

# A General-Purpose Heuristic for Multi-Attribute Vehicle Routing Problems

Thibaut Vidal  
Teodor Gabriel Crainic  
Michel Gendreau  
Christian Prins



**CIRRELT**  
Centre interuniversitaire  
de recherche  
sur les réseaux d'entreprise,  
la logistique et le transport



CONSEIL REGIONAL  
CHAMPAGNE ARDENNE



Chaire de recherche industrielle  
du **CRSNG** en management logistique  
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# Presentation outline

1. General-purpose solvers
2. Multi-attribute vehicle routing problems (MAVRPs)
3. An efficient and unified local search for MAVRPs
  - a) Route evaluation operators
  - b) Implementation for several attributes
4. A Unified Hybrid Genetic Search (UHGS) for MAVRPs
  - a) General framework
  - b) Unified solution representation and Split
  - c) Generic implementation of other genetic operators
5. Computational experiments

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# General-purpose solvers

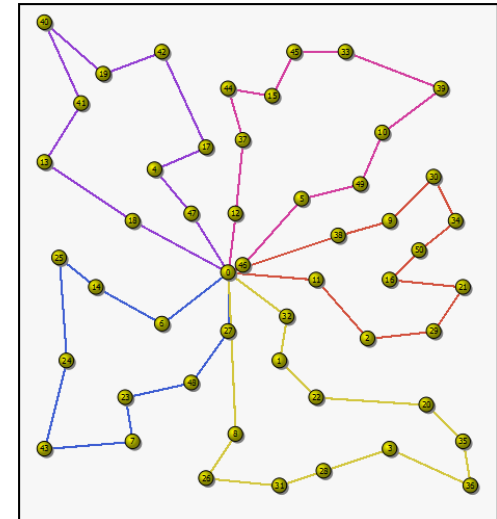
- ❑ **General-purpose solvers for combinatorial optimization**
  - Solvers that can address a wide range of problems without need for extensive adaptation or user expertise.
  
- ❑ **Necessary tools** for the timely application of current optimization methods to industrial settings.
  
- ❑ Examples of such solvers :
  - Integer & constraint programming solvers
  - Local search-based methods : “*LocalSolver*” (Benoist et al. 2011).
  - Methods designed to address a large compound problem model.
  
- ❑ Libraries of metaheuristic components and classes libraries:  
Open BEAGLE (Gagné and Parizeau 2002), ParadisEO (Cahon et al. 2004)...

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# Multi-attribute vehicle routing problems (MAVRPs)

- ❑ Classical “vehicle routing problem (VRP)”
  - wide range of exact and heuristic methods
- ❑ **Challenges** related to the resolution of **VRP variants with additional *attributes*** (multi-attribute VRPs, MAVRPs)
  - modeling the specificities of application cases, customers requirements, network and vehicle specificities, operators abilities...
  - Combining **several attributes** together can lead to highly complex **rich VRPs**.
  - Dramatic increase in the literature dedicated to specific VRP variants.



# Multi-attribute vehicle routing problems (MAVRPs)

- Some unified algorithms reporting high quality solutions on several MAVRPs:

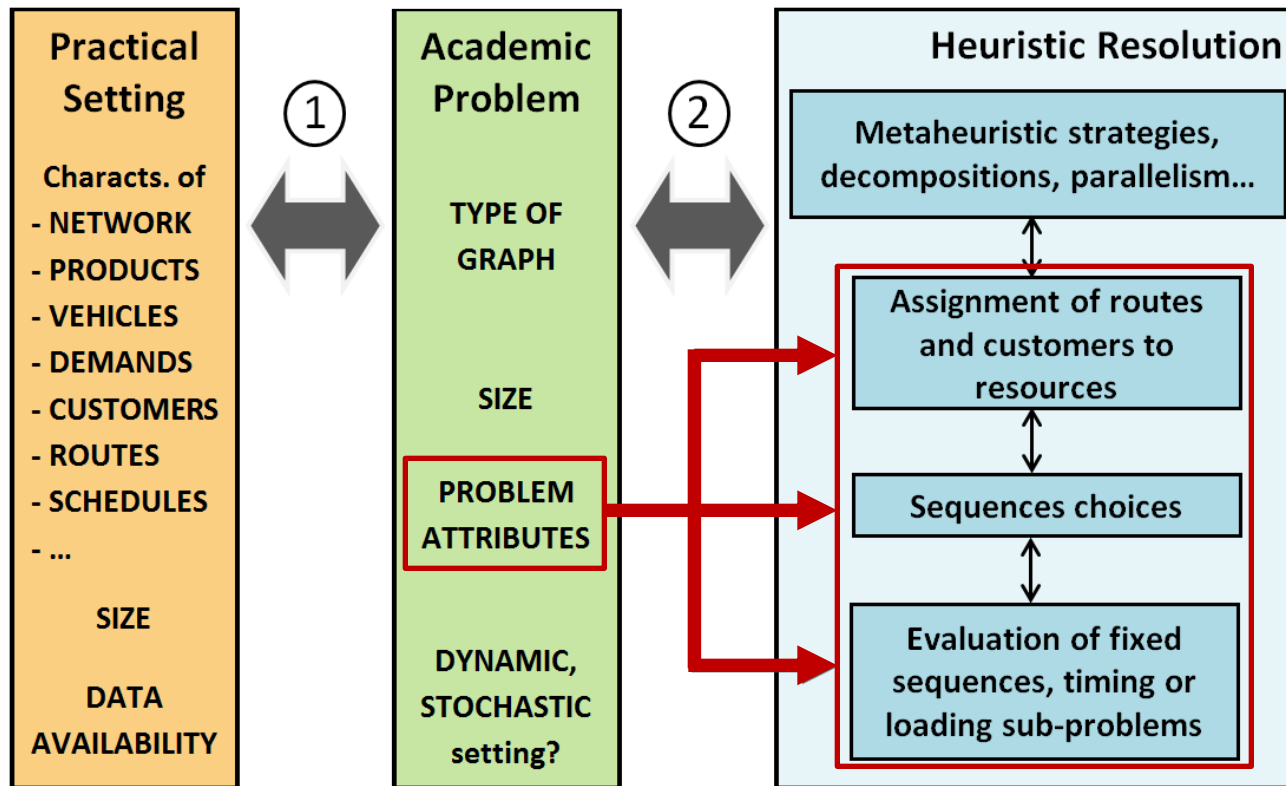
Type	Attribute	Acronym	UTS	ALNS	ILS	HYB	VNS	IPSP	UHGS
	Multiple depots	MDVRP	X	X		X		X	X
	Multiple periods	PVRP	X					X	X
	Heterogeneous fleet	HVRP				X		X	X
	Site-dependent	SDVRP	X	X				X	X
	Pickup & deliveries	VRPPD	X	X				X	
	Backhauls	VRPB		X					X
	Open	OVRP		X		X	X		X
	Cumulative	CCVRP							X
	Load-dependent costs	LDVRP							X
	Simultaneous P.&D.	VRPSDP		X		X			X
	Vehicle Fleet Mix	VFMP				X		X	X
	Duration constraints	DurVRP	X		X				X
	Hard TW	VRPTW	X	X	X		X	X	X
	Soft TW	VRPSTW			X		X		X
	Multiple TW	VRPMTW			X				X
	General TW	VRPGTW			X				X
	Time-dep. travel time	TDVRP			X		X		X
	Lunch breaks	VRPLB							X
	Work hours reg	VRTDSP							X
	Service site choice	GVRP <sup>2</sup>							X

