

## The Problem

The DVRP aims to find the **least cost routes** to serve a set of **stochastic customers** with a given number of **capacitated vehicles**

# Dynamic Vehicle Routing Problem

## Reinforcement Learning vs Traditional Methods

## Algorithms

### Traditional:

- Clarke-Wright Savings
- Tabu Search
- Ant Colony Optimisation (ACO)
- Adaptive Large Neighbourhood Search (ALNS)

### RL:

- Soft Actor-Critic (SAC)
- Advantage Actor-Critic (A2C)
- Proximal Policy Optimisation (PPO)

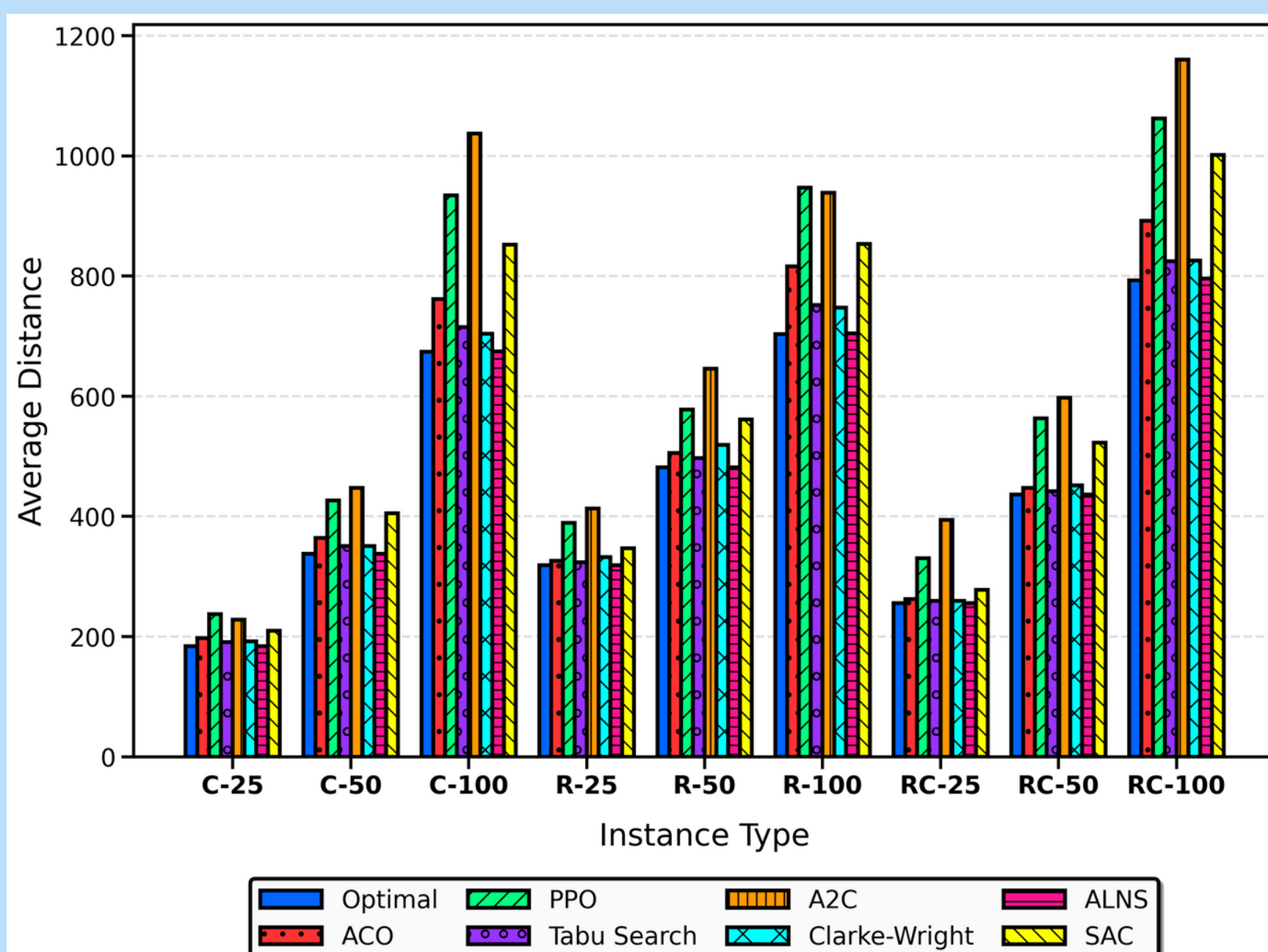
## Objective

Evaluate performance of RL algorithms against heuristic and metaheuristic algorithms - measured by **solution quality**, **computation time** and **dynamic adaption**

## Methodology

- **Evaluated** on adapted CVRP **Solomon Instances** - with random, clustered and random-clustered instances ranging from **25-100 customers**
- **Benchmark** performance obtained from **PYVRPs Genetic Algorithm Solver**

