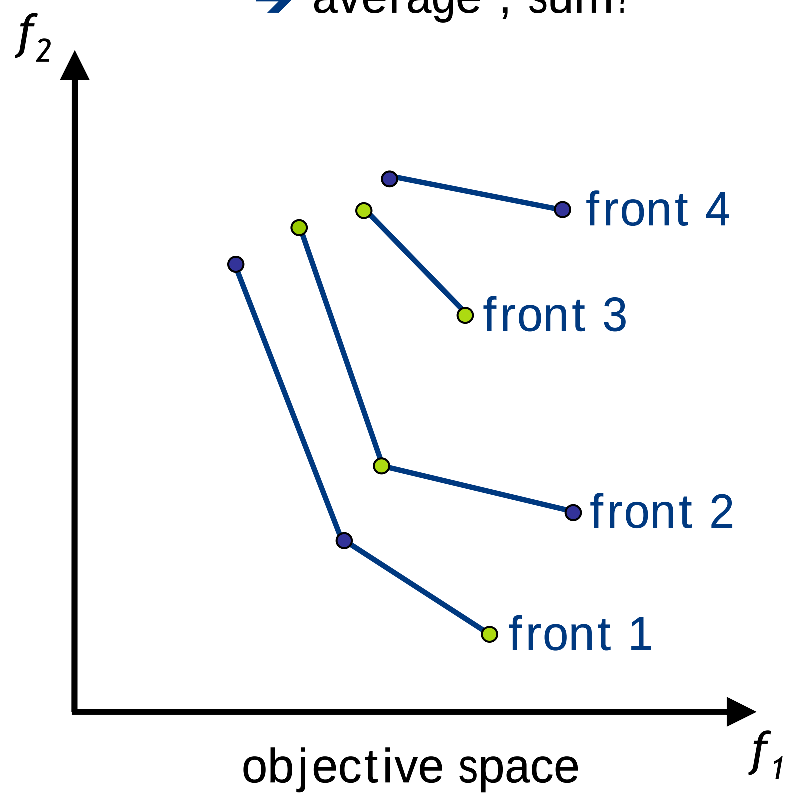
metrics taking both dominating and dominated sol. into account

exp: distance to PO*



dominance depth (n.-d. sorting) (or dominance rank, count)

➔ average , sum?



Performance Assessment – Protocol 1

$A = \{A^1, A^2, \ldots, A^i, \ldots, A^l\}$ $B = \{B^1, B^2, \ldots, B^i, \ldots, B^l\}$

$A^i = \{x^1, x^2, \ldots, x^j, \ldots, x^a\}$ $B^i = \{x'^1, x'^2, \ldots, x'^j, \ldots, x'^b\}$

(1), best, worst, avg, med

$Z^{A^i} = \{z^{*1}, z^{*2}, \ldots, z^{*j}, \ldots, z^{*a}\}$ $Z^{B^i} = \{z'^{*1}, z'^{*2}, \ldots, z'^{*j}, \ldots, z'^{*a}\}$

Z^{A^i} vs. $Z^{B^i} \rightarrow$ 1 performance measure (metric, ranking)

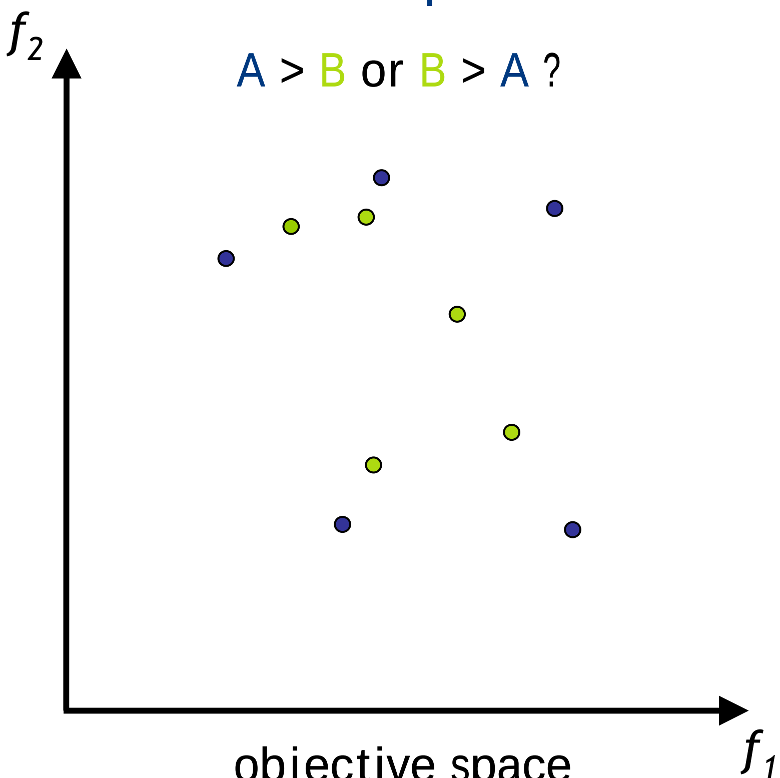
A^i vs. $B^i \rightarrow$ 1 performance measure

A vs. $B \rightarrow l$ performance measures (1 per run)

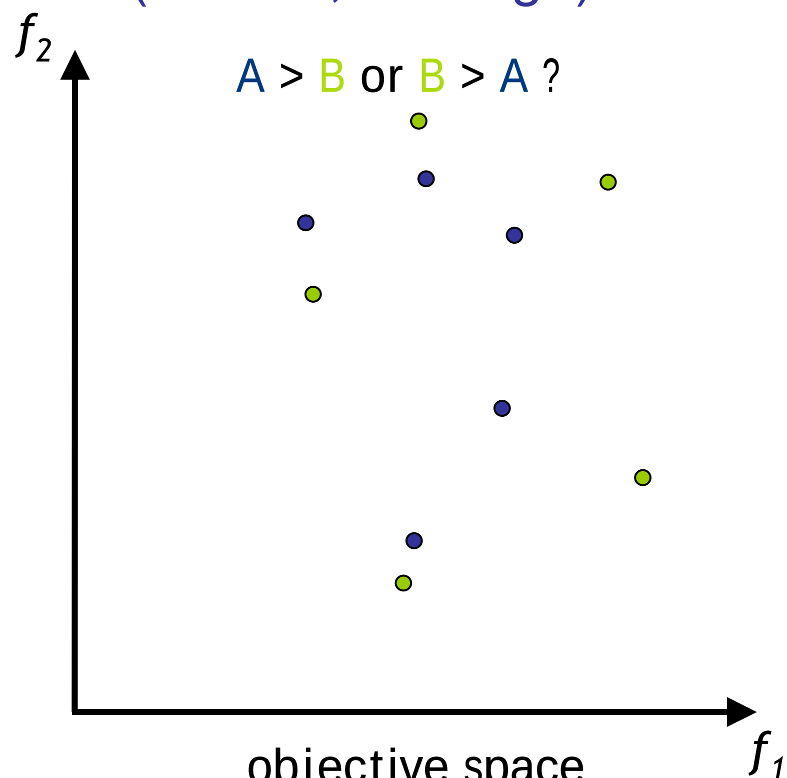
➔ statistical test (mean, variation...)

Performance Assessment – Protocol 2

scenario per scenario comparison (metrics, ranking?)



objective space
scenario 1



objective space
scenario 2

Performance Assessment – Protocol 2

$A = \{A^1, A^2, \ldots, A^i, \ldots, A^l\}$ $B = \{B^1, B^2, \ldots, B^i, \ldots, B^l\}$

$A^i = \{x^1, x^2, \ldots, x^a\}$ $B^i = \{x'^1, x'^2, \ldots, x'^b\}$

according to scenario s_k

$Z^{A^i(k)} = \{z^{1(k)}, z^{2(k)}, \ldots, z^{a(k)}\}$ $Z^{B^i(k)} = \{z'^{1(k)}, z'^{2(k)}, \ldots, z'^{b(k)}\}$

$Z^{A^i(k)}$ vs. $Z^{B^i(k)} \rightarrow$ 1 performance measure (metric, ranking?)

A^i vs. $B^i \rightarrow q$ performance measures (1 per scenario)

➔ statistical test (according to scenario s_k, $A > B$?)

