

DM204, 2010  
SCHEDULING, TIMETABLING AND ROUTING

Lecture 31  
Construction Heuristics  
and Local Search Methods  
for VRP/VRPTW

Marco Chiarandini

Department of Mathematics & Computer Science  
University of Southern Denmark

## Course Overview

- ✓ Problem Introduction
  - ✓ Scheduling classification
  - ✓ Scheduling complexity
  - ✓ RCPSP
- ✓ General Methods
  - ✓ Integer Programming
  - ✓ Constraint Programming
  - ✓ Heuristics
  - ✓ Dynamic Programming
  - ✓ Branch and Bound
- ✓ Scheduling Models
  - ✓ Single Machine
  - ✓ Parallel Machine and Flow Shop
  - ✓ Job Shop
  - ✓ Resource-Constrained Project Scheduling
- Timetabling
  - ✓ Reservations and Education
  - ✓ Course Timetabling
  - ✓ Workforce Timetabling
  - ✓ Crew Scheduling
- Vehicle Routing
  - Capacitated Models
  - Time Windows models
  - Rich Models

Marco Chiarandini ... 2

## Outline

1. Construction Heuristics
  - Construction Heuristics for CVRP
  - Construction Heuristics for VRPTW
2. Improvement Heuristics
3. Metaheuristics
4. Constraint Programming for VRP

Construction Heuristics  
Improvement Heuristics  
Metaheuristics  
CP for VRP

## Outline

1. Construction Heuristics
  - Construction Heuristics for CVRP
  - Construction Heuristics for VRPTW
2. Improvement Heuristics
3. Metaheuristics
4. Constraint Programming for VRP

Construction Heuristics  
Improvement Heuristics  
Metaheuristics  
CP for VRP

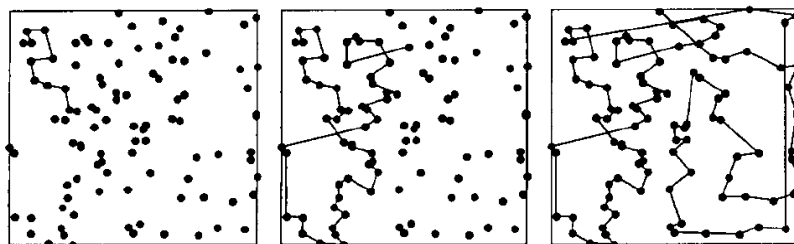
# Construction Heuristics for CVRP

- TSP based heuristics
- Saving heuristics (Clarke and Wright)
- Insertion heuristics
- Cluster-first route-second
  - Sweep algorithm
  - Generalized assignment
  - Location based heuristic
  - Petal algorithm
- Route-first cluster-second

Cluster-first route-second seems to perform better than route-first  
 (Note: distinction construction heuristic / iterative improvement is often blurred)

Marco Chiarandini ... 6

[Bentley, 1992]



**Figure 1.** The Nearest Neighbor heuristic.

NN (Flood, 1956)

1. Randomly select a starting node
2. Add to the last node the closest node until no more node is available
3. Connect the last node with the first node

Running time  $O(N^2)$

Marco Chiarandini ... 8

## Construction heuristics for TSP

They can be used for route-first cluster-second or for growing multiple tours subject to capacity constraints.

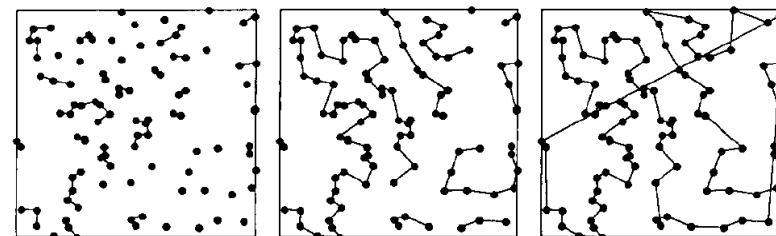
- Heuristics that Grow Fragments
  - Nearest neighborhood heuristics
  - Double-Ended Nearest Neighbor heuristic
  - Multiple Fragment heuristic (aka, greedy heuristic)
- Heuristics that Grow Tours
 

● Nearest Addition	● Nearest Insertion
● Farthest Addition	● Farthest Insertion
● Random Addition	● Random Insertion
- Clarke-Wright saving heuristic
- Heuristics based on Trees
  - Minimum spanning tree heuristic
  - Christofides' heuristics

(But recall! Concorde: <http://www.tsp.gatech.edu/>)

Marco Chiarandini ... 7

[Bentley, 1992]



**Figure 5.** The Multiple Fragment heuristic.

Add the cheapest edge provided it does not create a cycle.

