

Extending the Variable Neighborhood Search Metaheuristic into a Simheuristic for Stochastic Combinatorial Optimization

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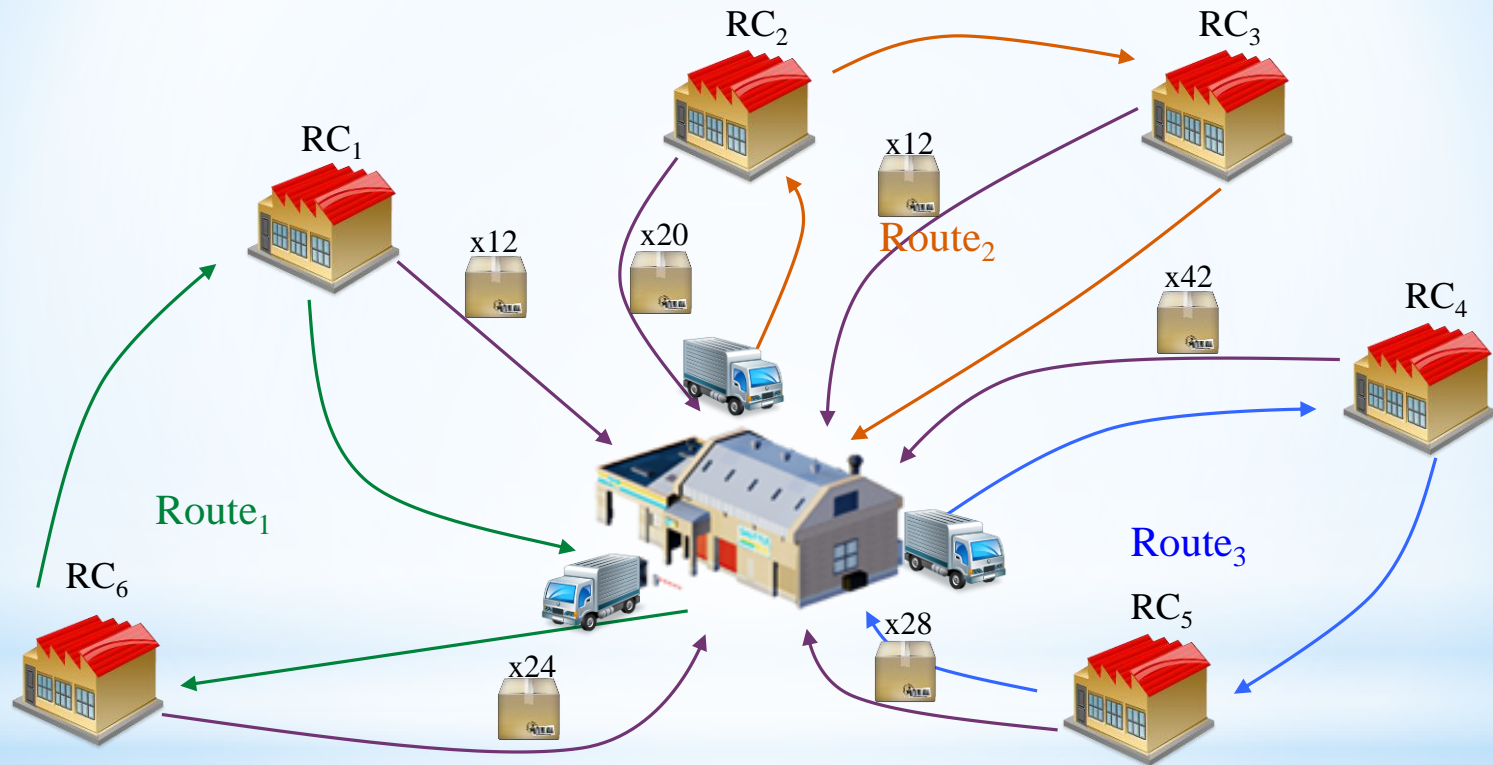
Perez

