Un algorithme génétique hybride à gestion adaptative de diversité pour le problème de tournées de véhicules et ses variantes

Thibaut VIDAL

LOSI et CIRRELT

Université de Technologie de Troyes

et Université de Montréal

Journée du GT Transport et Logistique

Paris, 14/06/11

Supervisors and co-authors

- Ph.D under the direction of
  - Christian Prins, Université de Technologie de Troyes
  - Teodor Gabriel Crainic, ESG, UQÀM
  - Michel Gendreau, Ecole Polytechnique de Montréal

- Joint work with
  - Nadia Lahrichi and Walter Rei, ESG, UQÀM

Presentation outline

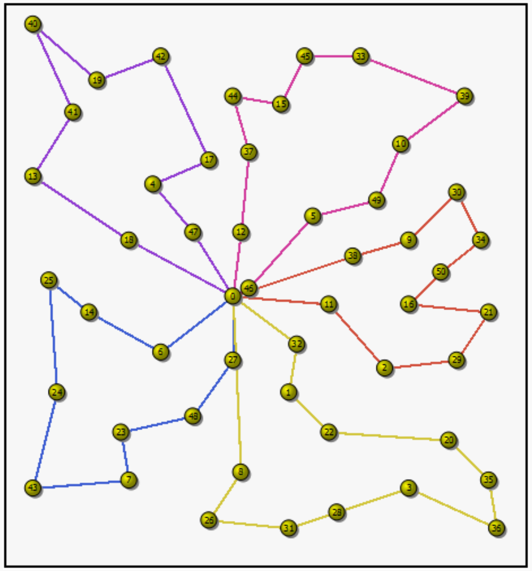
1) Rich vehicle routing problems: concepts and literature review

2) A hybrid genetic algorithm for the periodic multi-depot VRP

3) Empirical studies on diversity management procedures

4) Generalization to other multi-attribute VRPs

Rich Vehicle Routing Problems (1/3)



- Success story of the vehicle routing problem, but still many challenges to address efficiently real life applications
- In particular, when solving VRP with **many attributes** and **large size**

- *Attributes* = extensions of the academic VRP, such as heterogeneous fleet, variable travel times, multi-depots…
  - Book by Golden, Raghavan and Wasil : The vehicle routing problem: latest advances and new challenges

- Several attributes together = *rich formulations*

Rich Vehicle Routing Problems (2/3)

- Elements of literature on Rich VRP:
  - “Solving Rich VRP models” , Workshop Molde (2005)
  - Special issue of CEJOR (2006) edited by Hartl, Hasle, and Janssens
  - Two SINTEF working papers by Bräysy, Gendreau, Hasle, and Løkketangen (2008)
  - Several recent papers dealing with specific Rich VRPs

Rich Vehicle Routing Problems (3/3)

- Some very frequent attributes from the literature:
  - Route length and duration
  - Multi-Depot (MDVRP)
  - Periodic (PVRP)

  MDPVRP
  - Time-Windows
  - Mixed Fleet
  - Multi-Compartment
  - Pick-up and deliveries
  - Location routing
  - Time-dependent problems
  - Truck driver scheduling …

- Appear in many real life problem settings

The MDPVRP

- Multiple depots

- Periodic:
  - Planning on several days
  - For each customer, acceptable combinations of visits called *patterns*

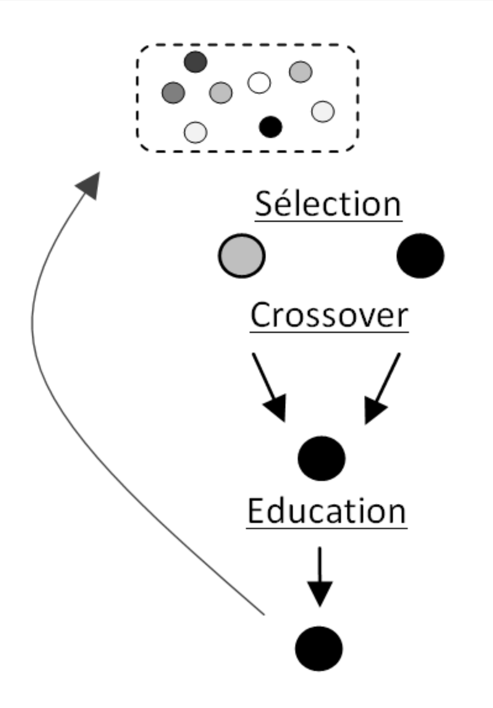
- Goal:
  - Each customer must be assigned to a single depot and a single pattern
  - Feasible routes must be constructed for each depot and day
  - In such a way that the total cost of all the resulting routes is minimized.