Marco Chiarandini ... 9

[Bentley, 1992]

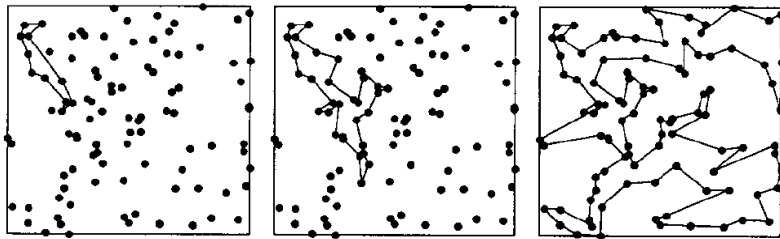


Figure 8. The Nearest Addition heuristic.

NA

1. Select a node and its closest node and build a tour of two nodes
2. Insert in the tour the closest node  $v$  until no more node is available

Running time  $O(N^3)$

Marco Chiarandini ... 10

Marco Chiarandini ... 11

[Bentley, 1992]

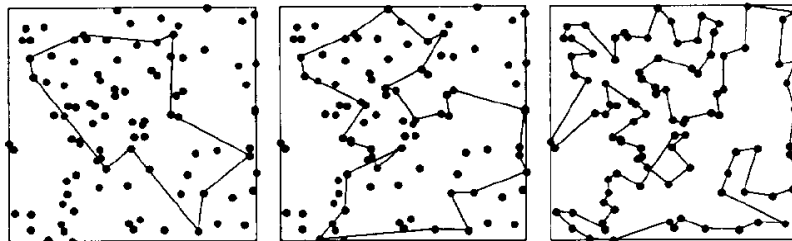


Figure 14. The Random Addition heuristic.

Marco Chiarandini ... 12

[Bentley, 1992]

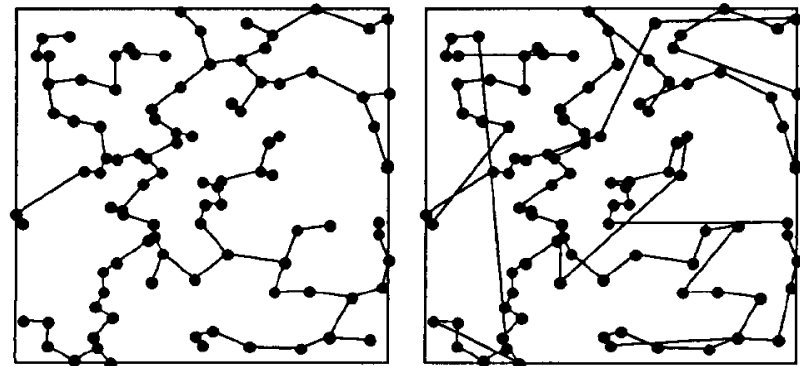


Figure 18. The Minimum Spanning Tree heuristic.

1. Find a minimum spanning tree  $O(N^2)$
2. Append the nodes in the tour in a depth-first, inorder traversal

Running time  $O(N^2)$

$$A = MST(I)/OPT(I) \leq 2$$

Marco Chiarandini ... 13

FA

1. Select a node and its farthest and build a tour of two nodes
2. Insert in the tour the farthest node  $v$  until no more node is available

FA is more effective than NA because the first few farthest points sketch a broad outline of the tour that is refined after.

Running time  $O(N^3)$

[Bentley, 1992]

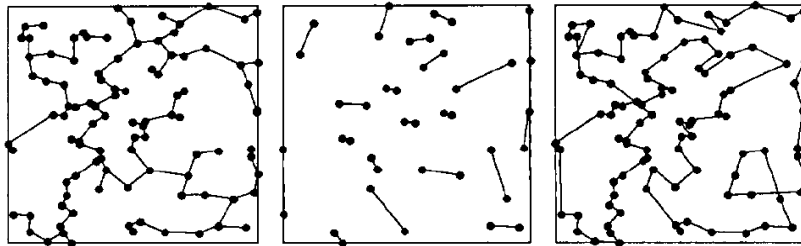


Figure 19. Christofides' heuristic.