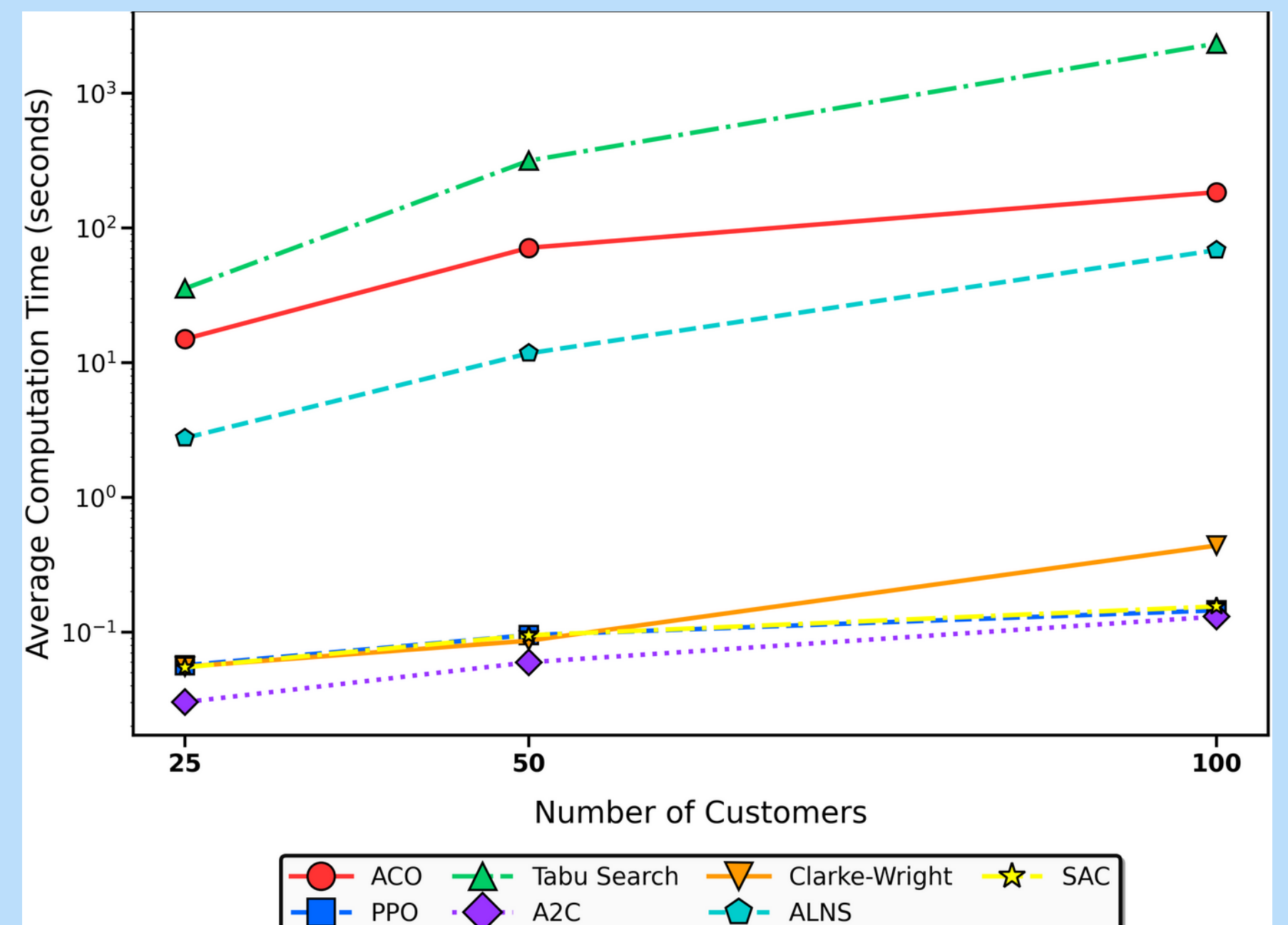
## Solution Quality



Traditional optimisation methods **consistently outperform** RL approaches. ALNS achieves near-optimal solutions (0.05% gap), followed by Clarke-Wright (4.26%) and ACO (4-20%). RL methods (PPO, A2C, SAC) show poor performance with 12-41% optimality gaps. All methods adapted to **dynamic customers**.

## Results

## Computation Time



RL algorithms offer extremely **fast inference** (0.03-0.16s) but require **substantial upfront training**. Clarke-Wright provides quick solutions (0.05-0.47s). ALNS balances quality and speed (2.4-79.8s). ACO and Tabu Search deliver solutions at significantly longer runtimes (15-2400+s).

## Conclusions

Current RL architectures are **fundamentally limited** for constrained vehicle routing problems, despite their ability to **adapt dynamically**. Traditional methods' superiority in this research demonstrates their continued effectiveness and highlights the need for **innovations** to render RL viable in this domain

