Machine Learning-based Route Reconstruction Heuristics for Supporting Diversification in Meta/Hyper-Heuristics

Supervisors: Jianjun Chen, Jun Qi
Yi Wang, Shuchen Yuan, Longsheng Yan, Haochen Xue

SURF CODE: 2022071

Abstract: ***In this project, Vehicle Routing Problem with Time Window (VRPTW) is considered to find its near optimal solution based on the Heuristic algorithm and an innovative scrambling algorithm. Furthermore, the optimization process is visualized in 3D graphics, and then evaluation and reflection are made.***

01. Introduction

In real-life problems, distribution systems are quotidian and appear when a set of customers demand for goods distributed by a fleet of vehicles. To minimize the global transportation cost, the algorithm seeks a set of routes, each performed by a single vehicle starting and ending at one depot, such that known demands for customers are satisfied, and vehicles serve customers within their capacity. This problem is called Vehicle Routing Problem (VRP). Taking time window into consideration, VRP becomes **VRPTW**, deriving from the situation that customers set the time period that can be served. This project aims to investigate the optimization process of VRPTW by Heuristic and an innovative scrambling algorithm, express this process in 3D graphics, and evaluate and summarize the optimization process.

02. Data

Source

All data comes from Solomon's web page. We use Solomon_100 C101 (1987) as our instance for VRPTW solving.

Parameters

In Solomon's instances, we have the following parameters.

Customer

- Number
- Coordinate
- Demand
- Time window
- Service time

Vehicle

- Fleet size
- Capacity

VEHICLE

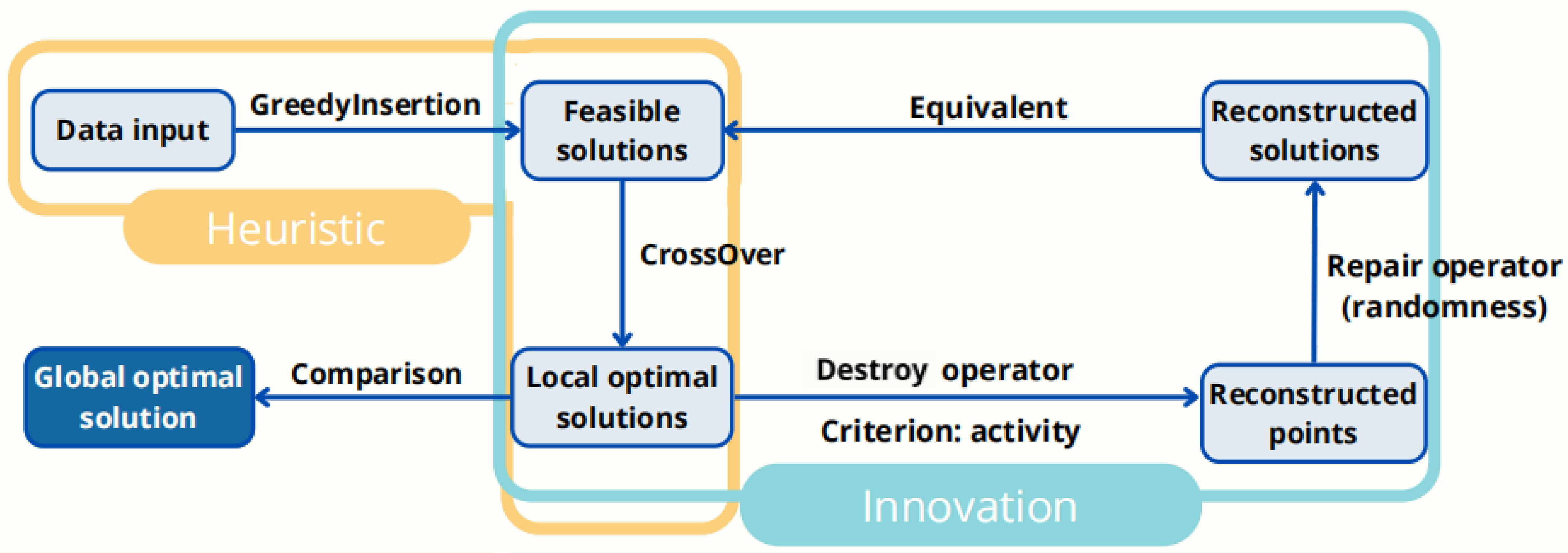
NUMBER	CAPACITY
25	200

CUSTOMER

CUST NO.	XCOORD.	YCOORD.	DEMAND	READY TIME	DUE DATE	SERVICE TIME
0	40	50	0	0	1236	0
1	45	68	10	912	967	90
2	45	70	30	825	870	90
3	42	66	10	65	146	90
4	42	68	10	727	782	90
5	42	65	10	15	67	90

