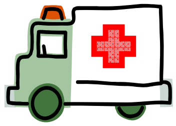
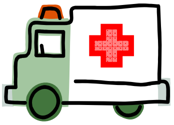


Solving the Dynamic **Ambulance Dispatching & Relocation Problem** using **Approximate Dynamic Programming**

Dr. Verena Schmid



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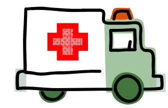
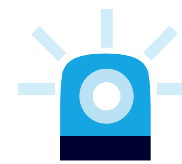
problem description & motivation

- **faced by Emergency Service Providers (ESPs)**
  - manage **fleet** of ambulances
  - reach **patients** in case of emengency asap



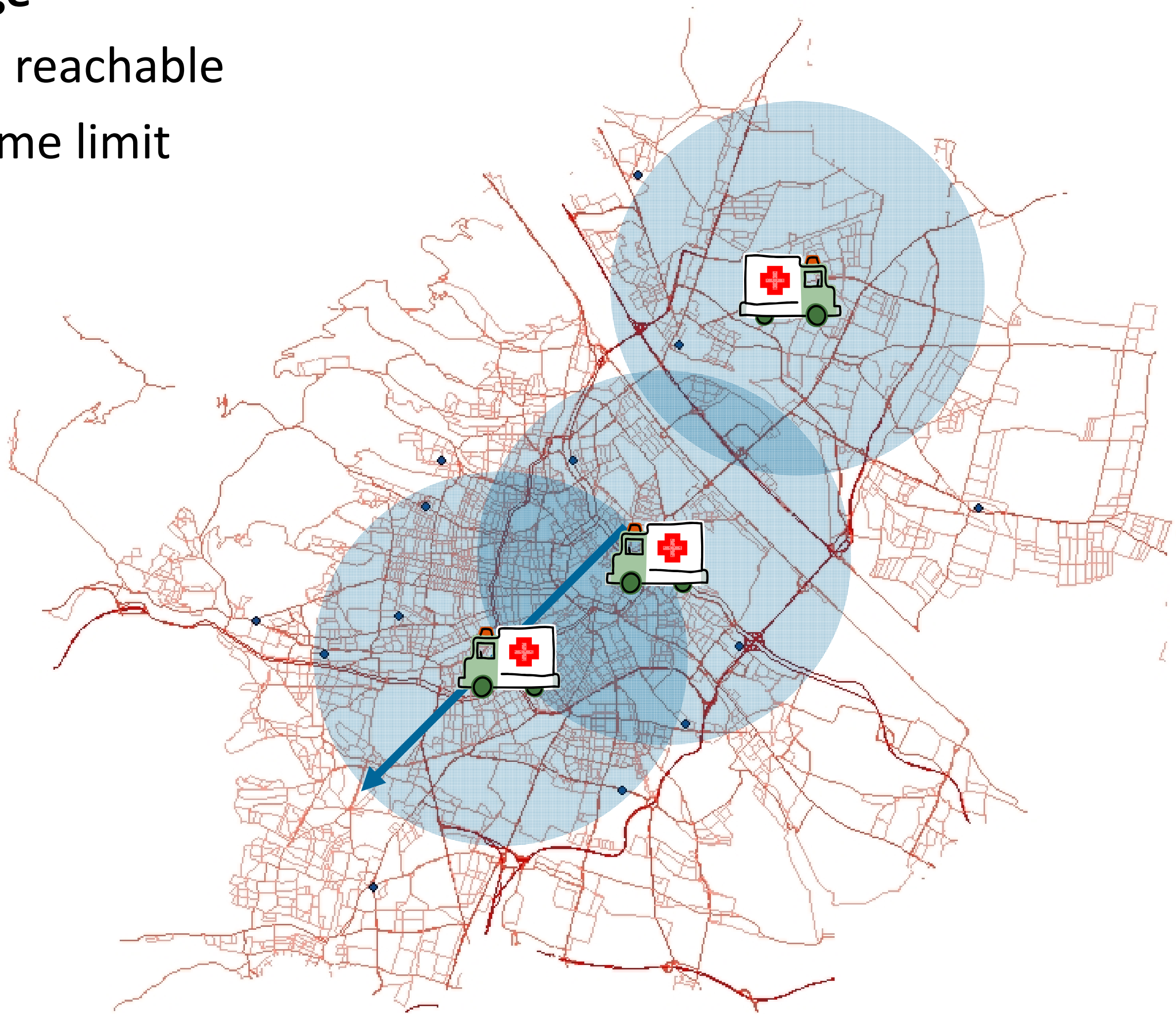


- **fundamental decisions**

• ambulance location	where?
• dispatching	which?
• reinsertion	where next?
• relocate	where else?

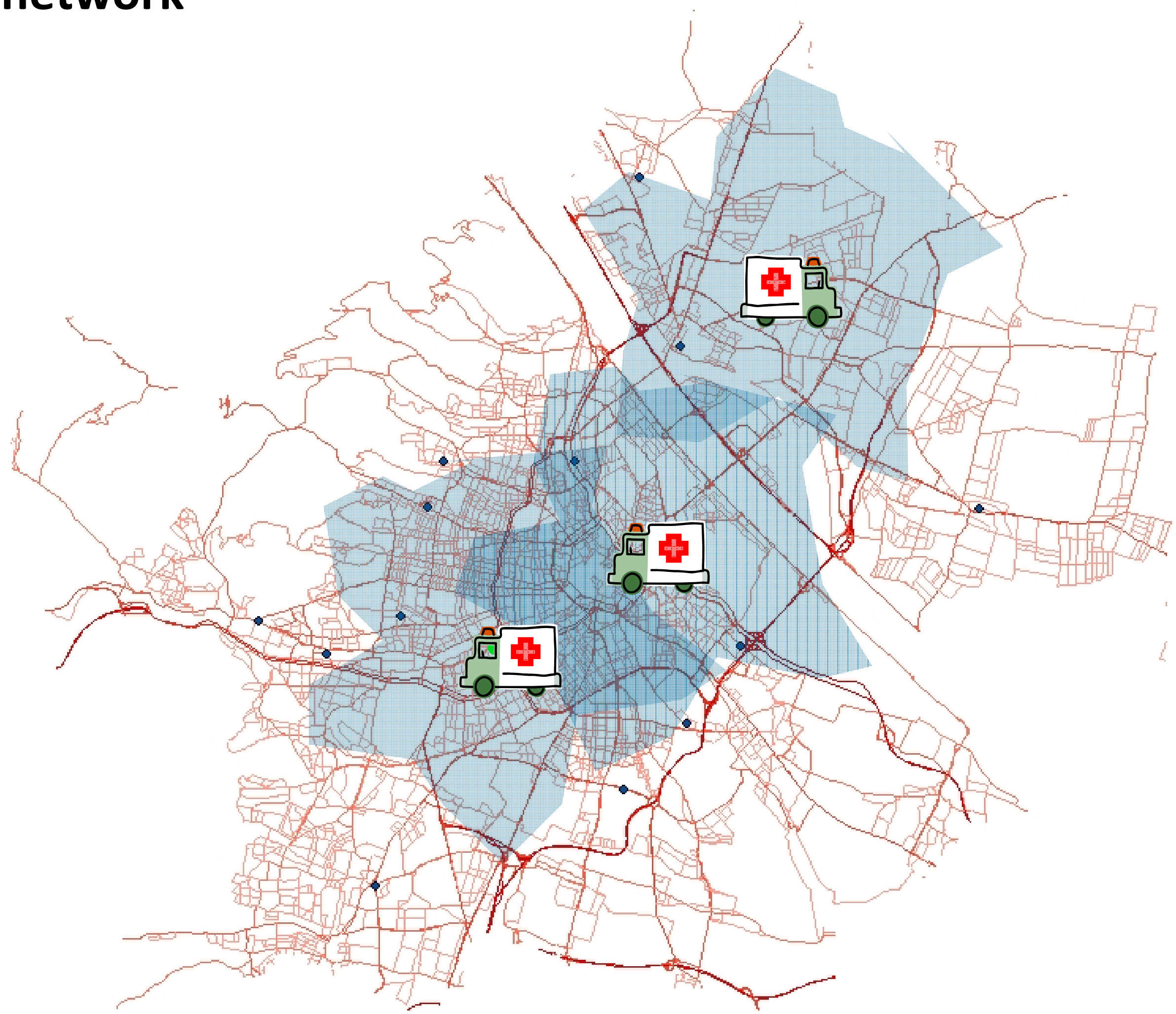
Q1: where to locate ambulances?