<sup>2</sup> Problem known as "Generalized Vehicle Routing Problem"

- Issues: dealing with a rich VRP model that includes several MAVRP as special cases → Still accounting for non-activated attributes

# Classification & Proposed Methodology

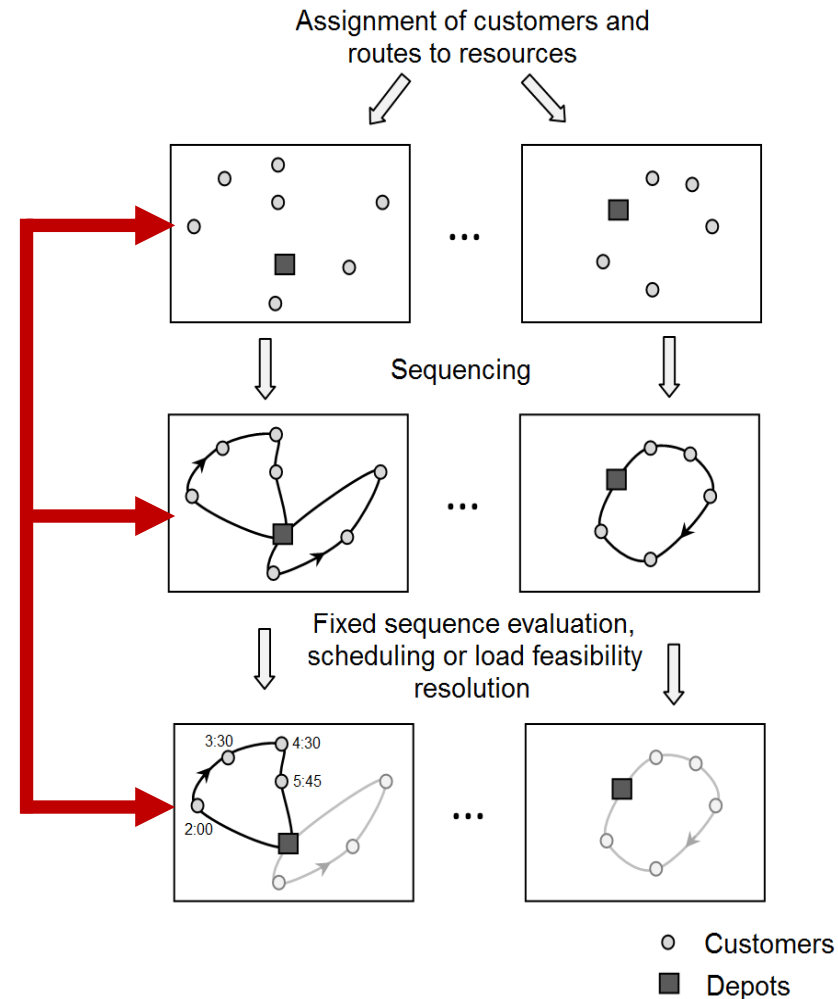
- We classified attributes into three categories related to their impact on VRP resolution methods :





# Classification & Proposed Methodology

- **ASSIGN ATTRIBUTES:** impacting the assignment of customers and routes
  - **Periodic, Multi-Depot, Heterogeneous Fleet, Location Routing...**
  
- **SEQ ATTRIBUTES:** impacting the nature of the network and the sequences
  - **P&D, Backhauls, Two Echelon, Multi Trips, Truck-and-Trailer...**
  
- **EVAL ATTRIBUTES:** impacting the evaluation of fixed routes
  - **Time windows, Time-dep. travel time, Loading constraints, HOS regulations Lunch breaks, Load-Dependent costs...**



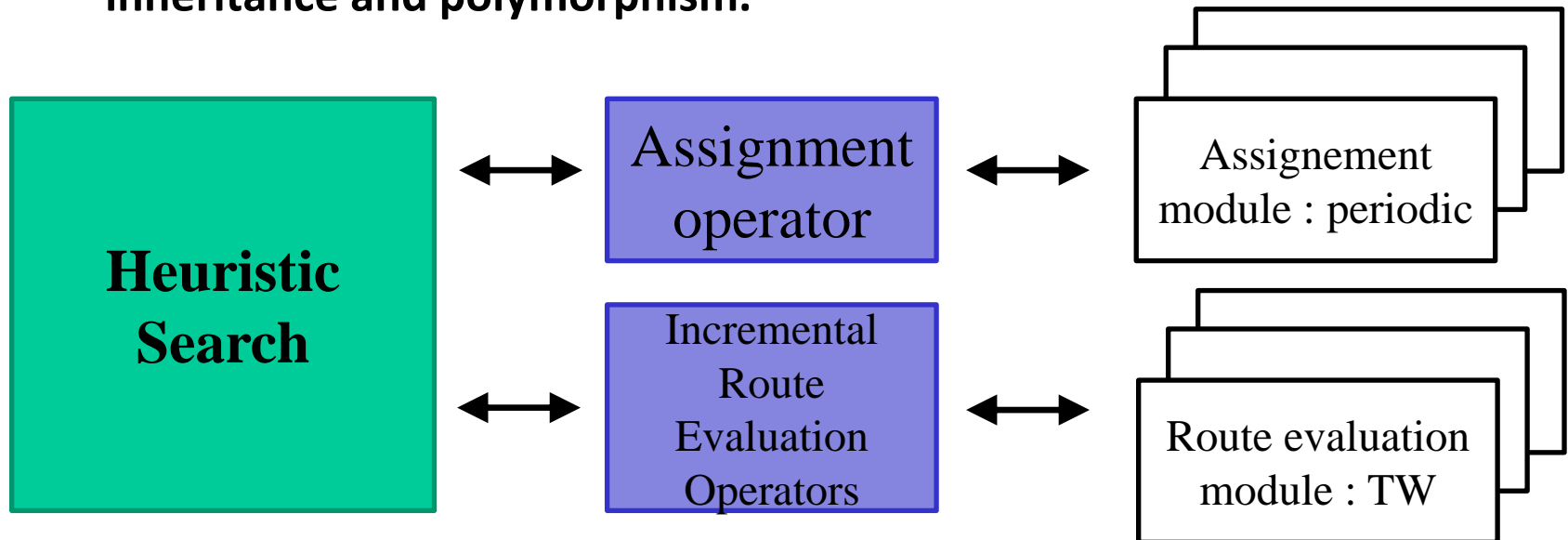
## □ Challenge: Achieving both genericity and efficiency

- Still need to address the problem → but relegating problem-specificities to small modular components
- Each separate MAVRP shall be still addressed with state-of-the-art solution evaluation and search procedures
- Not dealing with “dummy” attributes

# Classification & Proposed Methodology

## □ Proposed Methodology:

- Relying on assignment, sequencing & route evaluation operators → implemented in a generic way, based on a library of attribute-specific modules
- **Attribute-dependent modules are automatically selected by the algorithm to serve as the basis for the assignment, sequencing, and route evaluation operators → Object-oriented programming, using inheritance and polymorphism.**



