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# A Powerful Route Minimization Heuristic for the Vehicle Routing Problem with Time Windows

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# Introduction

- Vehicle routing problem with time window (VRPTW) is one of the most important and studied VRP variant.
  - primary objective: minimize the number of vehicles
  - secondary objective: minimize the total travel distance
- Recent trend of heuristic algorithms for the VRPTW is the two-stage approach (Bent and Hentenryck, 04).
- We propose an efficient route-minimization heuristic for the VRPTW.

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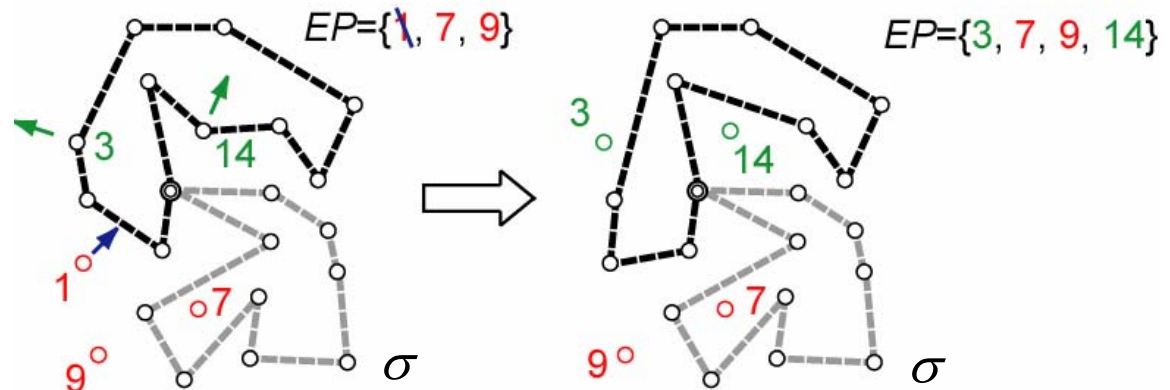
# Outline of this talk

- General framework using ejection pool
- Our solution method
- Experimental results
- Conclusions

# General framework of the *Ejection Pool* (1)

## Route-minimization procedure using the EP (Lim and Zhang, 07)

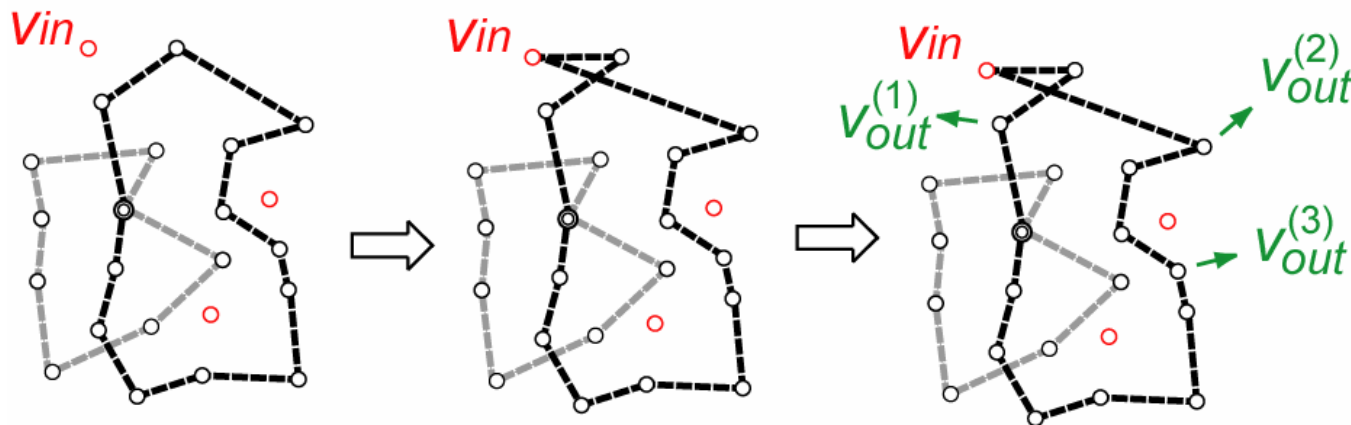
- 1: Remove a route from  $\sigma$  and initialize  $EP$  with the removed customers;
- 2: **while**  $EP$  is not empty **do**
- 3:     Select  $v_{in}$  from  $EP$  and remove it from  $EP$
- 4:     **if**  $v_{in}$  can be inserted into  $\sigma$  **then**
- 5:         Insert  $v_{in}$  into  $\sigma$ ;
- 6:     **else**
- 7:         Insert  $v_{in}$  into  $\sigma$  and eject customers from the resulting route;
- 8:         Add ejected customers to  $EP$ ;
- 9:     **end if**
- 10: **end while**