- **optimize coverage**
  - areas/patients reachable
  - within given time limit



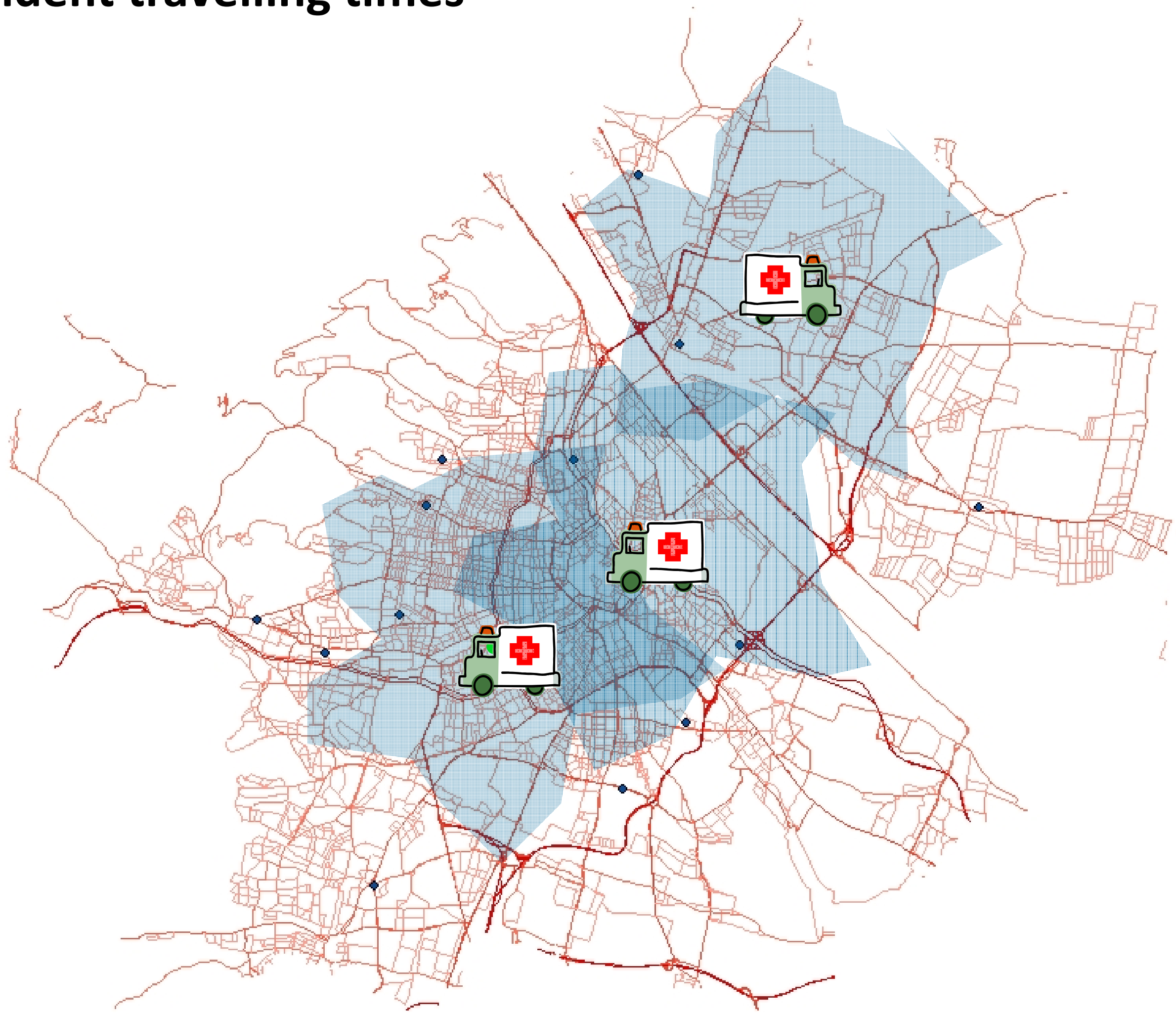
Q1: where to locate ambulances?

- **using real street network**



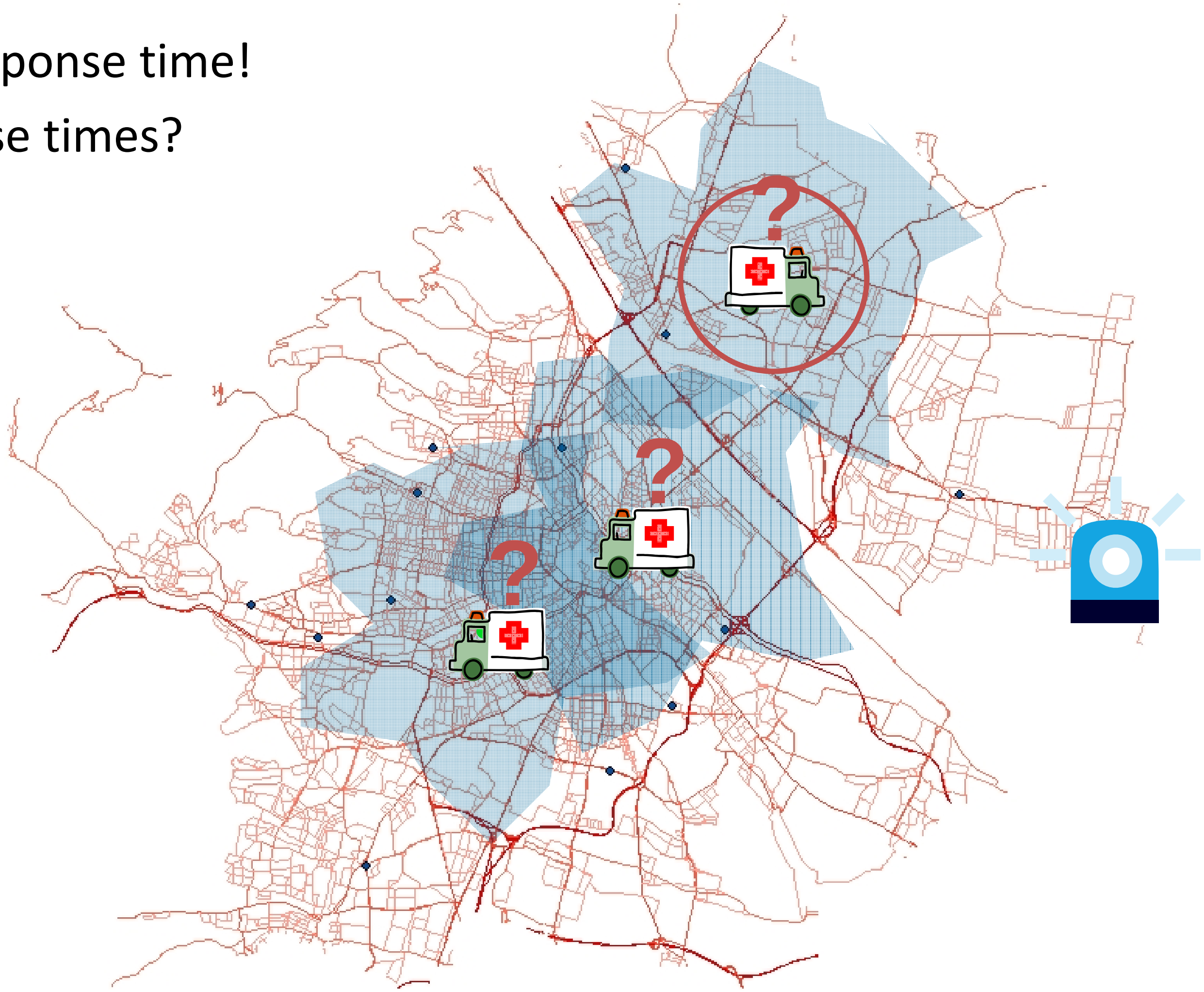
Q1: where to locate ambulances?