A vs. $B \rightarrow (q*l)$ performance measures (q per run)

➔ number of scenarios where $A > B$, $A \approx B$, $A < B$

Experiments (in progress)

Problems

8 benchmark test instances (from 20*5 to 50*20)

5 types of uncertainty on the processing times

- uniform, exponential, normal, log-normal, various (distribution ≠ on each machine)

2 levels of uncertainty

- + or - 10%, + or – 20%

➔ 80 configurations

Algorithms

10 algorithms

10 runs per algorithm

2 sample sizes (except for $I^{(1)}$)

- $|S| = 10$
- $|S| = 20$

Stopping criteria

- max. number of evaluations

➔ 200 configurations

➔ 16000 simulation runs

Dynamic optimization

M. Khaoudjia, L. Jourdan, E-G. Talbi. A particle swarm for the resolution of the Dynamic Vehicle Routing, META'08, 2008.

40 ans la révolution de l'information

INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

INRIA

centre de recherche FUTURS

Problem

The Management of transport and the logistic chain in companies.

How to reduce the cost of the transporting of the products?

- Rising of the fuel prices
- Impressive competition
- Emerging Trends
- e-Commerce
- Quickness and short delivery time (real time)

Dynamic elaboration of vehicle tours

⇨ **DVRP: Dynamic Vehicle Routing Problem**

Vehicle Routing Problem

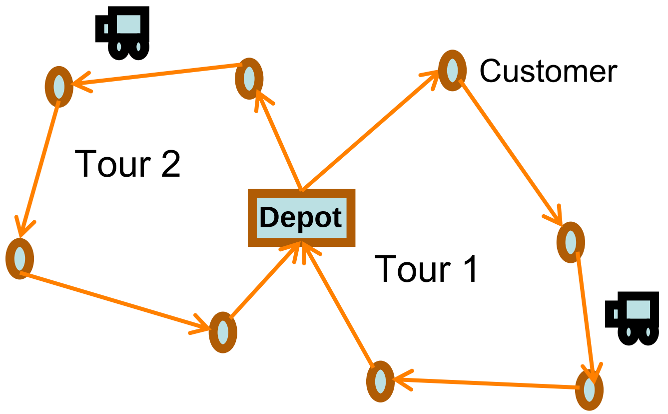
Background :

- Vehicles with finite capacity, domiciled in the same depot.
- All the customers are known before the planning of tours.

Objective:

- Identify a set of tours that minimizes the cost of the traveled distance.

Complexity : NP-complete Class



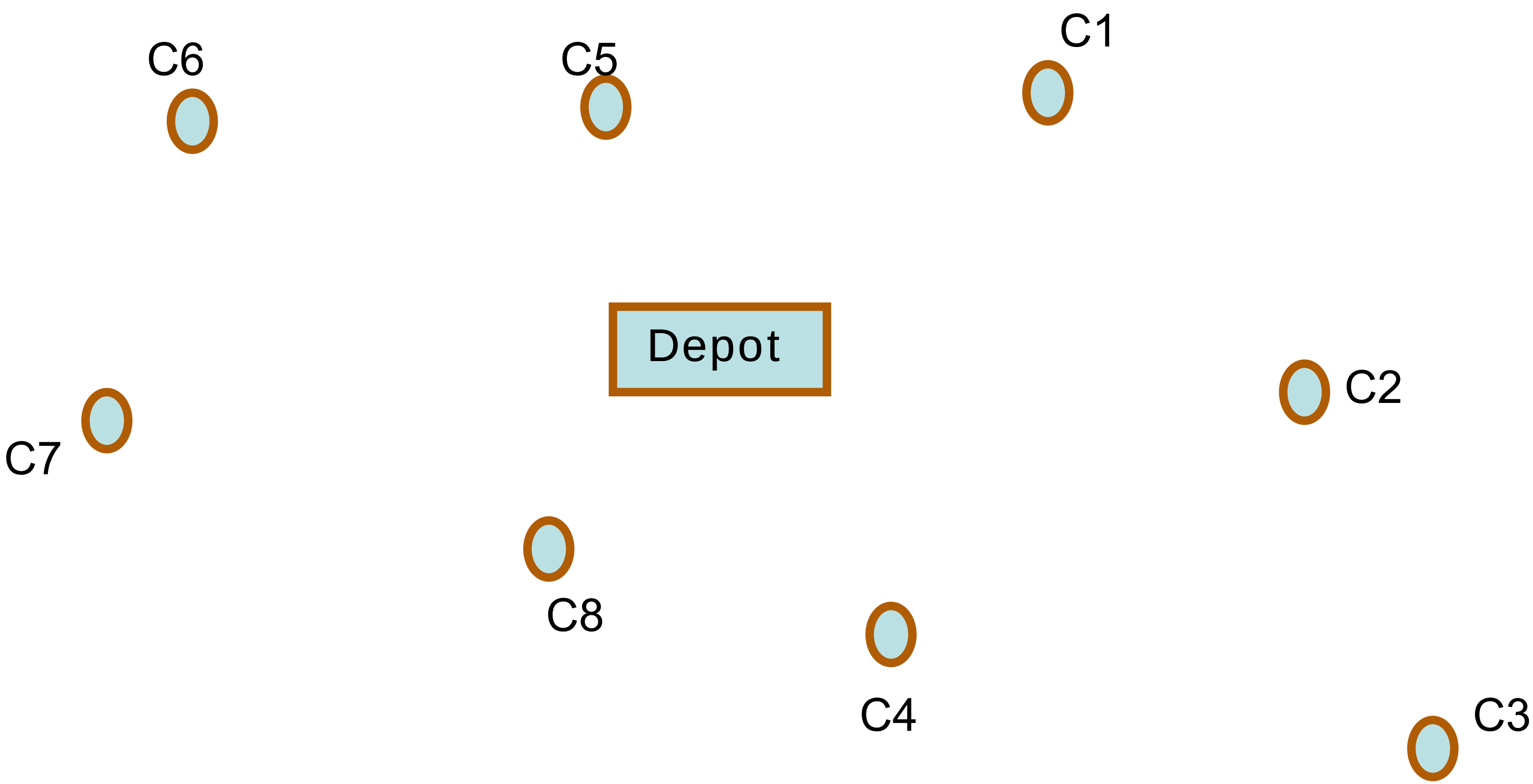
Dynamic Vehicle Routing Problem

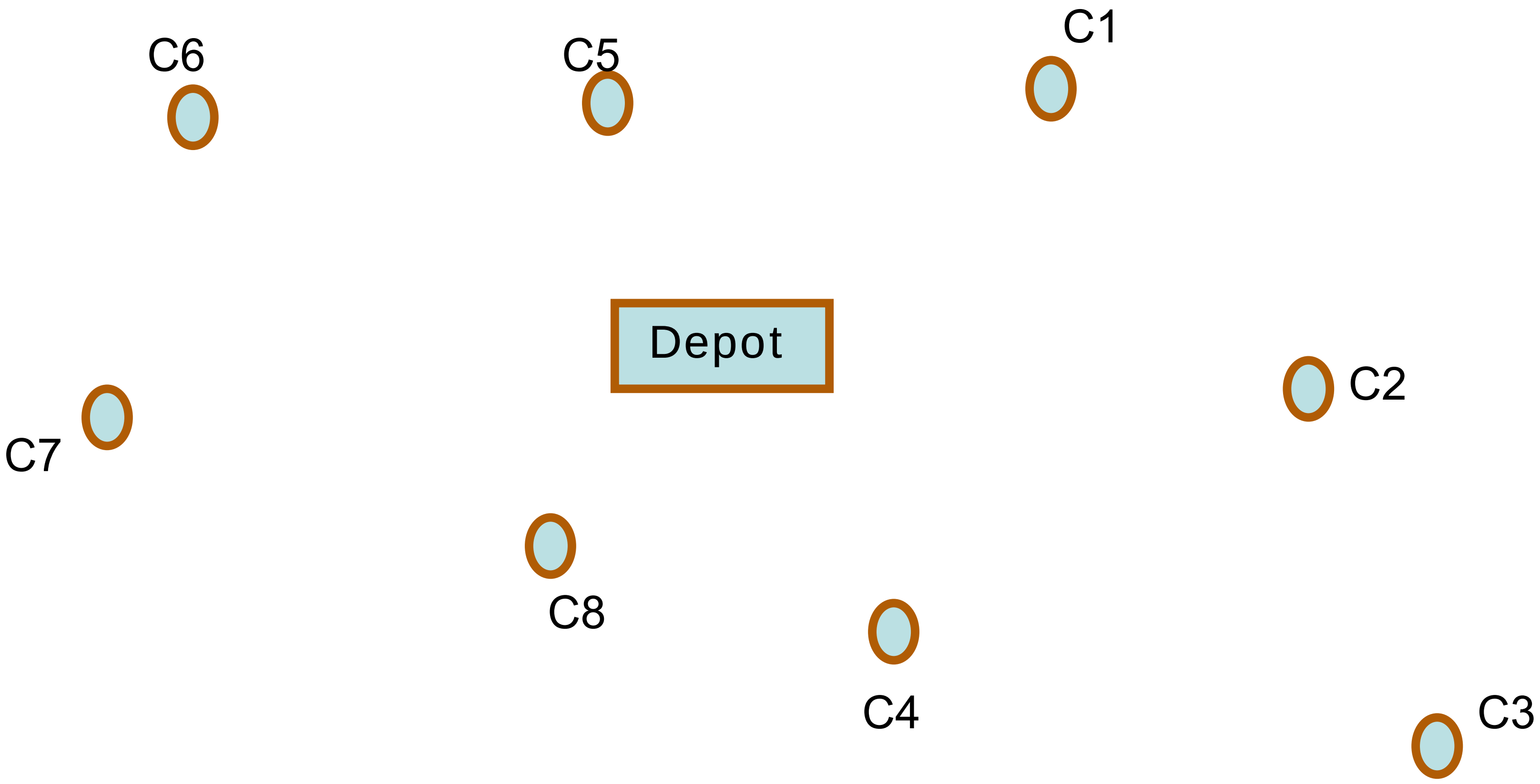
Background :

