Introduction to Dial-A-Ride Problems

Maria Bresich

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TU WIEN Informatics
ALGORITHMS AND COMPLEXITY GROUP

Outline

Dial-A-Ride Problem (DARP)

- Problem Motivation
- Features
- Problem Definition
- Classification
- Variants
- Objective Functions
- Solution Methods

Electric Autonomous DARP (e-ADARP)

- Problem Definition
- Related Work
- Our Project
- Solving Approach

Dial-A-Ride Problem (DARP)

Problem Motivation I Ho et al. (2018)

Transportation services:

- Classic public transit services (bus, train)
  - \+ many passengers, cost efficient
  - – fixed routes, scheduled times, unavailability
- Taxi services
  - \+ door-to-door service
  - – high cost
- On-demand public transit services = Dial-A-Ride (DAR)
  - \+ cost efficient, customizable service
  - – ride-sharing, detours

Problem Motivation II Ho et al. (2018)

DAR applications:

- Door-to-door transportation of disabled and elderly persons
- Airport transportation
- Health care / patient transportation
- Public transportation

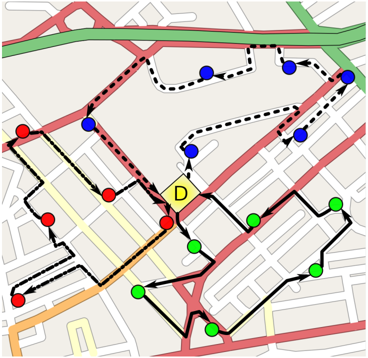
DARP - Typical Features Ho et al. (2018)

- **Request:** transportation from a pickup to a drop-off location
- **Time window:** earliest and latest times of pickup/drop-off
- **Depot(s):** starting and ending location(s) of a trip of a vehicle
- **Trip (route):** a vehicle's tour starting and ending at a depot
- **Vehicle capacity:** maximum number of users in a vehicle at once
- **Load:** number of users in a vehicle
- **(Maximum) Ride time:** (maximum) time a user spends in a vehicle
- **Waiting time:** time without service or travel
- **(Maximum) Route duration:** (maximum) travel time of a vehicle for one trip

Problem Definition I Cordeau and Laporte (2003)

Definition (Standard Dial-a-Ride Problem)

Given: n users with transportation requests from a pickup to a drop-off location, a fleet of m vehicles
Task: Design m vehicle routes serving all requests, s.t. the total routing cost is minimized and certain constraints are satisfied.



Problem Definition II Cordeau and Laporte (2003)

Constraints:

- Every route starts and ends at the depot.
- For every request, the pickup and drop-off location belong to the same route and the drop-off is visited after the pickup location.
- The load of a vehicle does not exceed the vehicle capacity at any time.
- The total duration of a route does not exceed the maximum route duration.
- The service at each location begins in the given time window, and every vehicle leaves the depot and returns to the depot within the planning horizon.
- The ride time of any user does not exceed the maximum ride time.

DARP & Related Problems

DARP:

- Combinatorial optimization problem
- NP-hard
- Generalization of:
  - Traveling Salesman Problem (TSP)
  - Vehicle Routing Problem (VRP)
  - Pickup and Delivery Problem (PDP)
- Considers user inconvenience: e.g., maximum user ride time
- Model: complete graph
  - Vertices: depot(s), pickup/drop-off locations

Classification

Static vs. Dynamic

- Static: all information known in advance, decisions made a priori
- Dynamic: new information revealed during operation, existing plans modified accordingly

Deterministic vs. Stochastic

- Deterministic: information known with certainty at the time of decision
- Stochastic: information still undetermined when decisions are made, information about the uncertainty may be available (e.g., probability distribution)

DARP Variants Molenbruch et al. (2017); Ho et al. (2018)

- Single vehicle vs. fleet of vehicles
- Homogeneous vs. heterogeneous
- Single- vs. multi-trip
- Single vs. multiple depots
- Passenger transfers
- Hard vs. soft constraints
- Single vs. multiple objectives

Objective Functions Molenbruch et al. (2017); Ho et al. (2018)

Operators' perspective:

- Operating cost minimization
- Vehicle usage efficiency maximization
- Demand satisfaction maximization

Users' perspective: inconvenience minimization

- Total and/or maximum ride time
- Waiting time
- Number of transfers (if allowed)

Others:

- Vehicle emissions
- Staff workload

Solution Methods Molenbruch et al. (2017); Ho et al. (2018)

Exact methods:

- Mainly based on branch-and-bound (B&B)
- Dynamic programming
- Small instances of deterministic and static DARP: 8 vehicles, 96 requests

Heuristics and metaheuristics (MHs):

- Classical algorithms: IH, LS, TS, SA, DA, VNS, (A)LNS, GA
- Hybrid algorithms: combination of MHs, with mathematical programming, or constraint programming
- Larger instances: 17 vehicles, 214 requests

Other methods:

- Approximation algorithms

State-Of-The-Art - Standard DARP Ho et al. (2018)