# General framework of the *Ejection Pool* (2)

- Insert-ejection move

- For customer  $v_{in}$  to be inserted, all edges can be insertion positions.
- For each insertion of  $v_{in}$ , there are a lot of customer combinations,  $v_{out}^{(1)}, \dots, v_{out}^{(k)}$ , to be ejected



- Which insertion-ejection move is better?

- The number of ejecting customers ( $k$ ) should be small.
- Ejecting more than two customers may benefit the subsequent insertion.

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# Our idea

- A concept of the guided local search (GLS) is employed to determine the insertion-ejection move.
- Guided local search (GLS) (Voudouris and Tsang, 95)
  - Penalizing solution features that are frequently appeared in local minima during the local search.
  - A modified objective function including the penalties are used to help the local search escape from local minima and to diversify the search.
- In our solution method, customers in the EP are solution features.

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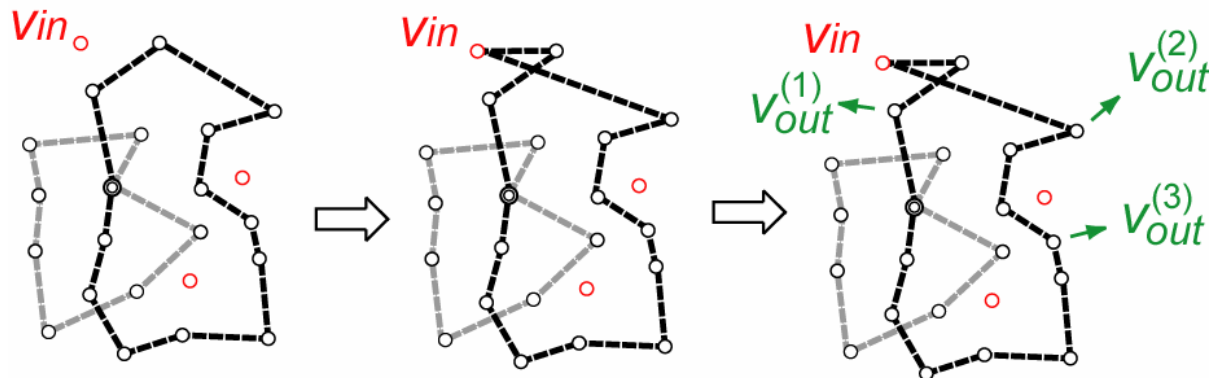
# Main framework

## Procedure Delete\_Route ( $\sigma$ )

- 1: Randomly remove a route from  $\sigma$  and initialize  $EP$  ;
- 2: Initialize all penalty counters:  $p[v] = 1$  ( $v = 1, \dots, N$ ) ;
- 3: **while**  $EP$  is not empty **do**
- 4:     Select and remove  $v_{in}$  from  $EP$  (LIFO queue)
- 5:     **if**  $v_{in}$  can be inserted into  $\sigma$  **then**
- 6:         Insert  $v_{in}$  into  $\sigma$  ;
- 7:     **else**
- 8:         Set:  $p[v_{in}] = p[v_{in}] + 1$  ;
- 9:         Execute the insertion-ejection move on  $\sigma$  such that  $P_{sum} = p[v_{out}^{(1)}] + \dots + p[v_{out}^{(k)}]$  is minimized ;
- 10:         Add  $v_{out}^{(1)}, \dots, v_{out}^{(k)}$  to  $EP$  ;
- 11:          $\sigma := \text{Perturb}(\sigma)$  ;
- 12:     **end if**
- 13: **end while**

