A Routing and Reservation System for Battery Swaps for Electric Vehicles

Jonathan Adler and Pitu Mirchandani
Arizona State University

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Overview

Electric vehicles &
Charging Infrastructure

Shortest Walk from O to D

Routing and Reservation System

Electric vehicles

- Growing in popularity: Tesla sold over 22,450 electric cars in 2013
- Have a limited range, which can cause drivers to have anxiety
  - Typically charged at home or at the office for long periods of time
  - Charging at origin and destination insufficient for long range trips

Source: Tesla

Charging an electric vehicle mid trip

Fast charging stations

- A station where a car charges its battery quickly to a partially full state
- Still require a half an hour to charge
- Placed on the US Eastern and Western seaboards by Tesla, and can be used for free

Battery exchange stations

- A station where a car swaps an empty battery with a fresh one
- Pioneered by Better Place, declared bankruptcy in May :(
- Expensive since many extra batteries are required to be at the stations
- Tesla has produced a vehicle that can battery swap in 90 seconds

Source: Better Place, Tesla

Alternative-fuel vehicles

- Several different types of alternative fuels
  - Compressed Natural Gas (CNG)
  - Hydrogen fuel cells
- Specialized fuel requires specialized refueling stations, thus vehicles have similar problems as electric ones
- Toyota is rolling out hydrogen powered cars in California in 2015, CNG vehicles already available

Source: Toyota, Bizjournals.com

Objective

- Optimization problems for design and operation of such vehicles are related to OR-type literature. E.g.,
  - **Routing vehicles from origin to destination (OD)**
  - Scheduling a fleet of vehicles to service customers
  - **Given OD demand, determining how the demand should be distributed along roads or constrained resources**
- Major Issue: Electric and alternative-fuel vehicles have a limited distance before they need to stop and refuel, which can only be done at a small number of locations
- *How can we solve these optimization problems for electric and alternative-fuel vehicles with fixed refueling locations?*

The electric vehicle shortest walk problem

Electric vehicle shortest walk problem

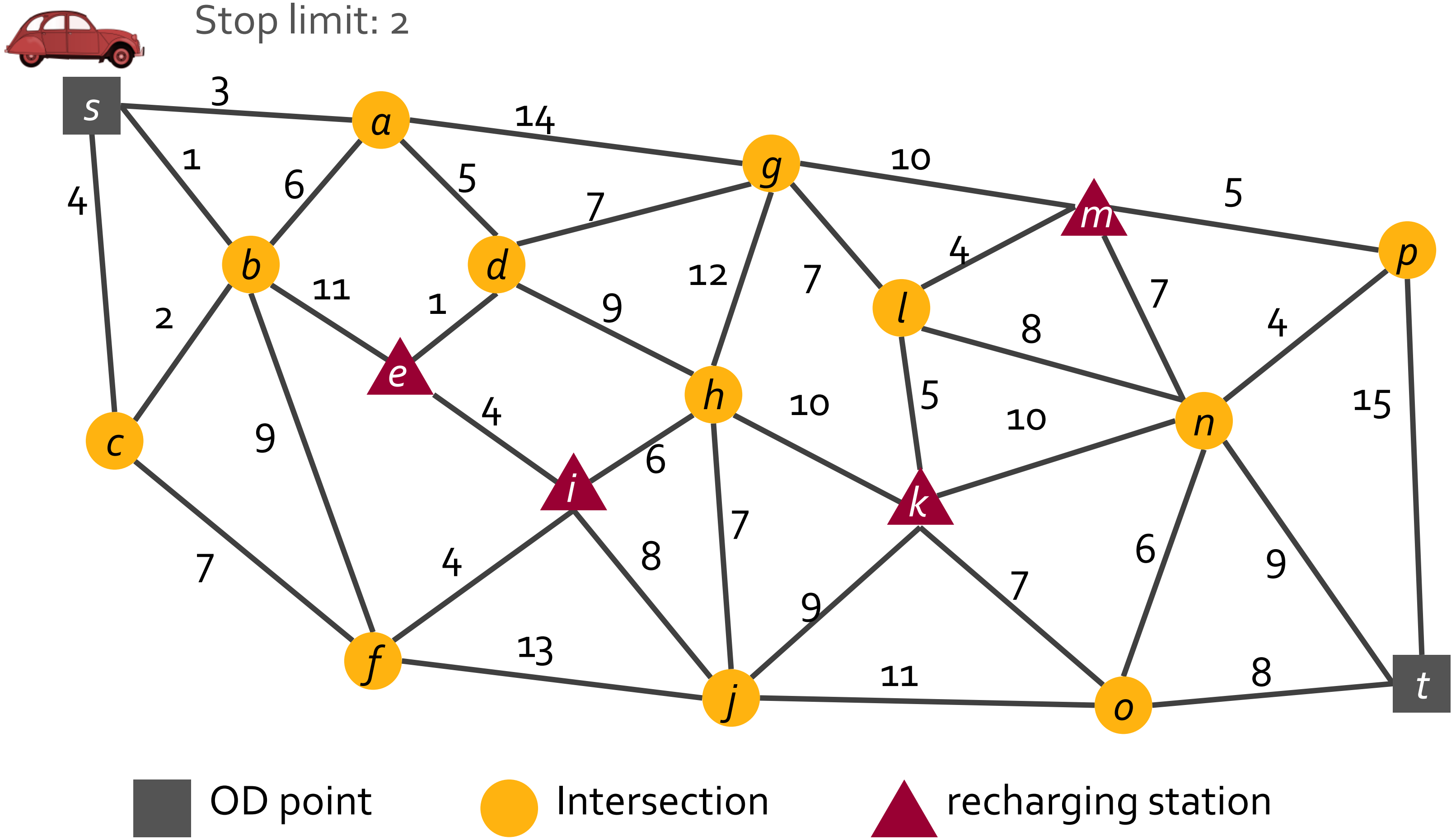
- Suppose we wanted to find the route an electric vehicle should take from an origin to a destination
- The route must include where to stop to recharge the battery
- Can't assume the shortest unconstrained path will have sufficient stops on the way
- Not necessarily a "path" since may have to traverse edges multiple times
- We may want to limit the number of stops to a certain number because they are frustrating
- *How do we find this shortest walk? Can it be done in polynomial time?*

Brief Lit Review

- Ichimori first analyzed this problem in 1981, didn't account for limiting the amount of times the vehicles stops
- We assume distance traveled and time are proportional, other people (Smith et al. 2012, Laporte & Pascoal 2011) analyzed the case where they are not
- Most modeling of where to locate charging stations (e.g., Kuby et al. 2005) assume no detouring