Angel Juan



Introduction

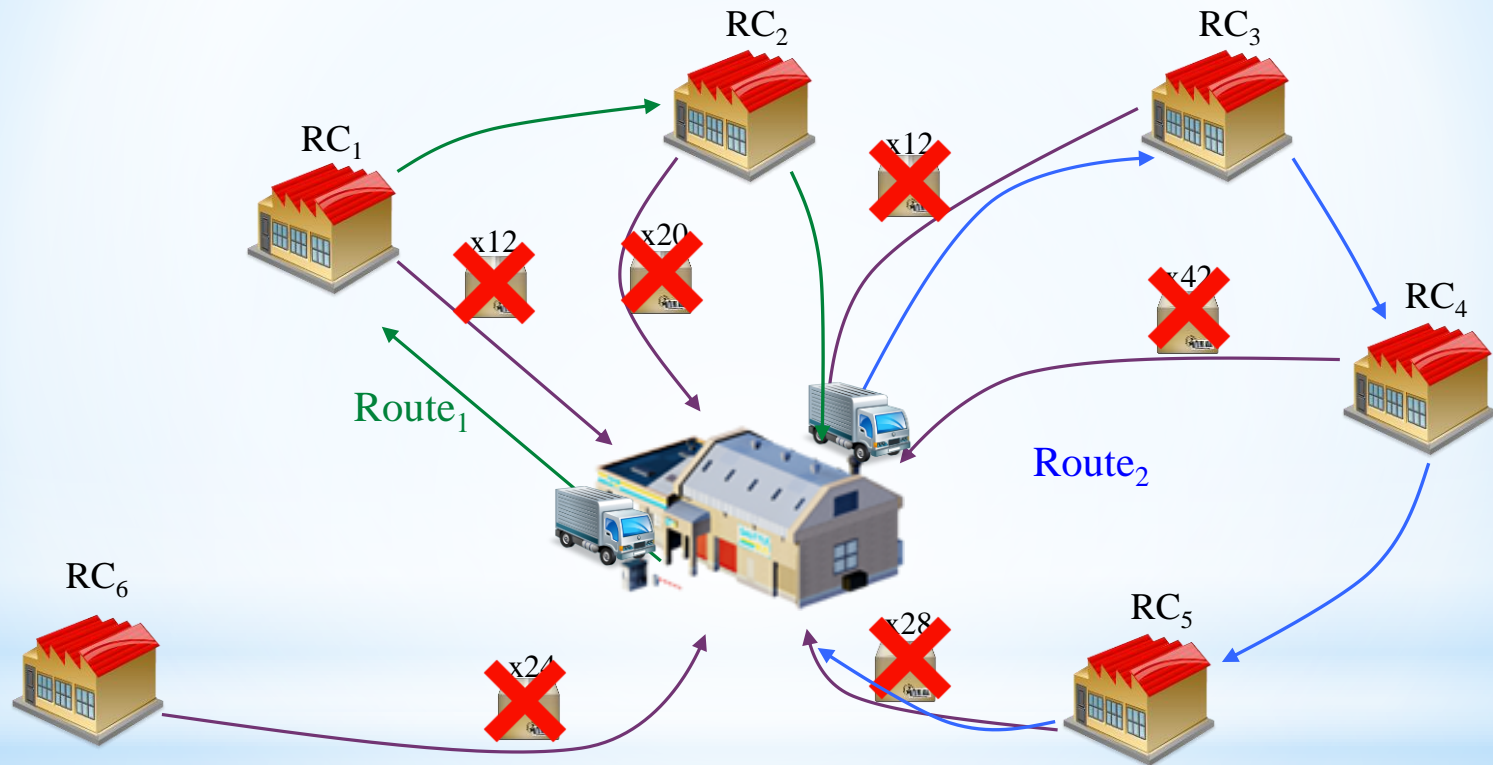
One the most important parading in supply chain management is to move from **descentralized decisions** to cooperative decisions



Each Retail Center determines its own actions independently of others Retail Centers