Literature on the MDPVRP

- Heuristics: Sequential or iterative approaches
  - Hadjiconstantinou & Baldacci (1998)
  - Yang and Chu (2000)
- Heuristics: Integrated approaches, tackle the problem as a whole
  - Parthanadee and Logendran (2006) : Tabu Search for a complex variant of the problem. However, customers may be served from different depots on different days.
  - Crainic et al. (2009) : *Integrative Cooperative Search*. No complete results published up to now.
- Exact approaches:
  - Kang et al. (2005)
  - Baldacci and Mingozzi (2009)

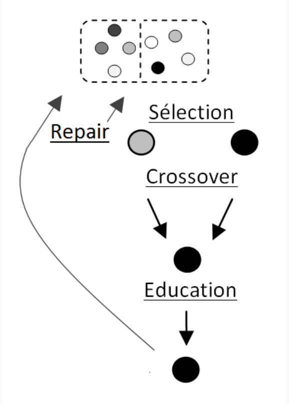
Hybrid genetic algorithm for the MDPVRP (1/4)

- Existing Hybrid GA's for VRP, VRPTW, MDVRP
  - Few work on periodic problems



- General Methodology:
  - Evolving a population of solutions by means of genetic operators such as *selection*, *crossover* and *mutation*.
  - Survival of the fittest drives the population towards good solutions.
  - To speed up the evolution, random mutation replaced by a local search based *education* operator.

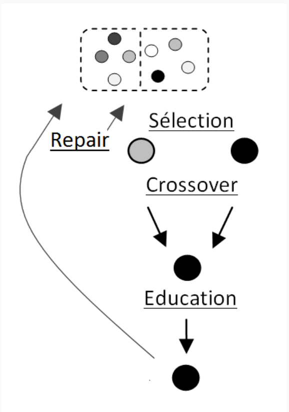
Hybrid genetic algorithm for the MDPVRP (2/4)



- Search Space:
  - Accepting infeasible solutions not respecting route related constraints : load or duration
  - Always respect the number of vehicles

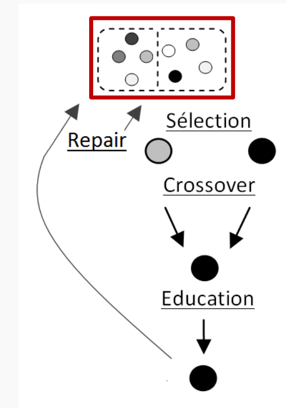
- Adaptive penalties:
  - Amount of infeasible solutions is monitored; penalties are adjusted during run time to obtain about 20% feasible solutions following education
  - Repair operator to obtain more feasible solutions
  - Double population to manage feasible and infeasible individuals

Hybrid genetic algorithm for the MDPVRP (3/4)