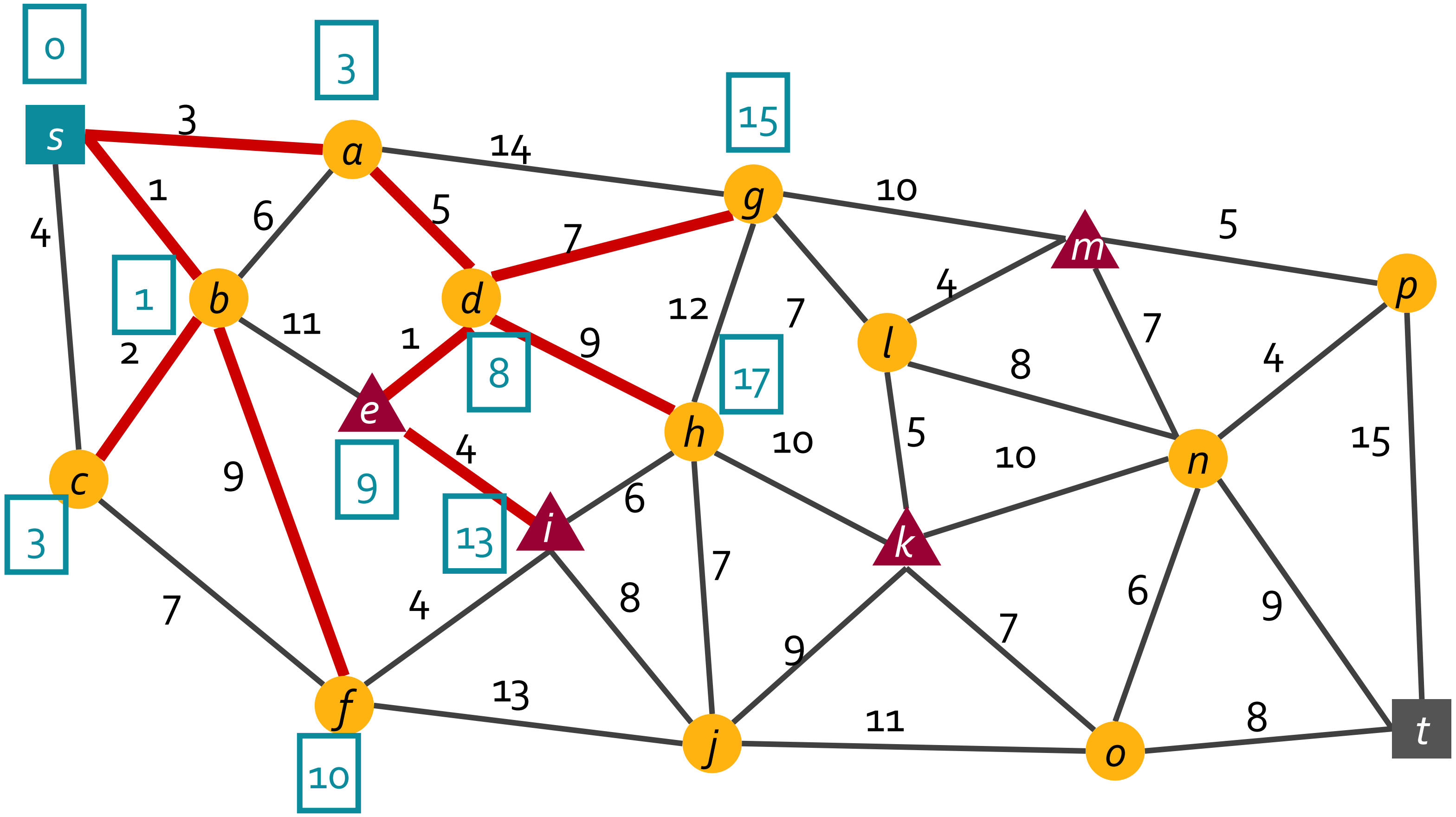
Example Problem

Driving limit: 20
Stop limit: 2



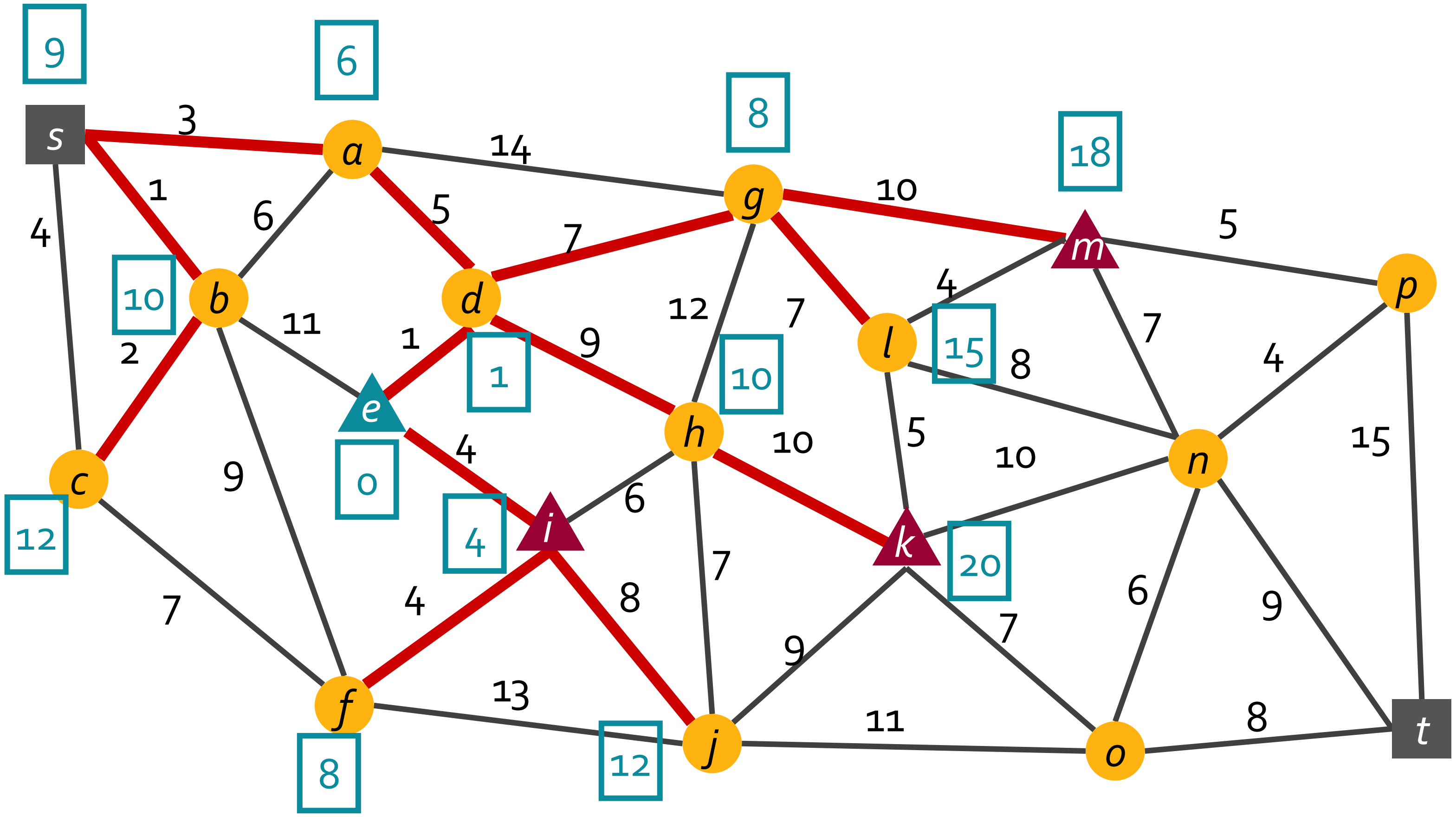
Objective is to get from s to t while stopping at most 2 times to charge the battery

Spanning tree from *s*



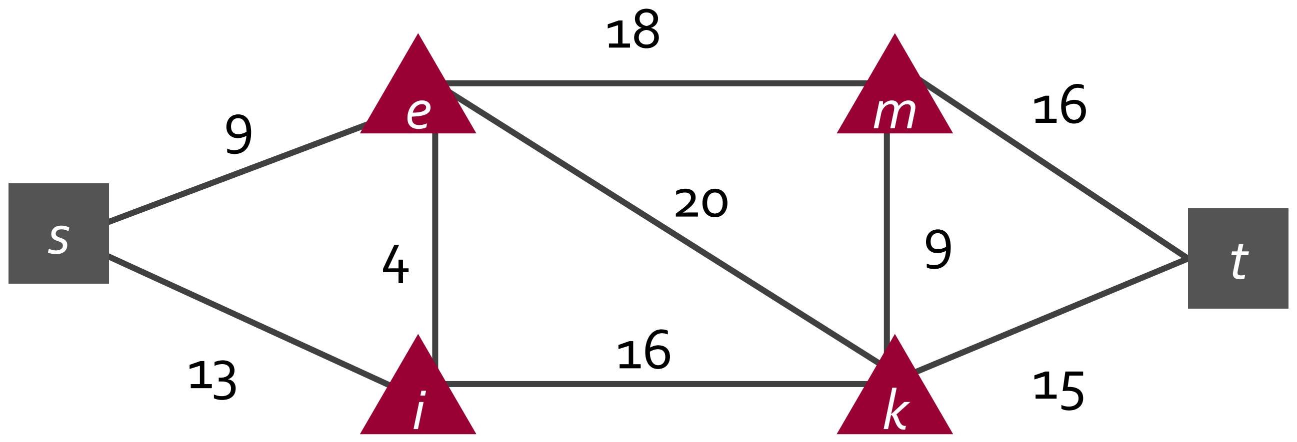
We can pre-calculate which charging stations are reachable from the start point

Spanning tree from *e*



We can also calculate which charging stations are reachable from each other, and which can reach the terminal vertex