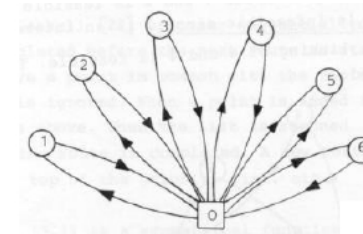
1. Find the minimum spanning tree  $T$ .  $O(N^2)$
2. Find nodes in  $T$  with odd degree and find the cheapest perfect matching  $M$  in the complete graph consisting of these nodes only. Let  $G$  be the multigraph of all nodes and edges in  $T$  and  $M$ .  $O(N^3)$
3. Find an Eulerian walk (each node appears at least once and each edge exactly once) on  $G$  and an embedded tour.  $O(N)$

Running time  $O(N^3)$

$$A = CH(I)/OPT(I) \leq 3/2$$

Marco Chiarandini ... 14

## Construction Heuristics Specific for VRP



Clarke-Wright Saving Heuristic (1964)

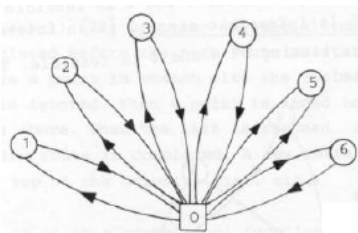
1. Start with an initial allocation of one vehicle to each customer ( $0$  is the depot for VRP or any chosen city for TSP)

Sequential:

2. consider in turn route  $(0, i, \dots, j, 0)$  determine  $s_{ki}$  and  $s_{jl}$
3. merge with  $(k, 0)$  or  $(0, l)$

Marco Chiarandini ... 15

## Construction Heuristics Specific for VRP

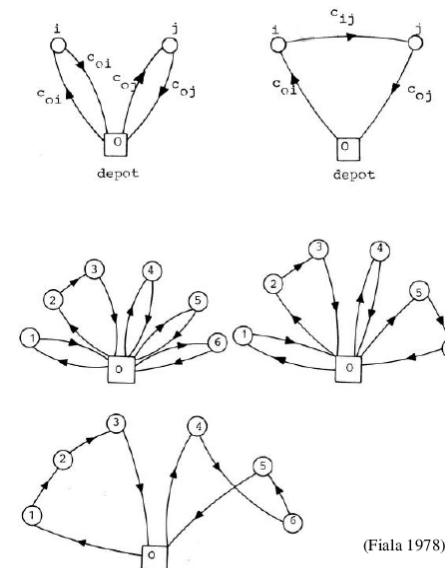


Clarke-Wright Saving Heuristic (1964)

1. Start with an initial allocation of one vehicle to each customer ( $0$  is the depot for VRP or any chosen city for TSP)

Parallel:

2. Calculate saving  $s_{ij} = c_{0i} + c_{0j} - c_{ij}$  and order the saving in non-increasing order
3. scan  $s_{ij}$   
merge routes if i)  $i$  and  $j$  are not in the same tour ii) neither  $i$  and  $j$  are interior to an existing route iii) vehicle and time capacity are not exceeded



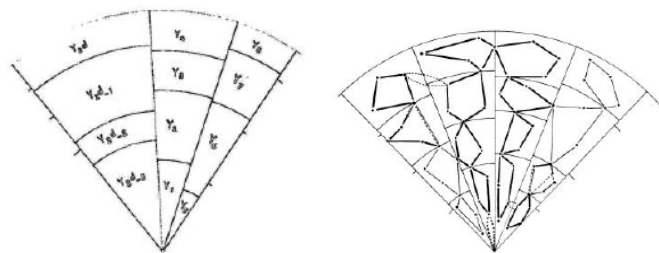
(Fiala 1978)

Marco Chiarandini ... 15

Marco Chiarandini ... 16

### Matching Based Saving Heuristic

1. Start with an initial allocation of one vehicle to each customer (0 is the depot for VRP or any chosen city for TSP)
2. Compute  $s_{pq} = t(S_p) + t(S_q) - t(S_p \cup S_q)$  where  $t(\cdot)$  is the TSP solution
3. Solve a max weighted matching on the  $S_k$  with weights  $s_{pq}$  on edges. A connection between a route  $p$  and  $q$  exists only if the merging is feasible.



### Cluster-first route-second: Sweep algorithm [Wren & Holliday (1971)]

1. Choose  $i^*$  and set  $\theta(i^*) = 0$  for the rotating ray
2. Compute and rank the polar coordinates  $(\theta, \rho)$  of each point
3. Assign customers to vehicles until capacity not exceeded. If needed start a new route. Repeat until all customers scheduled.