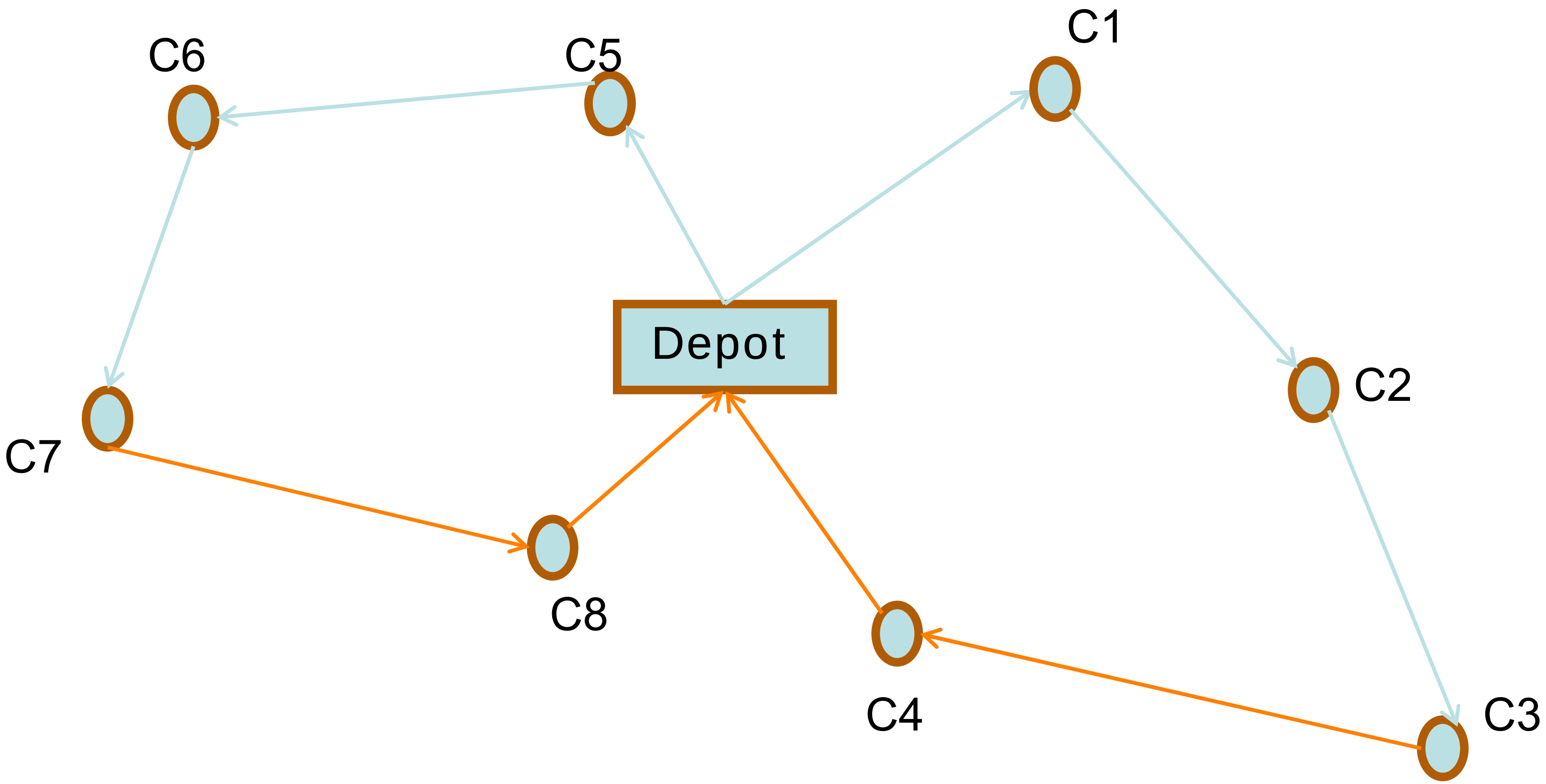
- The customers are not all known (dynamics).
- The vehicles are already committed on roads.

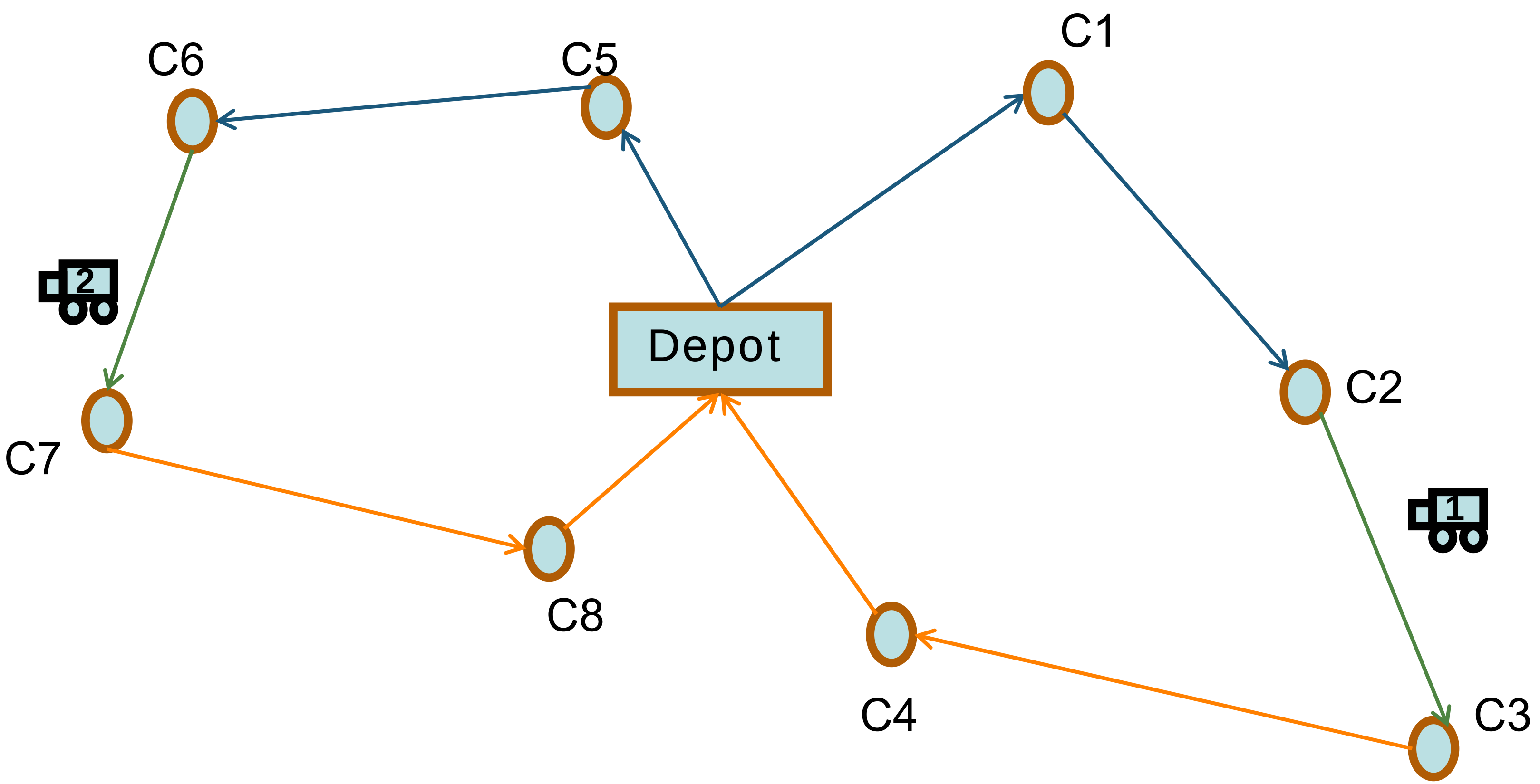
Objective:

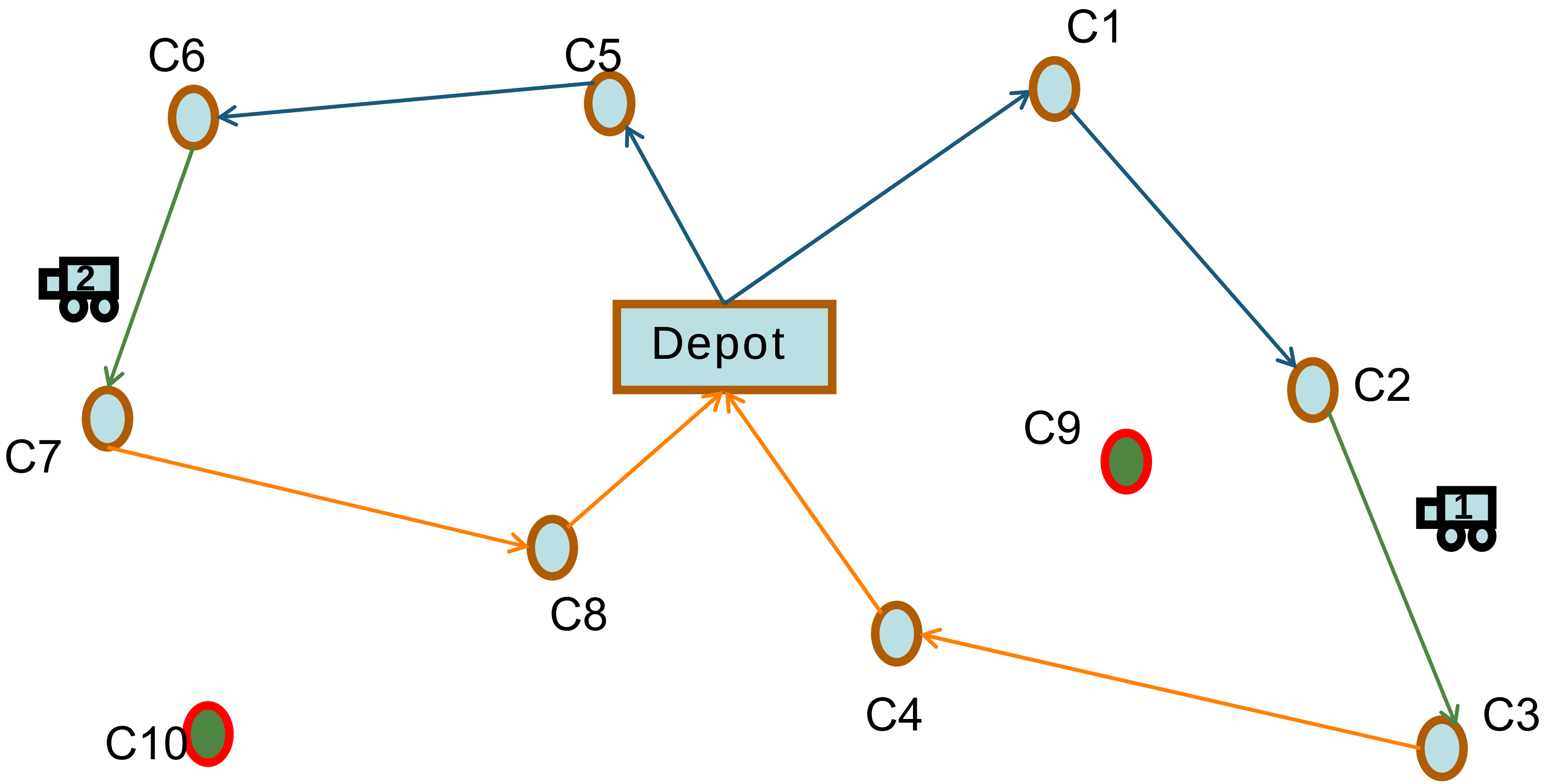
- Insert the new orders in the existing plan of routing.
- Minimize the traveled distance.
- Complexity: NP-complete Class.