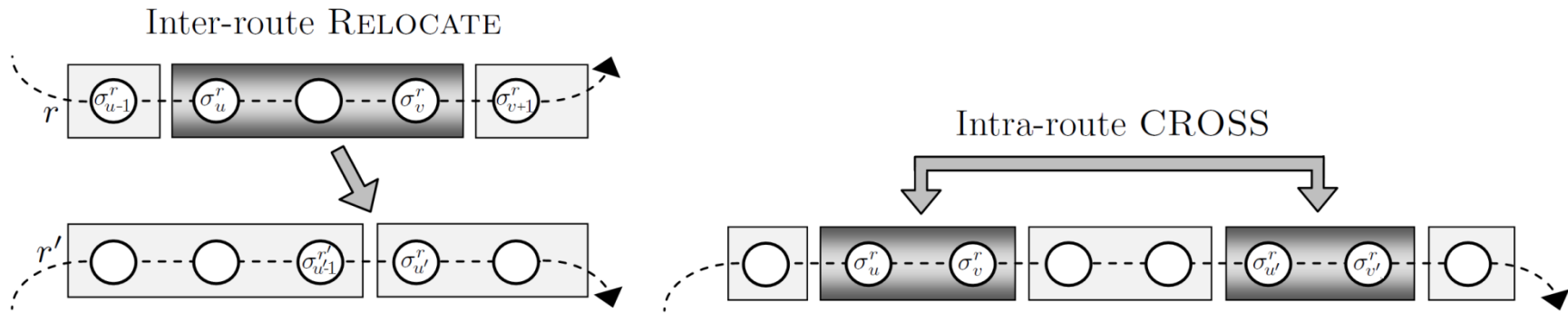
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# An efficient and unified local search for MAVRPs

## □ Route Evaluation Operators based on re-optimization

- Main Property : Any local-search move involving a bounded number of node relocations or arc exchanges can be assimilated to a concatenation of a bounded number of sub-sequences.
- The same subsequences appear many times during different moves



- Data preprocessing on sub-sequences to speed up the search (Savelsbergh 1985,1992 ...)
- The route evaluation modules must allow for such preprocessing.

# An efficient and unified local search for MAVRPs

## □ Route Evaluation Operators based on re-optimization

- Main Property : Any local-search move involving a bounded number of node relocations or arc exchanges can be assimilated to a concatenation of a bounded number of sub-sequences.
- Hence, to manage and exploit information on subsequences, five families of route evaluation operators are used :

*Operators for data construction:*

INIT( $\sigma$ )	Initialize the data $\mathcal{D}(v_0)$ for a sub-sequence containing a single visit.
FORW( $\sigma$ )	Compute the data of $\mathcal{D}(\sigma \oplus v_i)$ from the data of sub-sequence $\sigma$ and vertex $v_i$ .
BACK( $\sigma$ )	Compute the data of $\mathcal{D}(v_i \oplus \sigma)$ from the data of vertex $v_i$ and sub-sequence $\sigma$ .

*Operators for route evaluations:*

EVAL2( $\sigma_1, \sigma_2$ )	Evaluate the cost and feasibility of the combined sequence $\sigma_1 \oplus \sigma_2$ .
EVALN( $\sigma_1, \dots, \sigma_n$ )	Evaluate the cost and feasibility of the combined sequence $\sigma_1 \oplus \dots \oplus \sigma_n$ .

# Route evaluation operators examples

- **Example 1)** Route evaluation operators for **distance and capacity constraints**

**What is managed ?** → Partial loads  $L(\sigma)$  and distance  $D(\sigma)$

**Init** → For a sequence  $\sigma_0$  with a single visit  $v_i$ ,  $L(\sigma_0) = q_i$  and  $D(\sigma_0) = 0$

**Forw and Back** → increment  $L(\sigma)$  and  $D(\sigma)$

**Eval** → compute the data by induction on the concatenation operator

$$Q(\sigma_1 \oplus \sigma_2) = Q(\sigma_1) + Q(\sigma_2)$$

$$D(\sigma_1 \oplus \sigma_2) = D(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + D(\sigma_2)$$

# Route evaluation operators examples

- **Example 2)** Route evaluation operators for **cumulated arrival time objectives**

**What is managed ?** → Travel time  $D(\sigma)$ , Cumulated arrival time  $C(\sigma)$ , Delay Cost  $W(\sigma)$  associated to one unit of delay in starting time

**Init** → For a sequence  $\sigma_0$  with a single visit  $v_i$ ,  $D(\sigma_0) = 0$  and  $C(\sigma_0) = 0$ , and  $W(\sigma_0) = 1$  if  $v_i$  is a customer, and  $W(\sigma_0) = 0$  if  $v_i$  is a depot visit.

**Forw & Back & Eval** → induction on the concatenation operator:

$$D(\sigma_1 \oplus \sigma_2) = D(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + D(\sigma_2)$$

$$C(\sigma_1 \oplus \sigma_2) = C(\sigma_1) + W(\sigma_2)(D(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)}) + C(\sigma_2)$$

$$W(\sigma_1 \oplus \sigma_2) = W(\sigma_1) + W(\sigma_2)$$



# Route evaluation operators examples

- **Example 3)** Route evaluation operators for **time windows (and route duration constraints)**

**What is managed ?** → Travel time and service time  $T(\sigma)$ , earliest feasible completion time  $E(\sigma)$ , latest feasible starting date  $L(\sigma)$ , statement of feasibility  $F(\sigma)$ .

**Init** → For a sequence  $\sigma_0$  with a single visit  $v_i$ ,  $T(\sigma_0) = s_i$ ,  $E(\sigma_0) = e_i + s_i$ ,  $L(\sigma_0) = l_i$  and  $F(\sigma_0) = \text{true}$ .

**Forw & Back & Eval** → induction on the concatenation operator:

$$T(\sigma_1 \oplus \sigma_2) = T(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + T(\sigma_2)$$

$$E(\sigma_1 \oplus \sigma_2) = \max\{E(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + T(\sigma_2), E(\sigma_2)\}$$

$$L(\sigma_1 \oplus \sigma_2) = \min\{L(\sigma_1), L(\sigma_2) - d_{\sigma_1(|\sigma_1|)\sigma_2(1)} - T(\sigma_1)\}$$

$$F(\sigma_1 \oplus \sigma_2) \equiv F(\sigma_1) \wedge F(\sigma_2) \wedge (E(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} \leq L(\sigma_2))$$

# Route evaluation operators examples

- **Example 4)** Route evaluation operators for **lunch break positioning in presence of time-window constraints**

**What is managed ?** → Same set of data ( $T(\sigma)$ ,  $E(\sigma)$ ,  $L(\sigma)$ , and  $F(\sigma)$ ) as in the TW case, and it is duplicated to also provide  $T'(\sigma)$ ,  $E'(\sigma)$ ,  $L'(\sigma)$ , and  $F'(\sigma)$  for the sequence where exactly one lunch break was inserted.

**Init** → As previously for  $T(\sigma_0)$ ,  $E(\sigma_0)$ ,  $L(\sigma_0)$ , and  $F(\sigma_0)$ . Furthermore,  $T'(\sigma_0) = +\infty$ ,  $E'(\sigma_0) = +\infty$ ,  $L'(\sigma_0) = 0$ , and  $F'(\sigma_0) = false$ .