Introduction

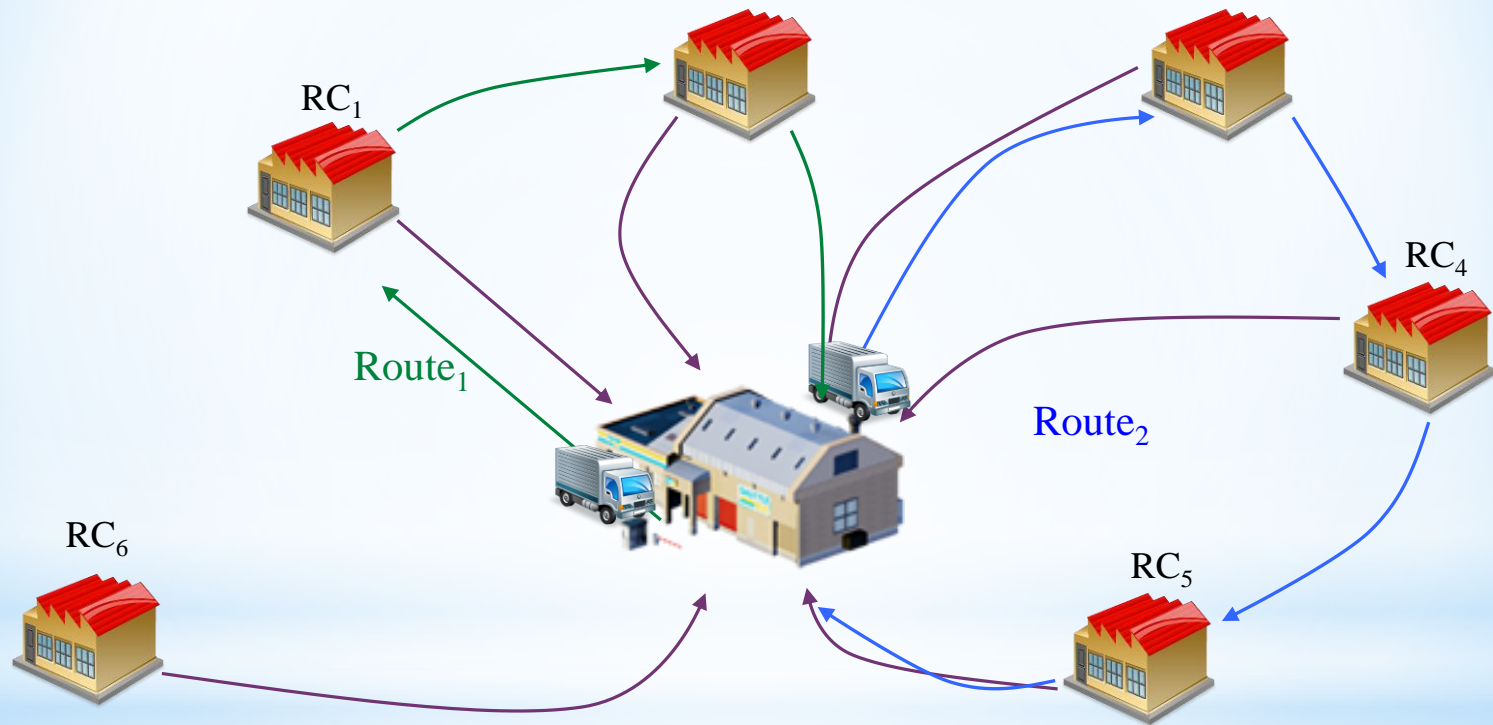
One the most important parading in supply chain management is to move from decentralized decisions to **cooperative decisions**



Vendor (Depot) takes decisions about the inventory levels of its retail centers

Introduction

One the most important parading in supply chain management is to move from decentralized decisions to **cooperative decisions**



Inventory Routing Problem (IRP)

Introduction

Inventory Routing Problem (IRP)

- * The vehicle routing problem (VRP)
- * Inventory Management \ Vendor Managed Inventory (VMI)
- Trade-off decisions:
 - * When to deliver a customer?
 - * How much to deliver a customer?
 - * Which delivery routes to use?



