

Fast Approximate Solutions using Reinforcement Learning for Dynamic Capacitated Vehicle Routing with Time Windows

Nazneen N Sultana, Vinita Baniwal, Ansuma Basumatary,
Piyush Mittal, Supratim Ghosh, Harshad Khadilkar

nn.sultana@tcs.com

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- ▶ The basic version involves computation of the optimal route for a single or multiple identical vehicles, given the nodes to be visited.
- ▶ Two basic variants of the problem are:
 - ★ Static routing
 - ★ Dynamic routing
- ▶ The variants that we have included in this paper are:
 - ★ Vehicle capacity in terms of load and range.
 - ★ Arbitrary number of customers and locations.
 - ★ Arbitrary number of vehicles.
 - ★ Customer service time windows.
 - ★ Dynamic arrival of demand at arbitrary locations.

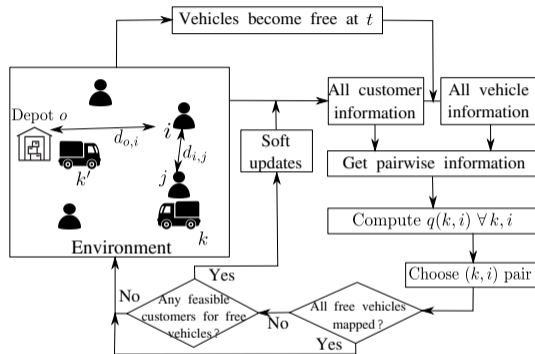
- ▶ Learning based techniques provide good solutions to problems with real world constraints.
- ▶ RL provide significantly faster solutions than exact methods and meta-heuristics.

- ▶ Objective of the problem is to find the total distance J that minimises,

$$J = \min_{a_{i,j,k}, f_{i,k}, l_{i,k}} \left(\sum_{i,j,k} d_{i,j} a_{i,j,k} + \sum_{i,k} d_{o,i} f_{i,k} + \sum_{i,k} d_{o,i} l_{i,k} \right), \quad (1)$$

Proposed Approach

Formulate the problem as a Markov Decision Process (MDP) where each vehicle independently evaluates the value of serving each available customer at each time step after which a centralised allocation heuristic maps each vehicles to customers.



- ▶ Workflow of decision-making at each time step t .
- ▶ The decision loop terminates either when all free vehicles are allocated a customer, or when all feasible customers are exhausted.

► Train Data

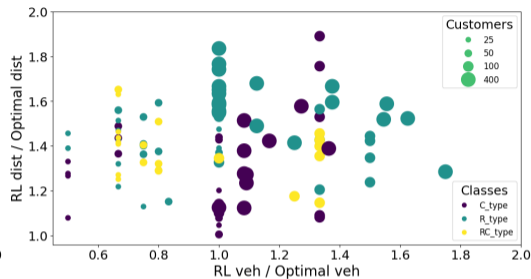
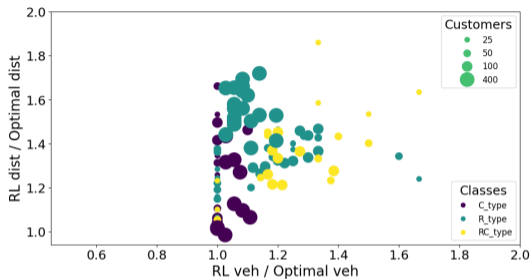
- ★ 20 randomly generated dataset ($|\mathcal{C}| = 20, |\mathcal{V}| = 4$).
- ★ Customer locations (x_i, y_i) are uniformly random distribution.
- ★ The demand of each customer is drawn from an exponential distribution with $\beta = 0.1$.
- ★ The time window width $(T_{i,max} - T_{i,min})$ is Gaussian with $(\mu = 35, \sigma = 5)$.

► Test Data

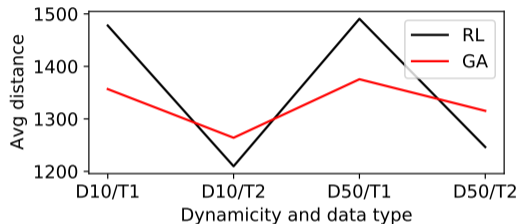
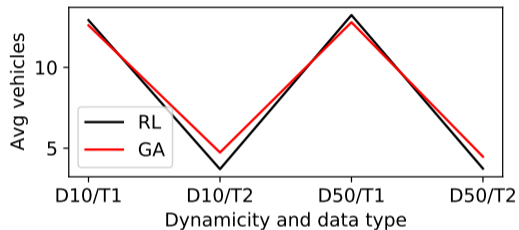
- ★ Solomon benchmark dataset.
- ★ Gehring and Homberger's extended CVRP-TW benchmark.
- ★ Dynamic arrival of customers: we use a simulated dataset that is a modified version of Solomon CVRP-TW.
- ★ An instance with X% dynamicity implies that X% of customers are not revealed at the start, and appear during execution.

- ▶ Mixed integer linear program formulation (MILP)
 - ★ Due to excessive computation times, we only report the results of the MILP formulation for the 25-customer case.
- ▶ Meta-heuristic algorithm based on genetic algorithms (GA).
- ▶ Best-known results from literature.¹

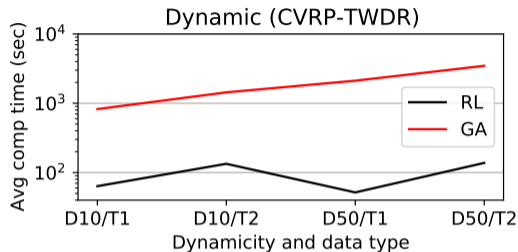
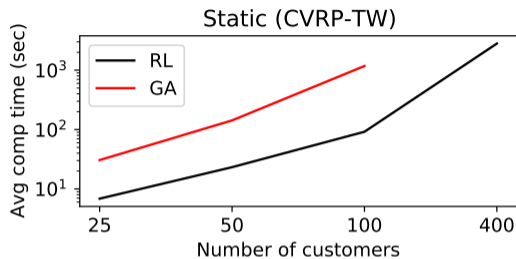
¹<https://www.sintef.no/projectweb/top/vrptw/>



- ▶ Scatter plots of relative distance and vehicle counts for RL in comparison with best-known solutions, for type-1 (left) and type-2 (right) data.
- ▶ RL performs close to the best-known solutions in terms of number of vehicles, and is approximately 35% above optimal in terms of distance travelled.



- ▶ RL outperforms GA in Type-2 data both in terms of vehicle counts and distance travelled.



- ▶ RL has a significant advantage over GA in terms of computation times for both static and dynamic version.
- ▶ RL computation times are nearly constant for both levels of dynamicity and types for dynamic case
- ▶ RL computation time for dynamic is approximately equal to static whereas GA computation time increases with dynamicity.

- ▶ The proposed approach was inherently suited for both dynamic and static vehicle routing with capacity constraints.
- ▶ Capable of producing competitive results with completely out-of-distribution test data demonstrate the scalability and flexibility of the proposed approach.
- ▶ We further wish to explore the options of parallelisability, and flexibility to handle even more constraints and stochasticity.

Thank You..