

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

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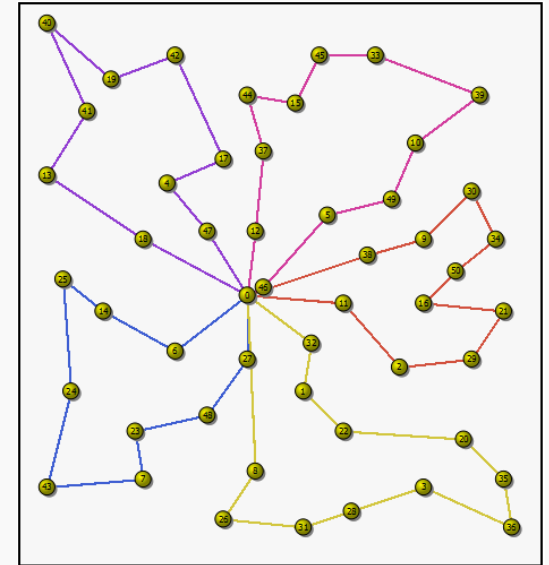
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Presentation outline

- 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

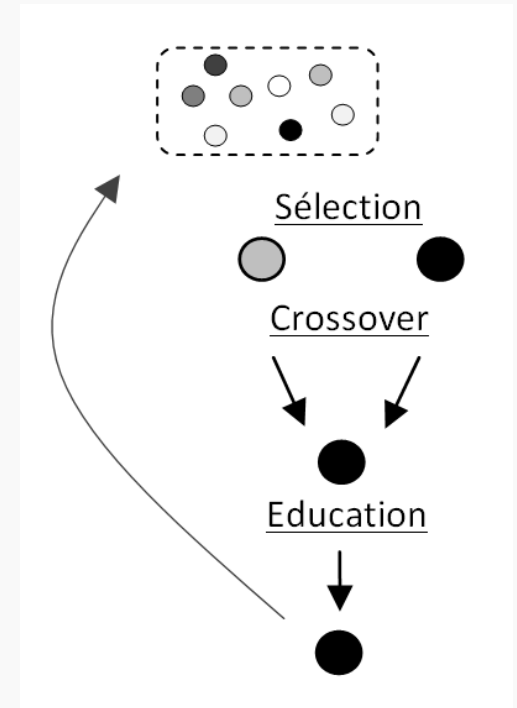
- Heuristics: Sequential or iterative approaches
 - Hadjiconstantinou & Baldacci (1998)
 - Yang and Chu (2000)

- 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.



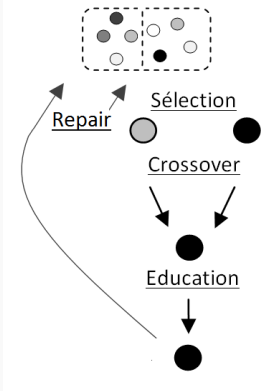
Hybrid genetic algorithm for the MDPVRP (2/4)

➤ Search Space:

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

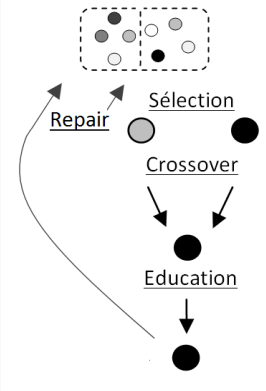
➤ Adaptive penalties:

- 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)