Take better decisions in the global system



Minimize the Total Cost (Inventory cost + Routing cost) for the planning period

Introduction

Inventory Routing Problem (IRP)

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High Level of complexity resulting for the integration



Methods to obtain optimal or quasi-optimal solutions in a bounded time

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- * **Objetives**
- * Formal description problem
- * Proposed Methodology

Objectives

Main Objective

Methodology to solve the IRP using a simheuristic approach in which a metaheuristic solution technique (VNS) is combined with Monte Carlo Simulation (MCS)

Context

Variable Neighborhood Search (VNS)

IRP with stochastic demands

Consider initial stock levels and possible inventory stock-outs

Single Period

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- * Proposed methodology
- * Experimental validation
- * Conclusions and future work

Formal description problem

IRP { Inventory Decision
Vehicle Routing Problem (VRP)

Total Inventory Cost

$$I(r_i, D_i; I \in V^*) = \sum_{\epsilon} f(,)$$

L_i Current (Initial) Inventory Level

L_i^* Maximun Stock Capacity

\leq \leq (Percentage of the Max. Stock Capacity)

$=$ \times (Replenishment level)

$= \begin{cases} - < \\ \geq \end{cases}$ (Order quantity)

(MCS)

$\geq = >$

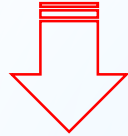
Suplus = -

Stock-Out

$\Rightarrow f(,) = \begin{cases} (-) \geq \\ \leq \end{cases}$ (Function cost)

Formal description problem

IRP { Inventory Decision
Vehicle Routing Problem (VRP)



$G = (V, A)$ (Complete and undirected graph)

$$V = V^* \cup 0$$

$$V^* = \{1, 2, 3, \dots, n\}$$

$$A = \{(i, j) \mid i \in V, j \in V\}$$

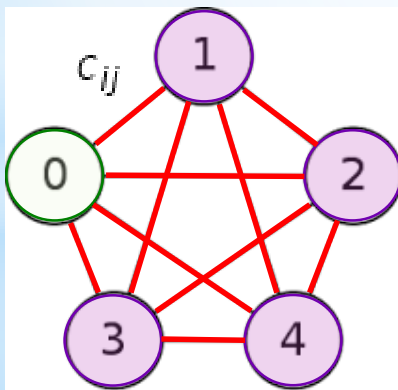
$$c_{ij} = c_{ji}$$

Total Inventory Cost

$$I(r_i, D_i; I \in V^*) = \sum_{\epsilon} f(,)$$

Total Routing Cost

$$() = \sum_{\epsilon} \sum_{\epsilon} \sum_{\epsilon} \left(\begin{array}{c} \\ \\ \end{array} \right) \\ X \in \{0, 1\}$$



Minimize { $E[I(r_i, D_i)] + R(x)$ }

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Proposed methodology



Proposed methodology

Algorithm 1: Calculate expected inventory costs

Input: set V^* of RCs, Inventory policies p , number of simulation runs $nSim$, initial stock $initStock_i$ of each RC i

```
1 foreach  $i \in V^*$  do
2    $simRun \leftarrow 0$ 
3   while  $simRun < nSim$  do
4      $d_i \leftarrow MSC()$  // Simulate from probability distribution
5     foreach Inventory Policy  $p$  do
6        $expInvCost = 0$ 
7        $surplus = unitsToServe(p) + initStock_i - d_i$ 
8         // unitsToServe is FIXED, as it only depends on
        policy
9        $expInvCost = calcInvCost(surplus)$ 
10         // Stock-out or holding
11        $invCosts_i(p) += expInvCost$ 
12     end
13    $simrun++$ 
14 end
15 foreach Inventory Policy  $p$  do
16    $invCosts_i(p) = invCosts_i(p)/nSim$ 
17 end
18 end
19 return expected inventory cost  $invCosts_i(p)$  for each policy at each RC
```