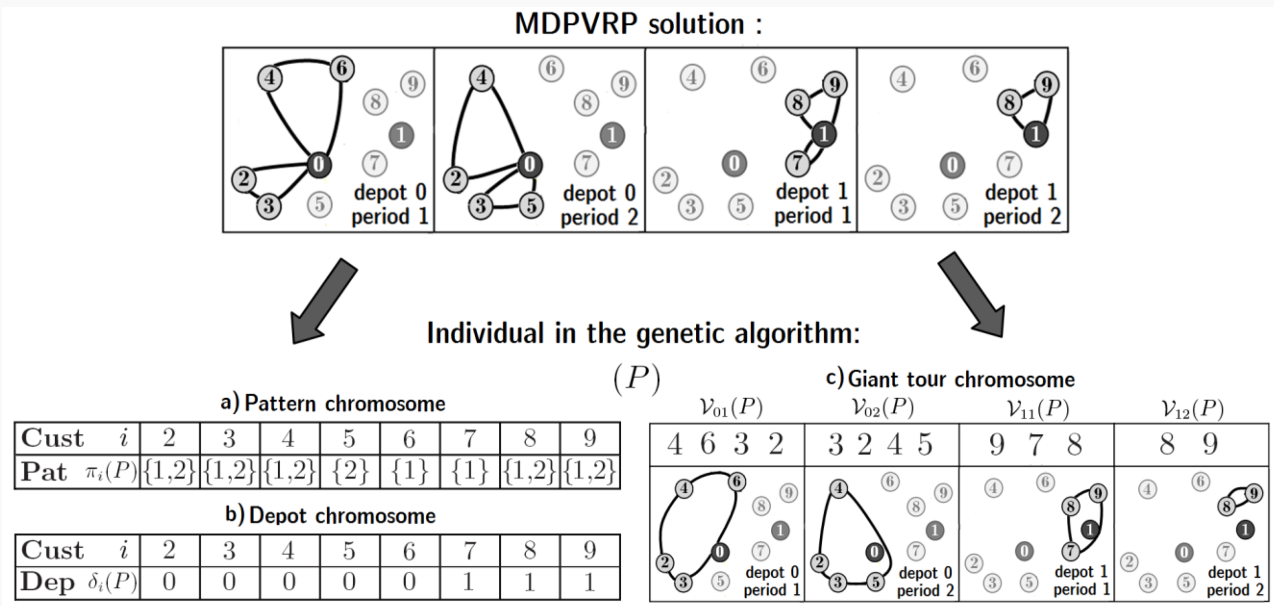


- Double population management:
  - A feasible individual goes in the feasible subpopulation
  - An infeasible individual → included in the infeasible subpopulation → probability P_{rep} to be repaired & added in the feasible one
- Each subpopulation → (μ+λ) strategy where any new offspring is directly included (and thus can reproduce):
  - μ individuals initially
  - Each new individual is included in the population
  - As a population reaches the size (μ+λ), selection of survivors to discard λ individuals
- Good properties :
  - Profit from new individuals, including those with bad fitness
  - Preserve an elite

Hybrid genetic algorithm for the MDPVRP (4/4)



- Solution representation
  - Representation as a giant TSP tour without trip delimiters (Prins 2004)
  - In MDPVRP context, a tour for each couple (day, depot)
  - Polynomial « Split » algorithm to obtain the best segmentation of each sequence into routes



a) Pattern chromosome

Cust i	2	3	4	5	6	7	8	9
Pat $\pi_i(P)$	{1,2}	{1,2}	{1,2}	{2}	{1}	{1}	{1,2}	{1,2}

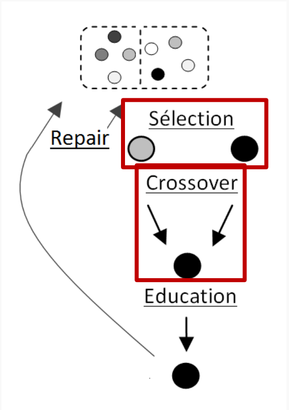
b) Depot chromosome

Cust i	2	3	4	5	6	7	8	9
Dep $\delta_i(P)$	0	0	0	0	0	1	1	1

c) Giant tour chromosome

$\mathcal{V}_{01}(P)$	$\mathcal{V}_{02}(P)$	$\mathcal{V}_{11}(P)$	$\mathcal{V}_{12}(P)$
4 6 3 2	3 2 4 5	9 7 8	8 9

New Crossover operator for the MDPVRP (1/3)



- Parent selection by *binary tournament*

- New *Periodic Crossover with insertions*:
  one offspring inherits information from both parents