- **using time dependent travelling times**



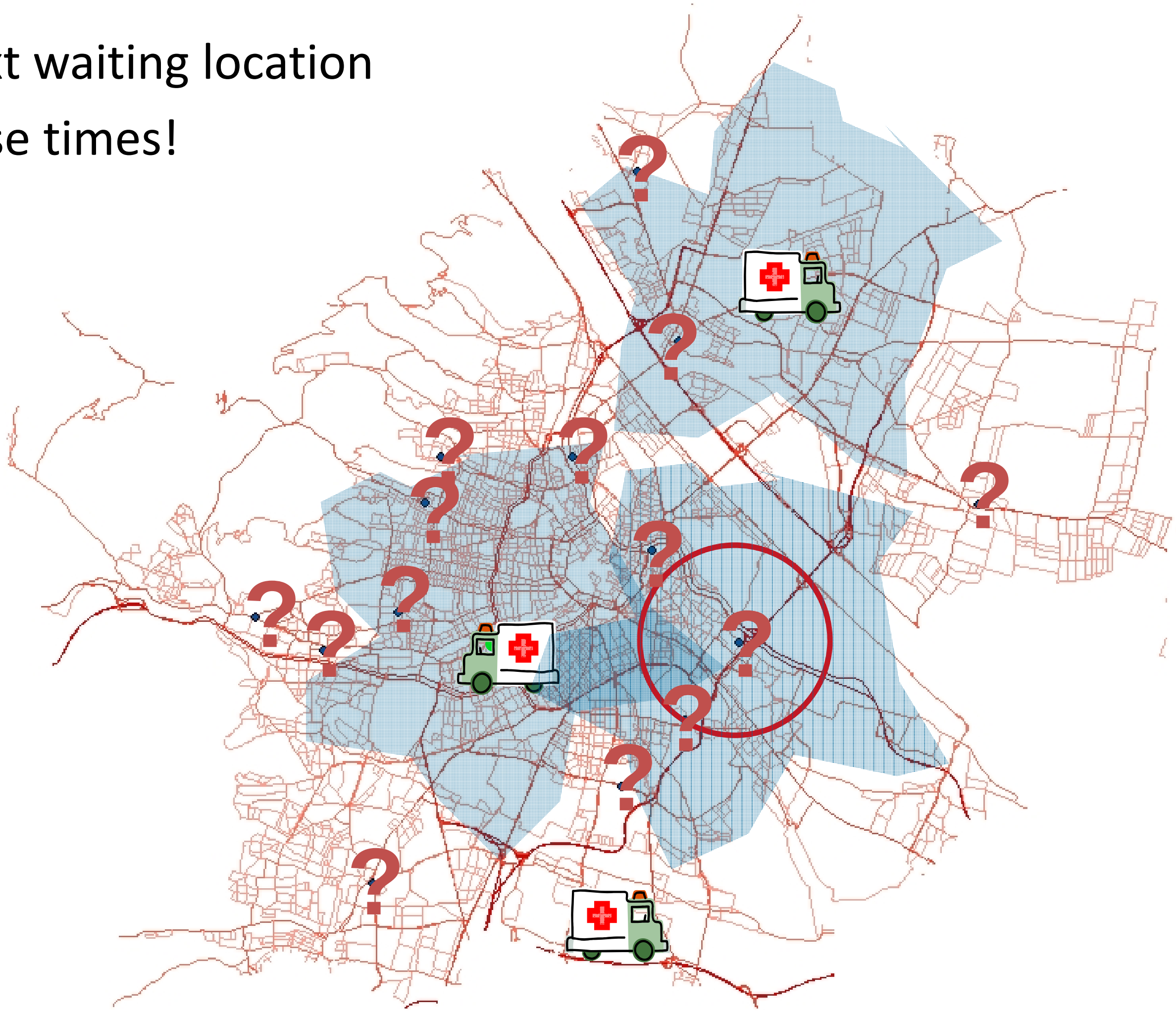
Q2: which ambulance shall be sent?

- **dispatching**
  - immediate response time!
  - future response times?



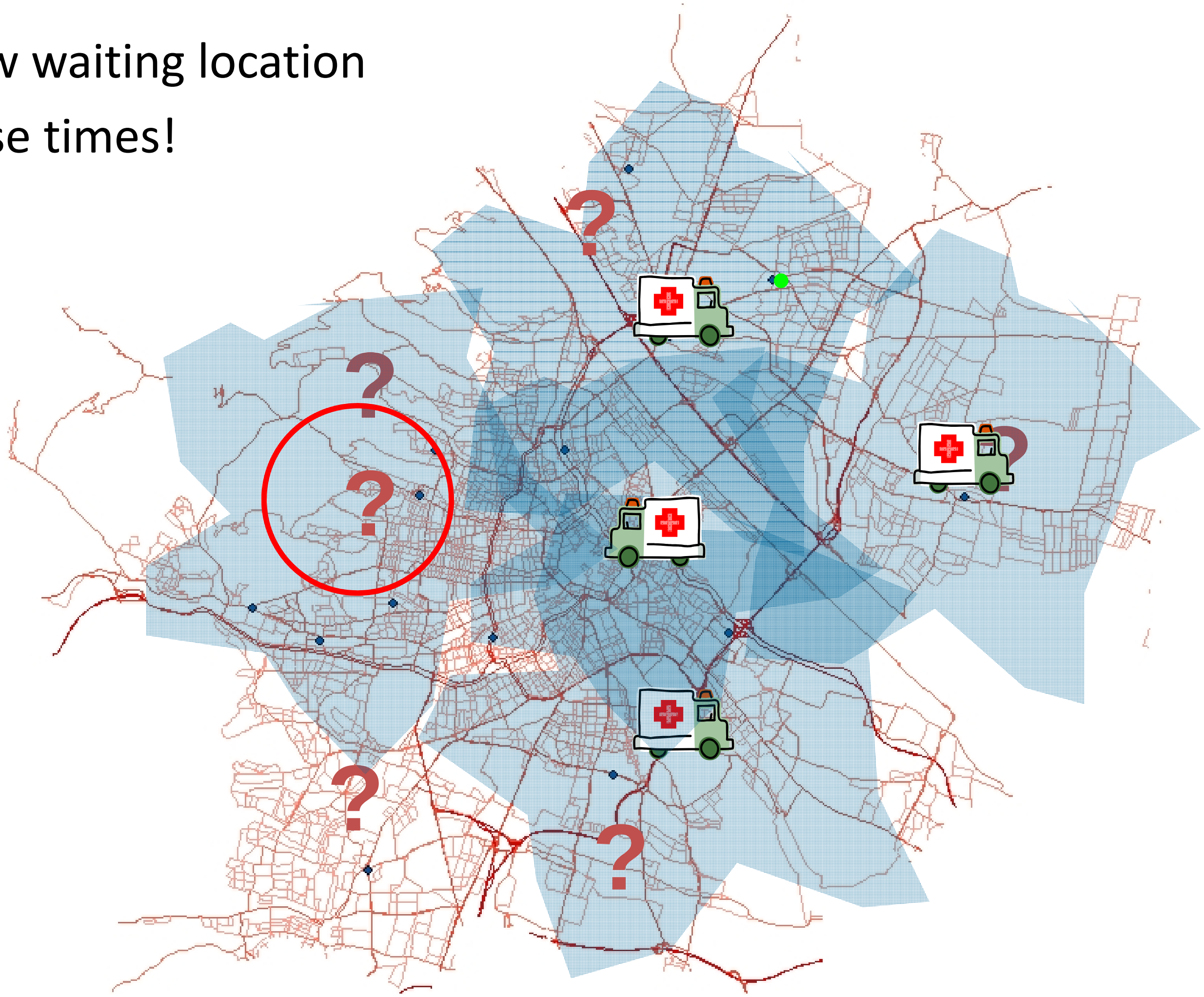
Q3: where to send ambulance next?

- **reinsertion**
  - determine next waiting location
  - future response times!