# Finding the best insertion-ejection move

- How to find the insertion-ejection move that minimizes  $P_{sum} = p[v_{out}^{(1)}] + \dots + p[v_{out}^{(k)}]$ .
- There are enormous numbers of insertion-ejection moves.
  - $v_{in}$  is given.
  - All insertion positions for  $v_{in}$  are tested.
  - For each insertion, there are a lot of customer combinations to be ejected. ( $k$  is limited up to  $k_{max} (=5)$ .)



- For each insertion, most of the ejection combinations can be ignored (the detail is omitted).



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## Main framework (again)

### Procedure Delete\_Route ( $\sigma$ )

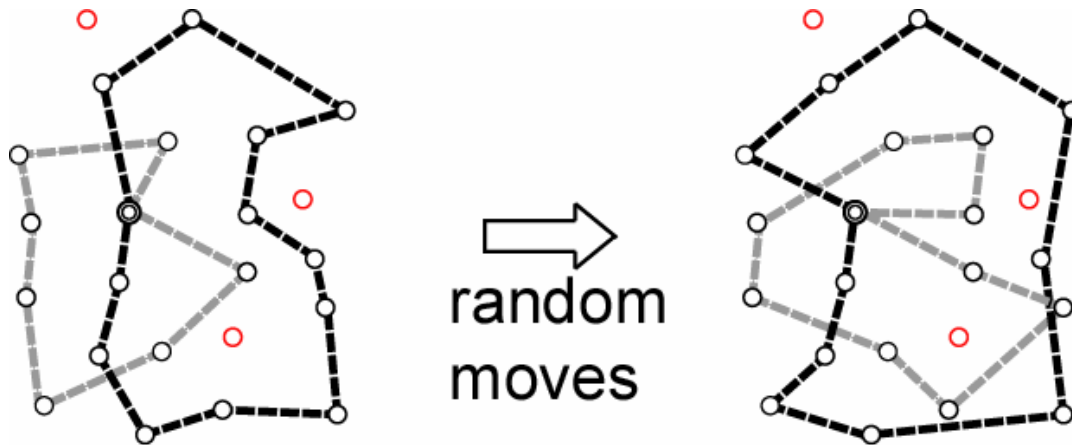
- 1: Randomly remove a route from  $\sigma$  and initialize  $EP$  ;
- 2: Initialize all penalty counters:  $p[v] = 1$  ( $v = 1, \dots, N$ ) ;
- 3: **while**  $EP$  is not empty **do**
- 4:     Select and remove  $v_{in}$  from  $EP$  (LIFO strategy)
- 5:     **if**  $v_{in}$  can be inserted into  $\sigma$  **then**
- 6:         Insert  $v_{in}$  into  $\sigma$  ;
- 7:     **else**
- 8:         Set:  $p[v_{in}] = p[v_{in}] + 1$  ;
- 9:         Execute the insertion-ejection move on  $\sigma$  such that  $P_{sum} = p[v_{out}^{(1)}] + \dots + p[v_{out}^{(k)}]$  is minimized ;
- 10:         Add  $v_{out}^{(1)}, \dots, v_{out}^{(k)}$  to  $EP$  ;
- 11:          $\sigma := \text{Perturb}(\sigma)$  ;
- 12:     **end if**
- 13: **end while**

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# Perturb procedure

## Procedure Perturb ( $\sigma$ ): Outline

- Random local search moves are executed inside  $\sigma$  for  $l_{rand}$  (=1000) times.
- Each move is randomly selected from 2-opt\*, relocation and exchange moves.
- $\sigma$  must be feasible after each move.