Hybrid adaptive large neighborhood search (ALNS) by Gschwind and Drexl (2019)

- ALNS with dynamic programming
  - Multiple destroy and repair operators
  - Roulette wheel selection
  - Adaptive weight adjustment
  - Simulated annealing acceptance criterion
  - Further optimize elite solutions
- Set covering problem on promising routes
- Results:
  - Instances: 13 vehicles, 144 requests
  - Runtime: 14 - 688 s, $\emptyset = 200$ s

Large Neighborhood Search (LNS) Shaw (1998); Pisinger and Ropke (2010)

- Local search metaheuristics
- Large neighborhoods with complex move operators
  - Destroy operator
  - Repair operator

Large Neighborhood Search (LNS) Shaw (1998); Pisinger and Ropke (2010)

- Local search metaheuristics
- Large neighborhoods with complex move operators
  - Destroy operator
  - Repair operator

Input: feasible solution x
Output: best found solution x^b
$x^b \leftarrow x$;
repeat
    $x^t \leftarrow r(d(x))$;
    if accept(x^t, x) **then**
        $x \leftarrow x^t$;
    if $c(x^t) < c(x^b)$ **then**
        $x^b \leftarrow x^t$;
until stop criterion is met;
return x^b;

Algorithm 1: Large Neighborhood Search

Large Neighborhood Search (LNS) Shaw (1998); Pisinger and Ropke (2010)

- Local search metaheuristics
- Large neighborhoods with complex move operators
  - Destroy operator
  - Repair operator

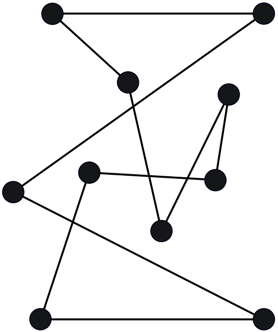


Figure: Initial solution.

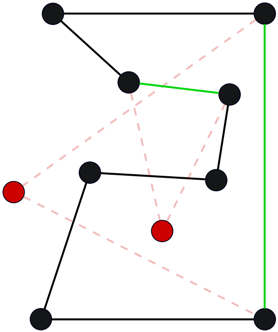


Figure: After destroy operation.

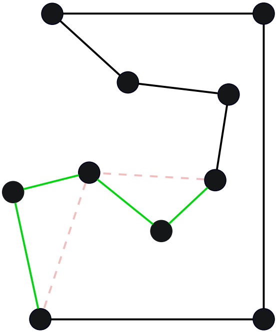


Figure: After repair operation.

Adaptive Large Neighborhood Search (ALNS)

Ropke and Pisinger (2006)

- Extension of LNS
- Multiple destroy and repair operators with weights
- Roulette wheel selection principle
- Adaptive weight adjustment based on previous performance

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Input: feasible solution x
Output: best found solution x^b
$x^b \leftarrow x$;
$\rho^- = (1, \ldots, 1)$; $\rho^+ = (1, \ldots, 1)$;
repeat
  select destroy and repair operators $d \in \Omega^-$ and $r \in \Omega^+$ using ρ^- and ρ^+;
  $x^t \leftarrow r(d(x))$;
  if accept(x^t, x) **then**
    $x \leftarrow x^t$;
  if $c(x^t) < c(x^b)$ **then**
    $x^b \leftarrow x^t$;
  update ρ^- and ρ^+;
until stop criterion is met;
return x^b;

Algorithm 3: Adaptive Large Neighborhood Search (Pisinger and Ropke (2010))

Electric Autonomous DARP (e-ADARP)

Problem Definition I Bongiovanni et al. (2019)

Definition (Static Electric Autonomous DARP)

Given: n users with transportation requests from a pickup to a drop-off location, a fleet of m electric autonomous vehicles

Task: Design m vehicle routes serving all requests, s.t. the total travel time and excess ride time of all users are minimized and certain constraints are satisfied.

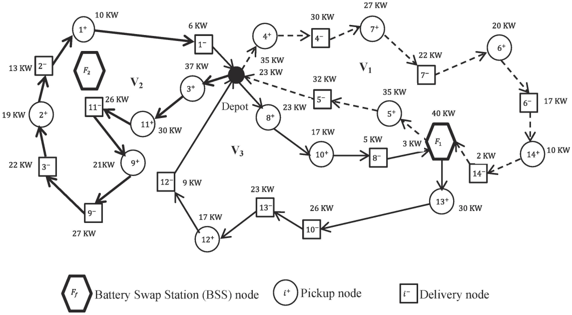

Figure: Example of e-DARP taken from Masmoudi et al. (2018).

Problem Definition II Bongiovanni et al. (2019)

DARP constraints:

- Every route starts and ends at the depot.
- For every request, the pickup and drop-off location belong to the same route and the drop-off is visited after the pickup location.
- The load of a vehicle does not exceed the vehicle capacity at any time.
- The total duration of a route does not exceed the maximum route duration.
- The service at each location begins in the given time window, and every vehicle leaves and returns to a depot within the planning horizon.
- The ride time of any user does not exceed the maximum ride time.