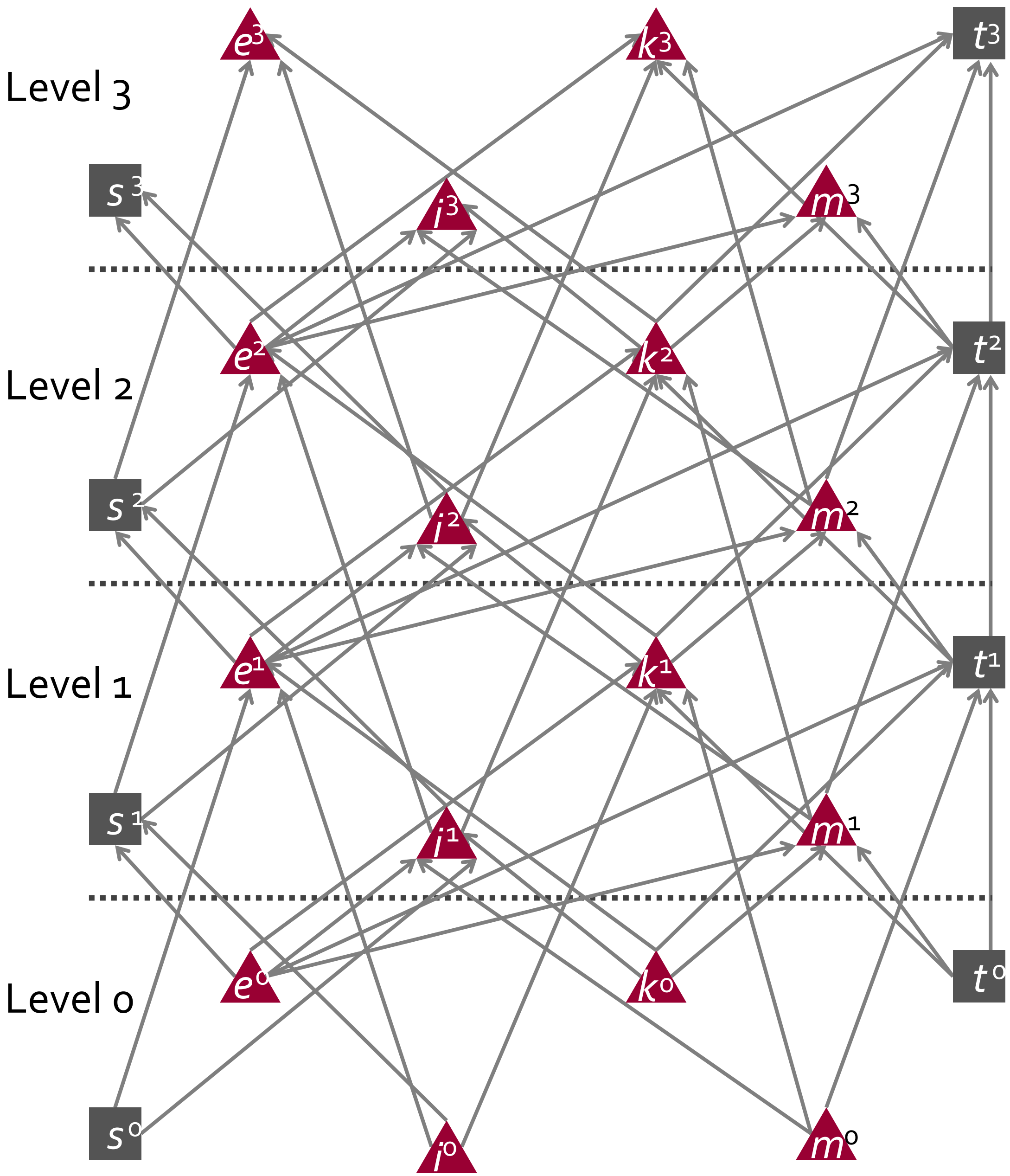
Meta-network



- With all of those shortest paths, we can make a new meta-network
- The nodes in the meta-network have an edge if the vertices can be reached in a single charge in the original graph
- The shortest path in this graph corresponds to the shortest walk in the original graph without a stop limit

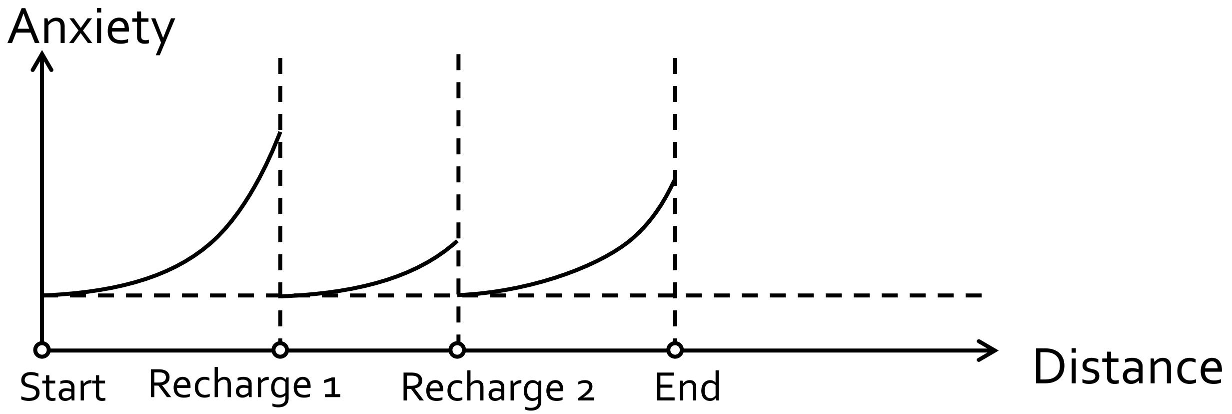
Stop limited meta-network

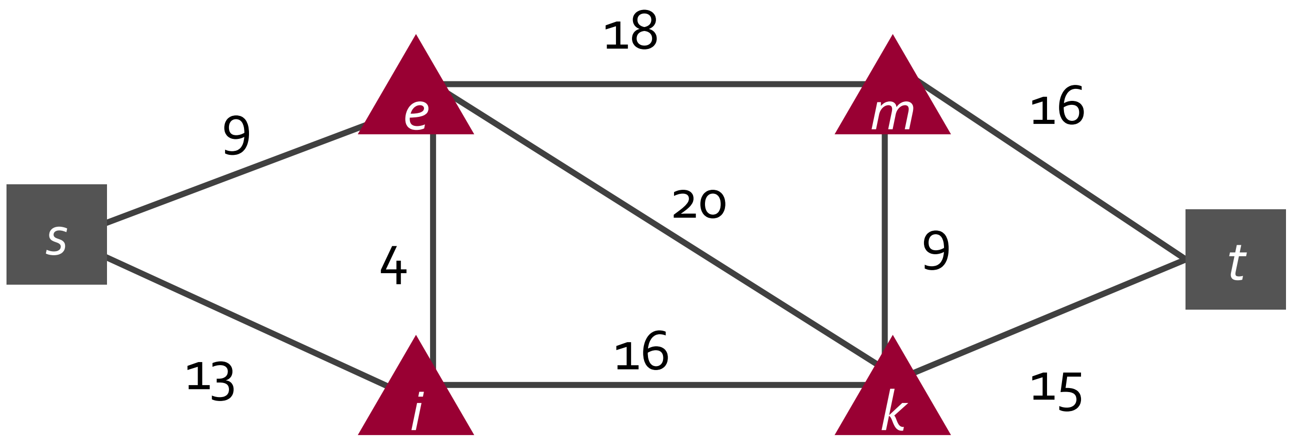
- If there is a stop limit of p, then a graph with $p+2$ copies of the meta-network vertices should be generated
- An edge between $\left(x_i^l, x_j^{l+1}\right)$ exists if there is an edge $\left(x_i, x_j\right)$ in meta-network, edges have the same cost
- $\left(t^l, t^{l+1}\right)$ edges exist with 0 cost
- Polynomial time to get the shortest path