**Forw & Back & Eval** → induction on the concatenation operator, see next page for the equations.

# Route evaluation operators examples

- **Example 4)** Route evaluation operators for **lunch break positioning in presence of time-window constraints**

$$E'(\sigma_1 \oplus \sigma_2) = \min(\{E'_{\text{case } i} | F'_{\text{case } i} = \text{true}\} \cup +\infty)$$

$$L'(\sigma_1 \oplus \sigma_2) = \max(\{L'_{\text{case } i} | F'_{\text{case } i} = \text{true}\} \cup -\infty)$$

$$F'(\sigma_1 \oplus \sigma_2) = F'_{\text{case } 1} \vee F'_{\text{case } 2} \vee F'_{\text{case } 3}$$

$$E'_{\text{case } 1} = \max\{E'(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + T(\sigma_2), E(\sigma_2)\}$$

$$E'_{\text{case } 2} = \max\{E(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + s_{\text{LB}} + T(\sigma_2), e_{\text{LB}} + s_{\text{LB}} + T(\sigma_2), E(\sigma_2)\}$$

$$E'_{\text{case } 3} = \max\{E(\sigma_1) + d_{\sigma_1(|\sigma_1|)\sigma_2(1)} + T'(\sigma_2), E'(\sigma_2)\}$$

$$L'_{\text{case } 1} = \min\{L'(\sigma_1), L(\sigma_2) - p_{\sigma_1(|\sigma_1|)\sigma_2(1)} - T'(\sigma_1)\}$$

$$L'_{\text{case } 2} = \min\{L(\sigma_1), l_{\text{LB}} - T(\sigma_1), L(\sigma_2) - p_{\sigma_1(|\sigma_1|)\sigma_2(1)} - s_{\text{LB}} - T(\sigma_1)\}$$

$$L'_{\text{case } 3} = \min\{L(\sigma_1), L'(\sigma_2) - p_{\sigma_1(|\sigma_1|)\sigma_2(1)} - T(\sigma_1)\}$$

$$F'_{\text{case } 1} = F'(\sigma_1) \wedge F(\sigma_2) \wedge (E'(\sigma_1) + p_{\sigma_1(|\sigma_1|)\sigma_2(1)} \leq L(\sigma_2))$$

$$F'_{\text{case } 2} = F(\sigma_1) \wedge F(\sigma_2) \wedge (E(\sigma_1) \leq l_{\text{LB}}) \wedge (E(\sigma_1) + s_{\text{LB}} + p_{\sigma_1(|\sigma_1|)\sigma_2(1)} \leq L(\sigma_2))$$

$$F'_{\text{case } 3} = F(\sigma_1) \wedge F'(\sigma_2) \wedge (E(\sigma_1) + p_{\sigma_1(|\sigma_1|)\sigma_2(1)} \leq L'(\sigma_2))$$

# Route evaluation operators examples

- **Example 5)** Route evaluation operators for **soft and general time windows**

**What is managed ?** → Minimum cost  $F(\sigma)(t)$  to process the sequence  $\sigma$  while starting the last service before time  $t$ , minimum cost  $B(\sigma)(t)$  to process the sequence  $\sigma$  after time  $t$ .

**Init** → For a sequence  $\sigma_0$  with a single visit  $v_i$  characterized by a service cost function  $c_i(t)$ ,  $F(\sigma_0)(t) = \min_{(x \leq t)} c_i(x)$  and  $B(\sigma_0)(t) = \min_{(x \geq t)} c_i(x)$ .

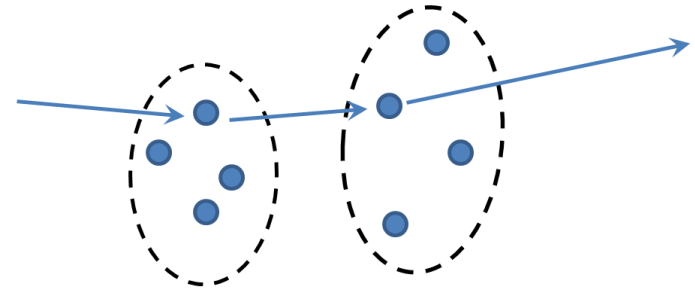
**Forw & Back** →

$$F(\sigma \oplus v_i)(t) = \min_{0 \leq x \leq t} \{c_i(x) + F(\sigma)(x - s_{\sigma(|\sigma|)} - d_{\sigma(|\sigma|),i})\}$$
$$B(v_i \oplus \sigma)(t) = \min_{x \geq t} \{c_i(t) + B(\sigma)(x + s_i + d_{i,\sigma(1)})\}$$

**Eval 2** →  $Z^*(\sigma_1 \oplus \sigma_2) = \min_{x \geq 0} \{F(\sigma_1)(x) + B(\sigma_2)(x + s_{\sigma_1(|\sigma_1|)} + d_{\sigma_1(|\sigma_1|)\sigma_2(1)})\}$

# Route evaluation operators examples

- **Example 6)** Route evaluation operators for the generalized VRP :



**What is managed ?** → The shortest path  $S(\sigma)[i,j]$  inside the sequence  $\sigma$  starting at the location  $i$  of the starting group and finishing at location  $j$  of the ending group.

**Init** → For a sequence  $\sigma_0$  with a single visit  $v_i$ ,  $S(\sigma)[i,j] = +\infty$  if  $i \neq j$ , and  $S(\sigma)[i,i] = 0$ .

**Forw & Back & Eval** → induction on the concatenation operator:

$$S(\sigma_1 \oplus \sigma_2)[i, j] = \min_{1 \leq x \leq \lambda_{\sigma_1}(|\sigma_1|), 1 \leq y \leq \lambda_{\sigma_2}(1)} S(\sigma_1)[i, x] + d_{xy} + S(\sigma_2)[y, j]$$

$$\forall i \in \{1, \dots, \lambda_{\sigma_1}(1)\}, \forall j \in \{1, \dots, \lambda_{\sigma_2}(|\sigma_2|)\}$$

# An efficient and unified local search for MAVRPs

- Generic local-search based on route evaluation operators

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## Algorithm 1 Unified local search based on route evaluation operators

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- 1: Detect the good combination of evaluation operators relatively to the problem attributes
  - 2: Build re-optimization data on subsequences using the INIT, FORW and BACK operators.
  - 3: **while** some improving moves exist in the neighborhood  $\mathcal{N}$  **do**
  - 4:   **for** each move  $\mu_i$  in  $\mathcal{N}$  **do**
  - 5:     **for** each route  $r_j^\mu$  produced by the move **do**
  - 6:       Determine the  $k$  sub-sequences  $[\sigma_1, \dots, \sigma_k]$  that are concatenated to produce  $r_j^\mu$
  - 7:       **if**  $k = 2$ , then  $\text{NEWCOST}(r) = \text{EVAL2}(\sigma_1, \sigma_2)$
  - 8:       **else if**  $k > 2$ , then  $\text{NEWCOST}(r) = \text{EVALN}(\sigma_1, \dots, \sigma_k)$
  - 9:     **if**  $\text{ACCEPTCRITERIA}(\mu_i)$  **then** perform the move  $\mu$  and update the re-optimization data on for each route  $r_j^\mu$  using the INIT, FORW and BACK operators.
- 

- Can serve as the basis to build any neighborhood-based unified solver based on VNS, Tabu, ILS for MAVRPs with EVAL attributes.
- Going one step further, designing a unified hybrid GA.