Proposed methodology



Proposed methodology

Algorithm 3: VNS framework

```

Input: initSol
1 while stopping criteria not reached do
2   bestSolList  $\leftarrow \emptyset$ 
3   bestSolList.add(initSol)
4   baseSol  $\leftarrow$  initSol
5   shuffle(neighborhoodsk)
6   k  $\leftarrow$  1
7   repeat
8     newSol  $\leftarrow$  shaking(baseSol, k)
9     improving  $\leftarrow$  true
10    while improving                                     // Local Search

```

Operator	Description
<i>Random policy change</i>	Randomly change inventory policy of $k\%$ customers.
<i>Splitting</i>	Destroy and repair part of current <i>baseSol</i> .

```

15   else
16     improving  $\leftarrow$  false
17   end
18   if totalCosts(newSol) < totalCosts(baseSol) then
19     bestSolList.add(newSol)
20     baseSol  $\leftarrow$  newSol
21     k  $\leftarrow$  1
22   end
23   else
24     k  $\leftarrow$  k+1
25   end
26   until k > kmax
27 end
28 return bestSolList

```

Proposed methodology



Proposed methodology

Algorithm 3: VNS framework

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```

Operator

Description

Greedy heuristic

One by one, the replenishment strategy for each client is adapted to the one with the highest associated decrease in the overall objective function.

Biased randomized heuristic

Biased changing of single customer inventory decisions while considering global inventory and routing costs.