### Insertion Heuristic

$$\alpha(i, k, j) = c_{ik} + c_{kj} - \lambda c_{ij}$$

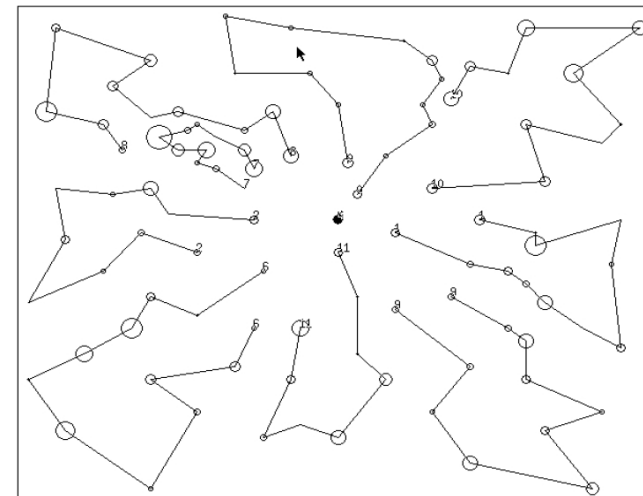
$$\beta(i, k, j) = \mu c_{0k} - \alpha(i, k, j)$$

1. construct emerging route  $(0, k, 0)$
2. compute for all  $k$  unrouted the feasible insertion cost:

$$\alpha^*(i_k, k, j_k) = \min_p \{\alpha(i_p, k, i_{p+1})\}$$

if no feasible insertion go to 1 otherwise choose  $k^*$  such that

$$\beta^*(i_k^*, k^*, j_k^*) = \max_k \{\beta(i_k, k, j_k)\}$$



Cluster-first route-second: Generalized-assignment-based algorithm [Fisher & Jaikumur (1981)]

1. Choose a  $j_k$  at random for each route  $k$
2. For each point compute

$$d_{ik} = \min\{c_{0,i} + c_{i,j_k} + c_{j_k,0}, c_{0j_k} + c_{j_k,i} + c_{i,0}\} - (c_{0,j_k} + c_{j_k,0})$$

3. Solve GAP with  $d_{ik}$ ,  $Q$  and  $q_i$

Cluster-first route-second: Location based heuristic [Bramel & Simchi-Levi (1995)]

1. Determine seeds by solving a capacitated location problem (k-median)
2. Assign customers to closest seed

(better performance than insertion and saving heuristics)

Marco Chiarandini ... 21

Marco Chiarandini ... 22

Cluster-first route-second: Petal Algorithm

1. Construct a subset of feasible routes
2. Solve a set partitioning problem

Route-first cluster-second [Beasley, 1983]

1. Construct a TSP tour over all customers
2. Choose an arbitrary orientation of the TSP; partition the tour according to capacity constraint; repeat for several orientations and select the best  
Alternatively, solve a shortest path in an acyclic digraph with costs on arcs:  $d_{ij} = c_{0i} + c_{0j} + l_{ij}$  where  $l_{ij}$  is the cost of traveling from  $i$  to  $j$  in the TSP tour.

(not very competitive)

Marco Chiarandini ... 23

Marco Chiarandini ... 24

Which heuristics can be used to minimize  $K$  and which ones need to have  $K$  fixed a priori?

Extensions of those for CVRP [Solomon (1987)]

- Saving heuristics (Clarke and Wright)
- Time-oriented nearest neighbors
- Insertion heuristics
- Time-oriented sweep heuristic

## Time-Oriented Nearest-Neighbor

- Add the unrouted node “closest” to the depot or the last node added without violating feasibility
- Metric for “closest”:

$$c_{ij} = \delta_1 d_{ij} + \delta_2 T_{ij} + \delta_3 v_{ij}$$

$d_{ij}$  geographical distance  
 $T_{ij}$  time distance  
 $v_{ij}$  urgency to serve  $j$

## Insertion Heuristics

Step 1: Compute for each unrouted customer  $u$  the *best feasible position* in the route:

$$c_1(i(u), u, j(u)) = \min_{p=1, \dots, m} \{c_1(i_{p-1}, u, i_p)\}$$

( $c_1$  is a composition of increased time and increase route length due to the insertion of  $u$ )  
(use push forward rule to check feasibility efficiently)