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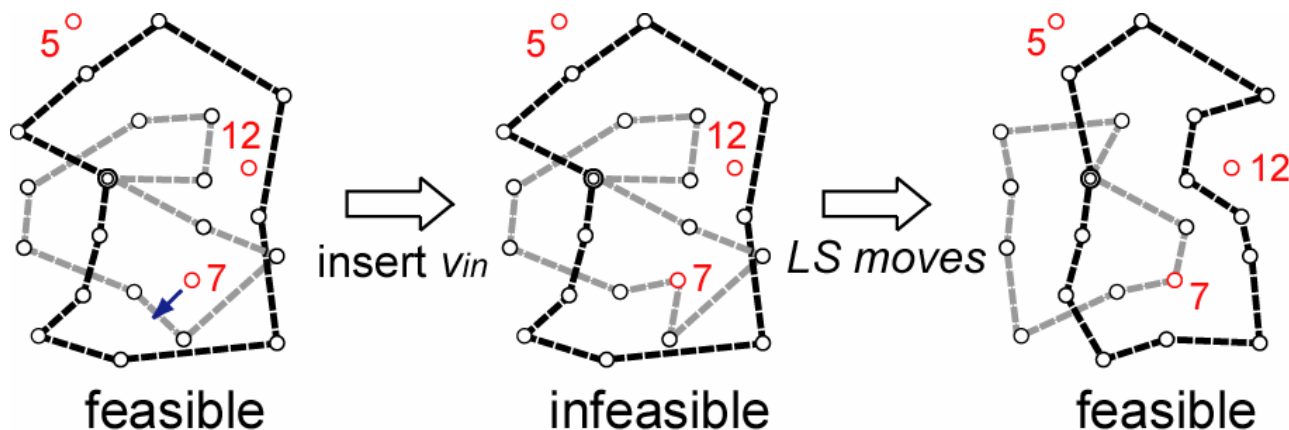
# Improving the main framework

