Dynamic Electric Vehicle Routing Problem using Population-Based Ant Colony Optimization

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Overview

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Introduction

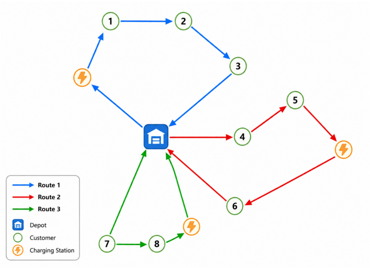
- What are dynamic optimization problems (DOPs)?
  - Problems that change over time
  - Changes may involve the objective function, constraints, problem instance etc.
  - Key properties: Speed and degree of dynamic change
- Why DOPs are important?
  - Similarities with many real-world problems

Introduction

- How to address DOPs?
  - Consider each dynamic change as the arrival of a new problem that need to be solved from scratch
  - Transfer knowledge from the past
- Why ant colony optimization (ACO)?
  - Transfer previous knowledge via pheromone trails

Base Problem

- Electric Vehicle Routing Problem is used as the base problem
- Control of key parameters to generate DOPs with different properties
  - The frequency of change ⇒ synchronized with the algorithmic evaluations
  - The magnitude of change ⇒ defined by the number of nodes modified



Generating Dynamic Test Environments

- Traffic factor to simulate the impact that traffic congestion has on the EV's energy range.
- Every dynamic change, $\lceil mn(n-1) \rceil$ arcs are randomly selected
- The value of arc (i, j) changes as follows:

$$d_{ij}(T+1) = \begin{cases} d_{ij}(0) + \mathcal{R}_{ij}, & \text{if } \mathrm{arc}(i,j) \in A_{rnd}(T), \\ d_{ij}(T), & \text{otherwise}, \end{cases}$$

  - $T = \lceil t/f \rceil$ is the period of a dynamic change
  - t is the evaluations counter
  - f is the frequency of change
  - m is the magnitude of change
  - n is the size of the problem

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P-ACO vs ACO

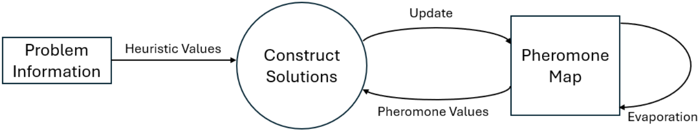


Figure: ACO

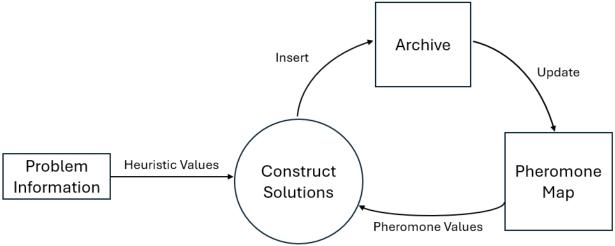


Figure: P-ACO

P-ACO Benefits

- Reduced memory requirements
- Well suited for dynamic optimization problems
- Preserves diversity through population management
    - How to manage the population?

Updating the Population List

- Age-Based Strategy: the eldest ant is replaced
- Quality-Based Strategy: the worst ant is replaced, if the new ant is better
- Elitist-Based Strategy: similar with the Age-Based but the best-so-far is always present
- Similarity-Based Strategy: the most similar ant is replaced, if the new ant is better
  - The similarity of two ants for the EVRP is defined the total number of common arcs.

Responding in Dynamic Changes

- A dynamic change may turn the population-list solutions infeasible
- A repair operator to satisfy the energy constraints of the EVRP is applied
- Pheromone trails are updated accordingly

Experimental Setup

- Three static EVRP benchmark problem instances are utilized: `X-n143-k7-s4`, `X-n351-k40-s35`, and `X-n573-k39-s6`
- Initially $100n$ iterations are executed before the dynamic changes
- $f = 25n$ and $m = 0.05$, $m = 0.1$, $m = 0.25$, $m = 0.5$, $m = 0.75$
- 30 independent executions on different random seeds
- Offline performance:

$$\bar{P}_{offline} = \frac{1}{E}\sum_{t=1}^{E}\pi^{*},$$

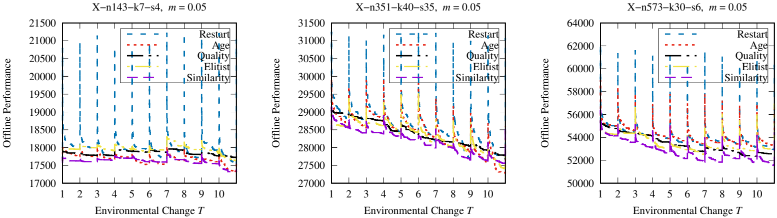
- Investigated update strategies: `Restart`, `Age`, `Quality`, and `Elitist`, against the `Similarity`

Offline Performance Results

- Similarity performs better than the other update strategies

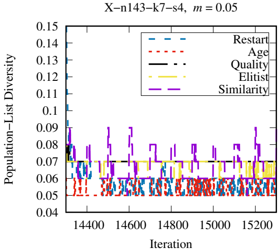
P-ACO, $m \Rightarrow$	0.05	0.1	0.25	0.5	0.75
			X-n143-k7-s4		
Restart	17897.57	17140.28	17072.81	16885.41	16954.35
Age	17676.88	16986.09	16895.32	**16763.24**	**16897.15**
Quality	17889.00	17214.03	17118.47	16947.68	17105.71
Elitist	17940.35	17109.54	17133.22	16941.15	17161.98
Similarity	**17613.72**	**16954.36**	**16864.06**	16808.15	17012.33
			X-n351-k40-s35		
Restart	28615.01	28368.37	27824.96	28372.34	28265.79
Age	28461.78	28347.44	27778.59	28364.14	28255.41
Quality	28570.56	28384.07	27882.98	28191.21	28045.42
Elitist	28422.14	28263.18	27854.47	28343.26	28228.86
Similarity	**28284.75**	**28070.35**	**27665.27**	**27754.91**	**27821.21**
			X-n573-k30-s6		
Restart	54406.74	54718.72	53932.54	53640.49	53053.23
Age	54415.44	54690.12	53929.67	53632.27	53009.77
Quality	53995.75	53697.57	53120.54	52781.50	52418.03
Elitist	53914.28	54335.99	53692.99	53470.71	52942.28
Similarity	**53299.51**	**52824.03**	**52342.23**	**52157.66**	**51704.00**

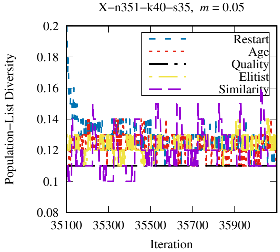
Offline Performance – cont'd

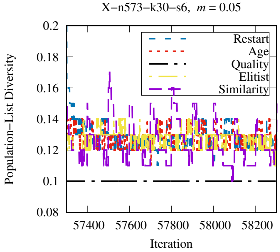


Population-List Diversity

- `Similarity` always maintains sufficient diversity







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Conclusions

- `Restart` is not efficient.
- P-ACO with `Similarity` utilizes more than one promising solution to begin the adaptation process.
- `Quality` and `Elitist` are more greedy, since they exploit the best solution found

Conclusions

Thank you!