Shortest anxiety walk

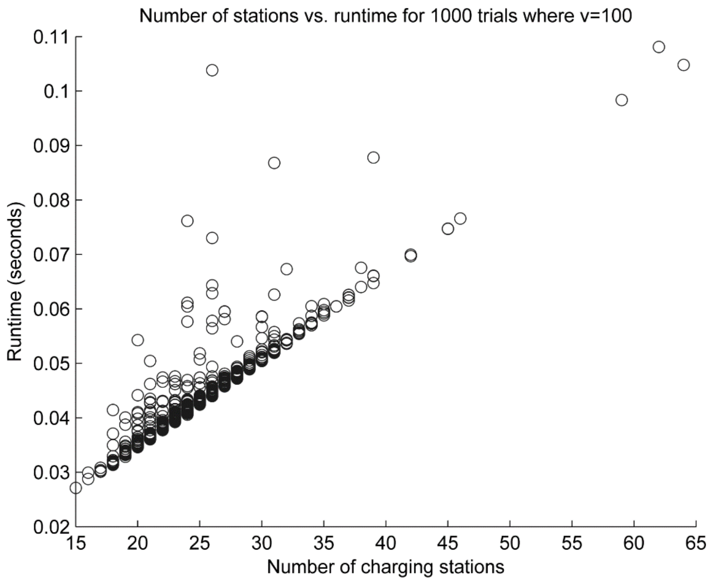
- A minimum anxiety walk minimizes the maximal path length between charging stations
- This generates the same meta-network (and multi-level meta-network), only now a modified Dijkstra's Algorithm needed to find best path

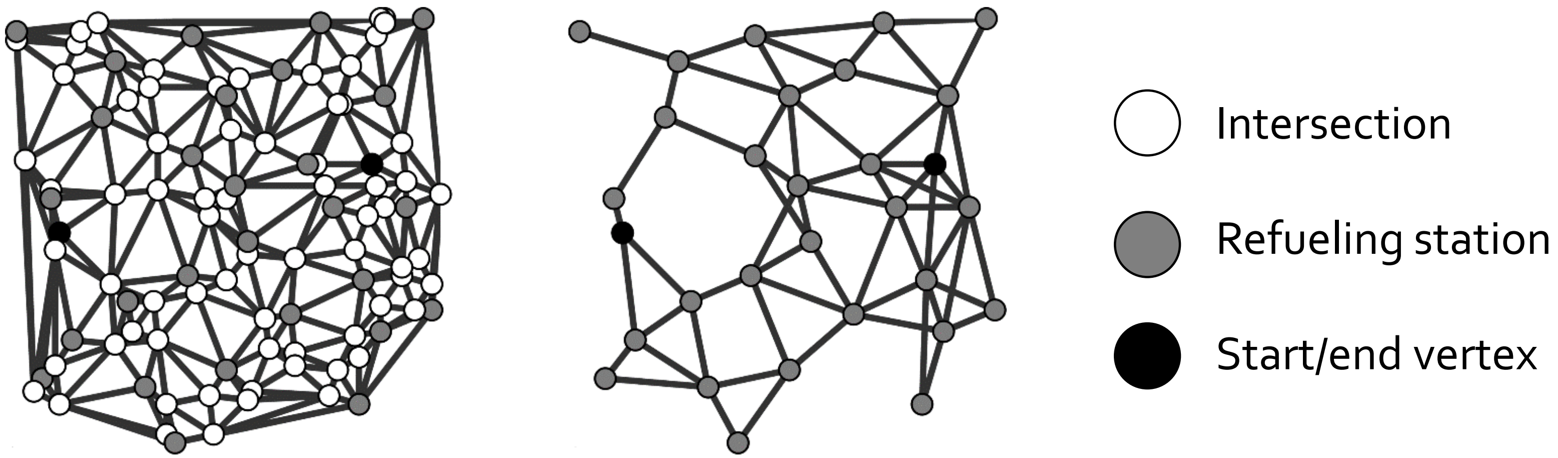




Results

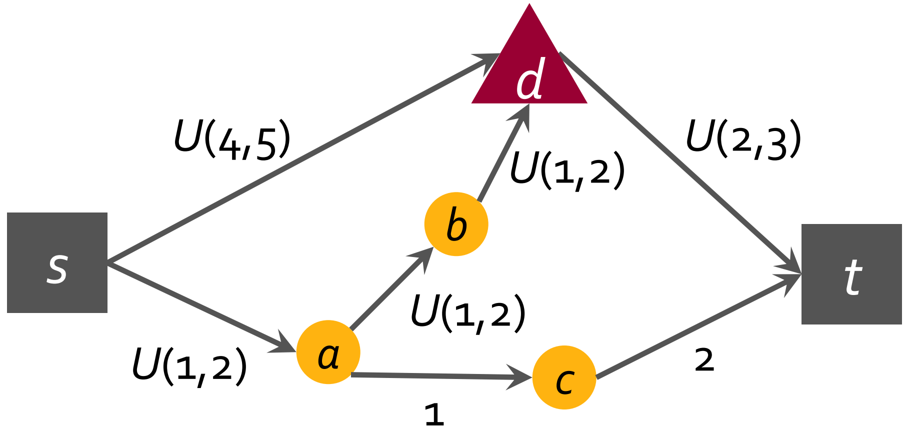
- Tested on randomly generated data
- Runtime grows polynomially with the number of stations (as expected through complexity analysis)





Extensions

- What if the arc lengths are stochastic? Each edge has a known distribution and random outcome is selected each time it is traversed
- Now the walk may to be altered during the traversal depending on the realization
- Driver's appetite for risk needs to be incorporated in the model as well
- Can be modeled as a Markov decision process where the set of actions is limited to those that are sufficiently risk adverse



Online routing and battery reservations for electric vehicles in a network with battery exchanges

Battery exchange stations

Source: Better Place

The steps in a routing and reservation system

Car turns on

Destination is inputted

The system plans a route

When driver accepts, batteries are reserved at stations

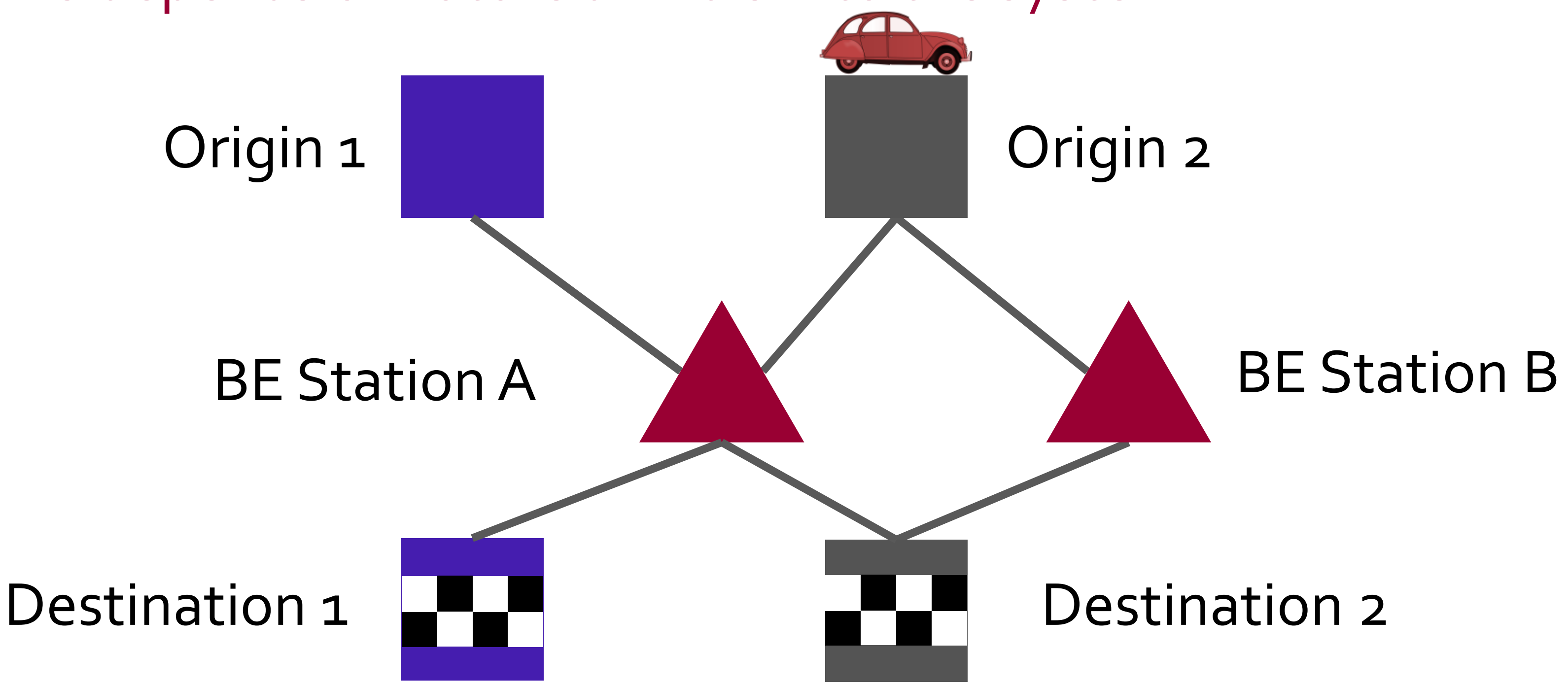
DRIVE!