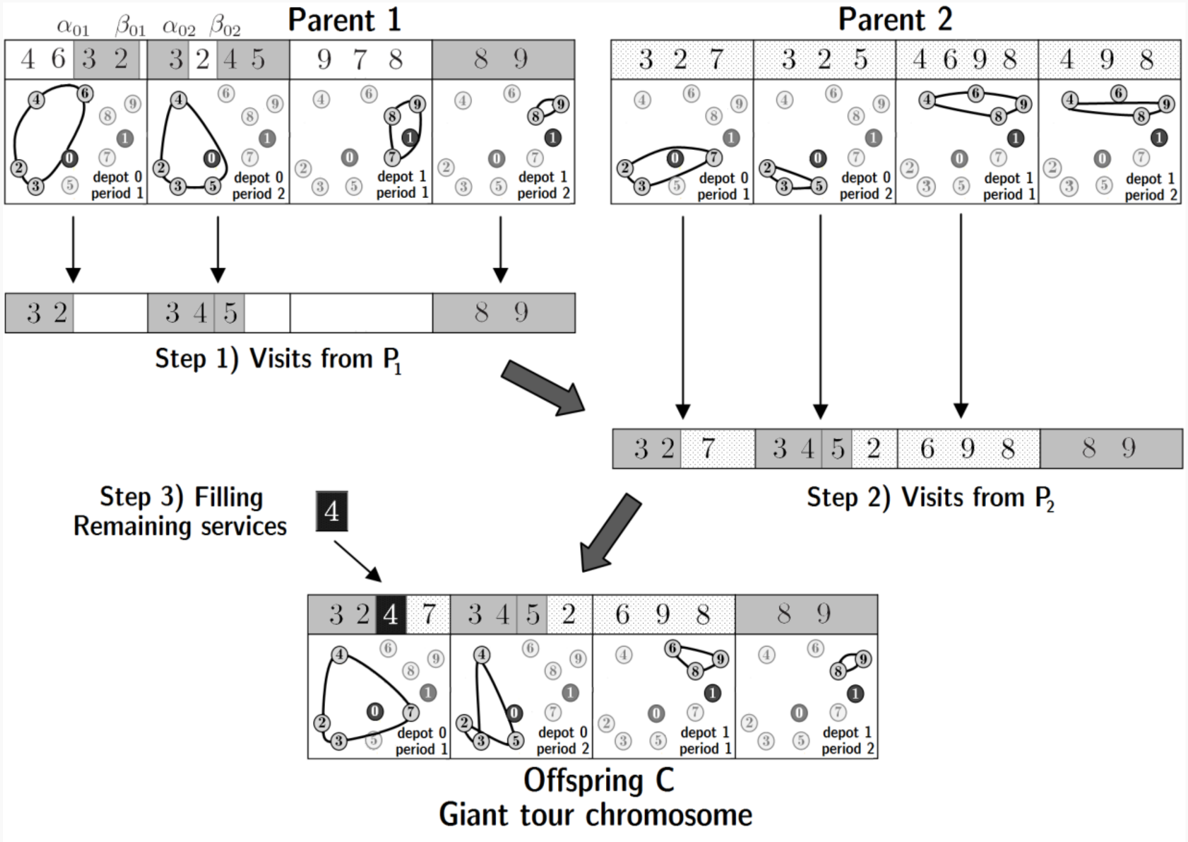
1) Choose for each day which parent (or both parents) provide the genetic material
2) Transmit the genetic information from the first parent
3) Complete with information from the second parent
4) Eventually fill the remaining required visits

New Crossover operator for the MDPVRP (2/3)

- For each couple (day, depot) choosing randomly the amount of information transmitted from parent 1 :
  - Copy the whole sequence of services for this couple,
  - **or** Do not copy any information for this couple,
  - **or** Copy a substring

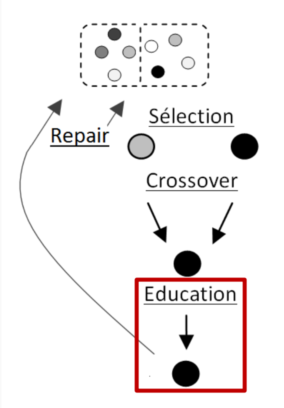
- In a random order of (day, depot), visits are added from parent 2. A visit is copied only if:
  - The entire sequence of parent 1 has not been copied for this couple
  - The insertion is compatible with at least one pattern of the customer

New Crossover operator for the MDPVRP (3/3)



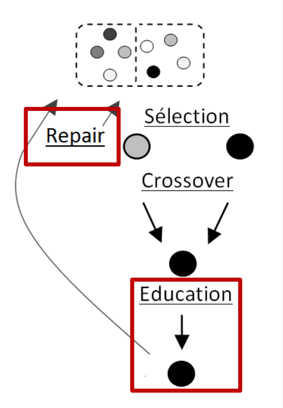
- After this process, some customers can have an “incomplete pattern”:
  - Remaining visits are added after the split algorithm, using a minimum cost insertion criteria.

Education operator (1/2)



- Two level local search:
  - *Route Improvement* (RI) dedicated to improve the routes by moving customer or depot visits (nodes).
    For each node v_1 in random order and each node v_2 in random order, we test *insertion, swap, 2-opt, 2-opt** involving v_1 and v_2 (some restrictions if v_1 is a depot).
  - *Pattern Improvement (PI)* = calculate for each route in each (day/depot) the insertion cost of a customer → evaluate the cost of a pattern change and operate if negative.
  - First improvement rule. Stops when all moves have been tested without success.
  - Called in sequence RI-PI-RI.