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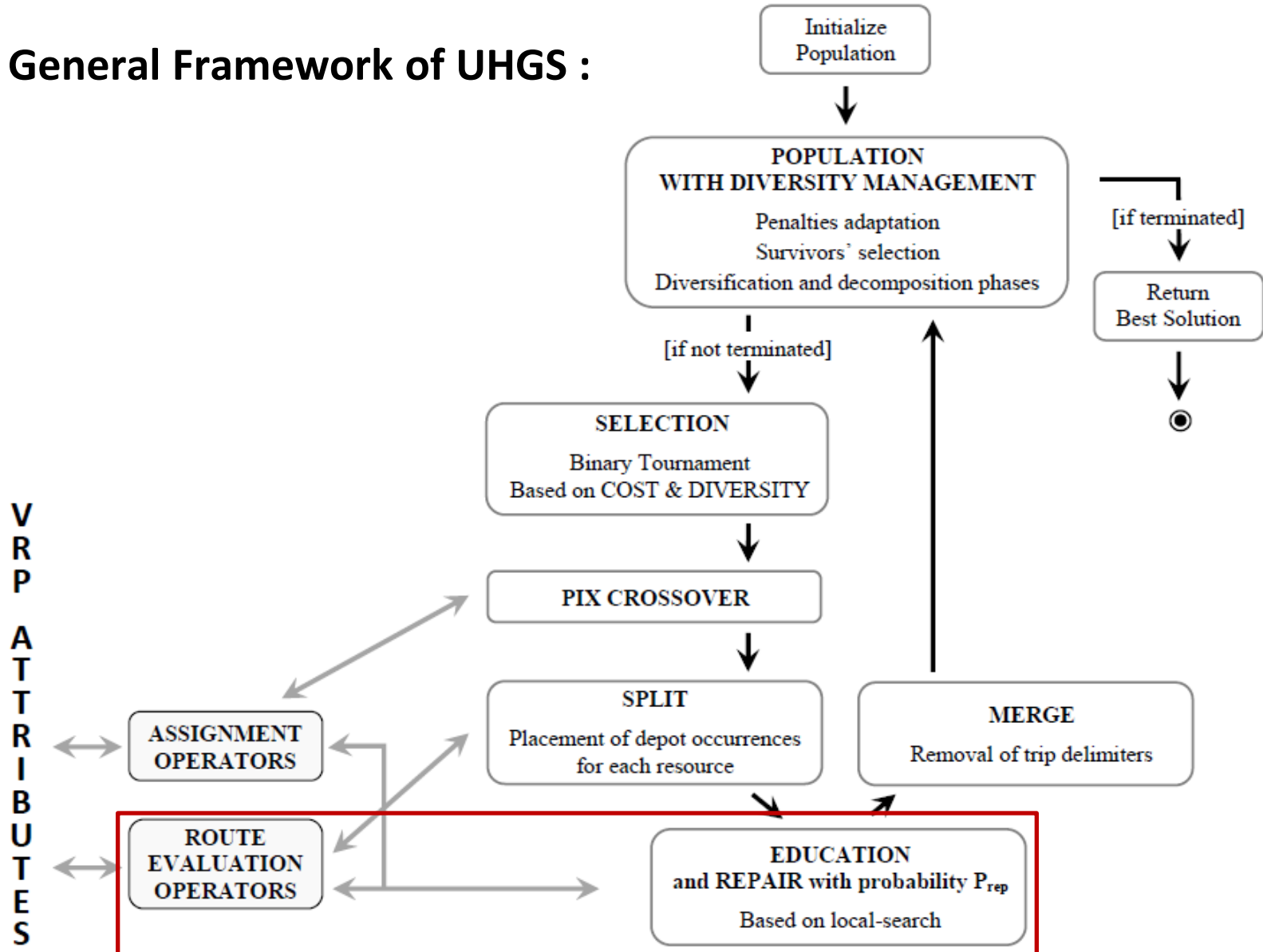
# A Unified Hybrid Genetic Search (UHGS) for MAVRPs

- UHGS = Classic GA framework + 4 main ingredients (Vidal et al. 2010)
  - Management of penalized infeasible solutions in two subpopulations
  - High-performance local search-based *Education* procedure
  - Solution Representation *without trip delimiters*
  - **Diversity & Cost objective for individuals evaluations**



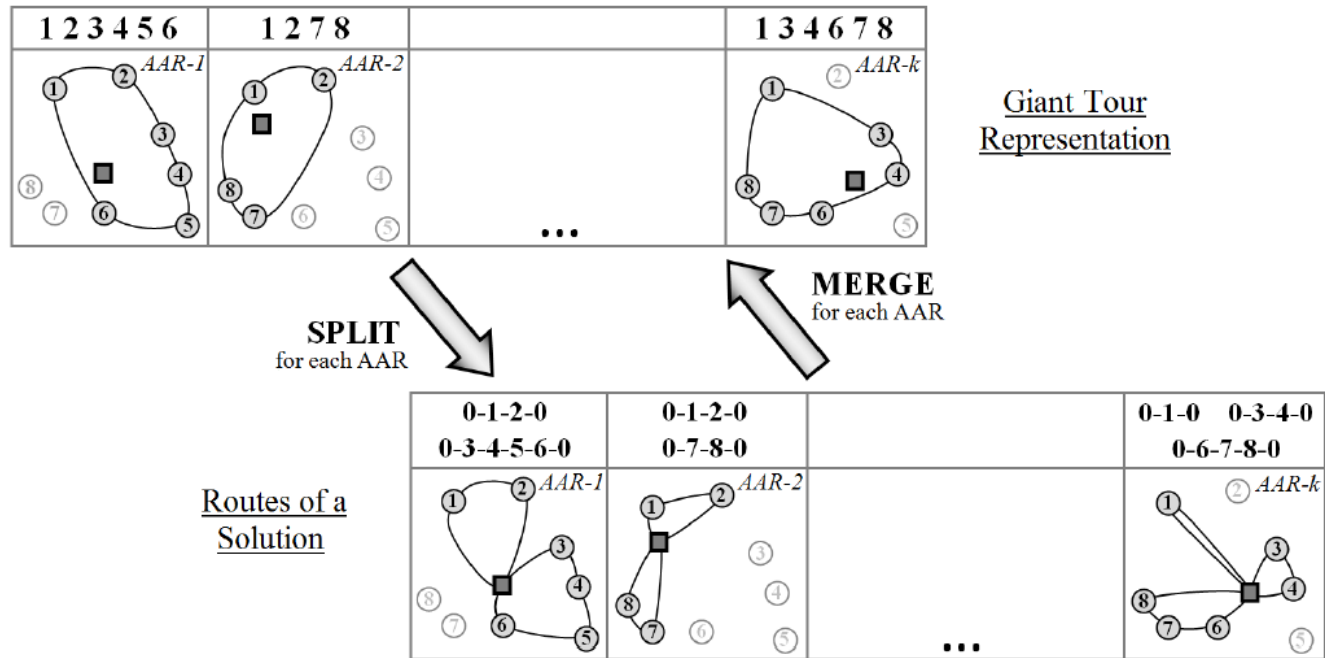
# A Unified Hybrid Genetic Search (UHGS) for MAVRPs

## General Framework of UHGS :



# Unified Solution Representation and Split

- ❑ Now dealing with MAVRPs with both ASSIGN and EVAL attributes: Assignment of customer services to some ASSIGN attributes resources (AARs) + separate optimization of routes for each AARs.
  - Solution representation is designed accordingly.
  - Furthermore, representation without trip delimiters for each AAR.