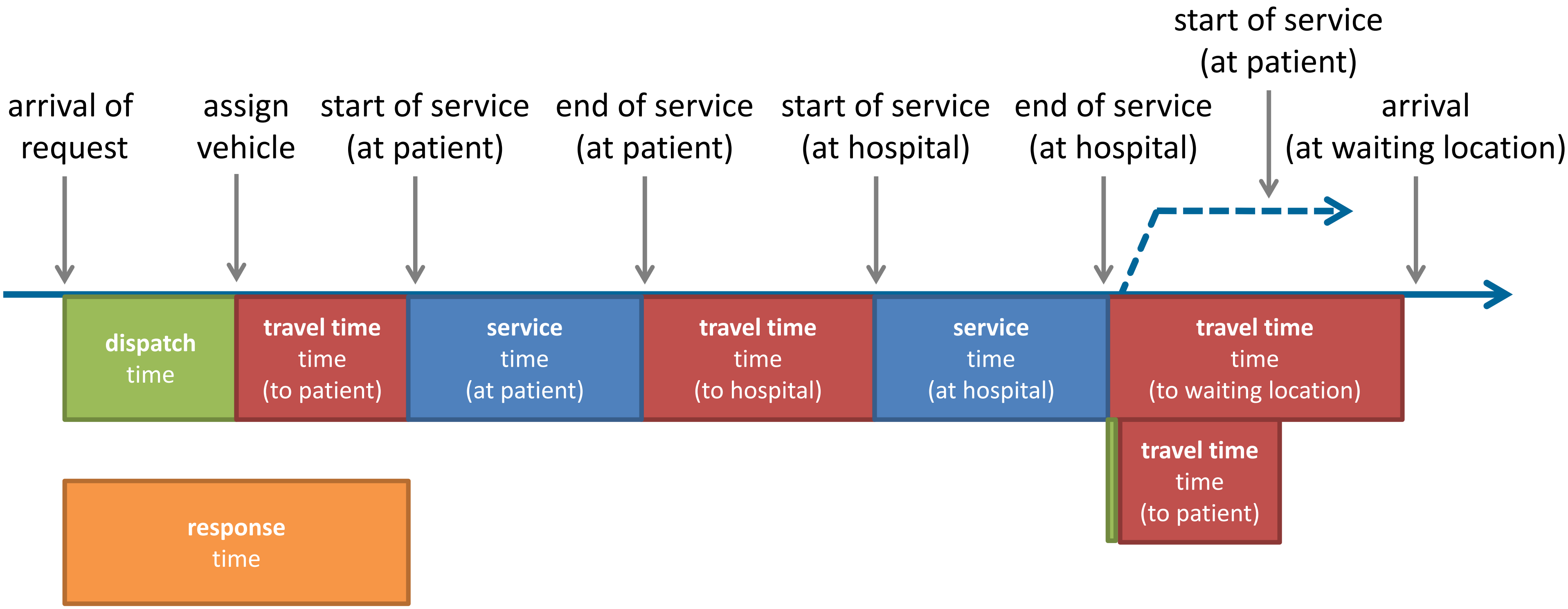


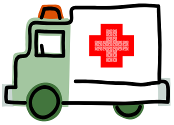
Q4: send ambulances somewhere else?

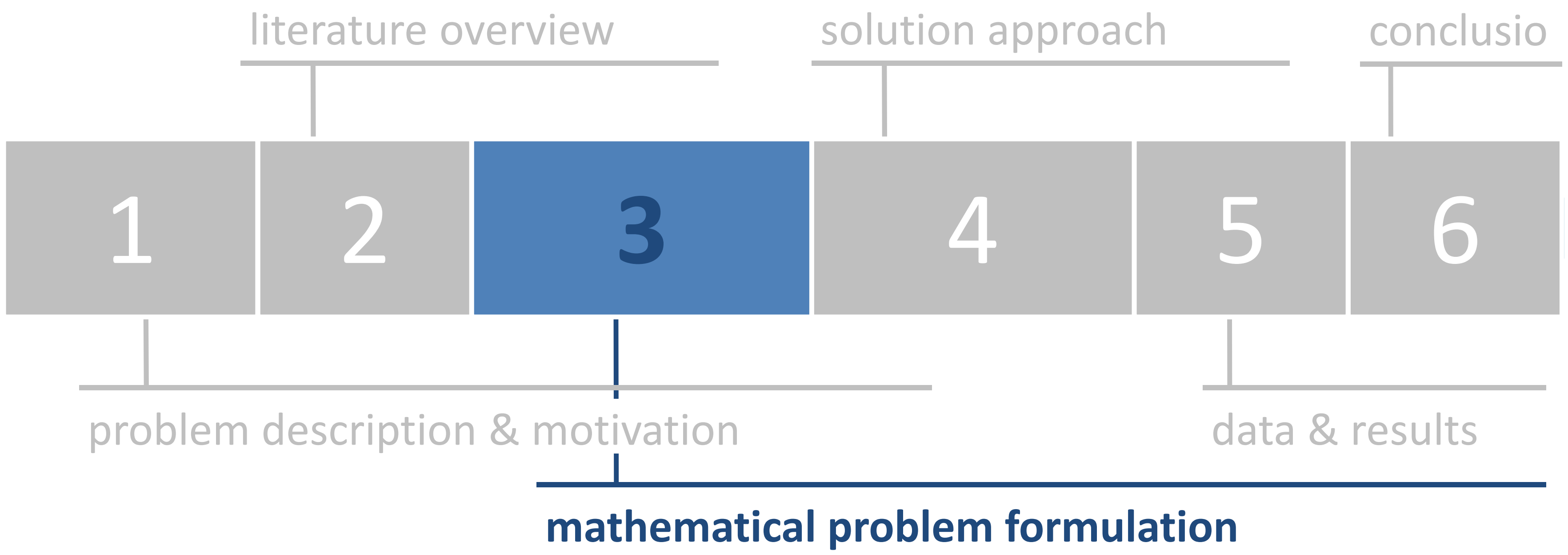
- **relocation**
  - determine new waiting location
  - future response times!



dispatching & reinsertion process



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basic notation

- **states**
  - capture current situation (ambulances + requests) S_t (R_t, D_t)
- **decisions**
  - made dynamically over time x_t
  - immediate contribution $C(S_t, x_t)$
  - decisions have a downstream impact on future
  - need estimate for value of being in a state $V_t(S_t)$
- **sources of randomness**
  - requests, durations W_t
- **dynamic evolution**

$$S_{t+1} = S^M(S_t, x_t, W_{t+1})$$

optimization

- **myopic policy**
  - optimize wrt immediate contribution

$$V_t(S_t) = \min_{x_t} C(S_t, x_t)$$

- **optimize underlying stochastic problem**

immediate contribution

expected **future** contribution

$$V_t(S_t) = \min_{x_t} \left(C(S_t, x_t) + \mathbb{E}\{ V_{t+1}(S_{t+1}(S_t, x_t, W_{t+1})) \} \right)$$

value of **next** state

current state

decision

random input

state (in more detail)

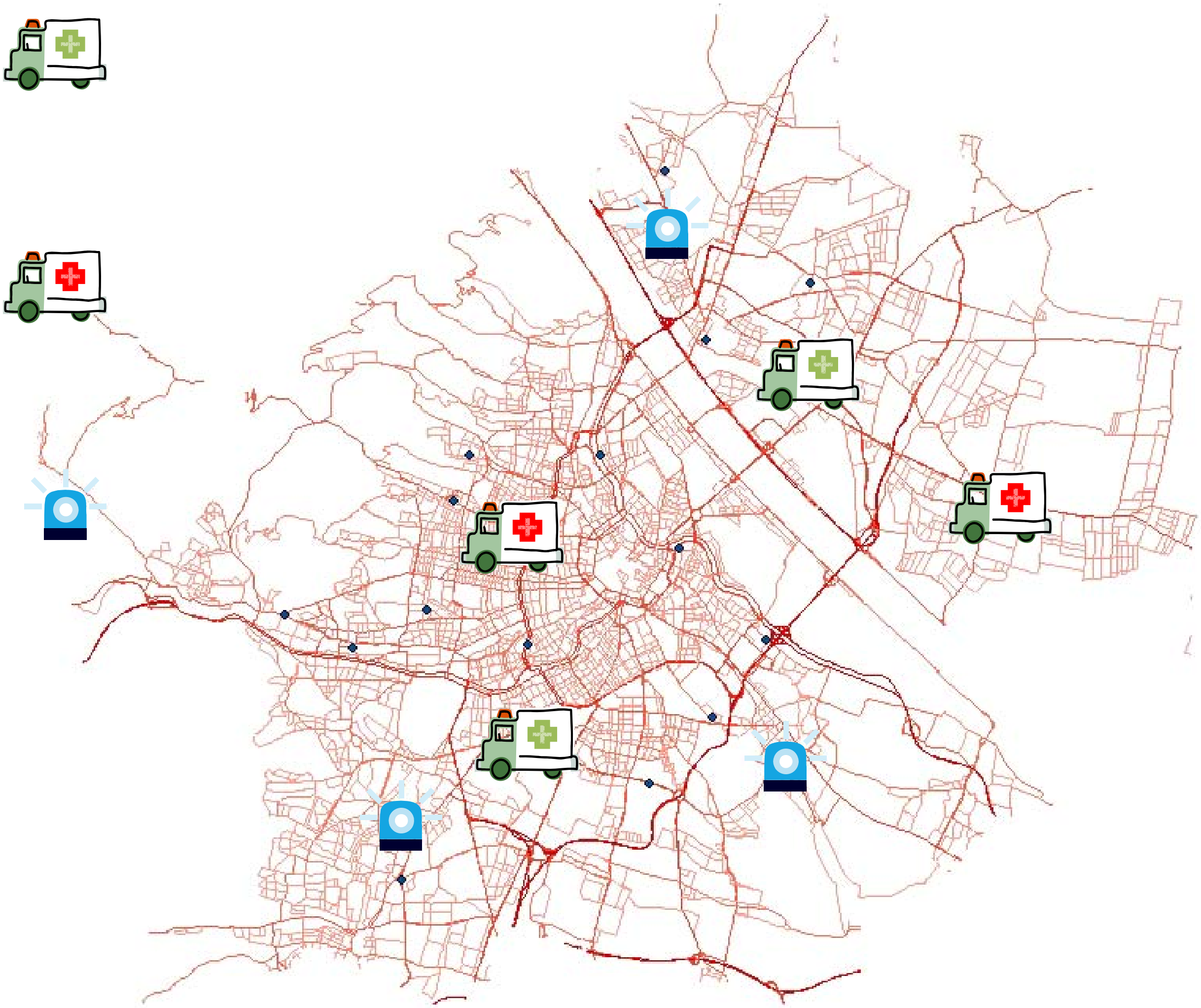
- **resources (ambulances)**
  - attribute vector $a_t \in \mathcal{A}$
  - resource state vector $R_t = (R_{ta})_{a \in \mathcal{A}}$
- **demand (requests)**
  - attribute vector $b_t \in \mathcal{B}$
  - demand state vector $D_t = (D_{tb})_{b \in \mathcal{B}}$
- **state** $S_t = (R_t, D_t)$