Source: Tesla, Google

Problem statement

Once the battery exchange system is in place…

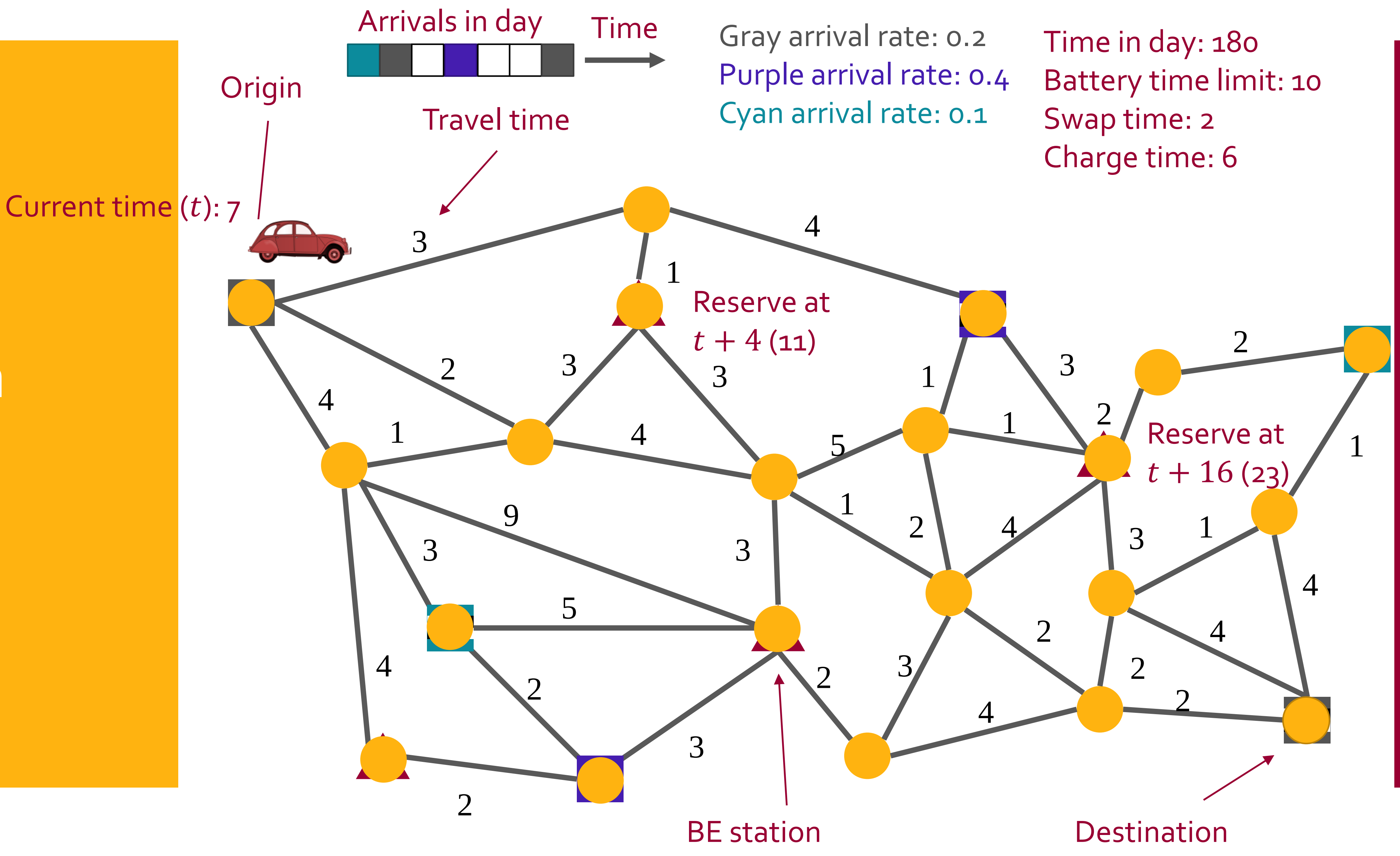
- If driver wants to make a trip given a current set of available batteries at stations, which route should they take?
- How do you route vehicles to minimize overall travel times?
- This depends on future arrivals into the system



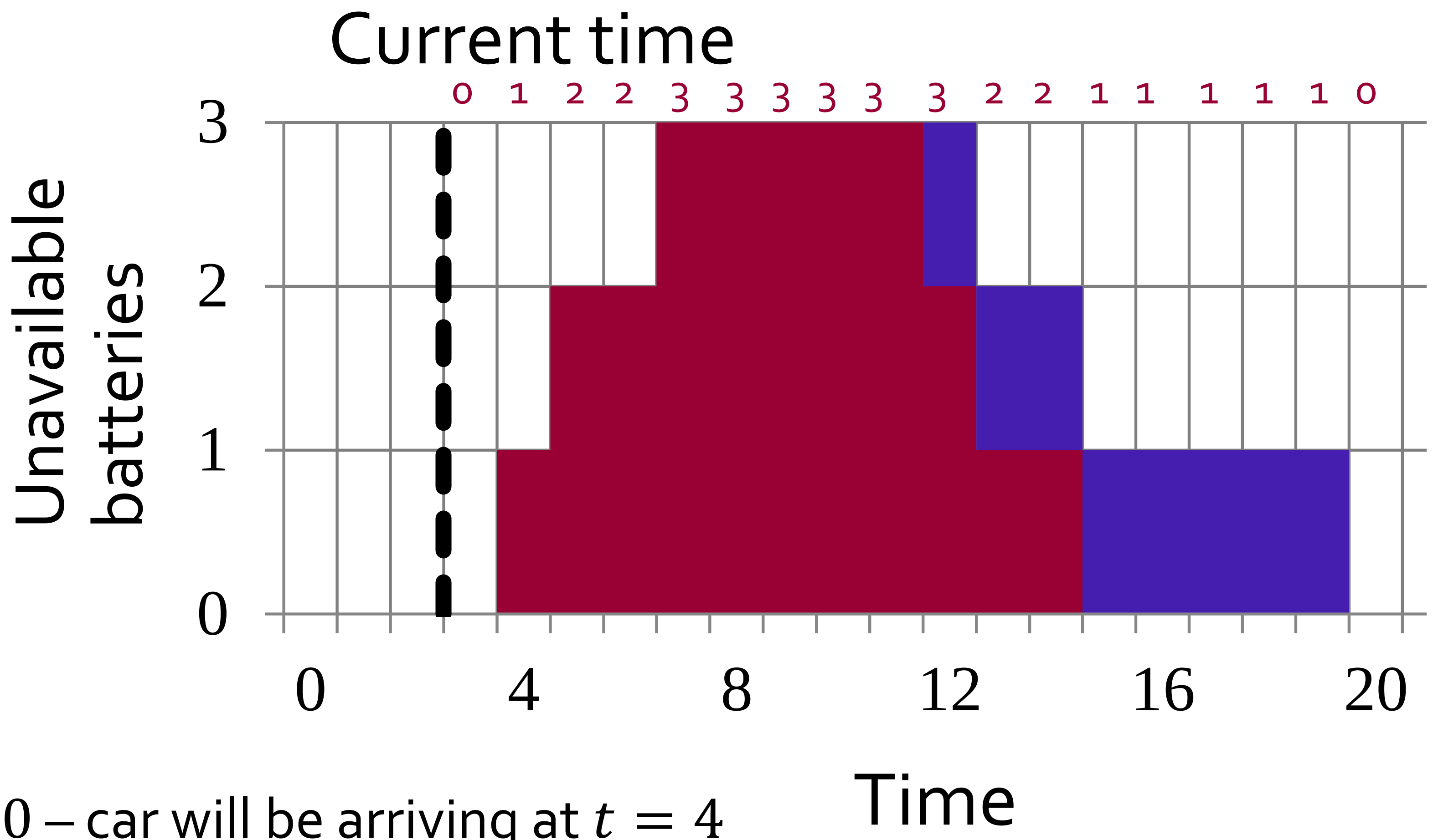
Lit Review

- de Weert et al. (2013) routed multiple electric vehicles based on future demand, but didn't optimize globally
- Mak (2012) determined optimal routes for stochastic EV demand, but there was no online component
- Worley & Klabjan (2011) modeled when to recharge a station given stochastic demand, but had no network routing component