C6
C5
C1
Depot
C2
C7
C8
C4
C3

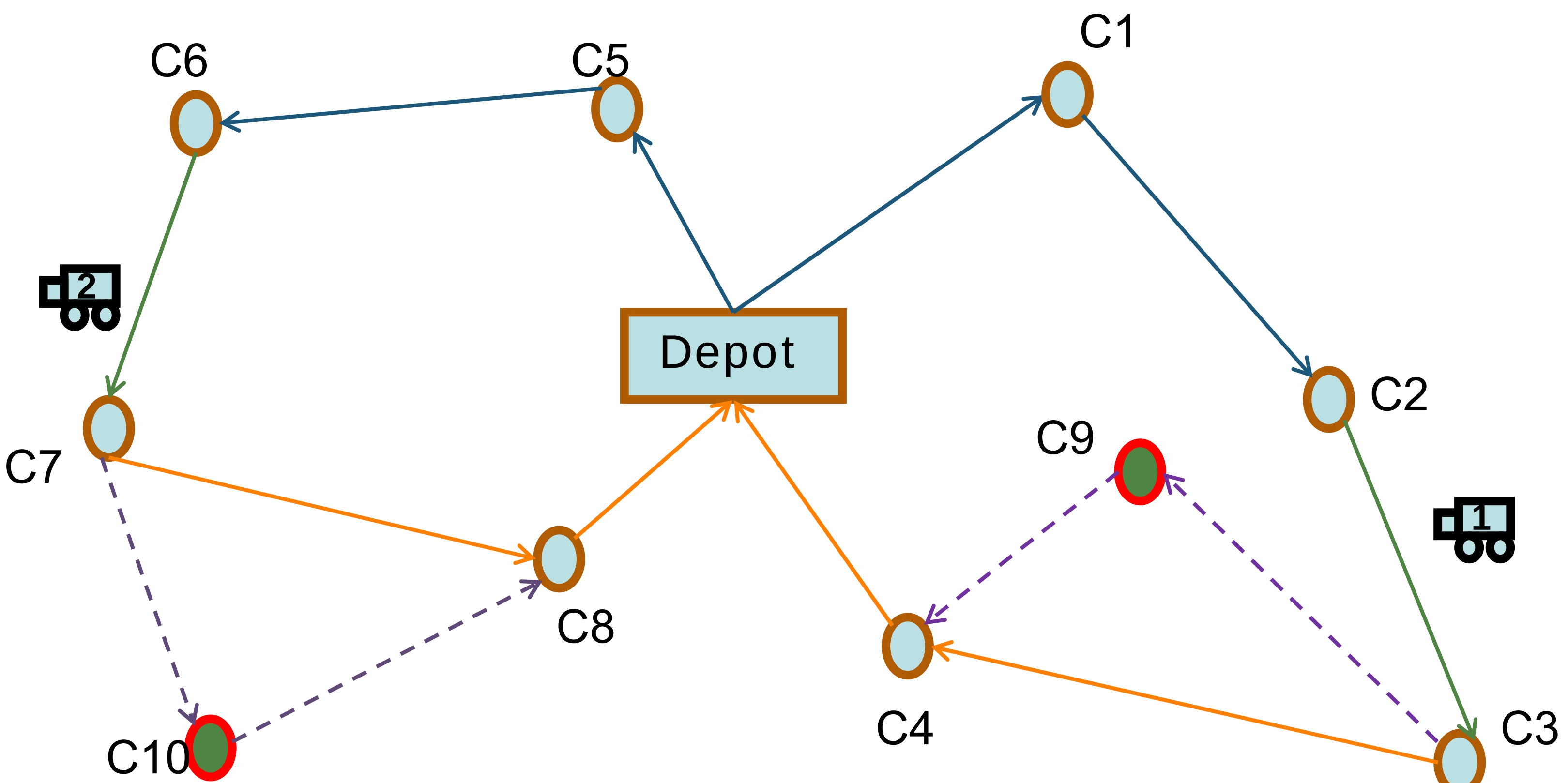

C6
C5
C1
Depot
C2
C7
C8
C4
C3

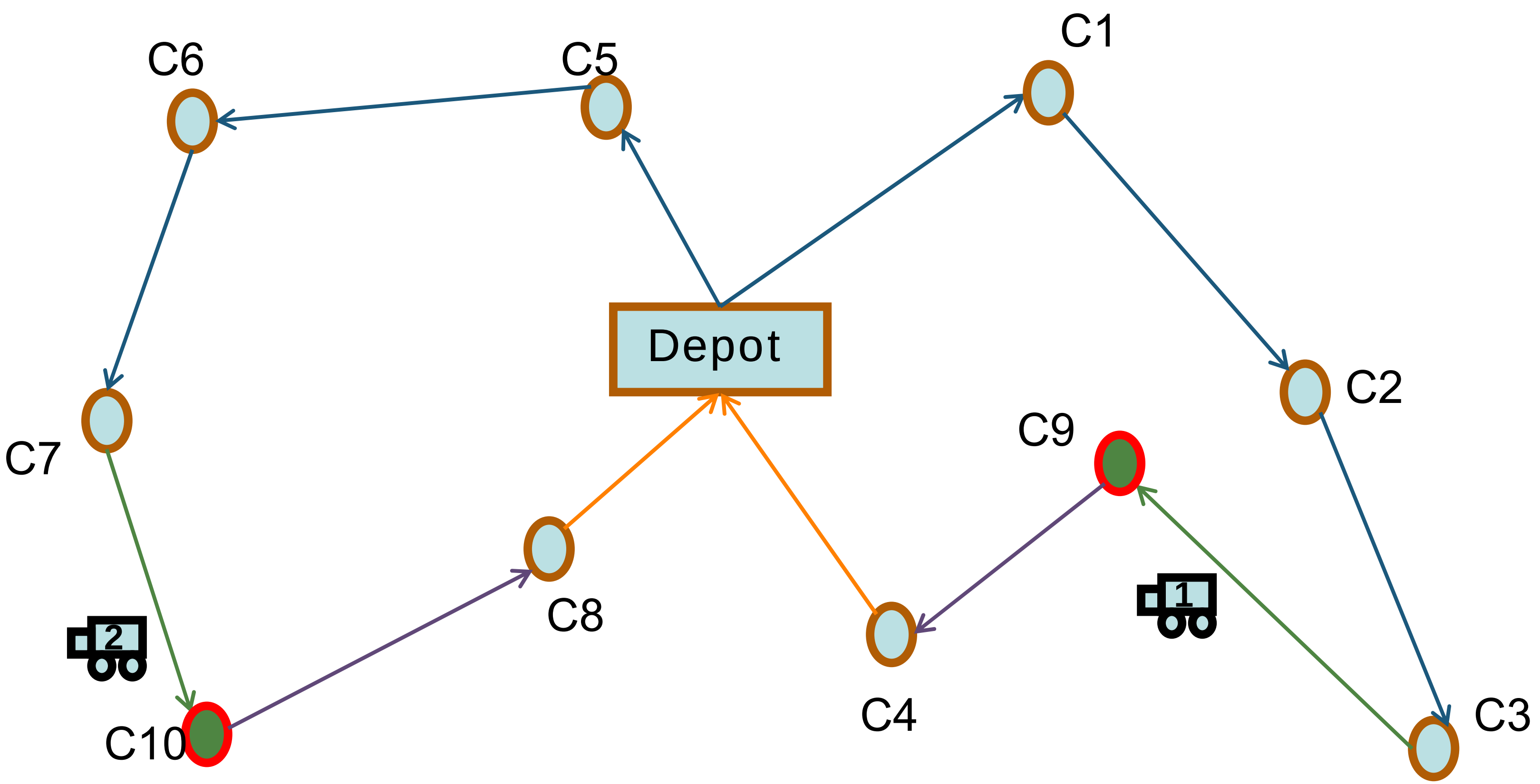

C6
C5
C1
Depot
C2
C7
C8
C4
C3


C6
C5
C1
2
Depot
C2
C7
1
C8
C4
C3



C6
C5
C1
2
Depot
C2
C7
C9
1
C8
C4
C3
C10


C6
C5
C1
2
Depot
C2
C9
C7
1
C8
C4
C3
C10


C6
C5
C1
Depot
C2
C9
C7
C8
C4
1
2
C10
C3

Adaptation of PSO for the DVRP

Adapt a metaheuristic designed for continuous problems

Adopt a suited coding for the problem

Taking into account the time

APSO-DVRP : Adaptive Particle Swarm Optimization

Encoding of a particle $X_i(t)$

- Customers

C1			C2			Ci			Cn		
t1	p1	s1	t2	p2	s2	ti	pi	si	tn	pn	sn

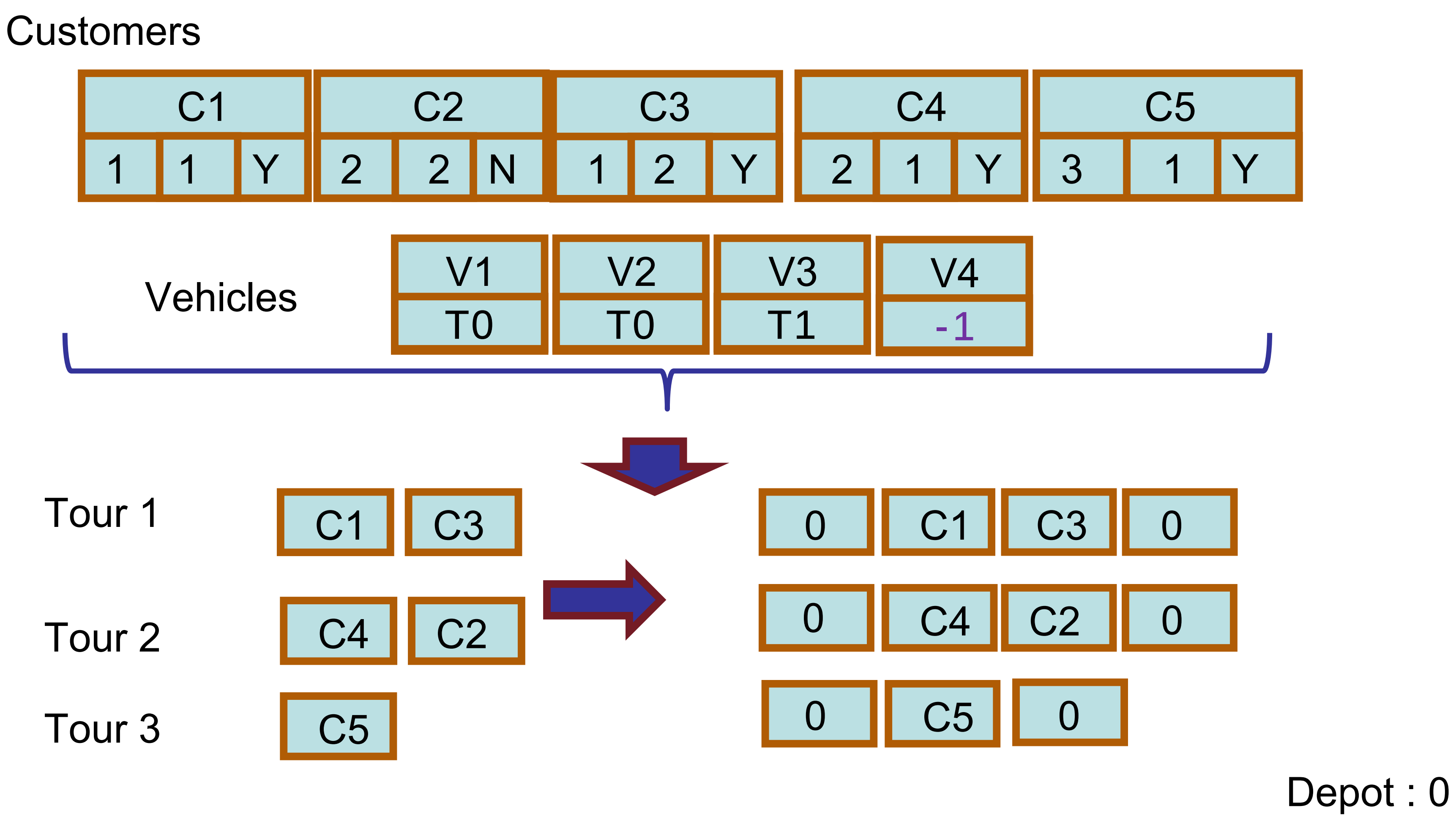
C_i : Customer, T_i: Tour, P_i : Location, S_i: (Y: served, N: unserved)

