

Reduced VNS - Sampling, Algorithm and Shaking

Purpose:

Fast exploration without local search refinement.

Algorithm

- ▶ Initialize: $\text{best} = \text{initial solution}$, $k = 1$
- ▶ While $k \leq k_{\max}$:
 - ▶ $\text{candidate} = \text{shake}(\text{best}, k)$
 - ▶ If $\text{cost}(\text{candidate}) < \text{cost}(\text{best})$:
 - ▶ $\text{best} = \text{candidate}$
 - ▶ $k = 1$
 - ▶ Else, $k = k + 1$
- ▶ Return best

Shaking Function (Random m -exchange)

- ▶ Select m customers and randomly reinsert elsewhere.
- ▶ $S' = \text{Shake}(S, m) = \text{RandomInsert}(\text{Select}(S, m))$.
- ▶ Accept if $C(S') < C(S)$.

Why Random m -exchange Works

- ▶ Cheap to compute and always feasible.
- ▶ Explores new areas of the solution space.
- ▶ Degree of shake controlled by parameter m .

Basic VNS - Neighborhood Expansion, Algorithm, and 2-opt Local Search

Purpose: Avoid local minima by structured neighborhood enlargement.

Algorithm

- ▶ Initialize: $\text{best} = \text{initial solution}$, $k = 1$
- ▶ While $k \leq k_{\max}$:
 - ▶ $\text{shaken} = \text{shake}(\text{best}, k)$
 - ▶ $\text{local_opt} = \text{local_search}(\text{shaken})$
 - ▶ If $\text{cost}(\text{local_opt}) < \text{cost}(\text{best})$:
 - ▶ $\text{best} = \text{local_opt}$
 - ▶ $k = 1$
 - ▶ Else, $k = k + 1$
- ▶ Return best

2-opt Local Search

- ▶ Applied intra-route to break and reconnect edges to eliminate crossings.
- ▶ For route $r = (v_0, \dots, v_i, v_{i+1}, \dots, v_j, v_{j+1}, \dots, v_n)$, reversal gives:
$$r' = (v_0, \dots, v_i, v_j, \dots, v_{i+1}, v_{j+1}, \dots, v_n)$$
- ▶ Cost improvement:
$$\Delta C = d(v_i, v_j) + d(v_{i+1}, v_{j+1}) - d(v_i, v_{i+1}) - d(v_j, v_{j+1})$$
- ▶ Accept move if $\Delta C < 0$.
- ▶ Lightweight and effective local optimizer.

Skewed VNS - Cost and Algorithm

Problem: Reduced VNS and Basic VNS may stagnate in local minima.

Skewed Cost Function:

$$C_{\text{skew}}(S') = C(S') + \alpha \cdot d(S', S_{\text{best}})$$

where:

- ▶ $C(S')$ is the cost of candidate solution S' .
- ▶ $d(S', S_{\text{best}})$ measures the distance between S' and the best solution found.
- ▶ α controls the tradeoff between cost and diversity.

Algorithm:

- ▶ Initialize: best = initial solution, $k = 1$
- ▶ While $k \leq k_{\text{max}}$:
 - ▶ shaken = shake(best, k)
 - ▶ local_opt = local_search(shaken)
 - ▶ skewed_cost = cost(local_opt) + $\alpha \times$ solution_distance(local_opt, best)
 - ▶ If skewed_cost $<$ cost(best), then
 - ▶ best = local_opt
 - ▶ $k = 1$
 - ▶ Else, $k = k + 1$
- ▶ Return best

Skewed VNS Effectiveness and Solution Distance Function

Why Skewed VNS is Effective:

- ▶ Penalizes solutions too similar to current best.
- ▶ Promotes exploration of distant basins of attraction.

Why symmetric difference?

- ▶ Captures node assignment and position mismatch.
- ▶ Reflects structural route changes.
- ▶ Efficient to compute vs edit distance or embeddings.

Solution Distance Function:

$$d(S_1, S_2) = \left| \bigcup_{r \in S_1} \text{PosPairs}(r) \triangle \bigcup_{r' \in S_2} \text{PosPairs}(r') \right|$$

where

$$\text{PosPairs}(r) = \{(i, \text{node}) \mid \text{node at position } i \text{ in route } r\}.$$

Solution Distance Function - Python Pseudocode:

- ▶ Define `pos_pairs(routes)` as the set of (position, node) pairs for all routes.
- ▶ Compute symmetric difference:

$$d = |\text{pos_pairs}(\text{routes}_1) \triangle \text{pos_pairs}(\text{routes}_2)|$$

VNS Comparative Summary and Insights

Comparative Analysis of VNS Variants

Feature	RVNS	BVNS	SVNS
Shake	Random m -exchange	Random m -exchange	Random m -exchange
Local Search	No	2-opt	2-opt
Neighborhood Control	Simple	Systematic	Systematic + Penalized
Exploration	Shake	Shake + Local	Shake + Local + Diversity
Acceptance Criterion	$C(S') < C(S)$	$C(S') < C(S)$	$C_{skew} < C_{best}$
Distance Function	No	No	Yes
Computational Cost	Low	Medium	Med-High
Effectiveness	Fast	Better	Best

Takeaways & Usage

- ▶ **RVNS:** Lightweight, stochastic. Use for real-time or quick heuristics.
- ▶ **BVNS:** Adds local improvement via 2-opt. Use for standard optimization routines.
- ▶ **SVNS:** Promotes exploration through diversity. Use for complex search spaces.

Future Directions

- ▶ Adaptive α tuning based on performance.
- ▶ Learnable and dynamic solution representations.
- ▶ Hybridization with deep reinforcement learning agents.
- ▶ Online adjustment of neighborhood structures.