Step 2: Compute for each unrouted customer  $u$  which can be feasibly inserted:

$$c_2(i(u^*), u^*, j(u^*)) = \max_u \{\lambda d_{0u} - c_1(i(u), u, j(u))\}$$

(max the benefit of servicing a node on a partial route rather than on a direct route)

Step 3: Insert the customer  $u^*$  from Step 2

## Outline

- Let's assume waiting is allowed and  $s_i$  indicates service times
- $[e_i, l_i]$  time window,  $w_i$  waiting time
- $b_i = \max\{e_i, b_j + s_j + t_{ji}\}$  begin of service
- insertion of  $u$ :  $(i_0, i_1, \dots, i_p, u, i_{p+1}, \dots, i_m)$
- $PF_{i_{p+1}} = b_{i_{p+1}}^{new} - b_{i_{p+1}} \geq 0$  push forward
- $PF_{i_{r+1}} = \max\{0, PF_{i_r} - w_{i_{r+1}}\}, \quad p \leq r \leq m - 1$

### Theorem

The insertion is feasible if and only if:

$$b_u \leq l_u \quad \text{and} \quad PF_{i_r} + b_{i_r} \leq l_{i_r} \quad \forall p < r \leq m$$

Check vertices  $k, u \leq k \leq m$  sequentially.

- if  $b_k + PF_k > l_k$  then stop: the insertion is infeasible
- if  $PF_k = 0$  then stop: the insertion is feasible

Marco Chiarandini ... 30

Marco Chiarandini ... 31

## Local Search for CVRP and VRPTW

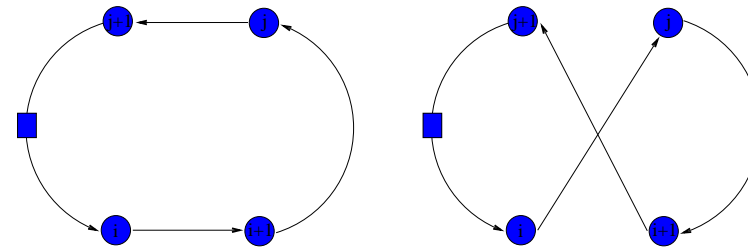
- Neighborhood structures:
  - Intra-route: 2-opt, 3-opt, Lin-Kernighan (not very well suited), Or-opt (2H-opt)
  - Inter-routes:  $\lambda$ -interchange, relocate, exchange, cross, 2-opt\*,  $b$ -cyclic  $k$ -transfer (ejection chains), GENI
- Solution representation and data structures
  - They depend on the neighborhood.
  - It can be advantageous to change them from one stage to another of the heuristic

Marco Chiarandini ... 32

## Intra-route Neighborhoods

2-opt

$$\{i, i+1\}\{j, j+1\} \rightarrow \{i, j\}\{i+1, j+1\}$$



$O(n^2)$  possible exchanges  
 One path is reversed

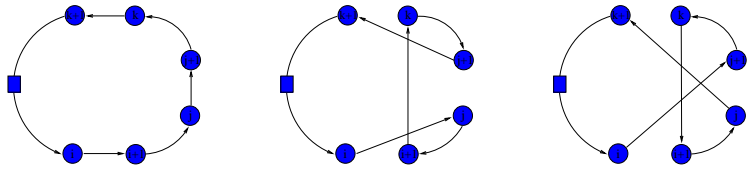
Marco Chiarandini ... 33



## Intra-route Neighborhoods

3-opt

$$\{i, i+1\}\{j, j+1\}\{k, k+1\} \rightarrow \dots$$



$O(n^3)$  possible exchanges  
 Paths can be reversed

## Inter-route Neighborhoods

[Savelsbergh, ORSA (1992)]

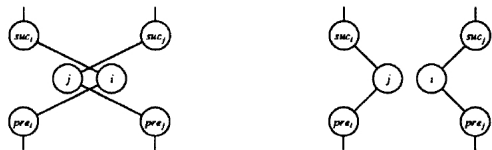
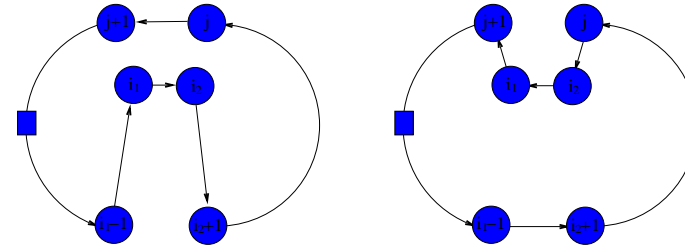


Figure 6. The exchange neighborhood.