Problem setup



Station information



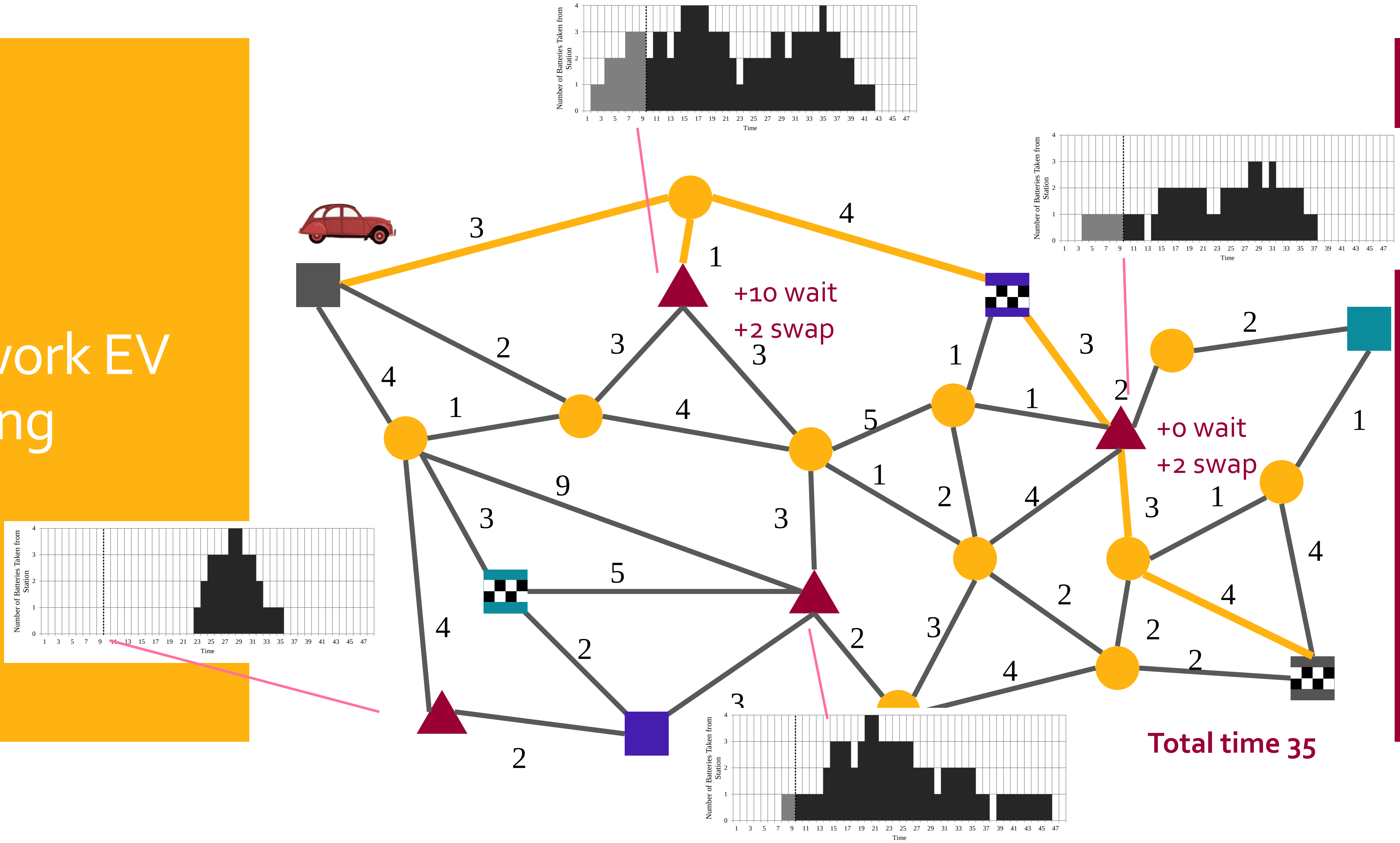
$t = 0$ – car will be arriving at $t = 4$

$t = 1$ – car will be arriving at $t = 7$

$t = 2$ – car will be arriving at $t = 5$

$t = 3$ – car will be arriving at $t = 6$

Network EV routing



Objective

- A vehicle arriving at time t spends
  - ψ_t^{drive} time units driving
  - $\psi_{t,i}^{swap}$ time units swapping batteries at station i
  - $\psi_{t,i}^{wait}$ time units waiting at station i
- And $\psi_t^{optimal}$ is the optimal time to travel between the OD pairs that the vehicle at time t
- The total delay for the vehicle arriving at time t is

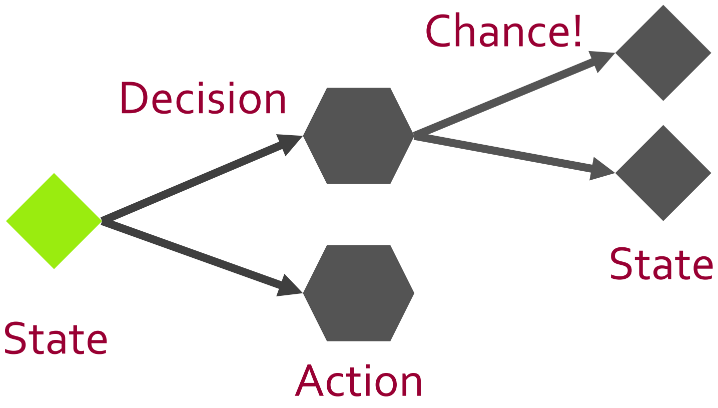
$$\psi_t = \psi_t^{drive} + \rho_1 \sum_{i=1}^{\beta} \psi_{t,i}^{swap} + \rho_2 \sum_{i=1}^{\beta} \psi_{t,i}^{wait} - \psi_t^{optimal}$$

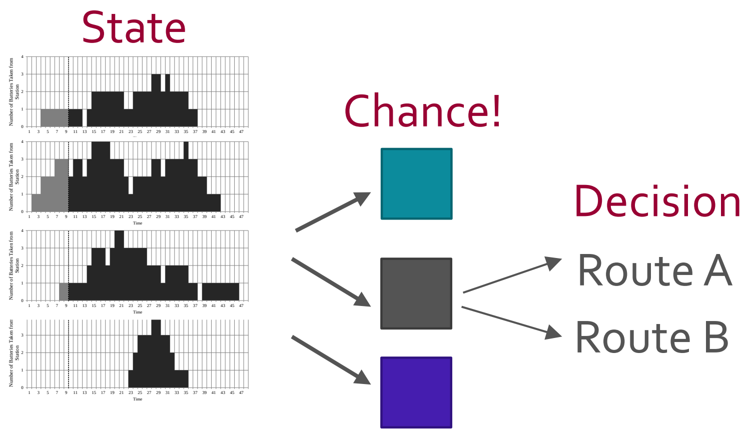
- To find a routing policy that minimizes the total delay