- **decision**
  - elementary decisions $d \in \mathcal{D}$
  - decision variable $x_t = (x_{tad})_{a \in \mathcal{A}, d \in \mathcal{D}}$

states (example)

t = 10:30am

- **resource state**
  - **idle** ambulances
    current location
    available since
  - **busy** ambulances
    next location
    available next
- **demand state**
  - location
  - arrival time
  - priority



model (constraints)

- **flow conservation on request**

  at most one idle ambulance can be dispatched to any request

$$\sum_{a \in \mathcal{A}_t^i} x_{tad} \leq D_{tb_d} \quad \forall d \in \mathcal{D}^D$$

- **for ambulances**

  only idle ambulances can be dispatched

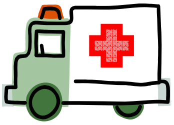
$$\sum_{d \in \mathcal{D}^D} x_{tad} \leq R_{ta} \quad \forall a \in \mathcal{A}_t^i$$

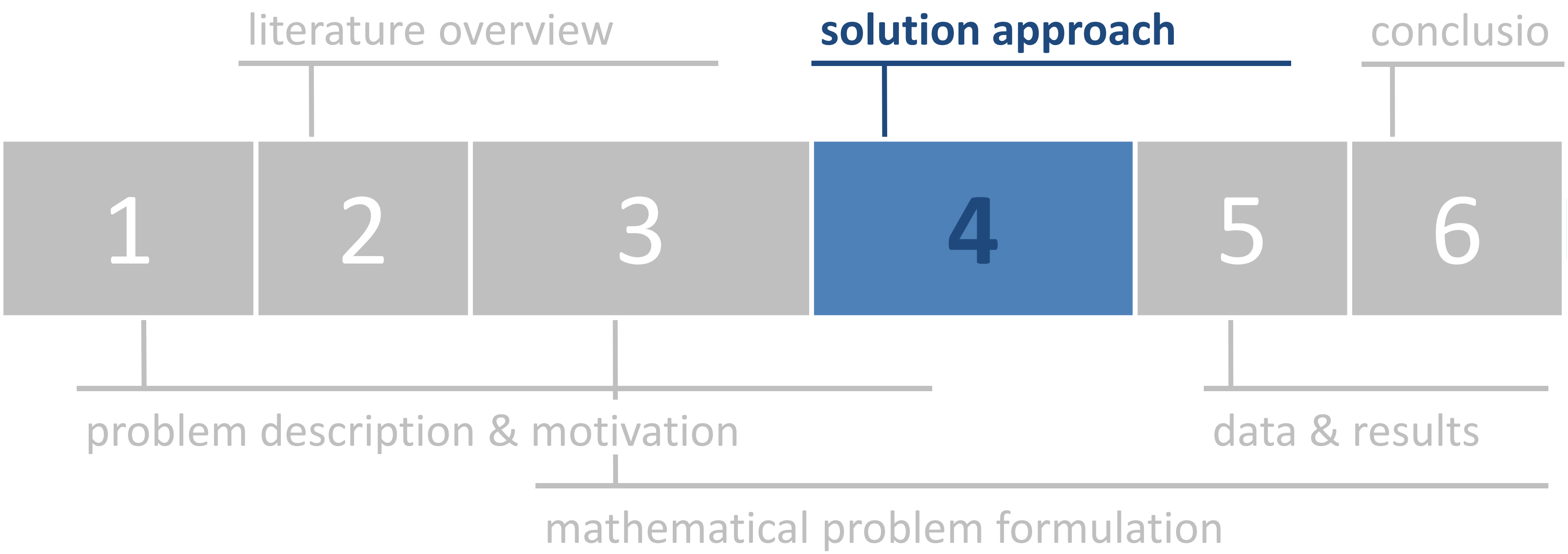
  ambulances just becoming idle have to be dispatched or relocated

$$\sum_{d \in \mathcal{D}^D \cup \mathcal{D}^R} x_{tad} = R_{ta} \quad \forall a \in \mathcal{A}_t^{i+}$$

  status of busy ambulances cannot be changed

$$\sum_{d \in \mathcal{D}} x_{tad} = 0 \quad \forall a \in \mathcal{A}_t^b$$

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dynamic programming

- **stochastic optimization problem**

$$V_t(S_t) = \min_{x_t \in \mathcal{X}_t} \left(C(S_t, x_t) + \mathbb{E}\{ V_{t+1}(S_{t+1}(S_t, x_t, W_{t+1})) \} \right)$$

- **basic idea**
  - recursive
  - step backward in time

- **curses of dimensionality**
  - state vector S_t grows very quickly $|\mathcal{A}| \times |\mathcal{B}|$
  - size of outcome space of random variable W_t $|\mathcal{A}| \times |\mathcal{B}|$
  - size of decision vector x_t $|\mathcal{A}| \times |\mathcal{D}|$

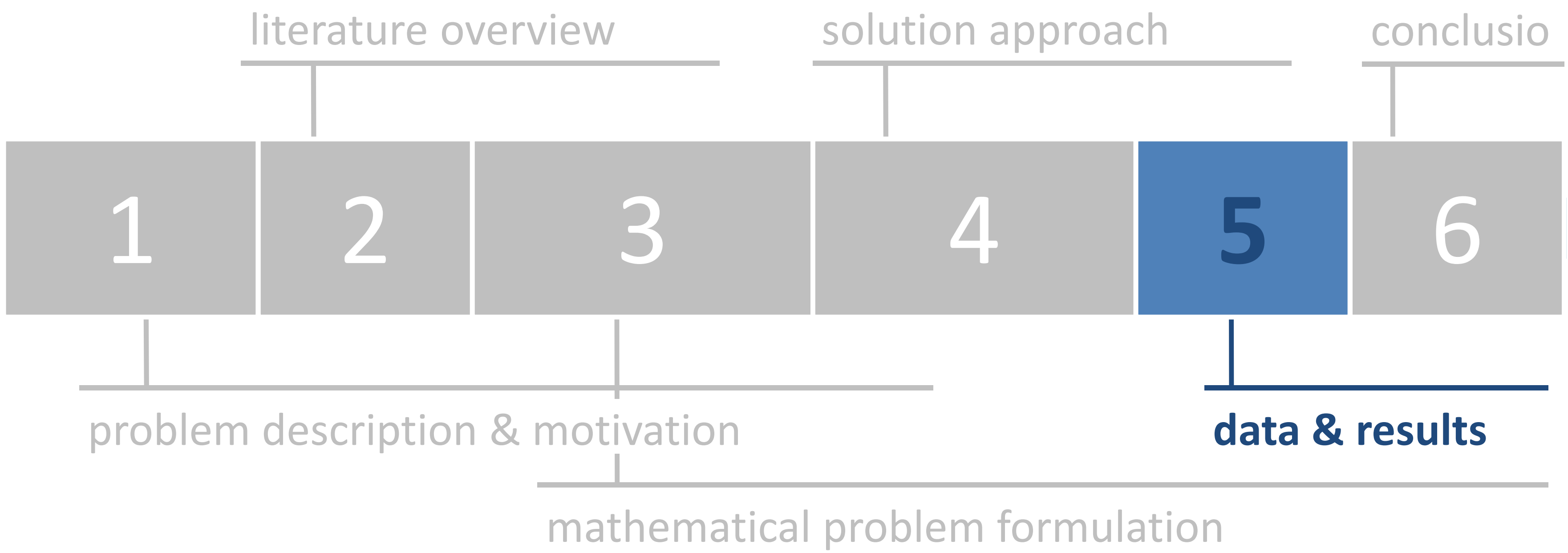
approximate dynamic programming (ADP)