## Intra-route Neighborhoods

Or-opt [Or (1976)]

$$\{i_1 - 1, i_1\}\{i_2, i_2 + 1\}\{j, j + 1\} \rightarrow \{i_1 - 1, i_2 + 1\}\{j, i_1\}\{i_2, j + 1\}$$



sequences of one, two, three consecutive vertices relocated  
 $O(n^2)$  possible exchanges — No paths reversed

## Inter-route Neighborhoods

[Savelsbergh, ORSA (1992)]

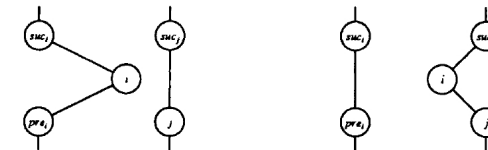


Figure 5. The relocate neighborhood.

# Inter-route Neighborhoods

[Savelsbergh, ORSA (1992)]



Figure 7. The cross neighborhood.

GENI: generalized insertion [Gendreau, Hertz, Laporte, Oper. Res. (1992)]

- select the insertion restricted to the neighborhood of the vertex to be added (not necessarily between consecutive vertices)
- perform the best 3- or 4-opt restricted to reconnecting arc links that are close to one another.

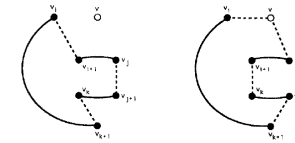


Figure 1. Type I insertion of vertex  $v$  between  $v_i$  and  $v_j$ .

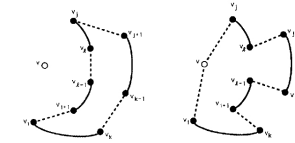


Figure 2. Type II insertion of vertex  $v$  between  $v_i$  and  $v_j$ .

Marco Chiarandini ... 38

# Efficient Implementation

Intra-route

Time windows: Feasibility check

In TSP verifying k-optimality requires  $O(n^k)$  time  
 In TSPTW feasibility has to be tested then  $O(n^{k+1})$  time

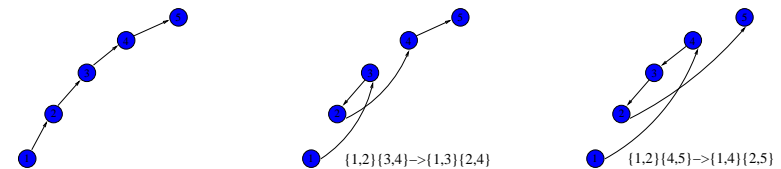
(Savelsbergh 1985) shows how to verify constraints in constant time  
 Search strategy + Global variables



$O(n^k)$  for k-optimality in TSPTW

Search Strategy

- Lexicographic search, for 2-exchange:
  - $i = 1, 2, \dots, n - 2$  (outer loop)
  - $j = i + 2, i + 3, \dots, n$  (inner loop)



Previous path is expanded by the edge  $\{j - 1, j\}$

Marco Chiarandini ... 40

Marco Chiarandini ... 41

Global variables (auxiliary data structure)

- Maintain auxiliary data such that it is possible to:
  - handle single move in constant time
  - update their values in constant time

Ex.: in case of time windows:

- total travel time of a path
- earliest departure time of a path
- latest arrival time of a path

[Irnich (2008)] uniform model

Marco Chiarandini ... 42

## Outline

1. Construction Heuristics  
Construction Heuristics for CVRP  
Construction Heuristics for VRPTW
2. Improvement Heuristics
3. Metaheuristics
4. Constraint Programming for VRP

Marco Chiarandini ... 44

## Metaheuristics

Many and fancy examples, but **first** thing to try:

- Variable Neighborhood Search + Iterated greedy

Marco Chiarandini ... 43

Marco Chiarandini ... 45

### Basic Variable Neighborhood Descent (BVND)

#### Procedure VND

**input** :  $\mathcal{N}_k, k = 1, 2, \dots, k_{max}$ , and an initial solution  $s$   
**output**: a local optimum  $s$  for  $\mathcal{N}_k, k = 1, 2, \dots, k_{max}$   
 $k \leftarrow 1$   
**repeat**  
      $s' \leftarrow \text{FindBestNeighbor}(s, \mathcal{N}_k)$   
     **if**  $g(s') < g(s)$  **then**  
          $s \leftarrow s'$   
          $k \leftarrow 1$   
     **else**  
          $k \leftarrow k + 1$   
**until**  $k = k_{max}$  ;