$$\mathbb{E}[\psi_0 + \mathbb{E}[\psi_1 + \mathbb{E}[\psi_2 + \cdots]]]$$

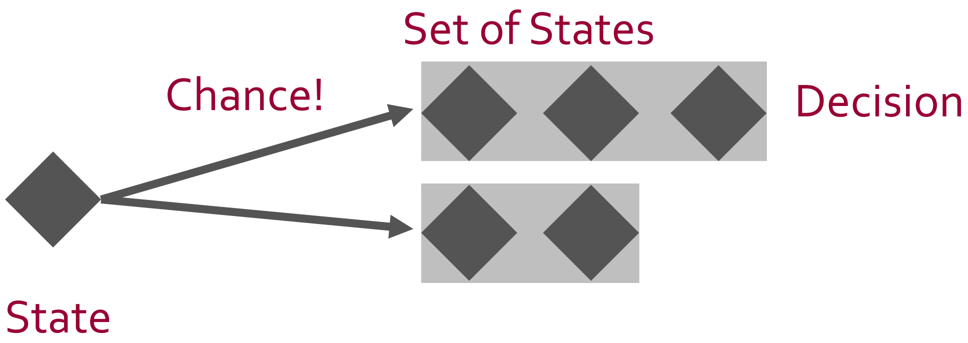
A Markov chance decision system

Markov Decision Problem





Markov Chance Decision Problem



Approximate Dynamic Programming

Approximate dynamic programming

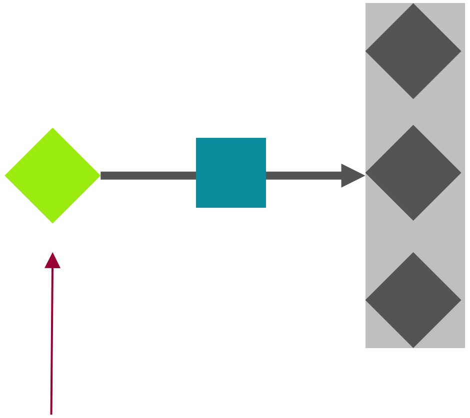
- Approximate the value of being in state S at time t as $\bar{V}_t^{m-1}(S)$.
- Run a simulation of the vehicles arriving $(j_0^m, j_1^m, \dots, j_T^m)$
- Compute $\hat{v}_t^m = \min_{S_{t+1} \in Y(S_t^m, j_t^m)} \left(C(S_t^m, j_t^m, S_{t+1}) + \bar{V}_{t+1}^{m-1}(S_{t+1}) \right)$
- Set $\bar{V}_t^m(S_t) = \begin{cases} (1-\alpha_m)\bar{V}_t^{m-1}(S_t) + \alpha_m \hat{v}_t^m & S_t = S_t^m \\ \bar{V}_t^{m-1}(S_t) & \text{otherwise.} \end{cases}$
- Repeat for $m = m + 1$

Temporal differencing

- Define $\delta_\tau^m = C(S_\tau^m, j_\tau^m, S_{\tau+1}^m) + \bar{V}_{\tau+1}^{m-1}(S_{\tau+1}^m | j_\tau) - \bar{V}_\tau^{m-1}(S_\tau^m | j_{\tau-1}^m)$ for $\tau = t \dots T$
- Instead set $\bar{V}_t^m(S_t) = \begin{cases} \bar{V}_t^{m-1}(S_t^m) + \alpha_m \sum_{\tau=t}^{T} \lambda^{T-\tau} \delta_\tau^m & S_t = S_t^m \\ \bar{V}_t^{m-1}(S_t) & \text{otherwise.} \end{cases}$

Approximate dynamic programming

Simulate the drivers…



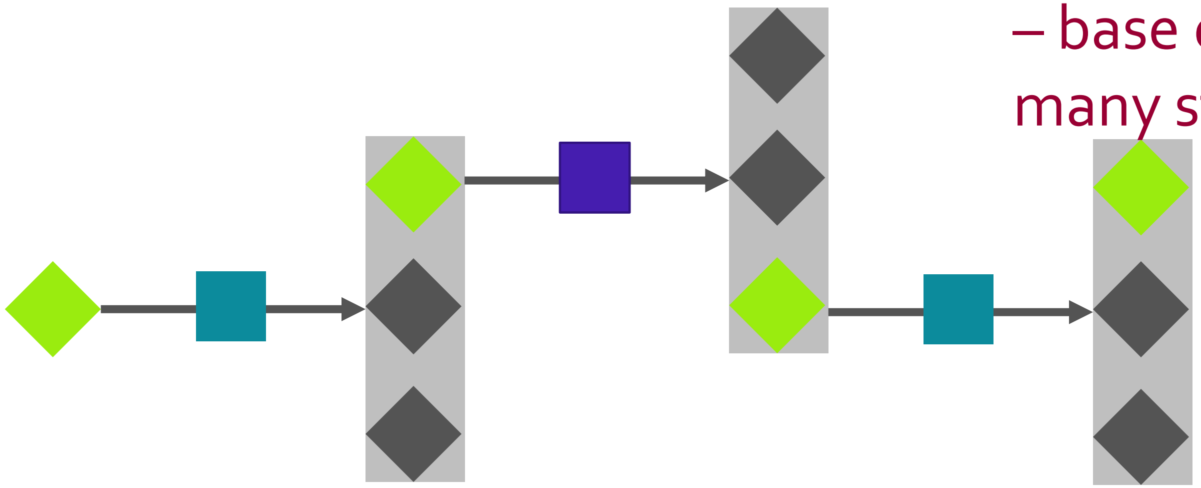
0 Delay 200 estimated future delay

0 Delay 180 estimated future delay

10 Delay 120 estimated future delay

130 estimated future delay

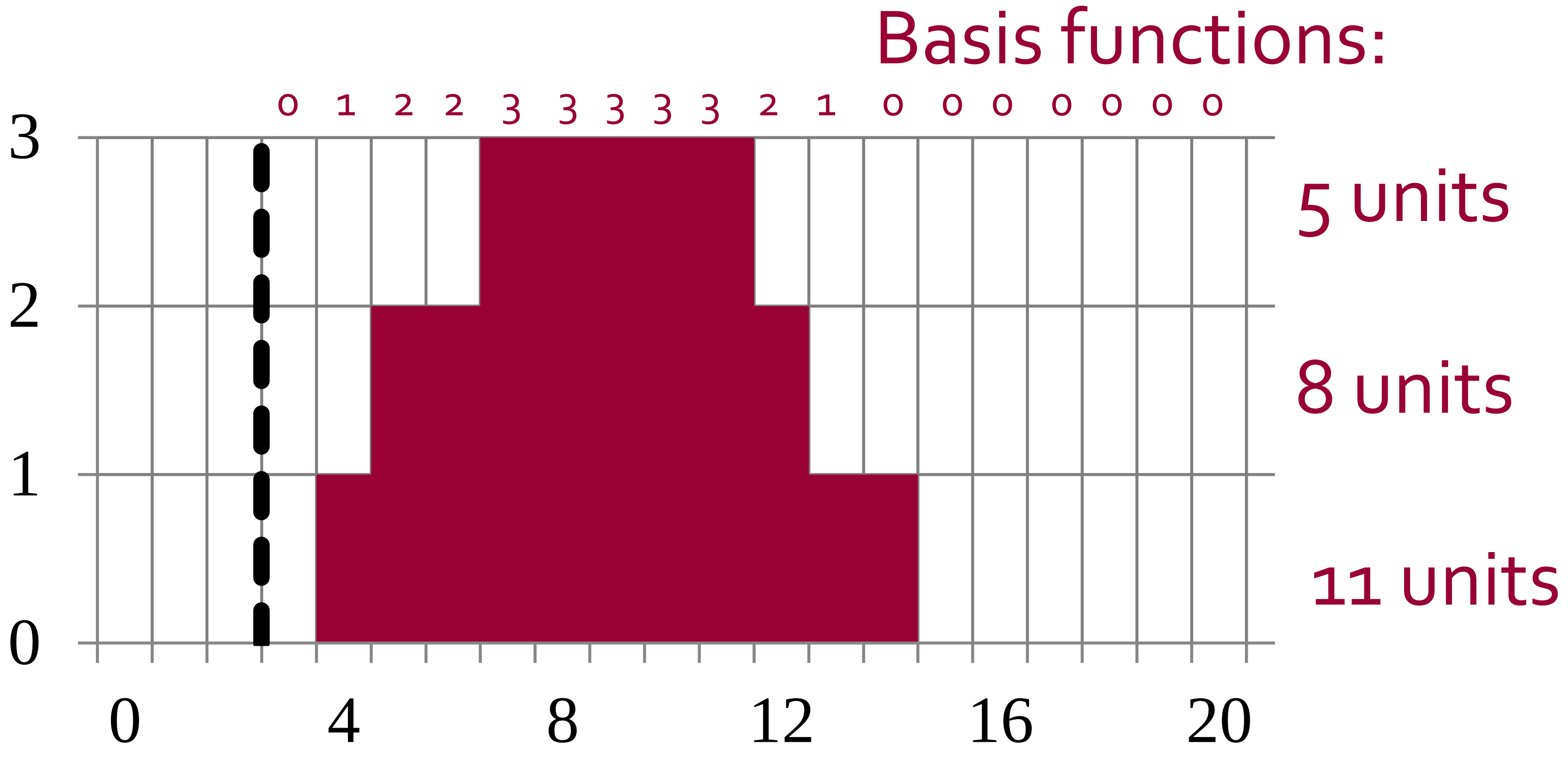
Temporal differencing – base estimate on many steps ahead



Linear value function approximation

- Still need to define $\bar{V}_t^m(S)$ for each S (and there are many!)
- Instead let: $\bar{V}_t^m(S) = \sum_{f \in \mathcal{F}} \theta_{tf}^m \phi_f^m(S)$, now goal is to find best θ_{tf}^m
- Approximation functions are:
  - For station b_i having n_i batteries: for each value $q = 1, \dots, n_i$, the define function ϕ_{iq} which maps state $S \in \mathcal{S}$ to the number of time periods in which station b_i has at least q batteries reserved.
- Only need one set of coefficients for all time since basis functions naturally decrease as time progresses, so $\theta_f^m = \theta_{tf}^m$ for all t