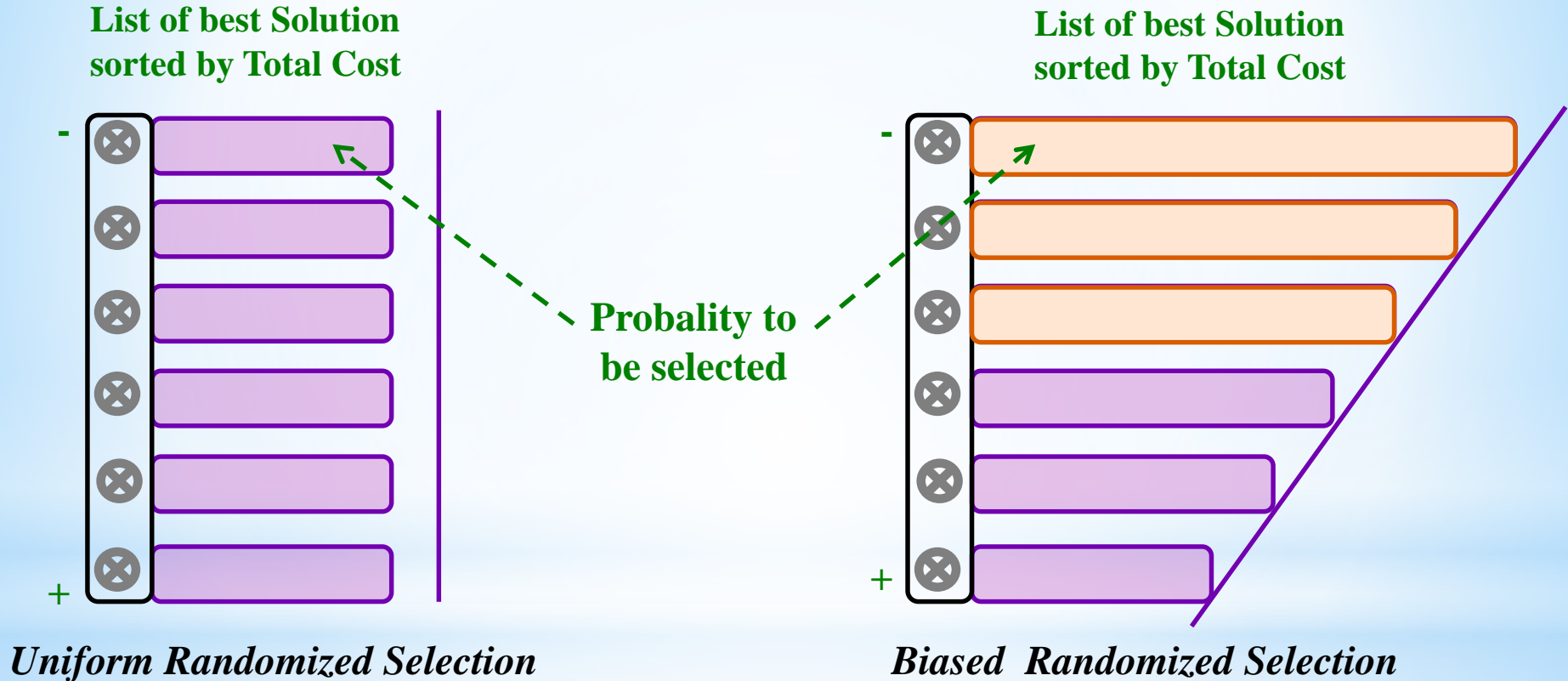
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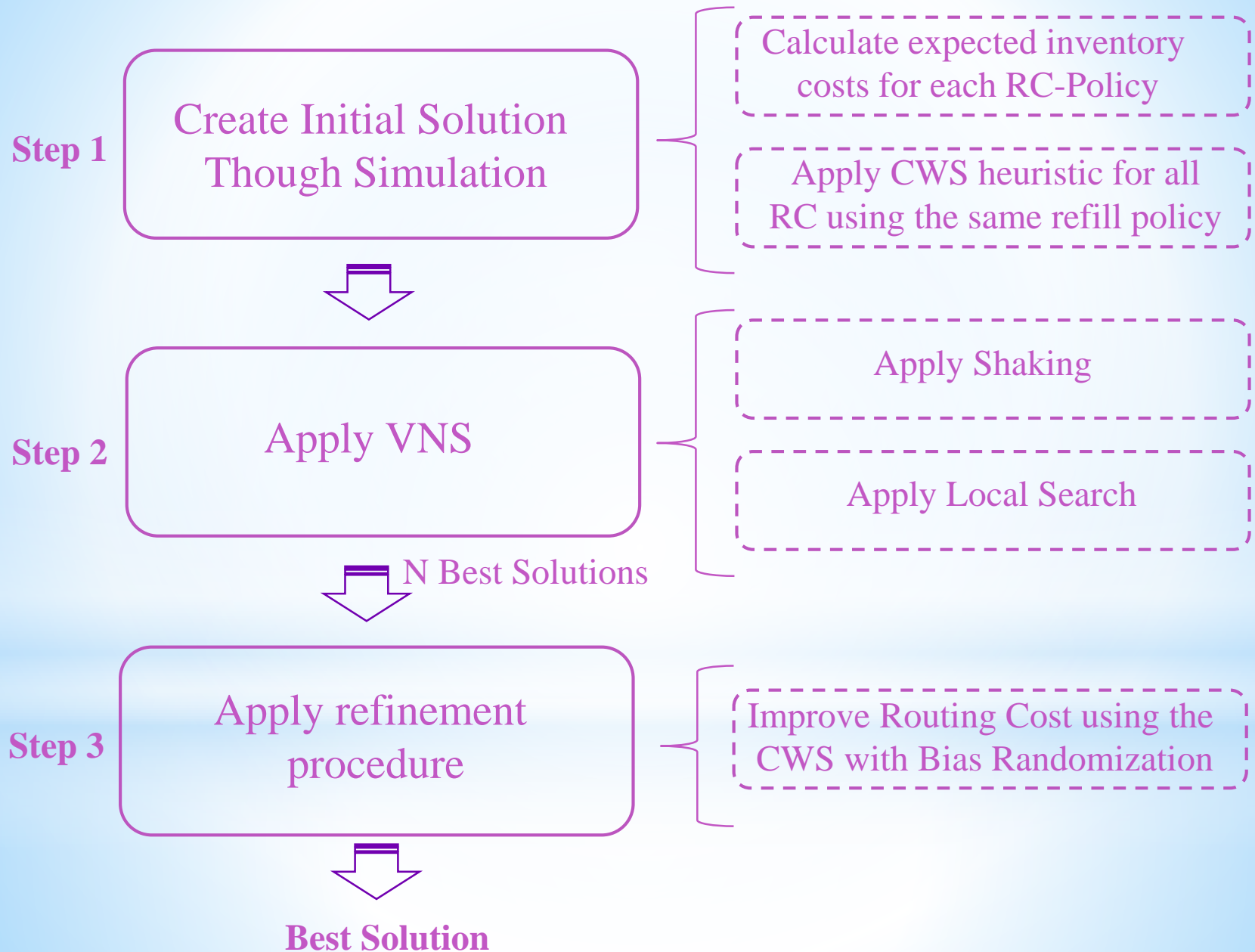
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Proposed methodology