### Variable Neighborhood Descent (VND)

#### Procedure VND

**input** :  $\mathcal{N}_k, k = 1, 2, \dots, k_{max}$ , and an initial solution  $s$   
**output**: a local optimum  $s$  for  $\mathcal{N}_k, k = 1, 2, \dots, k_{max}$   
 $k \leftarrow 1$   
**repeat**  
      $s' \leftarrow \text{IterativeImprovement}(s, \mathcal{N}_k)$   
     **if**  $g(s') < g(s)$  **then**  
          $s \leftarrow s'$   
          $k \leftarrow 1$   
     **else**  
          $k \leftarrow k + 1$   
**until**  $k = k_{max}$  ;

Marco Chiarandini ... 46

Marco Chiarandini ... 47

- Final solution is locally optimal w.r.t. all neighborhoods
- First improvement may be applied instead of best improvement
- Typically, order neighborhoods from smallest to largest
- If iterative improvement algorithms  $I_k, k = 1, \dots, k_{max}$  are available as black-box procedures:
  - order black-boxes
  - apply them in the given order
  - possibly iterate starting from the first one
  - order chosen by: *solution quality* and *speed*

General recommendation: use a combination of 2-opt\* + or-opt  
 [Potvin, Rousseau, (1995)]

However,

- Designing a local search algorithm is an **engineering** process in which learnings from other courses in CS might become important.
- It is important to make such algorithms as much efficient as possible.
- Many choices are to be taken (search strategy, order, auxiliary data structures, etc.) and they may interact with instance features. Often a trade-off between examination cost and solution quality must be decided.
- The assessment is conducted through:
  - analytical analysis (computational complexity)
  - **experimental analysis**

Marco Chiarandini ... 48

**Table 5.6.** The effect of 3-opt on the Clarke and Wright algorithm.

Problem	Sequential				Parallel			
	No 3-opt <sup>1</sup>	+ 3-opt FI <sup>2</sup>	+ 3-opt BI <sup>3</sup>	K <sup>4</sup>	No 3-opt <sup>5</sup>	+ 3-opt FI <sup>6</sup>	+ 3-opt BI <sup>7</sup>	K <sup>8</sup>
E051-05e	625.56	624.20	624.20	5	584.64	578.56	578.56	6
E076-10e	1005.25	991.94	991.94	10	900.26	888.04	888.04	10
E101-08e	982.48	980.93	980.93	8	886.83	878.70	878.70	8
E101-10c	939.99	930.78	928.64	10	833.51	824.42	824.42	10
E121-07c	1291.33	1232.90	1237.26	7	1071.07	1049.43	1048.53	7
E151-12c	1299.39	1270.34	1270.34	12	1133.43	1128.24	1128.24	12
E200-17c	1708.00	1667.65	1669.74	16	1395.74	1386.84	1386.84	17
D051-06c	670.01	663.59	663.59	6	618.40	616.66	616.66	6
D076-11c	989.42	988.74	988.74	12	975.46	974.79	974.79	12
D101-09c	1054.70	1046.69	1046.69	10	973.94	968.73	968.73	9
D101-11c	952.53	943.79	943.79	11	875.75	868.50	868.50	11
D121-11c	1646.60	1638.39	1637.07	11	1596.72	1587.93	1587.93	11
D151-14c	1383.87	1374.15	1374.15	15	1287.64	1284.63	1284.63	15
D200-18c	1671.29	1652.58	1652.58	20	1538.66	1523.24	1521.94	19

<sup>1</sup>Sequential savings.

<sup>2</sup>Sequential savings + 3-opt and first improvement.

<sup>3</sup>Sequential savings + 3-opt and best improvement.

<sup>4</sup>Sequential savings: number of vehicles in solution.

<sup>5</sup>Parallel savings.

<sup>6</sup>Parallel savings + 3-opt and first improvement.

<sup>7</sup>Parallel savings + 3-opt and best improvement.

<sup>8</sup>Parallel savings: number of vehicles in solution.

What is best?

## Iterated Greedy

**Key idea:** use the VRP construction heuristics

- alternation of Construction and Deconstruction phases
- an acceptance criterion decides whether the search continues from the new or from the old solution.