- **stochastic optimization problem**

$$\hat{v}_t^n = \min_{x_t \in \mathcal{X}_t^n} \left(C(S_t^n, x_t) + \mathbb{E}\{ \bar{V}_{t+1}^{n-1}(S_{t+1}(S_t^n, x_t, \hat{\omega}_{t+1}^n)) \} \right)$$

- **basic idea**
  - make decisions based on **approximation** of value function
  - step **forward** in time (sample what might happen)
  - **iteratively**. using a fresh set of sample realizations
  - **update** value function approximation

$$\bar{V}_t^n(S_t) = (1 - \alpha_{n-1})\bar{V}_t^{n-1}(S_t^n) + \alpha_{n-1}\hat{v}_t^n$$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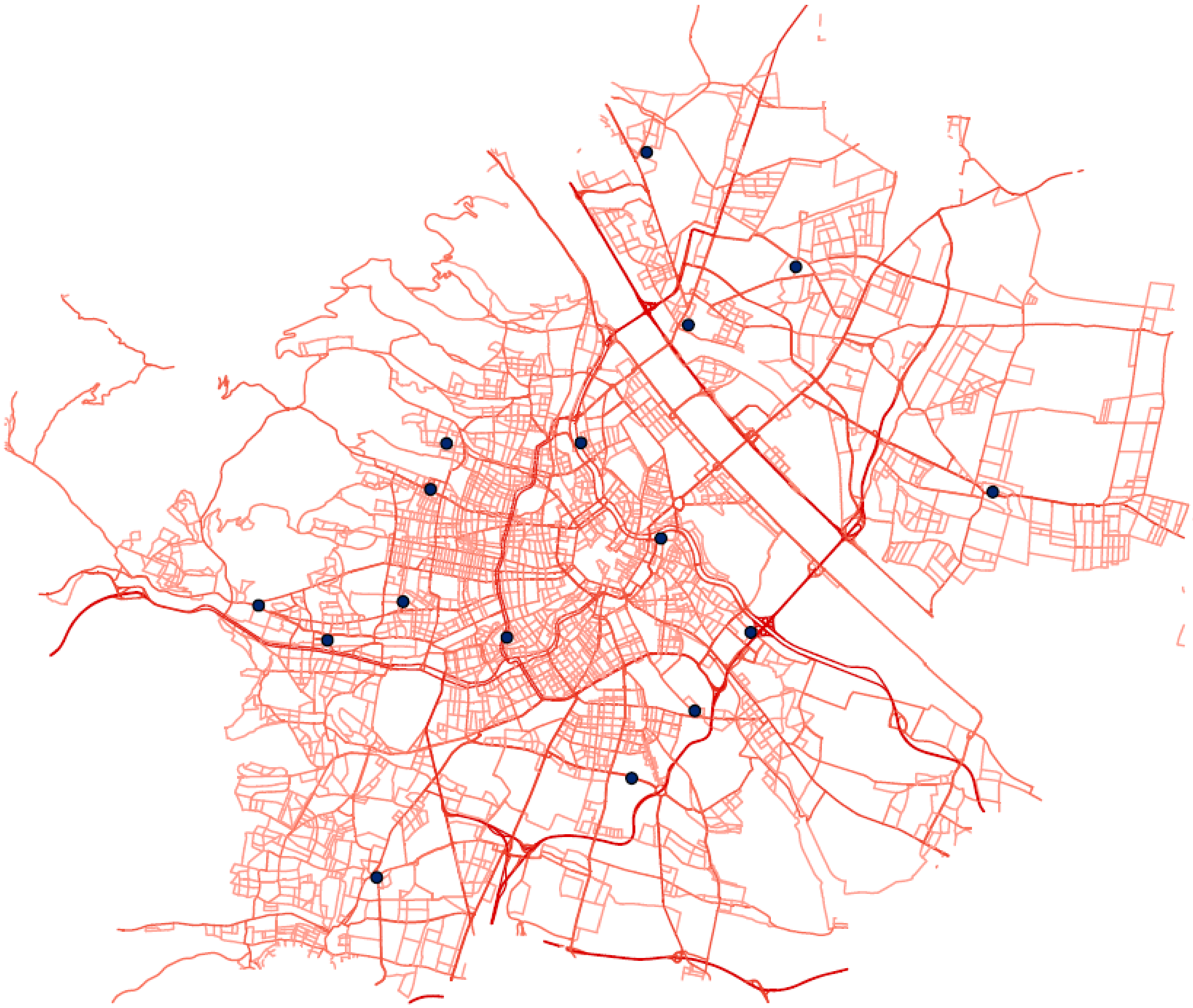
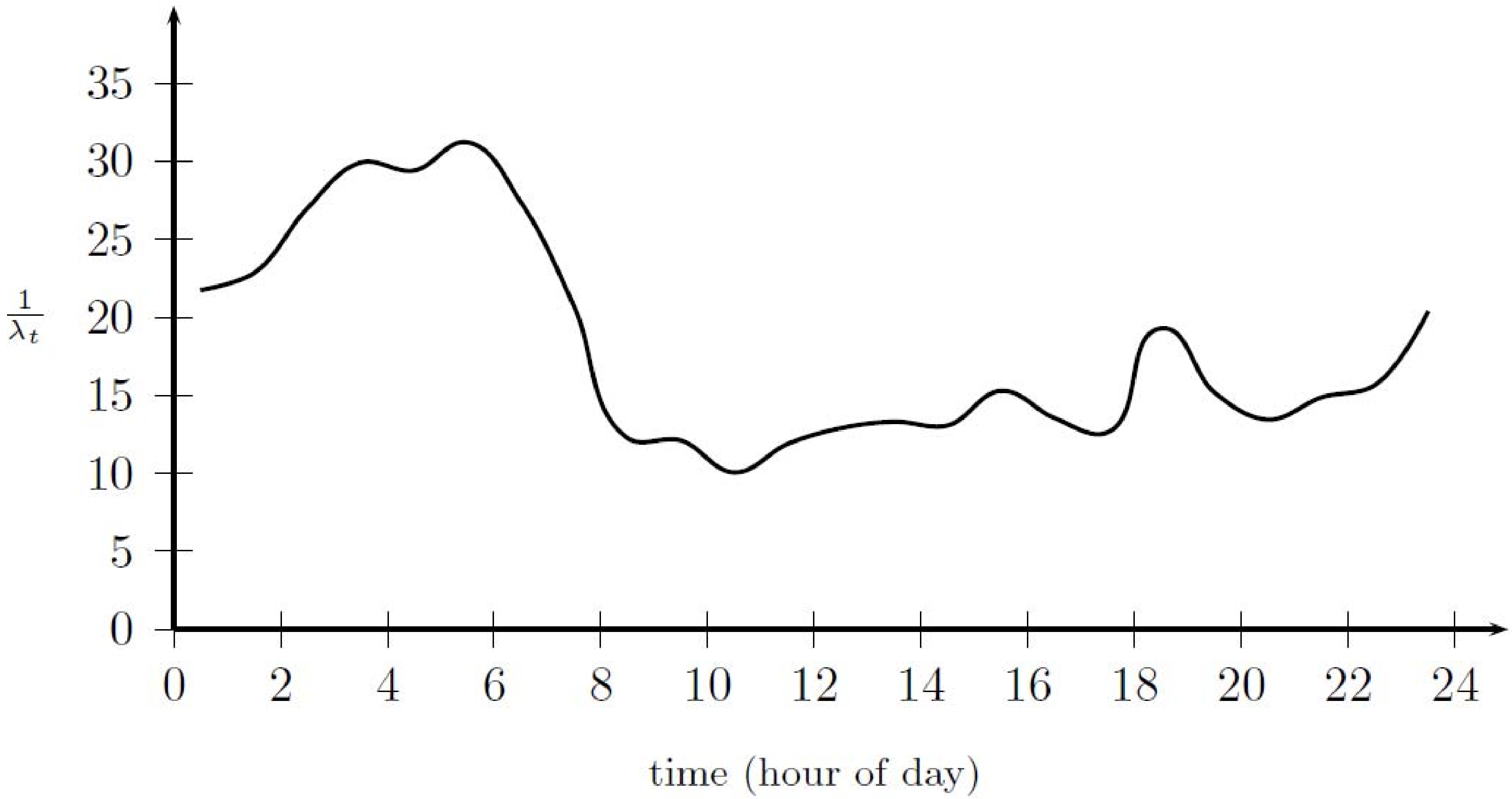
data