- Start time of vehicles

V1	V2	V3	Vi	Vn
Tv1	Tv2	Tv3	Tvi	Tvn

V_i : Vehicle, Tv_i : Departure Time from the depot

APSO-DVRP : Adaptive Particle Swarm Optimization



Movement of particle (2)

News tours

1	1	1	2	2

Change the tour of the unserved customers

Xi(t+1)

C1			C2			C3			C4			C5		
1	1	Y	1	3	N	1	2	Y	2	1	Y	2	2	N

Update the commitment

Vehicles

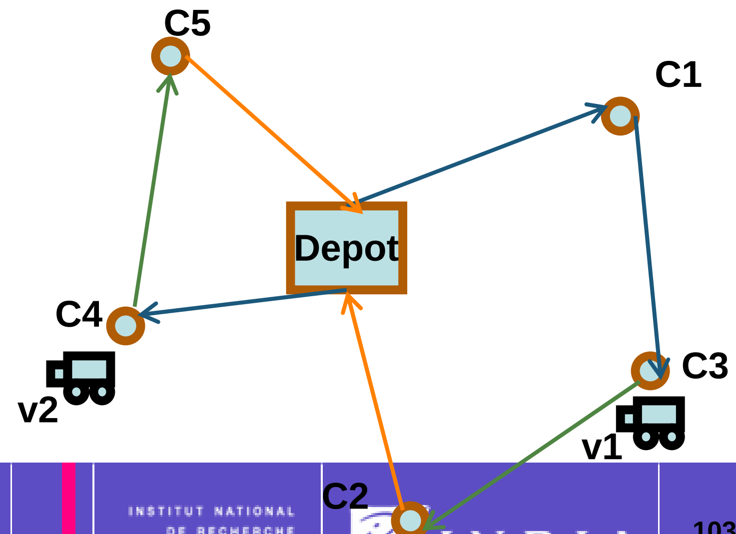
V1	V2	V3	V4
T0	T0	-1	-1

Tour 1

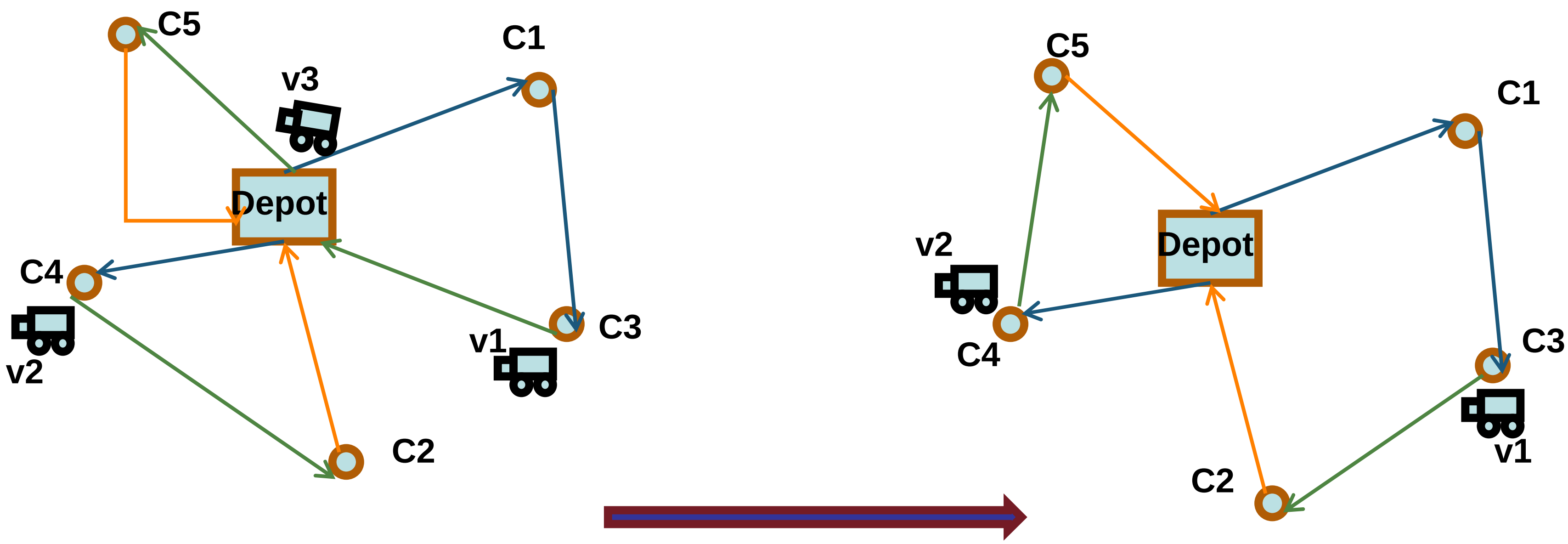
0	C1	C3	C2	0

Tour 2

0	C4	C5	0

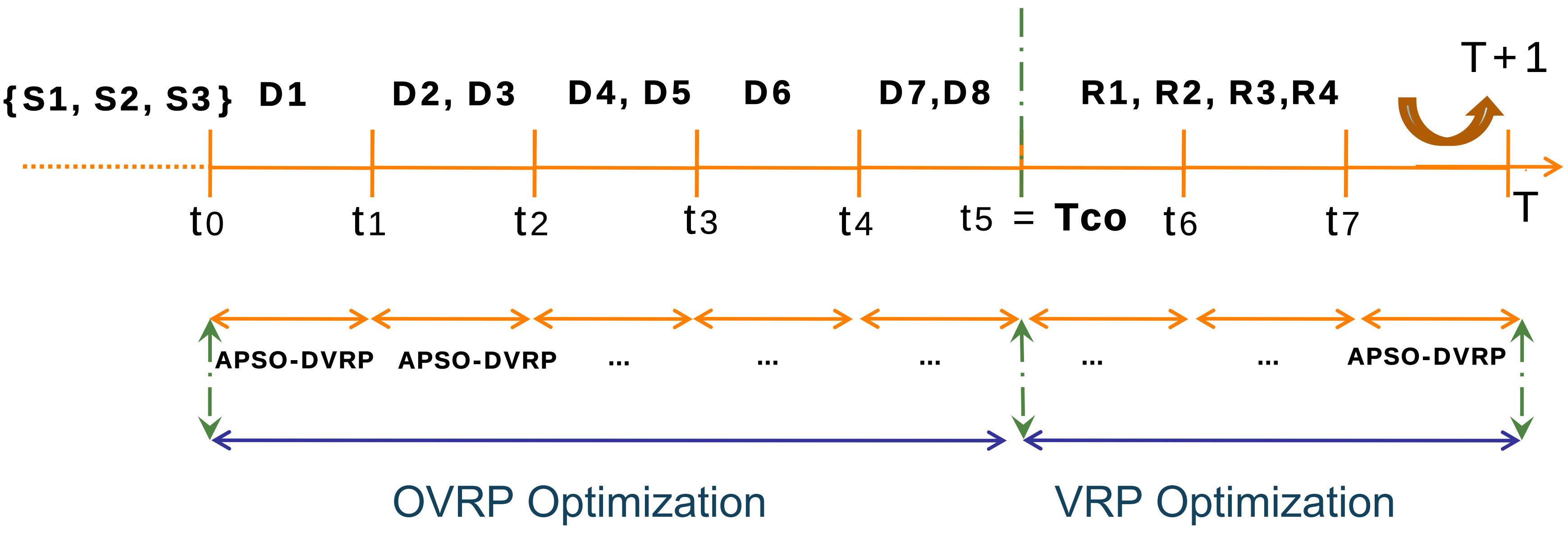


Movement of particle (3)