Biased Randomization



Proposed methodology



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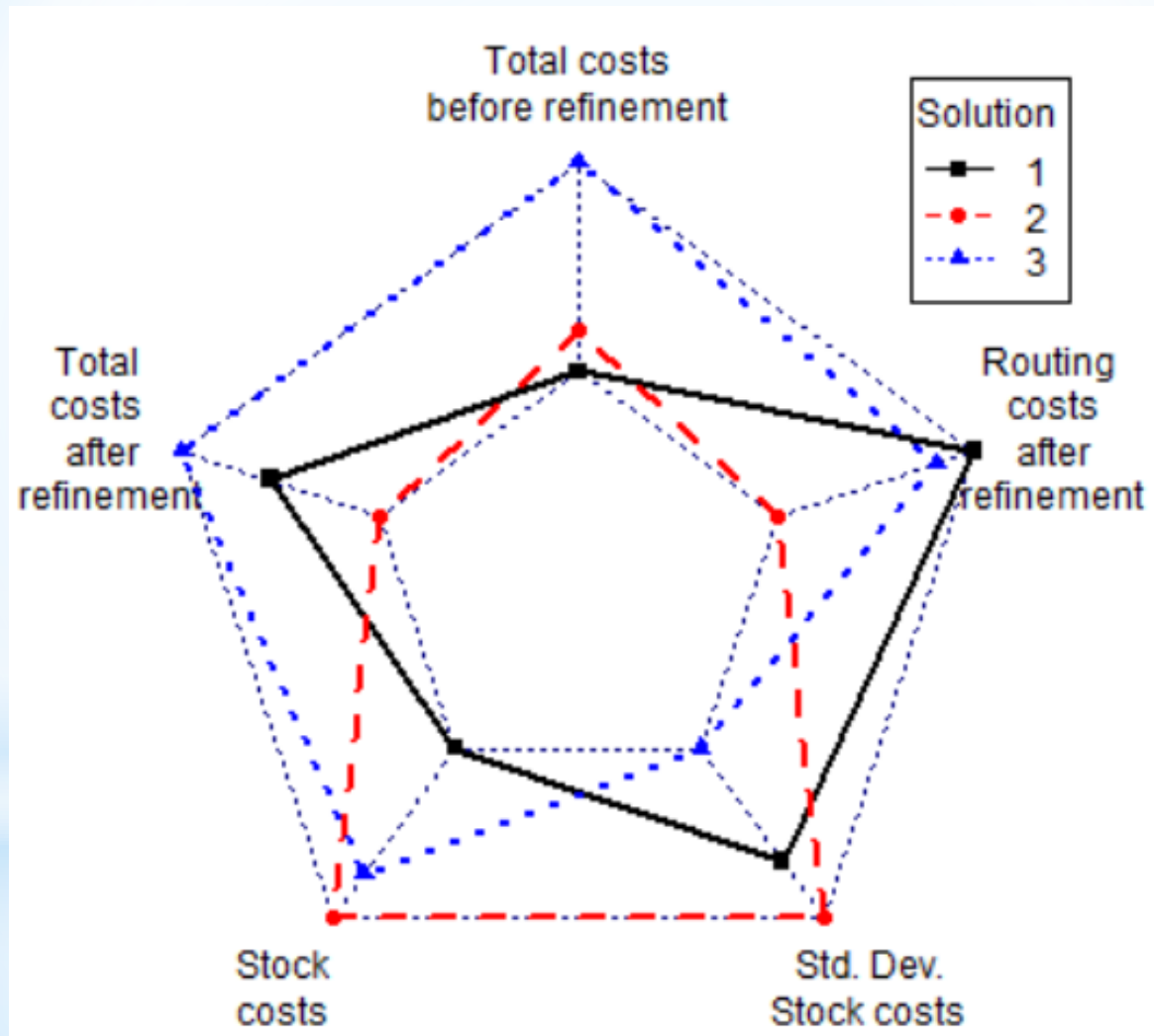
Experimental Validation