# Unified Solution Representation and Split

- ❑ Solution representation as a giant-tour per AAR  $\rightarrow$  requires a Split algorithm (Prins 2004) for optimal segmentation into routes.
- ❑ We propose a **unified Split algorithm**.
  - As usual, the problem is solved as a m-shortest path
  - The route evaluation operators are used to build the auxiliary graph

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## Algorithm 2 Generic Split

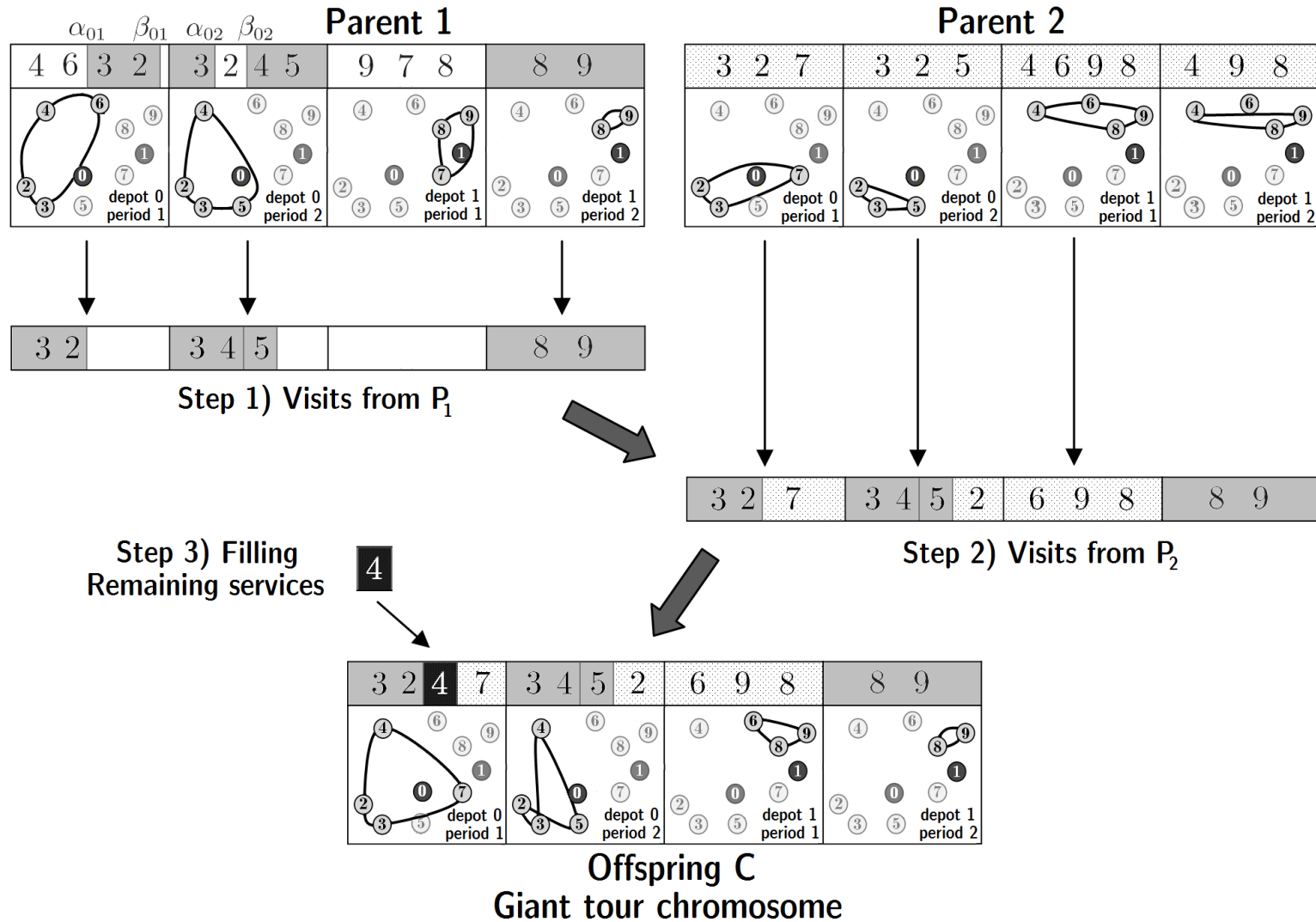
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- 1: for each node  $i \in \{0, \dots, \nu\}$  do
  - 2:    $SeqData(\sigma) = \text{INIT}(\{v_0\})$  // Initialize with depot vertex
  - 3:   for each node  $j \in \{i, \dots, \min(i + \bar{r}, \nu)\}$  do
  - 4:      $\phi(a_{ij}) = \text{EVAL2}(\sigma, \{v_0\})$  // Evaluate the route
  - 5:      $SeqData(\sigma) = \text{FORW}(\sigma, \{\tau_j\})$  // Append a new customer to the route end
  - 6: Solve the shortest path problem on  $\mathcal{G}' = (\mathcal{V}, \mathcal{A})$  with cost  $\phi(a_{ij})$  for each arc  $a_{ij}$
  - 7: Return the set of routes associated to the set of arcs of the shortest path
-

# Unified Crossover Operator

- ❑ 4 phases **Assignment and Insertion Crossover (AIX)**, to produce a single offspring C from two parents P1 and P2.
- ❑ Step 1) Choose for each AAR whether the genetic material of P1, P2, or both parents is inherited.
- ❑ Step 2) Fully transmit the selected material from P1
- ❑ Step 3) Complete with the selected material from P2, check at each step with an Assignment module whether the inheritance respects the ASSIGN attributes specifications.
- ❑ Step 4) Perform a best insertion of missing visits.

# Unified Crossover Operator



# Unified Education Procedure

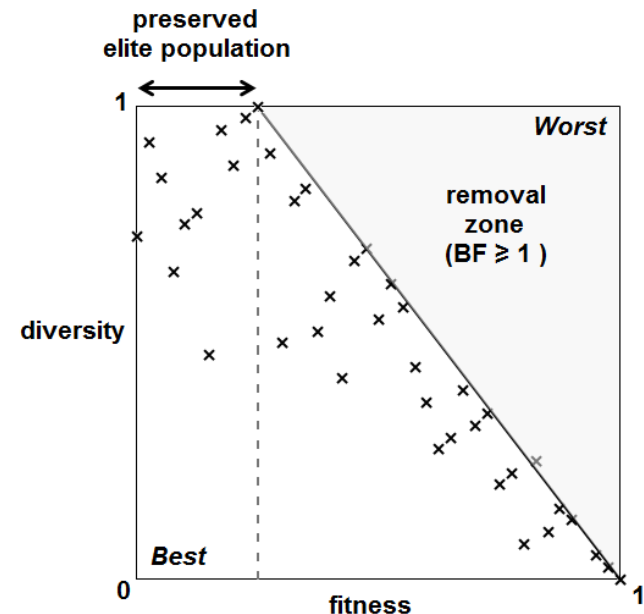
- ❑ Based on the previously described Unified Local Search to perform route improvement (RI) on separate AAR.
  - Using CROSS, I-CROSS, Relocate, 2-Opt\* and 2-Opt neighborhoods
  - Pruning procedures (granular search)
  - Hybrid acceptance strategy (intermediate between first improvement and best improvement)
  
- ❑ Combined with an assignment-improvement (AI) procedure to re-assign customer visits into different resources and routes.
  
- ❑ These two procedures are called in the sequence RI-AI-RI.