Xi(t) + **Vi(t+1)** = **Xi(t+1)**

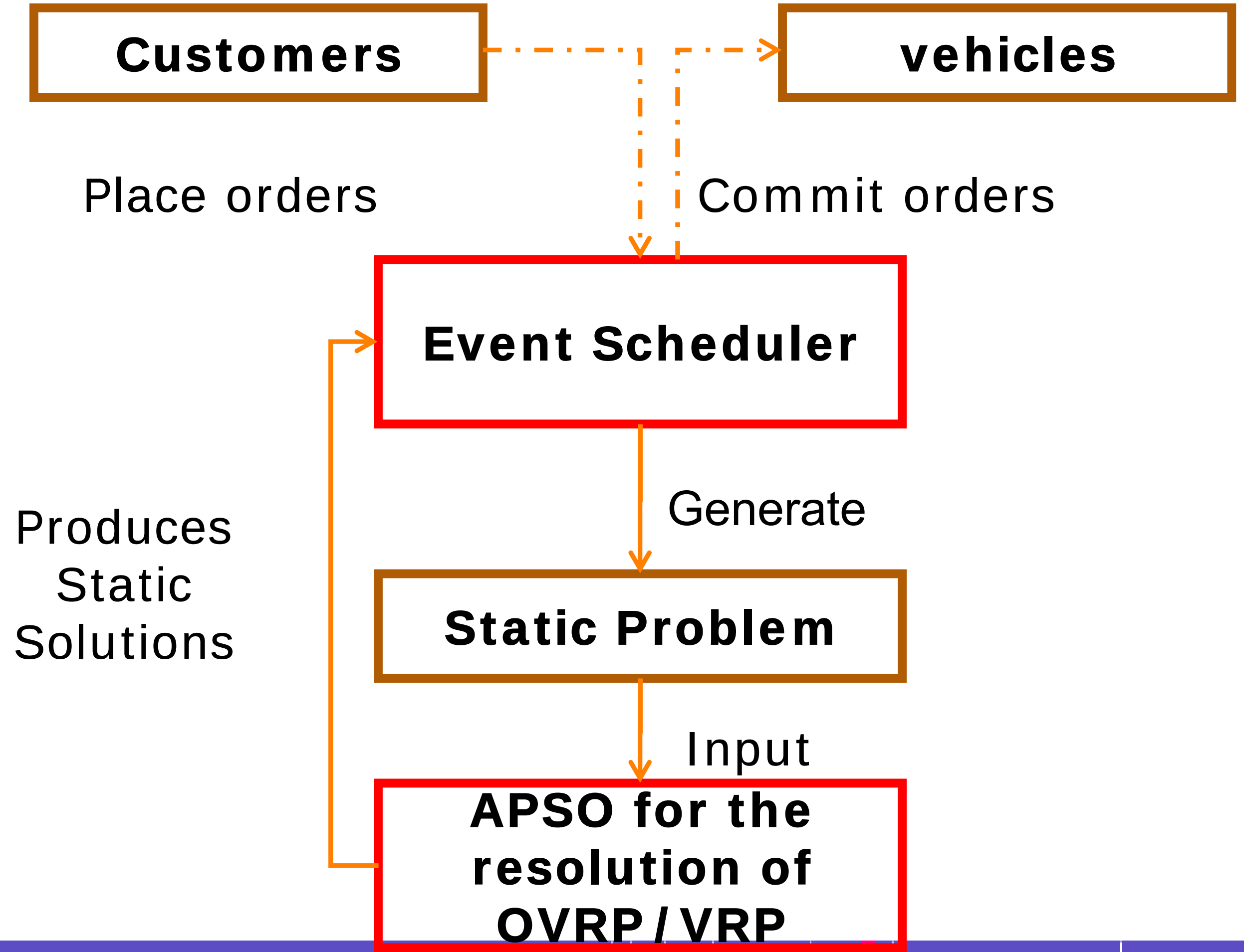
Simulation/Planning



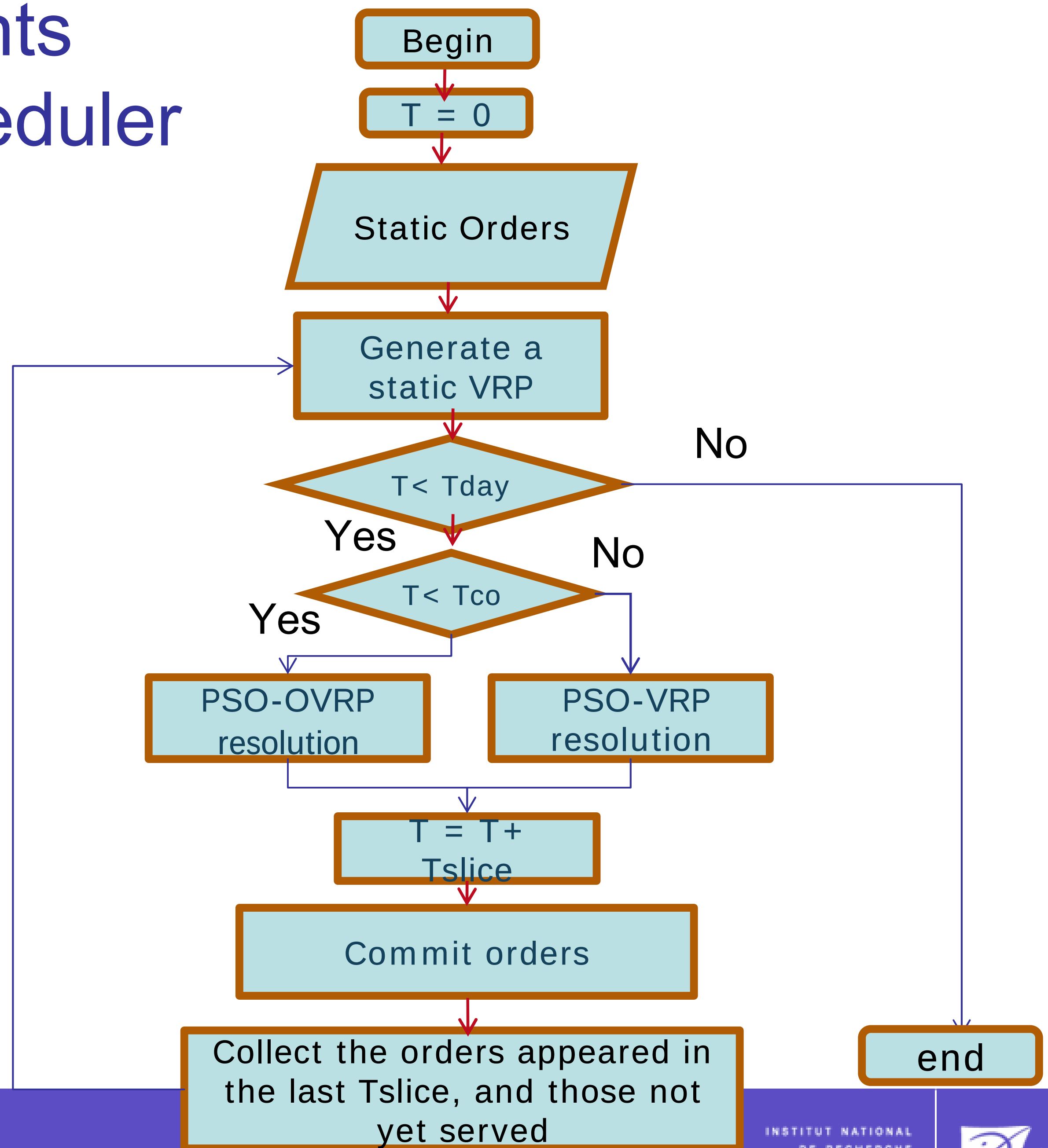
T : Planning horizon
Tco: Cut-off time. The suspension time of new orders.
Si : static orders
Di: dynamic ordrers
Ri: Orders dismissed to the next working day