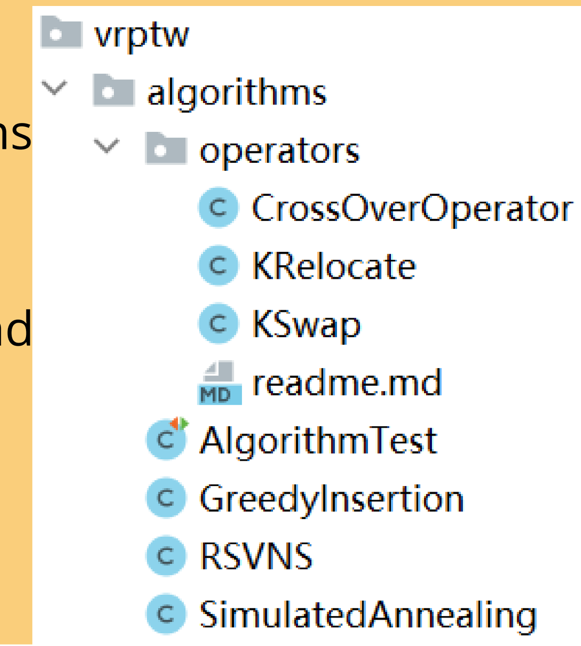
03. Methodology

Principle:



Step 1: Heuristic algorithm to find primitive local optimal solutions

- GreedyInsertion: traverse the nodes to find possible solutions according to the default parameters
- CrossOver: Swap sub-paths and selectively filter to get local optimal solutions
- Finally, we get primitive local optimal solutions



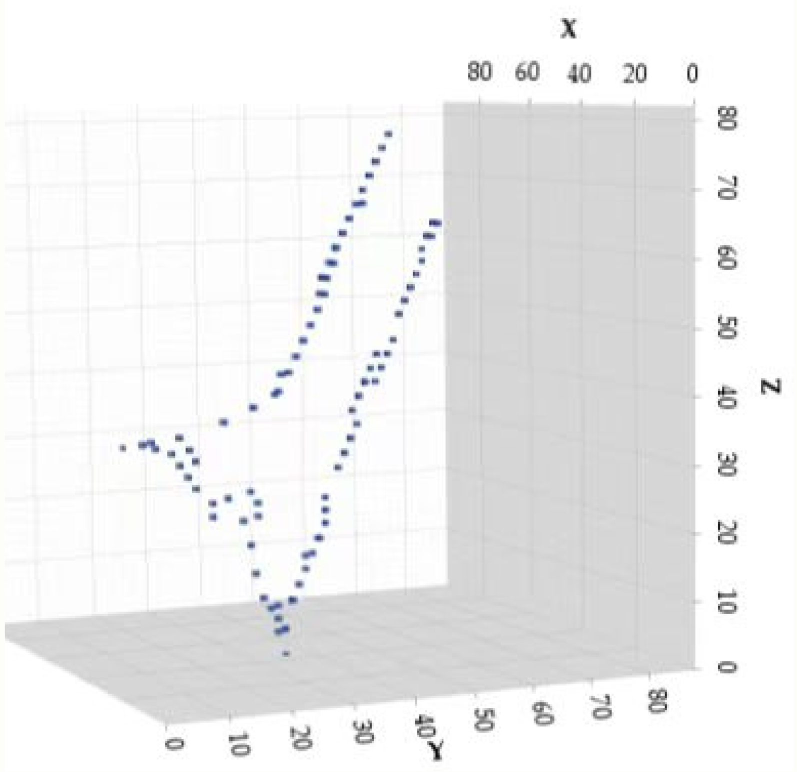
Step 2: Randomly disrupting solutions to find more local optimal solutions