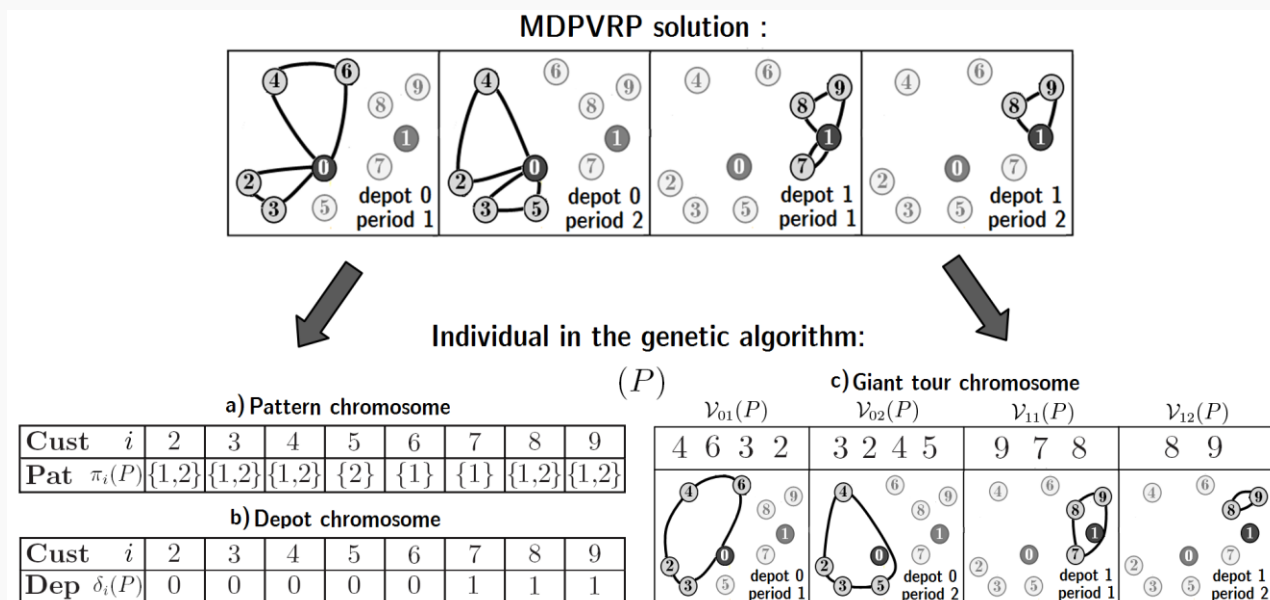
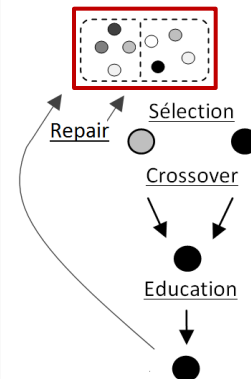
- Double population management:
 - A feasible individual is included in the feasible population
 - An infeasible individual \rightarrow included in the infeasible population \rightarrow probability P_{rep} to be repaired & added in the feasible one
- Each population \rightarrow $(\mu+\lambda)$ strategy where any new offspring is directly included (and thus can reproduce):
 - Initial populations of μ individuals
 - Each new individual is included in the population
 - As a population reaches the size $(\mu+\lambda)$, 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)