- **real data**
  - street network: city of Vienna (1.7 mio inhabitants, 41.5 hectare)
  - fleet of 14 ambulance vehicles, 16 locations
  - **requests**
    - average # of 89.24 emergencies per day
    - volume itself highly dependent on time of day
    - exponentially distributed interarrival times
    - spatial poisson process based on distribution of origins

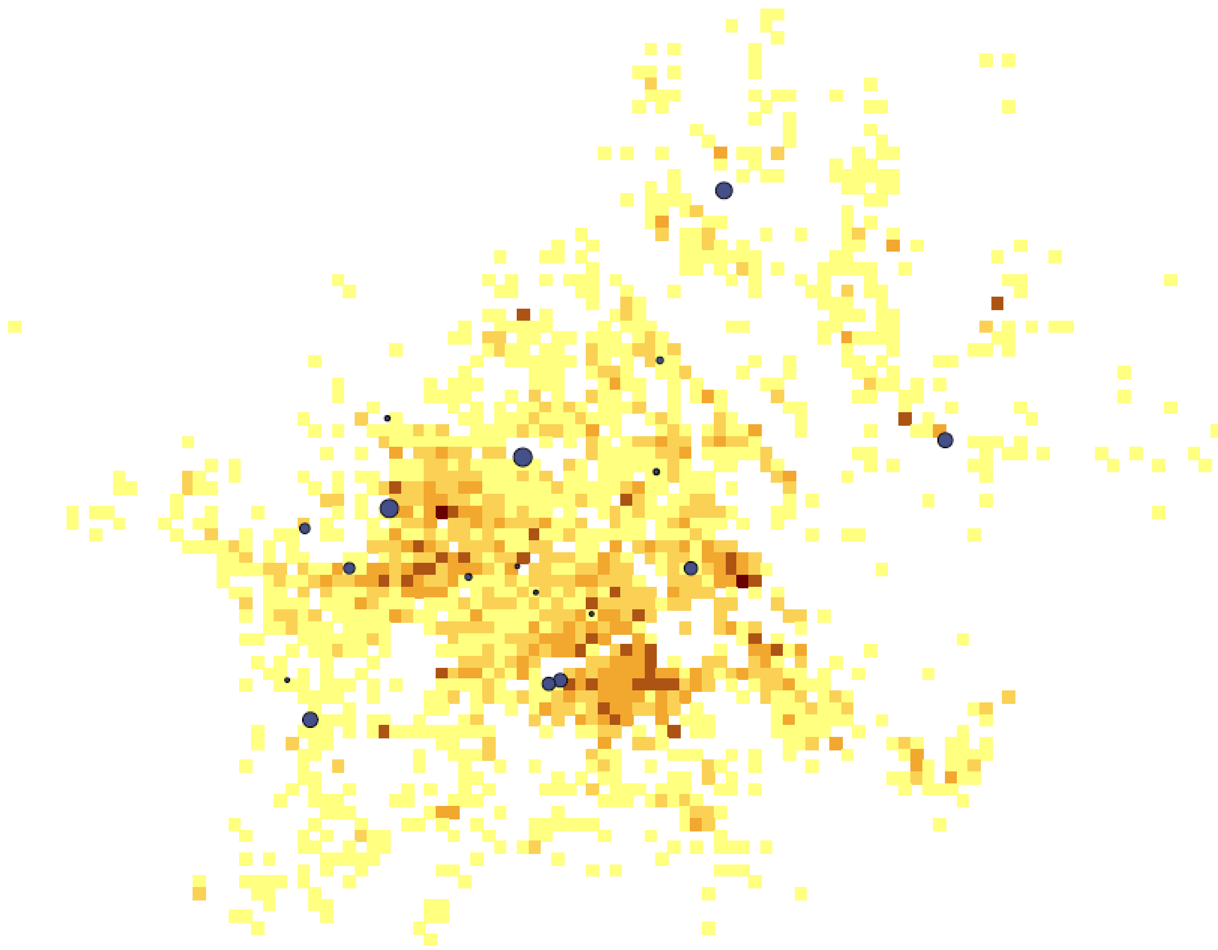
road network & waiting locations



interarrival times



origin & destination of requests

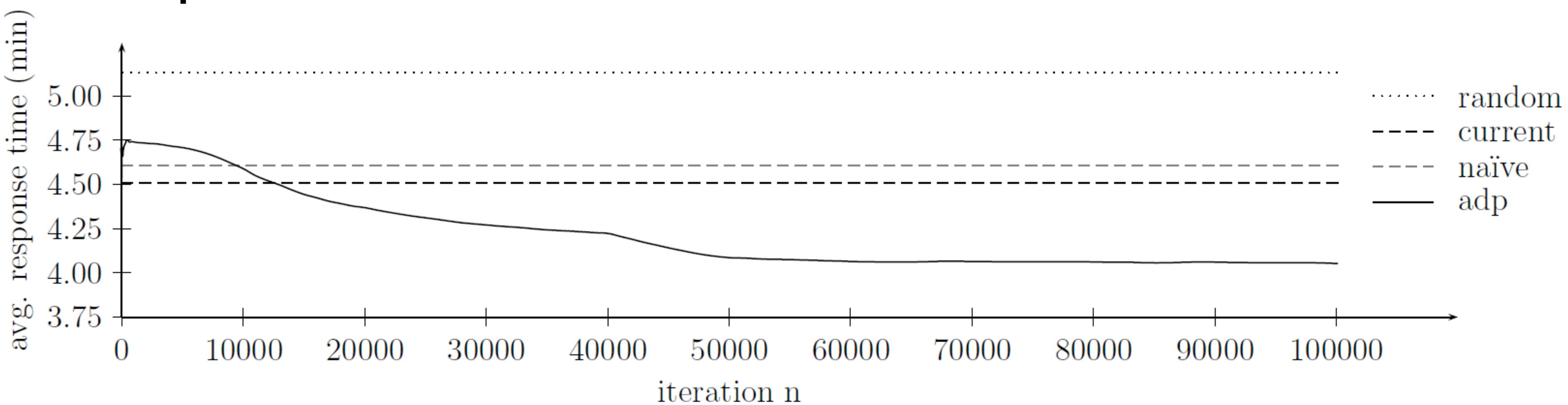


experiment setup

- **experiment setup**
  - training phase (10^5 iterations)
    - fixed step size $\alpha = 0.2$
    - temporal (spatial) aggregation parameter $\phi t = \phi s = 4$
    - sampled data from estimated distributions
  - 5 independent test runs