**Iterated Greedy (IG):**

determine initial candidate solution  $s$

**while** termination criterion is not satisfied **do**

$r := s$

greedily **deconstruct** part of  $s$

greedily **reconstruct** the missing part of  $s$

apply subsidiary **iterative improvement procedure** (eg, VNS)

based on **acceptance criterion**,

keep  $s$  or revert to  $s := r$

In the literature, the overall heuristic idea received different names:

- Removal and reinsertion
- Ruin and repair
- Iterated greedy
- Fix and re-optimize

**Removal procedures**

Remove some **related** customers

(their re-insertion is likely to change something, if independent would be reinserted in same place)

Relatedness measure  $r_{ij}$

- belong to same route
- geographical
- temporal and load based
- cluster removal
- history based

Dispersion sub-problem:

choose  $q$  customers to remove with minimal  $r_{ij}$

$$\begin{aligned} \min \quad & \sum_{ij} r_{ij} x_i x_j \\ & \sum_j x_j = q \\ & x_j \in \{0, 1\} \end{aligned}$$

Heuristic stochastic procedure:

- select  $i$  at random and find  $j$  that minimizes  $r_{ij}$
- Kruskal like, plus some randomization
- history based
- random

## Reinsertion procedures

- Greedy (cheapest insertion)
- Max regret:  
 $\Delta f_i^q$  due to insert  $i$  into its best position in its  $q^{th}$  best route  
 $i = \arg \max(\Delta f_i^2 - \Delta f_i^1)$
- Constraint programming (max 20 costumers)

Marco Chiarandini ... 54

Marco Chiarandini ... 55

Advantages of remove-reinsert procedure with many side constraints:

- the search space in local search may become **disconnected**
- it is easier to implement feasibility checks
- no need of computing delta functions in the objective function

## Further ideas

- Adaptive removal: start by removing 1 pair and increase after a certain number of iterations
- use of roulette wheel to decide which removal and reinsertion heuristic to use ( $\pi$  past contribution)

$$p_i = \frac{\pi_i}{\sum \pi_i} \quad \text{for each heuristic } i$$

- SA as accepting criterion after each reconstruction

Marco Chiarandini ... 56

Marco Chiarandini ... 57

# Outline

1. Construction Heuristics
  - Construction Heuristics for CVRP
  - Construction Heuristics for VRPTW
2. Improvement Heuristics
3. Metaheuristics
4. Constraint Programming for VRP

# Performance of exact methods

Current limits of exact methods [Ropke, Pisinger (2007)]:

CVRP: up to 135 customers by branch and cut and price

VRPTW: 50 customers (but 1000 customers can be solved if the instance has some structure)

CP can handle easily side constraints but hardly solve VRPs with more than 30 customers.

# Large Neighborhood Search

Other approach with CP:

[Shaw, 1998]

- Use an over all local search scheme
- Moves change a large portion of the solution
- CP system is used in the exploration of such moves.
- CP used to **check the validity** of moves and determine the values of constrained variables
- As a part of checking, constraint propagation takes place. Later, iterative improvement can take advantage of the reduced domains to speed up search by performing fast legality checks.

Solution representation:

- Handled by local search:  
**Next pointers:** A variable  $n_i$  for every customer  $i$  representing the next visit performed by the same vehicle

$$n_i \in N U S U E$$

where  $S = \cup S_k$  and  $E = \cup E_k$  are additional visits for each vehicle  $k$  marking the start and the end of the route for vehicle  $k$

- Handled by the CP system: time and capacity variables.

[Shaw, 1998]

## Insertion

by CP:

- constraint propagation rules: time windows, load and bound considerations
- search heuristic most constrained variable + least constrained valued (for each  $v$  find cheapest insertion and choose  $v$  with largest such cost)
- Complete search: ok for 15 visits (25 for VRPTW) but with heavy tails
- Limited discrepancy search

```
Reinsert(RoutingPlan plan, VisitSet visits, integer discrep)
  if |visits| = 0 then
    if Cost(plan) < Cost(bestplan) then
      bestplan := plan
    end if
  else
    Visit v := ChooseFarthestVisit(visits)
    integer i := 0
    for p in rankedPositions(v) and i ≤ discrep do
      Store(plan) // Preserve plan on stack
      InsertVisit(plan, v, p)
      Reinsert(plan, visits - v, discrep - i)
      Restore(plan) // Restore plan from stack
      i := i + 1
    end for
  end if
end Reinsert
```