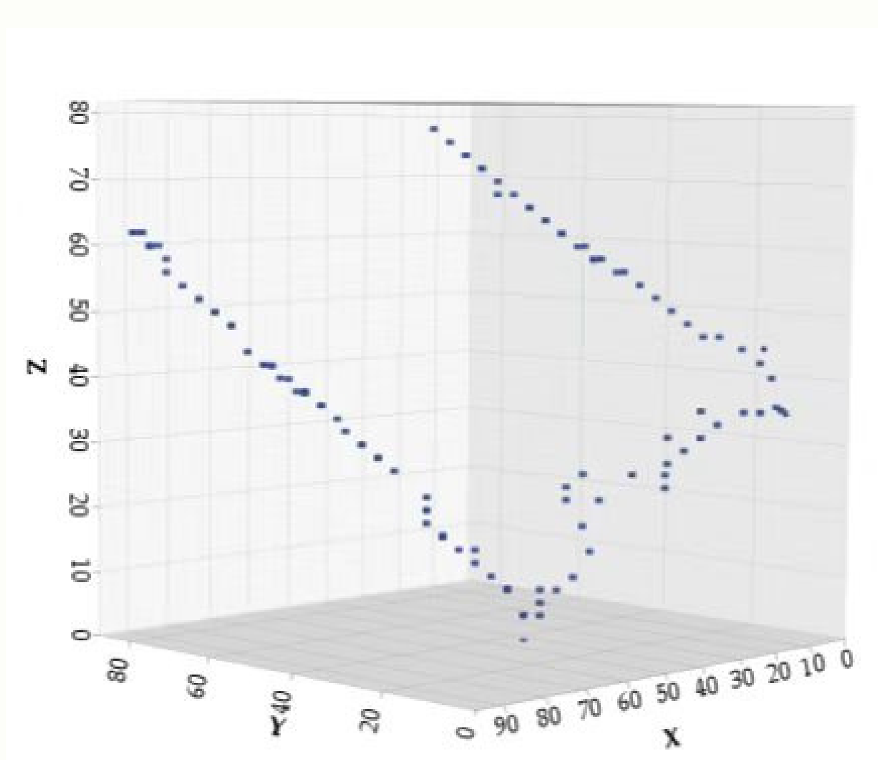
- Choose activity as the destroy operator →
- The number of exchanges per node in the crossover algorithm is used as a measure of node activity →
- Select a number of nodes based on their activity and extract them from the original path →
- Each node traverses the current path in turn to select all insertion positions that satisfy the condition

Step 3: Reinstruct solution place by randomly selectinRandomly disrupting solutions to find more local optimal solutions

- Initially, it is necessary receiving the input that concludes the points to be inserted and their positions that meet the insertion criteria →
- Then randomly picking up an inserted place from the positions to achieve a random effect →
- In the end, the selected node is inserted into a specific node and the original route is deleted to make the similarity of the newly reconstructed space solution and the original one as less as it can

04. Evaluation





- **Evaluation Criteria**:The longer the moving trace is, the better the destroy/repair operators are.
- **Evaluation**: As the given 3D graph shows, the solution space is shifted by a large distance in each direction of the 3D coordinate axes, which proves that the solution space is highly variable and achieves a desirable destruction and reconstruction which show a potential of those chosen operators. Such shifted distances also reflect the kernel of the greedy insertion algorithm. At the same time, the shifted trajectory reveals the function of the algorithm, to find the local optimum in the solution space to a large extent and to achieve adaptive large domain search.

05.Reflection

- **Algorithm**:

The effectiveness of using activity as the destruction operator is to be verified, but the experiment shows a good effect. And only one node is considered each time to insert into the solution with restriction of time window to reconstruct a new solution, which limits the variation range of the solution space.

- **Visualization**:

The graph can be more visible if nodes of the graph are capable of revealing the information of the node quantity and the sequential trait.

05. Conclusion

This experiment makes an attempt in investigating VRPTW of optimizing the disruption/repair operator. Achievements are gained in the selection of disruption operator, while the optimization of repair operator is an urgency to be improved considering the number of vehicles, time spent and other factors rather then merely randomly selecting. Anyway, due to the experimentality of this surf, the correctness of the design is yet to be verified. But in this experiment, there are reasonable results, the rationality of the experiment is somehow preliminary validated.

For the future development, more than optimizing single operator, possible improvment can be conduction if multiple operator is applied.

References:

Toth, P. and Vigo, D. (2002). The vehicle routing problem. Philadelphia: Society For Industrial And Applied Mathematics.
web.cba.neu.edu. (n.d.). c101. [online] Available at: http://web.cba.neu.edu/~msolomon/c101.htm [Accessed 26 Aug. 2022].