[Kilby&al, 98]

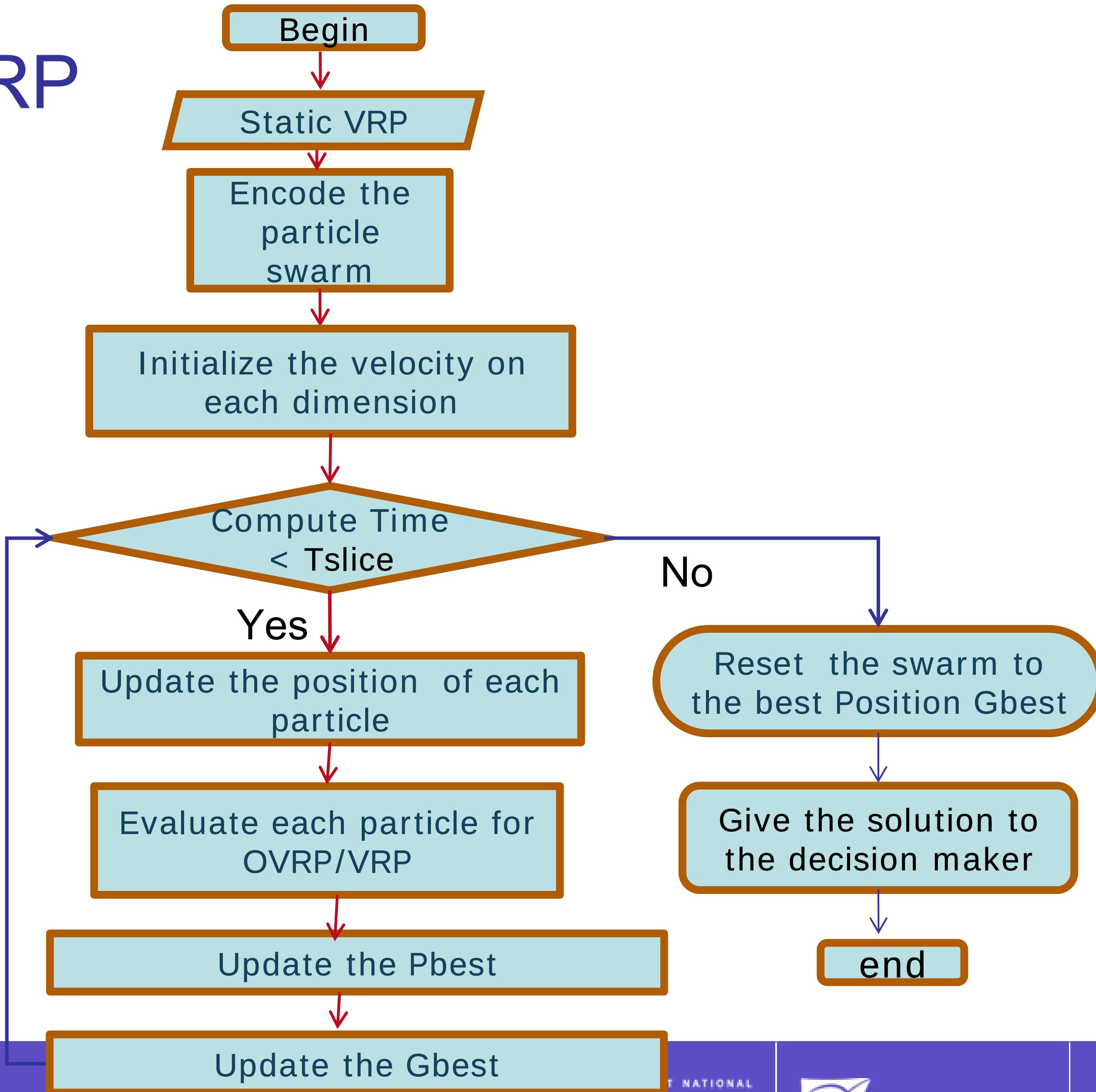
Diagram of the proposed approach



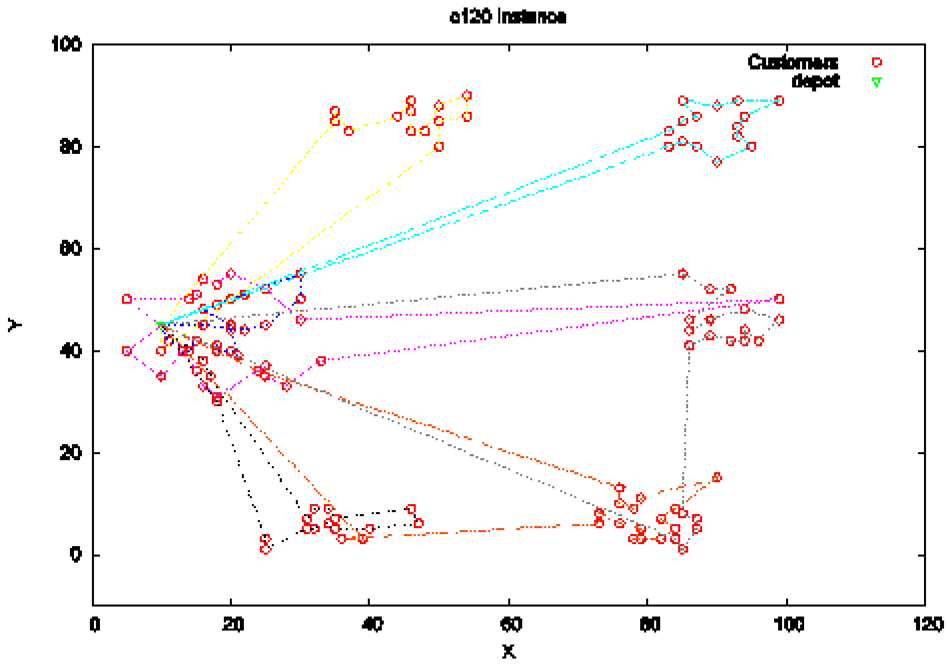
Events Scheduler



PSO – OVRP/VRP


Begin
Static VRP
Encode the particle swarm
Initialize the velocity on each dimension
Compute Time < Tslice
Yes
No
Update the position of each particle
Evaluate each particle for OVRP/VRP
Update the Pbest
Update the Gbest
Reset the swarm to the best Position Gbest
Give the solution to the decision maker
end

Example of results



Results

	Metaheuristics								
Benchmarks	APSO		AS [61]]		GA [41]		TS [41]		
	Min	Average	Min	Average	Min	Average	Min	Average	Ratio
c50	575,889	591,208	631,3	681,86	**570,89**	593,42	603,57	627,9	-0,87%
c75	1029,75	1166,85	1009,36	1042,39	981,57	1013,45	981,51	1013,82	-4,83%
c100	1111,7	1158,12	973,26	1066,16	961,1	987,59	997,15	1047,6	-15,66%
c100b	947,704	1111,89	944,23	1023,6	881,92	900,94	891,42	932,14	-7,45%
c120	**1276,88**	1450,82	1416,45	1525,15	1303,59	1390,58	1331,22	1468,12	+2,09 %
c150	1542,86	1618,21	1345,73	1455,5	1348,88	1386,93	1318,22	1401,06	-17,04%
c199	1962,39	2036,62	1771,04	1844,82	1654,51	1758,51	1750,09	1783,43	-18,60%
f71	**279,519**	368,053	311,18	358,69	301,79	309,94	280,23	306,33	+0,25 %
f134	15875	17629,6	15135,51	16083,56	15528,81	15986,84	15717,9	16582,04	-4,88%
tai75a	1816,07	1992,29	1843,08	1945,2	1782,91	1856,66	1778,52	1883,47	-2,11%

Conclusion

Conclusion

• Wide aera of research in optimization

• Contributions in problem modelization, new hybridizations, …

•Open issues: machine learning cooperation, stochastic and dynamic multi objective optimization

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