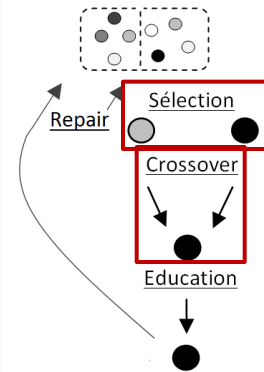
➤ Solution representation

- 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



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

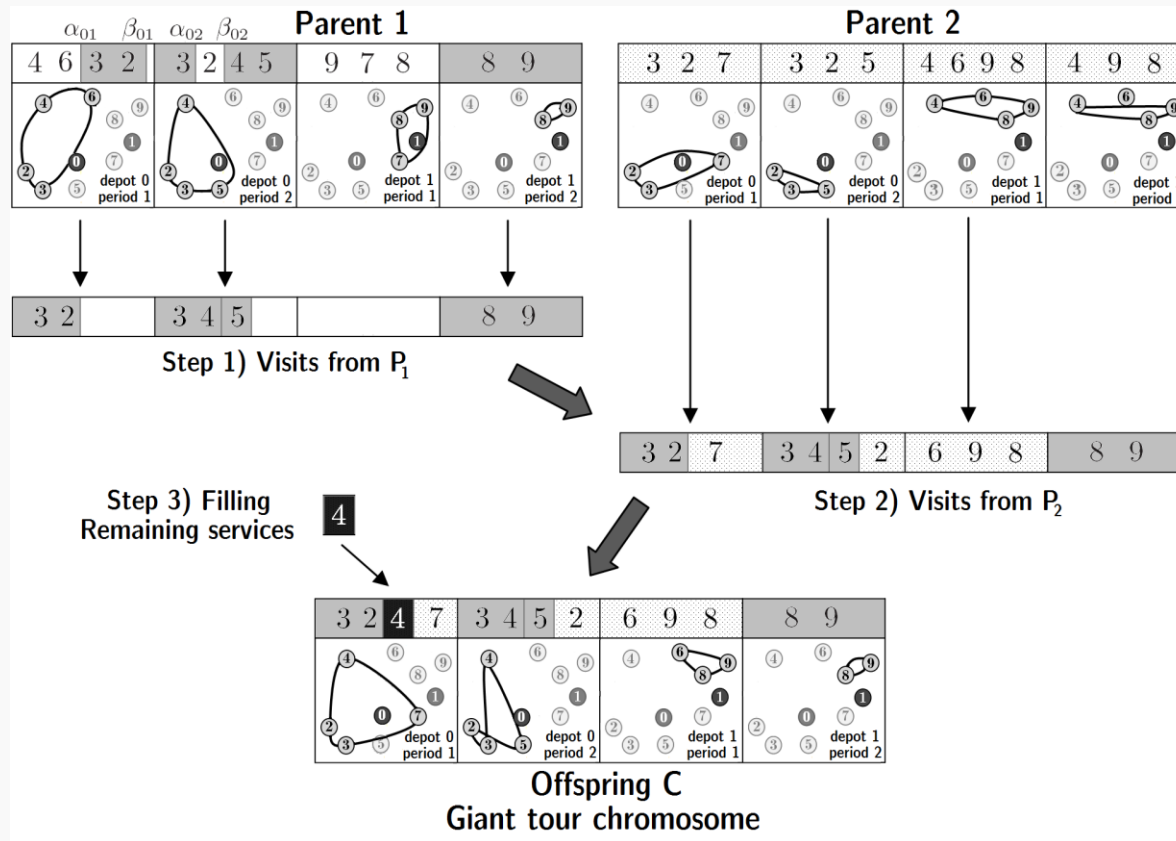
- 1) Choose for each day which parent (or both parents) provide the genetic material
- 2) Transmit the genetic information from the first parent
- 3) Complete with information from the second parent
- 4) Eventually fill the remaining required visits

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)

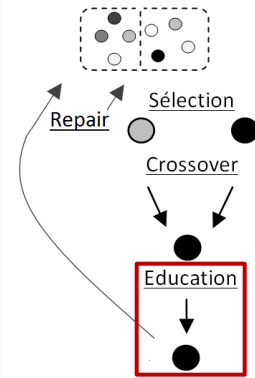


- After this process, some customers can have an “incomplete pattern”:
 - Remaining visits are added after the split algorithm, using a minimum cost insertion criteria.

Education operator (1/2)

➤ Two level local search:

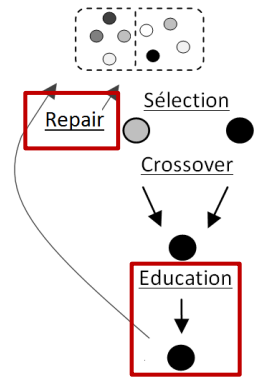
- *Route Improvement (RI)* dedicated to improve the routes by moving customer or depot visits (nodes).
For each node v_1 in random order and each node v_2 in random order, we test *insertion*, *swap*, *2-opt*, *2-opt** involving v_1 and v_2 (some restrictions if v_1 is a depot).
- *Pattern Improvement (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 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:

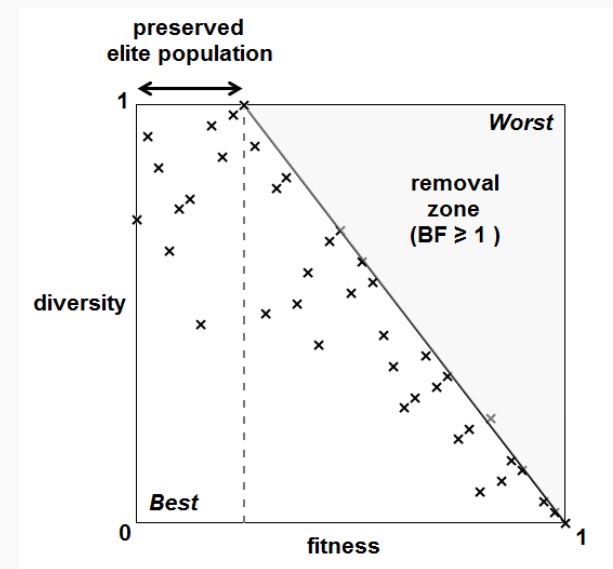
Biased Fitness is a tradeoff between fitness rank $fit(I)$, and rank in terms of contribution to the diversity $dc(I)$.

➤ 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	<i>30 min</i>	<i>300 min</i>	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 : $\approx 0.13\%$ 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 : $\approx 0.03\%$

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 $\approx 0.30\%$
- 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

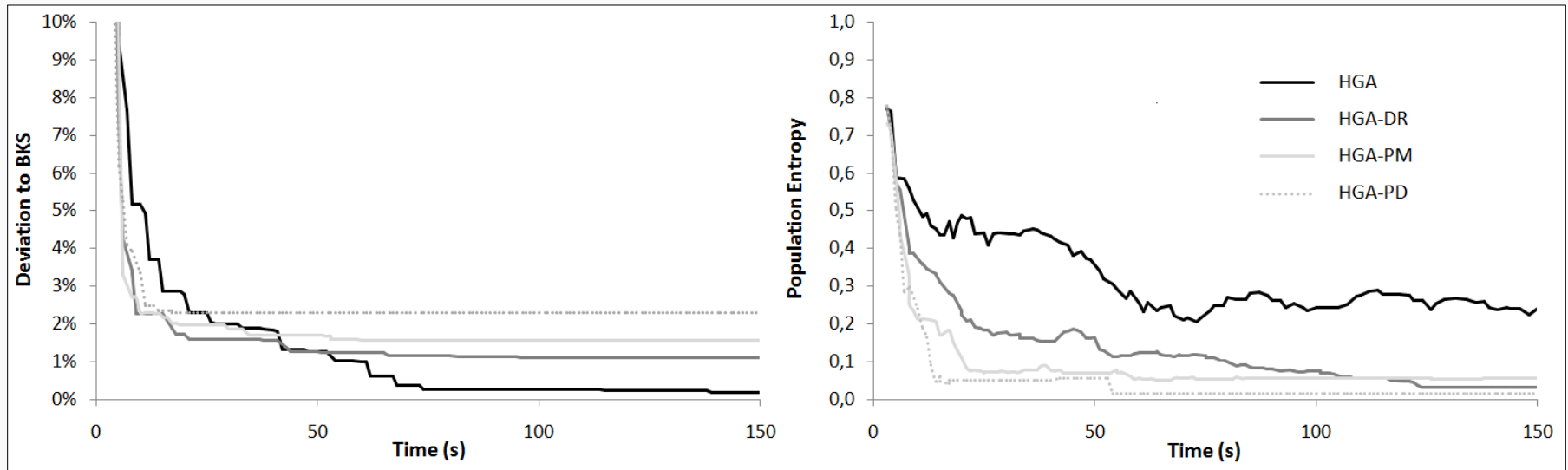
Empirical studies on diversity management methods (1/2)

- 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



Progression 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.

Progression 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**

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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)