- We use the benchmarks for the VRP provided by Augerat et al. (1995).
- The data set consists of 27 instances ranging from 27-80 Retail Centers.
- Each instance is tested with different λ values (0.01/0.25/0.5/0.75/1.0) and three demand variance levels (0.25/0.5/0.75), leading to a total of 15 test per instance (405 total test).
- We have defined 5 *refill policies* (no refill, 0.25%, 0.50%, 0.75%, 1%)
- We compare our results with the obtained results in Juan et al. (2014) (BKS), using the same benchmarks. The algorithm proposed by Juan et al. (2014) has been executed in order to compare our results in the same machine. (30 seconds for each execution in both cases)
- The algorithm is implemented using Java Standard Edition 7 and computational experiments have been performed using a 2.3 Ghz Quad-Core AMD Opteron(tm) processor with 8GB of RAM running under CentOS release 6.6.

Experimental Validation

λ / Variance-combination	(1) BKS	(2) Routing costs ¹	(3) Inventory costs ¹	(4) Total Costs ¹	(5) Total Costs ²	%-Gap (1)-(4)	%-Gap (1)-(5)
0.01/0.25	821.47	783.64	30.70	815.99	814.88	-0.67	-0.80
0.01/0.5	891.29	797.24	83.11	877.72	876.6	-1.52	-1.65
0.01/0.75	961.81	800.46	137.53	937.99	937.13	-2.48	-2.57
0.25/0.25	907.4	771.98	114.24	891.81	890.57	-1.72	-1.85
0.25/0.5	976.09	785.48	167.97	963.77	962.63	-1.26	-1.38
0.25/0.75	1049.02	799.88	230.23	1030.11	1029.05	-1.80	-1.90
0.5/0.25	991.52	766.90	201.84	979.74	978.13	-1.19	-1.35
0.5/0.5	1062.43	780.98	257.15	1050.38	1049.34	-1.13	-1.23
0.5/0.75	1138.28	787.01	332.32	1119.33	1117.98	-1.66	-1.78
0.75/0.25	1074.92	756.95	304.68	1061.67	1059.05	-1.23	-1.48
0.75/0.5	1149.34	772.25	365.07	1137.33	1136.04	-1.05	-1.16
0.75/0.75	1224.37	777.59	433.68	1211.29	1209.22	-1.07	-1.24
1/0.25	1154.91	743.32	376.14	1141.86	1140.71	-1.13	-1.23
1/0.5	1234.49	760.18	437.37	1224.17	1222.26	-0.84	-0.99
1/0.75	1311.33	760.24	536.12	1296.38	1296.13	-1.14	-1.16
Average	1063.24	776.27	267.21	1049.31	1047.99	-1.33	-1.45

Experimental Validation



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Conclusions and future work

Conclusions

- We have presented an initial Simheuristic approach in which the VNS metaheuristic is combined with Monte Carlo Simulation.
- Our algorithm is easy-to-to implement and provides solutions to large IRP problem settings in only a few seconds
- A range of experiments underline the algorithm's competitiveness compared to previously used heuristic methodologies.

Future Work

- Extend the Single Period IRP to Multiperiod.
- Extend to multidepot IRP.

Thanks!