# Population management and search guidance

- **Biased Fitness** is a tradeoff between ranks in terms of **solution penalized cost**  $cost(I)$ , and **contribution to the diversity**  $dc(I)$ , measured as a distance to others individuals in the population.

$$BF(I) = fit(I) + \left(1 - \frac{nbElit}{nbIndiv - 1}\right) \times dc(I)$$

- Used during selection of the parents
  - Balancing strength with innovation during reproduction, and thus favoring exploration of the search space.
- and during selection of the survivors:
  - Removing the individual  $I$  with worst  $BF(I)$  also guarantees some elitism in terms of solution value.



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# Comparison with problem-tailored state-of-the-art methods

- ❑ Extensive computational experiments on 26 structurally different VRP variants and 39 sets of benchmark instances.
  
- ❑ Comparing UHGS with the best problem-tailored method for each benchmark.
  
- ❑ In the following, we indicate for each method
  - % Gap to the BKS of an average run (out of 10 for UHGS).
  - % Gap to the BKS of a best run (out of 10 for UHGS).
  - Computational effort (total work time) for an average run
  - Type of processor used.

# Comparison with problem-tailored state-of-the-art methods

Variant	Bench.	$n$	Obj.	State-of-the-art methods				
				Author	Avg.%	Best%	T(min)	CPU
CVRP	CMT79	[50,199]	C	GG11:	—	+0.03%	8×2.38	8×Xe 2.3G
				MB07:	+0.03%	—	2.80	P-IV 2.8G
				<b>UHGS*:</b>	<b>+0.02%</b>	<b>+0.00%</b>	11.90	Opt 2.4G
CVRP	GWKC98	[200,483]	C	GG11:	—	+0.29%	8×5	8×Xe 2.3G
				NB09:	+0.27%	+0.16%	21.51	Opt 2.4G
				<b>UHGS*:</b>	<b>+0.15%</b>	<b>+0.02%</b>	71.41	Opt 2.4G
VRPB	GJ89	[25,200]	C	ZK12:	+0.38%	+0.00%	1.09	T5500 1.67G
				GA09:	+0.09%	+0.00%	1.13	Xe 2.4G
				<b>UHGS:</b>	<b>+0.01%</b>	<b>+0.00%</b>	0.99	Opt 2.4G
CCVRP	CMT79	[50,199]	C	NPW10:	+0.74%	+0.28%	5.20	Core2 2G
				RL12:	+0.37%	+0.07%	2.69	Core2 2G
				<b>UHGS:</b>	<b>+0.01%</b>	<b>-0.01%</b>	1.42	Opt 2.2G
CCVRP	GWKC98	[200,483]	C	NPW10:	+2.03%	+1.38%	94.13	Core2 2G
				RL12:	+0.34%	+0.07%	21.11	Core2 2G
				<b>UHGS:</b>	<b>-0.14%</b>	<b>-0.23%</b>	17.16	Opt 2.2G
VRPSDP	SN99	[50,199]	C	SDBOF10:	+0.16%	+0.00%	256×0.37	256×Xe 2.67G
				ZTK10:	—	+0.11%	—	T5500 1.66G
				<b>UHGS:</b>	<b>+0.01%</b>	<b>+0.00%</b>	2.79	Opt 2.4G
VRPSDP	MG06	[100,400]	C	SDBOF10:	+0.30%	+0.17%	256×3.11	256×Xe 2.67G
				<b>UHGS:</b>	<b>+0.20%</b>	<b>+0.07%</b>	12.00	Opt 2.4G
				<b>S12 :</b>	<b>+0.08%</b>	<b>+0.00%</b>	7.23	I7 2.93G

# Comparison with problem-tailored state-of-the-art methods

Variant	Bench.	$n$	Obj.	State-of-the-art methods				
				Author	Avg.%	Best%	T(min)	CPU
VFMP-F	G84	[20,100]	C	ISW09:	—	+0.07%	8.34	P-M 1.7G
				SPUO12:	+0.12%	+0.01%	0.15	I7 2.93G
				<b>UHGS:</b>	<b>+0.04%</b>	<b>+0.01%</b>	1.13	Opt 2.4G
VFMP-V	G84	[20,100]	C	ISW09:	—	+0.02%	8.85	P-M 1.7G
				SPUO12:	+0.17%	+0.00%	0.06	I7 2.93G
				<b>UHGS:</b>	<b>+0.03%</b>	<b>+0.00%</b>	0.85	Opt 2.4G
VFMP-FV	G84	[20,100]	C	P09:	—	+0.02%	0.39	P4M 1.8G
				UHGS:	+0.01%	+0.00%	0.99	Opt 2.4G
				<b>SPUO12:</b>	<b>+0.01%</b>	<b>+0.00%</b>	0.13	I7 2.93G
LDVRP	CMT79	[50,199]	C	XZKX12:	+0.48%	+0.00%	1.3	NC 1.6G
				<b>UHGS:</b>	<b>-0.28%</b>	<b>-0.33%</b>	2.34	Opt 2.2G
LDVRP	GWKC98	[200,483]	C	XZKX12:	+0.66%	+0.00%	3.3	NC 1.6G
				<b>UHGS:</b>	<b>-1.38%</b>	<b>-1.52%</b>	23.81	Opt 2.2G
PVRP	CGL97	[50,417]	C	HDH09:	+1.69%	+0.28%	3.09	P-IV 3.2G
				UHGS*:	+0.43%	+0.02%	6.78	Opt 2.4G
				<b>CM12:</b>	<b>+0.24%</b>	<b>+0.06%</b>	64×3.55	64×Xe 3G
MDVRP	CGL97	[50,288]	C	CM12:	+0.09%	+0.03%	64×3.28	64×Xe 3G
				S12:	+0.07%	+0.02%	11.81	I7 2.93G
				<b>UHGS*:</b>	<b>+0.08%</b>	<b>+0.00%</b>	5.17	Opt 2.4G
GVRP	B11	[16,262]	C	BER11:	+0.06%	—	0.01	Opt 2.4G
				MCR12:	+0.11%	—	0.34	Duo 1.83G
				<b>UHGS:</b>	<b>+0.00%</b>	<b>-0.01%</b>	1.53	Opt 2.4G

# Comparison with problem-tailored state-of-the-art methods

Variant	Bench.	n	Obj.	State-of-the-art methods				
				Author	Avg.%	Best%	T(min)	CPU
OVRP	CMT79 &F94	[50,199]	F/C	RTBI10:	0%/+0.32%	—	9.54	P-IV 2.8G
				S12:	—/+0.16%	0%/+0.00%	2.39	I7 2.93G
				UHGS:	0%/+0.11%	0%/+0.00%	1.97	Opt 2.4G
OVRP	GWKC98	[200,480]	F/C	ZK10:	0%/+0.39%	0%/+0.21%	14.79	T5500 1.66G
				S12:	0%/+0.13%	0%/+0.00%	64.07	I7 2.93G
				UHGS:	0%/-0.11%	0%/-0.19%	16.82	Opt 2.4G
VRPTW	SD88	100	F/C	RTI09:	0%/+0.11%	0%/+0.04%	17.9	Opt 2.3G
				UHGS*:	0%/+0.04%	0%/+0.01%	2.68	Xe 2.93G
				NBD10:	0%/+0.02%	0%/+0.00%	5.0	Opt 2.4G
VRPTW	HG99	[200,1000]	F/C	RTI09b:	—	+0.16%/+3.36%	270	Opt 2.3G
				NBD10:	+0.20%/+0.42%	+0.10%/+0.27%	21,7	Opt 2.4G
				UHGS*:	+0.18%/+0.11%	+0.08%/-0.10%	141	Xe 2.93G
OVRPTW	SD88	100	F/C	RTI09a:	+0.89%/+0.42%	0%/+0.24%	10.0	P-IV 3.0G
				KTDHS12:	0%/+0.79%	0%/+0.18%	10.0	Xe 2.67G
				UHGS:	+0.09%/-0.10%	0%/-0.10%	5.27	Opt 2.2G
TDVRPTW	SD88	100	F/C	KTDHS12:	+2.25%	0%	10.0	Xe 2.67G
				UHGS:	-3.31%	-3.68%	21.94	Opt 2.2G
VFMPPTW	LS99	100	D	BDHMG08:	—	+0.59%	10.15	Ath 2.6G
				RT10:	+0.22%	—	16.67	P-IV 3.4G
				UHGS:	-0.15%	-0.24%	4.58	Opt 2.2G
VFMPPTW	LS99	100	C	BDHMG08:	—	+0.25%	3.55	Ath 2.6G
				BPDRT09:	—	+0.17%	0.06	Duo 2.4G
				UHGS:	-0.38%	-0.49%	4.82	Opt 2.2G