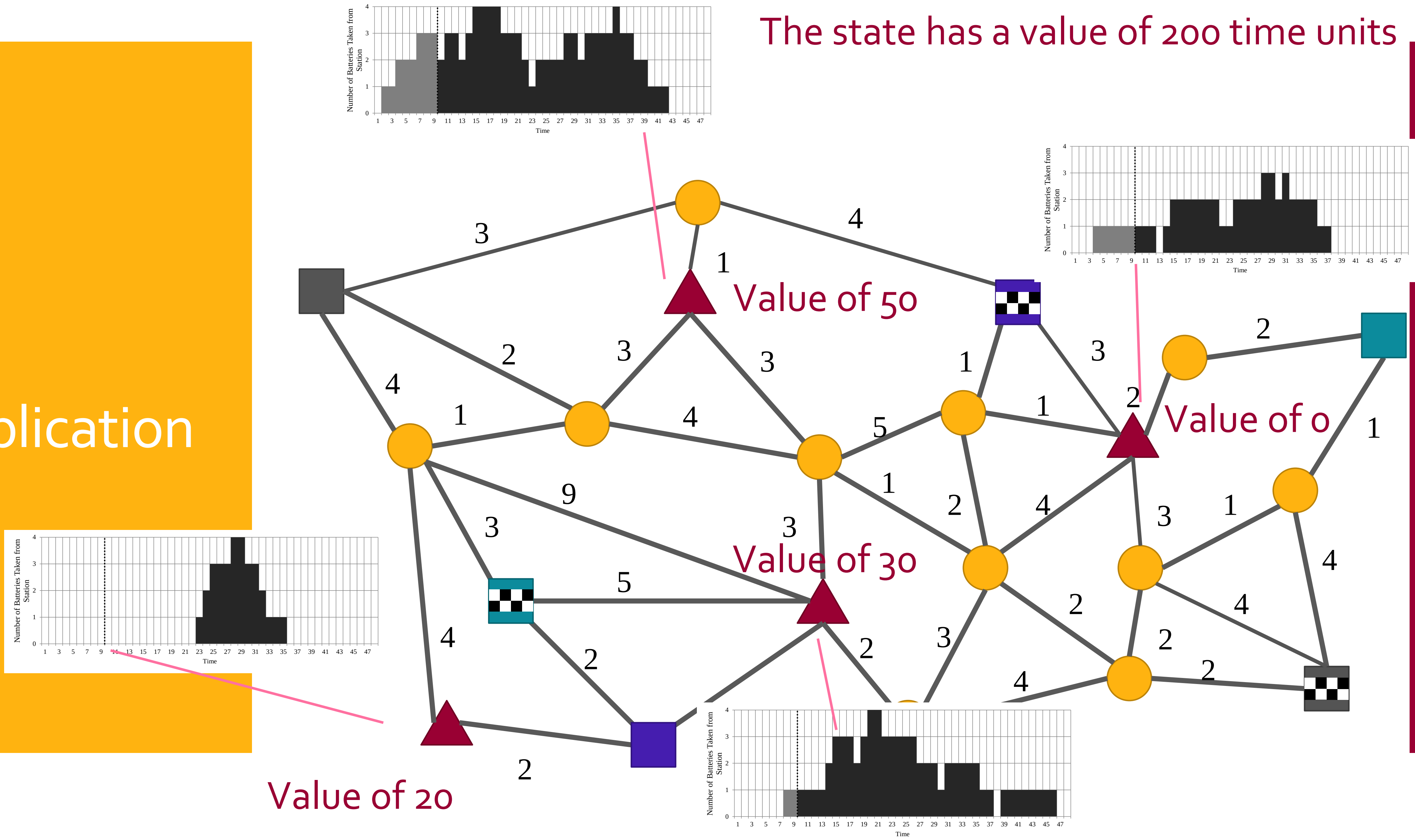
Simplify using linear functions



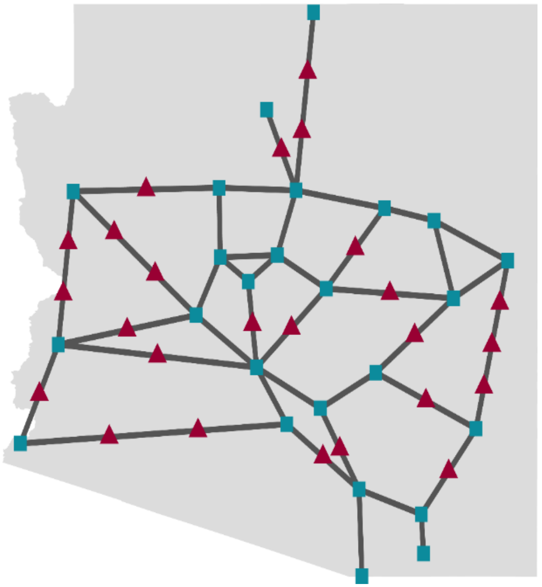
One last complication

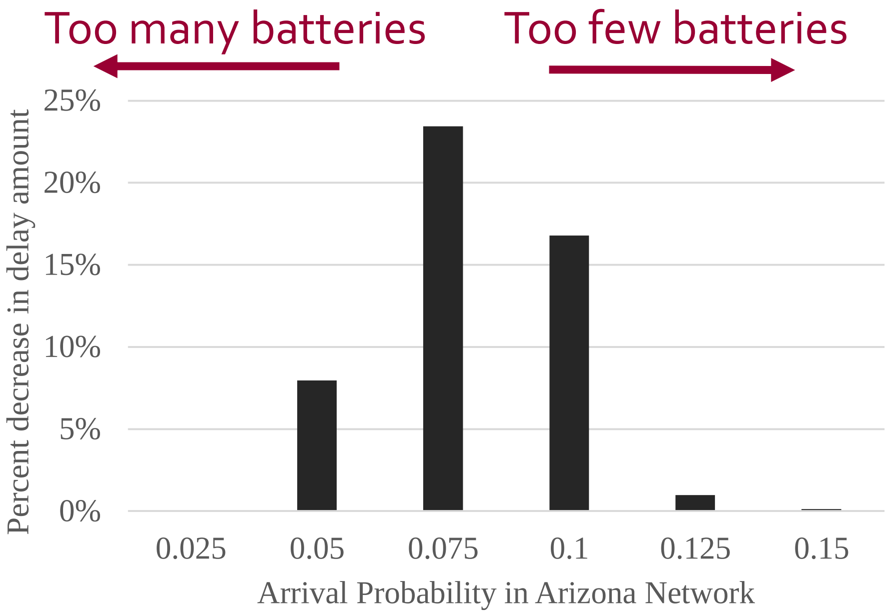
- We know where the costs are being incurred (either from waiting at a particular station or a longer route)
- We don't want stations to be penalized for vehicles waiting at other stations
- So let $\bar{V}_t^{m,1}(S_t)$ be the cost from a longer path and swap times and let $\bar{V}_{t,i}^{m,2}(S_t)$ be the cost from having to wait at a particular station i
- $\bar{V}_t^m(S_t) = \bar{V}_t^{m,1}(S_t) + \sum_{i=1}^{\beta} \bar{V}_{t,i}^{m,2}(S_t)$
- And the costs can be calculated directly for more accurate approximations

Last complication



Results tested on Arizona network





- Arizona road network used
- Arrival probability of vehicles adjusted over several runs
- Compared to greedy policy (cars always act in best interest)
- Up to 23% shorter delays on average

Extensions

- How do you adjust the problem to:
  - Handle non-constant demand throughout the day?
  - Have vehicles drop off batteries that are not empty?
  - Start the route with a not full battery?

Contributions

- Formulated a new model for minimizing travel times globally for a set of electric vehicles in a stochastic online setting
- Found a method for finding good policies based on Markov chance-decision processes and approximate dynamic programming
- Tested the method on Arizona highway data and got a 23% improvement compared to greedy routing

Future work

1. EV shortest walk problem
   - Allow for stochastic cases with learning
   - Improve speed of stochastic case
2. Online EV routing and reservations
   - Add stochastic arc lengths and surprise arrivals
   - Improve ADP results

Questions?

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