Education operator (2/2)



- Speeding-up the local search:
  - *Granular search*: Testing only moves in RI involving correlated nodes (X% close in terms of distance)
  - *Memories*: Remembering the insertion costs in PI. During RI: remembering for each couple (node, route) if the route has changed since last cycle of moves involving the node.

- Repair = increasing temporarily the penalty values and use Education.

Promotion of diversity (1/2)

- Diversity management is crucial to evade premature convergence and obtain high quality solutions.

- Previous methods to maintain diversity:
  - Prins (2004): dispersal rule based on fitness during insertion in the population
  - Sörensen et Sevaux (2006) « *Memetic Algorithm with Population Management (MA|PM)*»: dispersal rule based on a distance measure

- We go a step further, and introduce a *promotion of diversity* during the very evaluation of individuals
  - *Hybrid Genetic Search with Adaptive Diversity Management* (HGSADC)

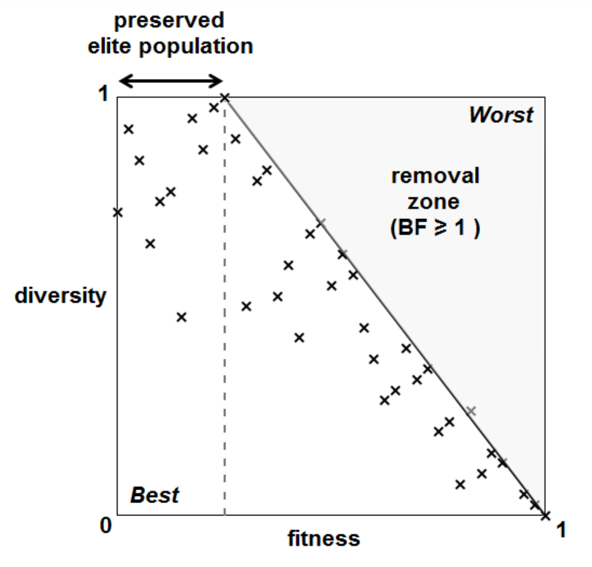
Promotion of diversity (2/2)

- Individual evaluation:

  Biased Fitness is a tradeoff between fitness rank *fit(I),* and rank in terms of contribution to the diversity *dc(I).*

- During selection of the parents:
  - Balance strength with innovation during reproduction, and thus favors exploration of the search space. -> Increased level of diversity in the population.

- During selection of the survivors:
  - Removing the individual *I* with worst *BF(I)* also guarantees some elitism in terms of solution value.



Experimental setup

- Problem benchmarks:
  - Cordeau, Gendreau, Laporte (1998) instances for PVRP and MDVRP
  - New instances for MDPVRP derived from the previous benchmarks
  - CVRP instances of Christofides et al. (1979) and Golden et al. (1998)
  - Instances ranging from 48 to 483 customers, up to a planning horizon of 10 days, and 6 depots. Up to about 900 total services for some periodic problems.

- Experiments conducted on a 2.4 Ghz AMD Opteron 250 CPU
- Conversion of run-times using Dongarra factors, to compare with other authors
- Meta-calibration of parameters

Results on PVRP instances (1/2)

- State of the art algorithms then and now. We compare deviations to Best Known Solutions (BKS) :
  - Cordeau, Gendreau, Laporte (CGL-97): Tabu Search
  - Hemmelmayr, Doerner, Hartl (HDH-09): Variable Neighborhood Search
  - Gulczynski, Golden,Wasil (GGW-11): Integer programming + record-to-record travel

Benchmark	Best approach in 1997	Best approach in 2011	HGSADC
PVRP "old" set	Cordeau et al. (1997) Dev. to BKS : +1.62%	Gulczynski et al. (2011) +0.94%	**+0.14%**
PVRP "new" set	Cordeau et al. (1997) +2.48%	Hemmelmayr et al. (2009) +1.53%	**+0.38%**
Nb. customers > 150	Cordeau et al. (1997) +3.23%	Hemmelmayr et al. (2009) +2.16%	**+0.35%**

Results on PVRP instances (2/2)

- Behavior as the termination criterion increases:

	CGL-97 15.10^3 it	**HDH-09** 10^7 it	**HDH-09** 10^8 it	**HDH-09** 10^9 it	**HGSADC** 10^4 it	**HGSADC** 2.10^4 it	**HGSADC** 5.10^4 it
T	3.96 min	3.09 min	*30 min*	*300 min*	5.56 min	13.74 min	28.21 min
%	+1.82%	+1.45%	+0.76%	+0.39%	+0.20%	+0.12%	+0.07%

- All best known solutions have been retrieved, including 15 optimal results from Baldacci et al. (2010)
- Many have been improved → 19 new BKS
- Small standard deviation : ≈ 0.13% for the previous results

Results on MDVRP instances (1/2)

- State of the art algorithms then and now:
  - Cordeau, Gendreau, Laporte (CGL-97) : Tabu Search
  - Pisinger and Ropke (PR-07) : Adaptive Large Neighborhood Search

Benchmark	**Best approach in 1997**	**Best approach in 2011**	**HGSADC**
MDVRP "old" set	Cordeau et al. (1997) +0.58%	Pisinger and Ropke (2007) +0.35%	**+0.00%**
MDVRP "new" set	Cordeau et al. (1997) +1.85%	Pisinger and Ropke (2007) +0.34%	**-0.04%**
Nb. customers > 150	Cordeau et al. (1997) +1.40%	Pisinger and Ropke (2007) +0.45%	**-0.03%**

Results on MDVRP instances (2/2)

- Results with different running times:

	CGL 15.10^3 it	RP 25.10^3 it	RP 50.10^3 it	HGSADC 10^4 it	HGSADC 2.10^4 it	HGSADC 5.10^4 it
T	---	1.97 min	3.54 min	2.24 min	8.99 min	19.11 min
%	+0.96%	+0.52%	+0.34%	-0.01%	-0.04%	-0.06%

- All best known solutions have been retrieved, including 5 optimal results from Baldacci and Mingozzi (2009)
- Many have been improved → 9 new BKS
- Very small standard deviation : ≈ 0.03%

Results on MDPVRP instances

➢ New instances → Compare to our BKS from multiple long runs

Inst	n	d	t	Average	Gap %	T (min)	BKS
p01	48	4	4	**2019.07**	0%	0.35	2019.07
p02	96	4	4	**3547.45**	0%	1.49	3547.45
p03	144	4	4	4491.08	0,12%	7.72	4480.87
p04	192	4	4	5151.73	0,23%	22.10	5141.17
p05	240	4	4	5605.60	0,49%	30	5570.45
p06	288	4	4	6570.28	0,36%	30	6524.42
p07	72	6	6	4502.06	0,04%	2.18	4502.02
p08	144	6	6	6029.58	0,43%	7.96	6023.98
p09	216	6	6	8310.19	0,90%	27.79	8257.80
p10	288	6	6	9972.35	1,86%	30	9818.42
					+0.42%	15.96 min	

- Good overall gap for a hard problem, a relatively small standard deviation of ≈ 0.30%
- One could investigate cooperation schemes to increase performance

Results on CVRP instances

- Excellent results on Christofides et al. (1979), and Golden et al. (1998) CVRP instances.
  - Average gap of 0.11% comparable to 0.10% for Nagata and Bräysy (2010), which is the best actual state-of-the-art method, specially tailored for CVRP.
  - All BKS have been retrieved, 12 BKS improved