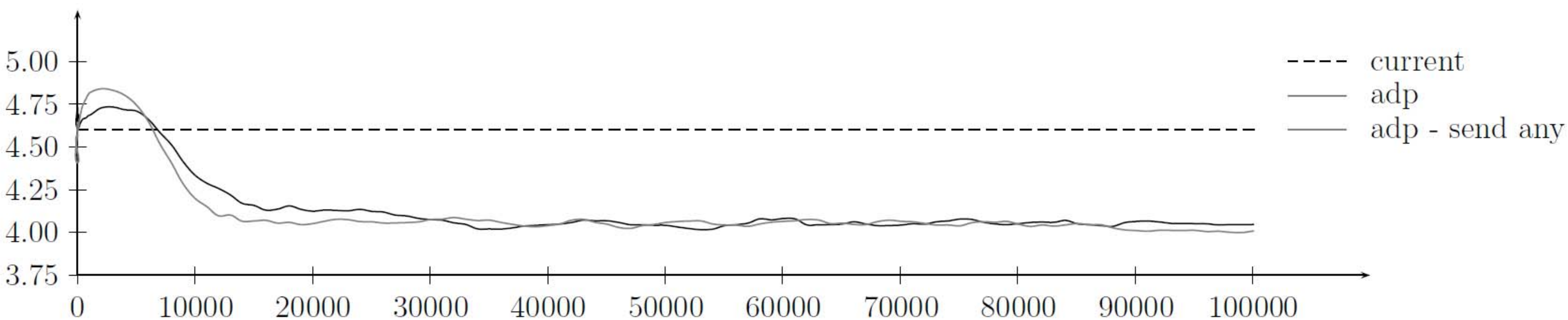
first training: 10^5 iterations

- **2 decisions**
  - ~~**which** vehicle to dispatch~~
  - **where** to relocate?
- **benchmark policies**
  - relocate to **home** location 4.51 min (current strategy)
  - relocate to **closest** location 4.61 min (naïve strategy)
  - relocate to **random** location 5.12 min
- **adp** **4.05 min**

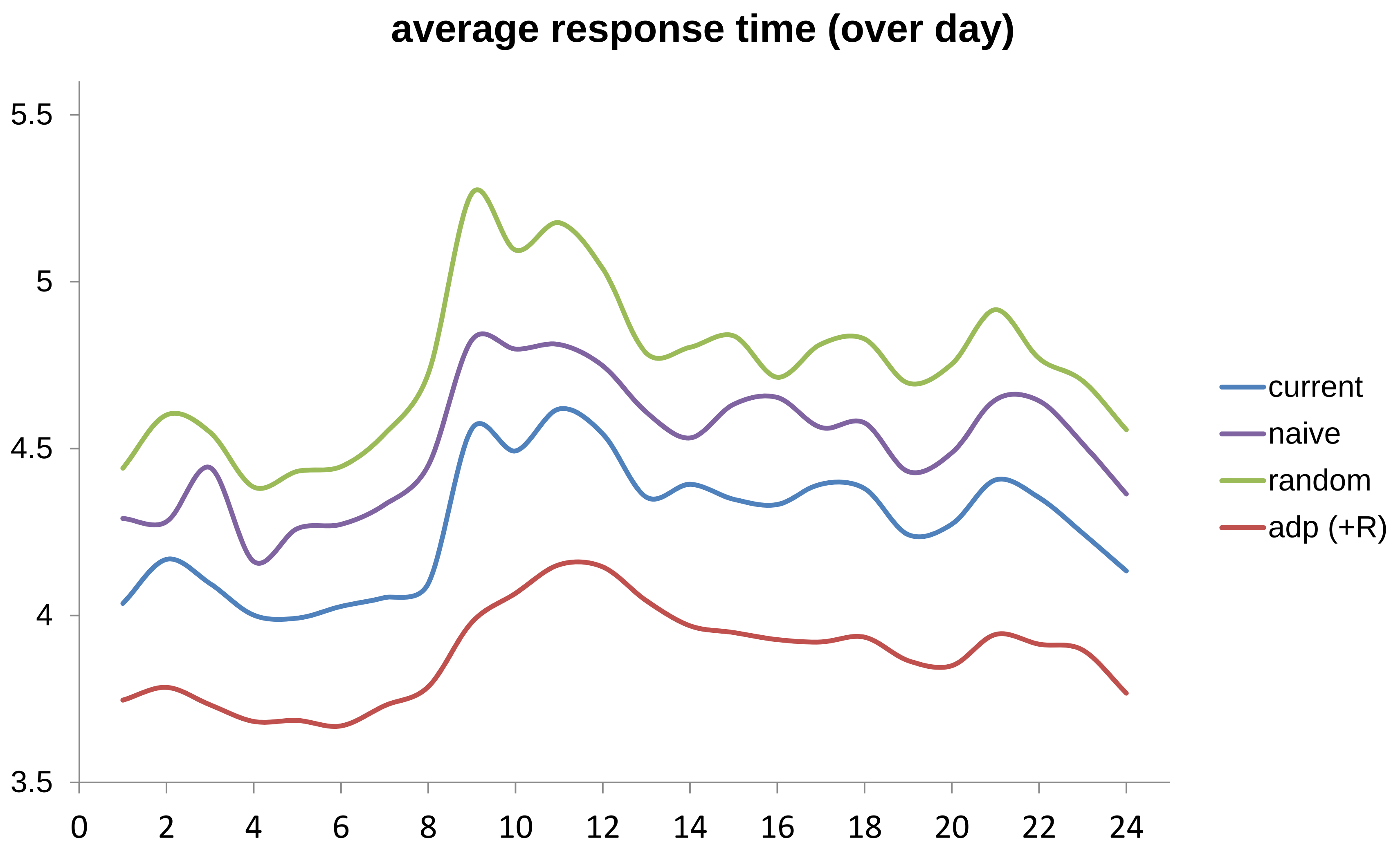


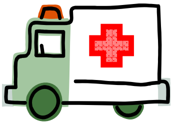
relax this assumption

- **2 decisions**
  - which vehicle to dispatch (closest! regulatory rules)
  - where to relocate?
- **benchmark policy**
  - relocate to home location 4.60 min (current strategy)
- **adp**
  - send closest 4.05 min
  - send any 4.01 min



response times over course of day





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conclusion

- **contribution**
  - **formulated a dynamic model** for the ambulance dispatching and relocation model
  - solved using **ADP**
  - **outperformed** benchmark policies (random/naïve/current)

  - **pays off to deviate** from current dispatching rules (13%)
    - consider other vehicles (not just closest one) for **dispatching**
    - **relocate** vehicles adequately **after** finishing service
    - **relocate** vehicles **empty** to cope with current situation

European Journal of Operational Research 219 (2012) 611–621

Contents lists available at SciVerse ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming

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ARTICLE INFO

Article history:
Available online 10 November 2011

Keywords:
OR in health services
Emergency vehicles
Ambulance location
Approximate dynamic programming
Stochastic optimization

ABSTRACT

Emergency service providers are supposed to locate ambulances such that in case of emergency patients can be reached in a time-efficient manner. Two fundamental decisions and choices need to be made real-time. First of all immediately after a request emerges an appropriate vehicle needs to be dispatched and send to the requests' site. After having served a request the vehicle needs to be relocated to its next waiting location. We are going to propose a model and solve the underlying optimization problem using approximate dynamic programming (ADP), an emerging and powerful tool for solving stochastic and dynamic problems typically arising in the field of operations research. Empirical tests based on real data from the city of Vienna indicate that by deviating from the classical dispatching rules the average response time can be decreased from 4.60 to 4.01 minutes, which corresponds to an improvement of 12.89%. Furthermore we are going to show that it is essential to consider time-dependent information such as travel times and changes with respect to the request volume explicitly. Ignoring the current time and its consequences thereafter during the stage of modeling and optimization leads to suboptimal decisions.

1. Introduction and related work

Emergency service providers are supposed to locate ambulances such that in case of emergency patients can be reached in a time-efficient manner. Two fundamental decisions and choices need to be made real-time. First of all immediately after a request emerges an appropriate vehicle needs to be *dispatched* and send to the requests' site. Ambulances, when idle, are located at designated waiting sites. Hence after having served a request the vehicle needs to be *relocated* (i.e. its next waiting site has to be chosen). For a close match to reality, time-dependent information for both traveling times and the request volume will be considered explicitly. We

cardiac and circulatory arrest the chances for a resuscitation to be successful decrease dramatically. Typically chances decrease by 10% per minute as long as the patient is not treated accordingly. Providing a quick response to emergency requests is crucial for the patients' state of health.

The contribution of this paper is threefold.

(i) We propose a stochastic dynamic model for the ambulance relocation and dispatching problem, which will be solved by means of ADP.
(ii) In order to get a preferably accurate model of reality we will explicitly take into account time-dependent information and

Thank you for your attention!

Questions?

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