Problem Definition II Bongiovanni et al. (2019)

e-ADARP constraints:

- Every route starts and ends at ~~the depot~~ $\rightarrow$ a depot.
- For every request, the pickup and drop-off location belong to the same route and the drop-off is visited after the pickup location.
- The load of a vehicle does not exceed the vehicle capacity at any time.
- ~~The total duration of a route does not exceed the maximum route duration.~~
- The service at each location begins in the given time window, and every vehicle leaves and returns to a depot within the planning horizon.
- The ride time of any user does not exceed the maximum ride time.

Problem Definition III Bongiovanni et al. (2019)

New constraints:

- The battery level of vehicles cannot exceed the battery capacity and cannot fall below zero at any time.
- Vehicles have to return with minimal battery levels to the destination depots.
- Recharging stations can only be visited when there is no user on board.
- Each recharging station can only be visited at most once by all vehicles.

Problem Definition IV Bongiovanni et al. (2019)

Extension of DARP with supplementary features:

- Battery management
- Intermediate stops for (partial) vehicle recharge
- Heterogeneous vehicles: capacity, battery
- Different origin and destination depots
- No restrictions on maximum route durations
- Total excess ride time of users in objective

Simplifying assumptions:

- Constant battery consumption independent from load, speed, and state-of-charge (SOC)
- Linear increase of SOC with time considering a recharge rate

Problem Definition V Cordeau and Laporte (2007); Bongiovanni (2020)

Challenge: scheduling problem

- DARP: determine the departure time from the depot and the time at which service should begin at each location such that time windows are satisfied and route duration is minimized
- e-ADARP: additionally determine time for partial recharging while also minimizing user excess ride time
- Delays (sometimes) beneficial

Related Work

Static e-ADARP:

- MILP formulations and branch-and-cut algorithm by Bongiovanni et al. (2019)
- Bilevel large neighborhood search (BI-LNS) by Limmer
  - Outer level: set/optimize visits to recharging stations
  - Inner level: insert/optimize requests
- Deterministic annealing local search (DA-LS) by Su et al. (2023)

Dynamic e-ADARP:

- Machine learning-based 2-phase metaheuristic (ML-LNS) by Bongiovanni et al. (2022)
  - First phase: greedy insertion algorithm
  - Second phase: ML-based LNS

Our Project

Static and deterministic e-ADARP (for now)

- Dynamic and stochastic variants later

Solving approach: combination of LNS and ML

- Multiple operators: simple, fast
- Learn LNS operator selection

Challenges:

- Fast prediction with ML model
- Efficient evaluation and scheduling for routes

Solving Approach - Preprocessing Cordeau (2006); Bongiovanni et al. (2019)

Time window tightening:

- Determine missing time windows
- Tighten known time windows

Arc elimination:

- Remove infeasible arcs from the complete graph
- Includes identification of incompatible user pairs
- Based on constraints:
  - Time windows
  - Pairing and precedence
  - User ride time
  - Battery capacity

Solving Approach - LNS I

Request operators: (Ropke and Pisinger (2006); Shaw (1998))

- Destroy:
  - random removal
  - worst removal
  - Shaw removal
- Repair:
  - basic greedy heuristic
  - regret heuristics: regret-2, regret-3
- Possible approach:
  - disregard battery feasibility
  - apply recharging station insertion operator after destroy+repair

Solving Approach - LNS II

Recharging station operators: (Keskin and Çatay (2016))

- Destroy:
  - random removal
  - worst distance removal
  - worst charge usage removal
- Repair:
  - greedy insertion
  - best insertion

Solving Approach - ML

Ideas:

- Learn LNS operator selection
  - Similar to Bongiovanni et al. (2022): random forest classification
  - Select pair of destroy and repair operators (for now)
  - Sequentially select destroy and repair operator (maybe later)
- Reinforcement learning (RL)
  - Avoid the need for labeled data
  - Similar to Johnn et al. (2023): Graph Reinforcement Learning for Operator Selection in the ALNS Metaheuristic
- ML model: neural network with multi-layer perceptron architecture
- Aggregated features
  - Efficient computation
  - E.g., features by Bongiovanni et al. (2022)

Discussion & Questions

Thank you!

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e-ADARP Benchmark Instances

Small size: 2 - 5 vehicles, 16 - 50 requests

- 14 instances:
  - introduced by Bongiovanni et al. (2019)
  - based on DARP benchmark instances by Cordeau (2006)
- 14 instances:
  - introduced by Bongiovanni et al. (2019)
  - based on ride sharing data from Uber Technologies Inc.

Medium size: 5 - 8 vehicles, 60 - 96 requests

- 10 instances:
  - introduced by Su et al. (2023)
  - based on DARP benchmark instances by Ropke et al. (2007)

Large size: 180 - 260 vehicles, 3600 - 5200 requests

- 5 instances
- introduced by Limmer