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3: while  $EP$  is not empty do
4:   Select and remove  $v_{in}$  from  $EP$  (LIFO queue)
5:   if  $v_{in}$  can be inserted into  $\sigma$  (by the simple insertion) then
6:     Insert  $v_{in}$  into  $\sigma$ ;           // simple insertion for  $v_{in}$ 
7:   else
8:      $\sigma := \text{Squeeze}(v_{in}, \sigma)$ ; // more powerful insertion for  $v_{in}$ 
9:   endif
10:  if ( $v_{in}$  is not inserted) then
11:    Set:  $p[v_{in}] = p[v_{in}] + 1$ ;
12:    Execute the insertion-ejection move on  $\sigma$  ..... ;
13:    Add  $v_{out}^{(1)}, \dots, v_{out}^{(k)}$  to  $EP$ ;
14:     $\sigma := \text{Perturb}(\sigma)$ ;
15:  end if
15: end while
```

# Squeeze procedure

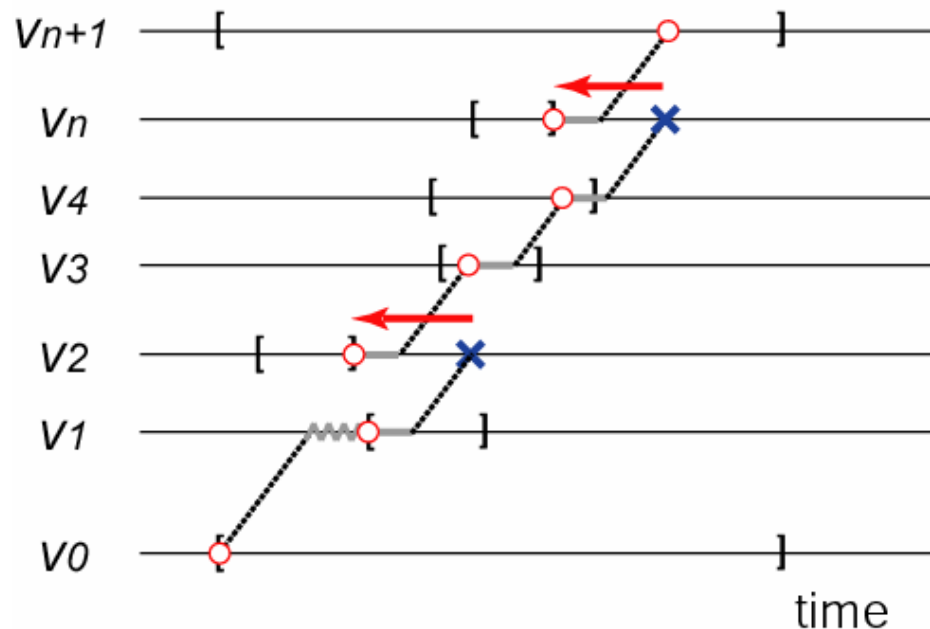
## Procedure Squeeze ( $v_{in}, \sigma$ ) : Outline

- Insert  $v_{in}$  into  $\sigma$  by allowing the violation of the constraints.
- Local search based repair procedure restores the feasibility.
  - 2-opt, relocation, exchange moves are applied inside  $\sigma$
  - A solution is evaluated by a penalty function to guide it toward feasible solutions.
  - A standard hill climbing.
- Penalty function:  $F_p(\sigma) = F_c(\sigma) + \alpha \cdot F_{tw}(\sigma)$ 
  - penalty terms for the capacity and time window constraints



# Penalty term: $F_{tw}(\sigma)$ (Nagata, 07)

- Time window penalty for a route:  $TW_r$ 
  - A sequence of a route:  $r = \langle V_0, V_1, \dots, V_n, V_{n+1} \rangle$
  - $TW_r =$  sum of the length of the red arrows
- Time window penalty for  $\sigma$ 
  - $F_{tw}(\sigma) = \sum_{r=1}^m TW_r$



- $\Delta F_{tw}(\sigma)$  by a local search move from 2-opt, relocation and exchange is calculated in  $O(1)$  time

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# Experiments

## Experimental settings

- Algorithm-G: Squeeze procedure is **not** used.
- Algorithm-GS: Squeeze procedure is used.

## Benchmarks

- Gehring and Homberger's benchmarks
  - Instance sets of 200, 400, 600, 800 and 1000-customer
  - Each set consists of 60 instances.

## Comparisons

- The best-known solutions taken from (Pisinger and Ropke, 07), (Ibaraki et. al., to appear), (Lim and Zhang, 07), (Gagnon et. al., 07), and SINTEF website (ignore several wrong solutions).

# Results

- CNV: The cumulative number of vehicles in each problem size instances
- Best CNV: CNV in the best-known solutions.
- Our result: The difference in the CNV from the Best CNV

$N$	Best CNV	Algorithm-G			Algorithm-GS			
		1min	10min	60min	1min	10min	60min	$N/200$ h
200	694	0	0	0	0	0	0	0
400	1382	+3	+2	+2	+3	0	-2	-2
600	2068	+7	-1	-1	+1	-1	-3	-3
800	2739	+15	-1	-3	+2	-2	-4	-5
1000	3425	+12	0	-2	+2	-5	-6	-8
total	10308	+37	0	-4	+8	-8	-15	-18
# Fail to reach best-known		37	6	4	10	2	0	0
# Find new best		0	6	8	2	10	15	18

# New best-know solutions

- The 18 new best-known solutions

Instances	$N$	Best-known	New Best	Time (min)
C2_4_8	400	12	11	60
RC2_4_5	400	9	8	10
C1_6_6	600	60	59	60
C1_6_7	600	58	57	60
RC2_6_5	600	12	11	10
C1_8_2	800	73	72	1
C1_8_6	800	80	79	10
C1_8_8	800	74	73	240
C2_8_6	800	24	23	60
RC2_8_1	800	19	18	1
C110_6	1000	100	99	10
C110_7	1000	98	97	60
C110_8	1000	93	92	300
C210_3	1000	29	28	10
C210_6	1000	30	29	10
C210_7	1000	30	29	10
C210_8	1000	29	28	300
C21010	1000	29	28	10



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# Conclusions

- A powerful route minimization heuristic for the VRPTW is presented.
- The idea of the main framework is simple.
  - The concept of GLS is combined with a general framework of the *EP*.
- The main framework is further improved by the Squeeze procedure.
- The results of these methods are promising.
- The main framework can be generalized and applied to other combinatorial optimization problems (ongoing work).