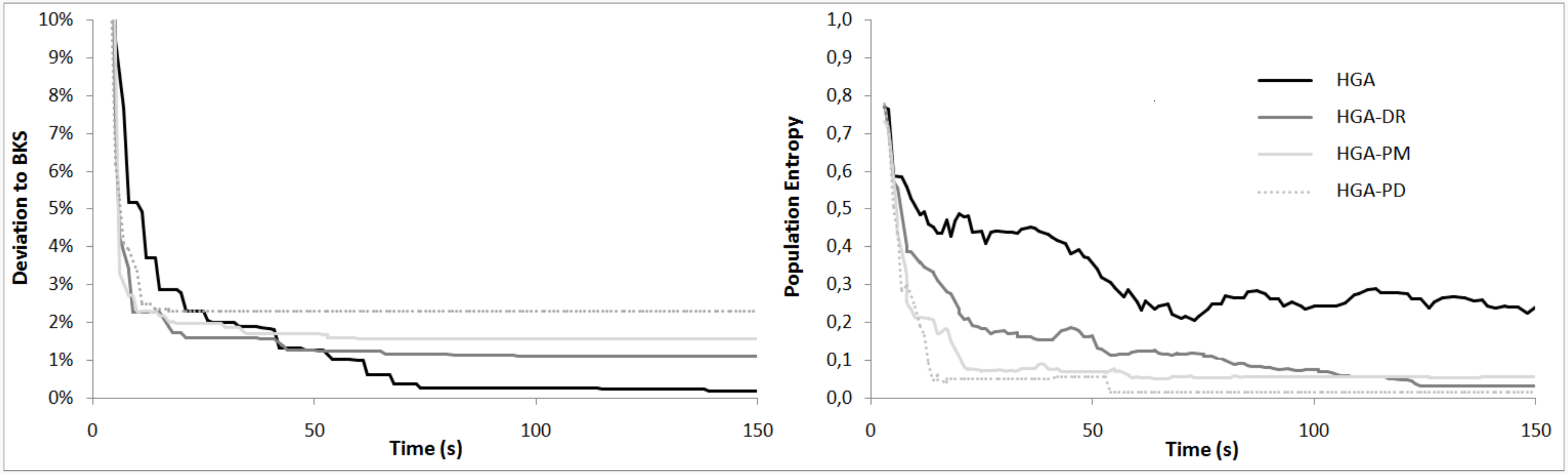
Empirical studies on diversity management methods (1/2)

- Several diversity management methods, average results:
  - **HGA** : No diversity management method
  - **HGA-DR** : Dispersal rule on objective space
  - **HGA-PM** : Dispersal rule on solution space
  - **HGSADC** : The proposed approach

Benchmark		**HGA**	**HGA-DR**	**HGA-PM**	**HGSADC**
PVRP	T	6.86 min	7.01 min	7.66 min	8.17 min
	%	+0.64%	+0.49%	+0.39%	+0.13%
MDVRP	T	7.93 min	7.58 min	9.03 min	8.56 min
	%	+1.04%	+0.87%	+0.25%	-0.04%
MDPVRP	T	25.32 min	26.68 min	28.33 min	40.15 min
	%	+4.80%	+4.07%	+3.60%	+0.44%

Empirical studies on diversity management methods (2/2)

- Behavior of HGSADC during a random run:
  - Higher entropy (average distance between two individuals)
  - Better final solution
  - Diversity can increase during run time



Progressing towards multi-attribute VRPs

- HGSADC also outperforms other methods on:
  - Periodic TSP
  - Site-dependent VRP (SDVRP)
  - MDVRPTW
  - PVRPTW
  - SDVRPTW

- Can tackle any combination of these problems

- Experiments on VRPTW instances with distance or fleet minimization, very promising results, several new BKS on Gehring and Homberger (1999) benchmark.

Progressing towards multi-attribute VRPs

- Work in progress on VRP with a wide range of temporal constraints on routes, such as flexible travel times, time-dependent travel times and cost, multiple TW, soft-TW…

- Work in progress on VRP with truck driver scheduling: taking into account the legislation on long-haul transportation, explicit break scheduling

Conclusions

- Hybrid genetic algorithm for a class of rich VRPs, methodological contributions:
  - Specialized crossover for the MDPVRP
  - Education : two level local search, with granularity and memory
  - **Promotion of diversity during fitness evaluation**
  - Management of infeasible solutions in a separate population
- Improvement of the state of the art on all the problems under consideration
- New promising concepts to generalize
- **Progress towards even more attributes, and real life case studies**

Un algorithme génétique hybride à gestion adaptative de diversité pour le problème de tournées de véhicules et ses variantes

Thibaut VIDAL

LOSI et CIRRELT

Université de Technologie de Troyes

et Université de Montréal

Journée du GT Transport et Logistique

Paris, 14/06/11

Parameter calibration

- Genetic algorithms are known to rely on many parameters
  - Finding good parameter values is already a very hard problem, correlation between parameters
  - Often, a lot of research time is dedicated to calibration

- Meta-calibration setup
  - A metaheuristic to solve the *calibration problem* P:

P

Finding suitable parameters for the GA

Solution *= parameter values*

Evaluation *= launching the GA with these parameters on a training set of instances*

  - Solved using the *Evolutionary Strategy with Covariance Matrix Adaptation* (CMA-ES) of Hansen and Ostermeier (2001)