# Comparison with problem-tailored state-of-the-art methods

Variant	Bench.	n	Obj.	State-of-the-art methods				
				Author	Avg.%	Best%	T(min)	CPU
PVRPTW	CL01	[48,288]	C	PR08:	—	+1.75%	—	Opt 2.2G
				CM12:	+1.10%	+0.76%	64×11.3	64×Xe 3G
				UHGS*:	+0.63%	+0.22%	32.7	Xe 2.93G
MDVRPTW	CL01	[48,288]	C	PBDH08:	—	+1.37%	147	P-IV 3.6G
				CM12:	+0.36%	+0.15%	64×6.57	64×Xe 3G
				UHGS*:	+0.19%	+0.03%	6.49	Xe 2.93G
SDVRPTW	CL01	[48,288]	C	B10:	+2.23%	—	2.94	Qd 2.67G
				CM12:	+0.62%	+0.36%	64×5.60	64×Xe 3G
				UHGS*:	+0.36%	+0.10%	5.48	Xe 2.93G
VRPSTW (type 1, $\alpha=100$ )	SD88	100	F/TW/C	F10:	0%	—	9.69	P-M 1.6G
				UHGS:	-3.05%	-4.42%	18.62	Opt 2.2G
VRPSTW (type 1, $\alpha=1$ )	SD88	100	C+TW	KTDHS12:	+0.62%	+0.00%	10.0	Xe 2.67G
				UHGS:	-0.13%	-0.18%	5.82	Opt 2.2G
VRPSTW (type 2, $\alpha=100$ )	SD88	100	F/TW/C	FEL07:	0%	—	5.98	P-II 600M
				UHGS:	-13.91%	-13.91%	41.16	Opt 2.2G
VRPSTW (type 2, $\alpha=1$ )	SD88	100	C+TW	UHGS:	+0.26%	0%	29.96	Opt 2.2G
MDPVRPTW	New	[48,288]	C	UHGS:	+0.77%	0%	16.89	Opt 2.2G
VRTDSP (E.U. rules)	G09	100	F/C	PDDR10:	0%/0%	0%/0%	88	Opt 2.3G
				UHGS*:	-0.56%/-0.54%	-0.85%/-0.70%	228	Xe 2.93G

# Comparison with problem-tailored state-of-the-art methods

## List of acronyms for benchmarks

B11	Bektas et al. (2011)	G84	Golden (1984)	LS99	Liu and Shen (1999)
CGL97	Cordeau et al. (1997)	G09	Goel (2009)	MG06	Montané and Galvão (2006)
CL01	Cordeau and Laporte (2001)	GH99	Gehring and Homberger (1999)	SD88	Solomon and Desrosiers (1988)
CMT79	Christofides et al. (1979)	GJ89	Goetschalckx and J.-B. (1989)	SN99	Salhi and Nagy (1999)
F94	Fisher (1994)	GWKC98	Golden et al. (1998)		

## List of acronyms for state-of-the-art algorithms

B10	Belhaiza (2010)	KTDHS12	Kritzing et al. (2012)	RT10	Repoussis and Tarantilis (2010)
BDHMG08	Bräysy et al. (2008a)	MB07	Mester and Bräysy (2007)	RTBI10	Repoussis et al. (2010)
BER11	Bektas et al. (2011)	MCR12	Moccia et al. (2012)	RTI09a	Repoussis et al. (2009a)
BLR11	Balseiro et al. (2011)	NB09	Nagata and Bräysy (2009)	RTI09b	Repoussis et al. (2009b)
BPDRT09	Bräysy et al. (2009)	NBD10	Nagata et al. (2010)	S12	Subramanian (2012)
CM12	Cordeau and M. (2012)	NPW10	Ngueveu et al. (2010)	SDBOF10	Subramanian et al. (2010)
F10	Figliozzi (2010)	P09	Prins (2009)	SPUO12	Subramanian et al. (2012)
FEL07	Fu et al. (2007)	PBDH08	Polacek et al. (2008)	XZKX12	Xiao et al. (2012)
GA09	Gajpal and Abad (2009)	PDDR10	Prescott-Gagnon et al. (2010)	ZTK10	Zachariadis et al. (2010)
GG11	Groër and Golden (2011)	PR07	Pisinger and Ropke (2007)	ZK10	Zachariadis and Kiranoudis (2010)
HDH09	Hemmelmayr et al. (2009)	PR08	Pirkwieser and Raidl (2008)	ZK11	Zachariadis and Kiranoudis (2011)
ISW09	Imran et al. (2009)	RL12	Ribeiro and Laporte (2012)	ZK12	Zachariadis and Kiranoudis (2012)

# Conclusions and Research Perspectives

- ❑ A unified hybrid genetic search
  - Using a local-search framework which is generic and computationally efficient.
  - With generalized solution representation, Split procedure, genetic operators (Crossover) and population management methods.
  - State-of-the-art results when compared to each problem-tailored method for 26 VRP variants.
  
- ❑ It appears that **generality does not necessarily impede performance for a wide class of VRP variants.**

# Conclusions and Research Perspectives

## □ Perspectives :

- Extend the range of problems (especially SEQ attributes, stochastic and multi-objective settings)
- Use UHGS to conduct experiments on metaheuristic strategies on a wide range of VRPs
- Further study of the combinatorial aspect of attributes relatively to UHGS operators.



## THANK YOU

### □ For more details on this work:

- Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N., & Rei, W. (2012). A Hybrid Genetic Algorithm for Multi-Depot and Periodic Vehicle Routing Problems. *Operations Research (To appear)*.
- Vidal, T., Crainic, T. G., Gendreau, M., & Prins, C. (2012). *Heuristics for Multi-Attribute Vehicle Routing Problems : A Survey and Synthesis*. Tech Rep. CIRRELT 2012-05.
- The CIRRELT technical report on the unified algorithm will appear very soon.

# Empirical studies on diversity management methods (1/2)

- Sensitivity analysis on diversity management methods:
  - **HGA** : No diversity management method
  - **HGA-DR** : Dispersal rule on objective space
  - **HGA-PM** : Dispersal rule on solution space
  - **HGSADC** : The proposed approach

Benchmark		<b>HGA</b>	<b>HGA-DR</b>	<b>HGA-PM</b>	<b>HGSADC</b>
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

