

Predicting EMS system state in the near future

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1. Problem
2. Motivation and Application
3. Related work
4. Methodology
5. Validation
6. Validation Results
7. Conclusion

- Predicting emergency medical services (EMS) state in the near future
- EMS state
 - State of ambulances: position and availability
 - State of calls: position and status
 - Continuously changing
 - In future, affected by dispatch and relocation decisions

- Motivation

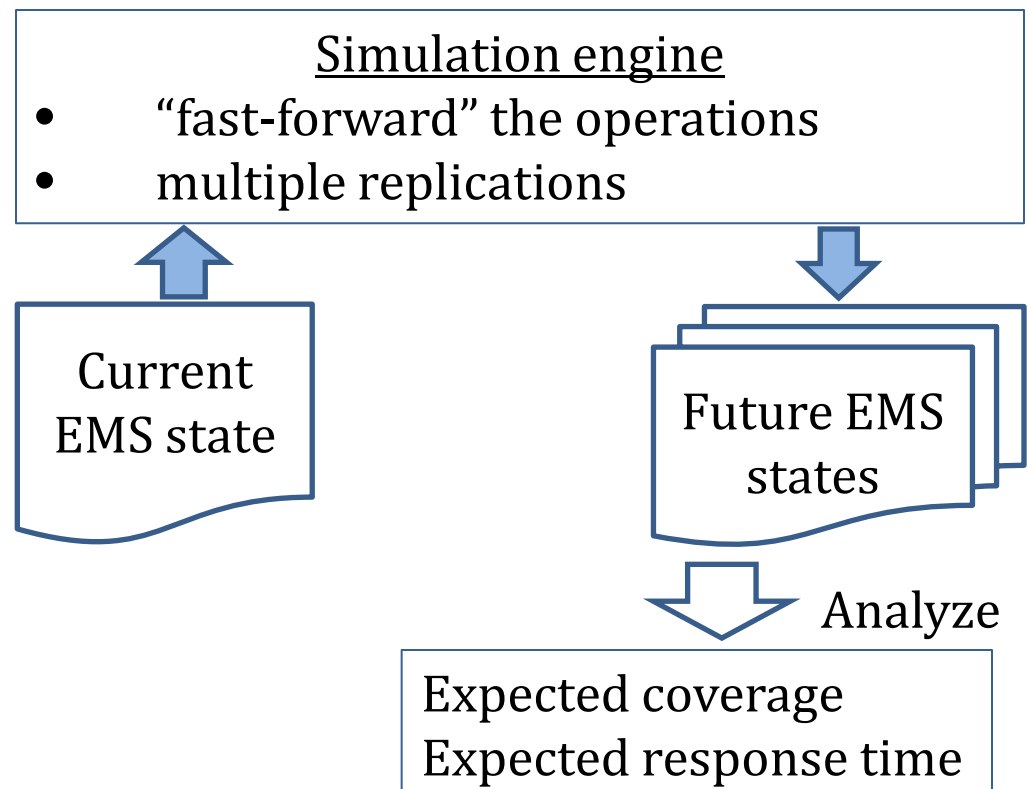
Dispatch and relocation decisions

- considering possible moves of a candidate vehicle,
- often assuming other vehicles do not change in position or availability.

- Application

- evaluating the impact of possible dispatch and relocation decisions in coming hours (*Goldberg, 2004. OR models for the deployment of emergency services vehicles*)

- Discrete event simulation is used.
- Conceptual model



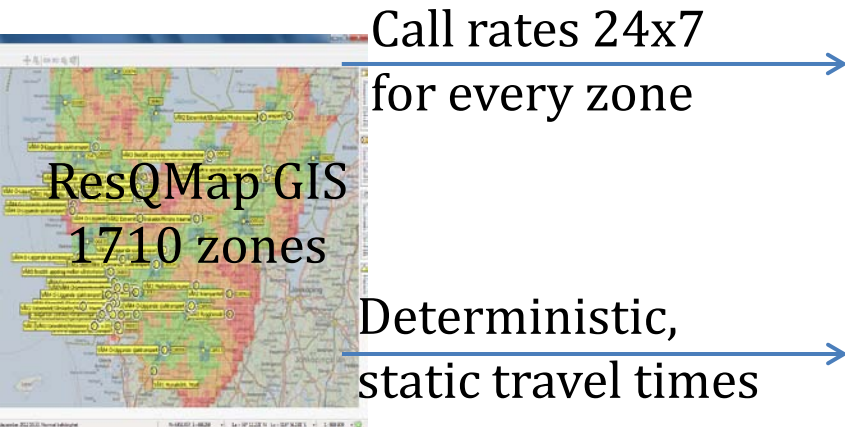
- Mason A. J., 2013. Simulation and Real-Time Optimized Relocation for Improving Ambulance Operations

“Because repositioning takes time, it is important to consider changes in the availability of vehicles that are likely to occur in the near future. Because the status and position of each vehicle are known, it is possible to predict the likely vehicle positions and availabilities once their current activities are completed”

- Critical period of 20 minutes
- A single future scenario is predicted
- Future view is displayed in the form of a predicted future call coverage map (Optima Live for reposition problem)

- Application to Västra Götaland County, Sweden
- System states are extracted from log files (snapshots)
 - inputs to the simulation model: fleet size, state of vehicles, state of active calls
 - empirical bases (i.e. real system states) to which the simulated outputs are compared.

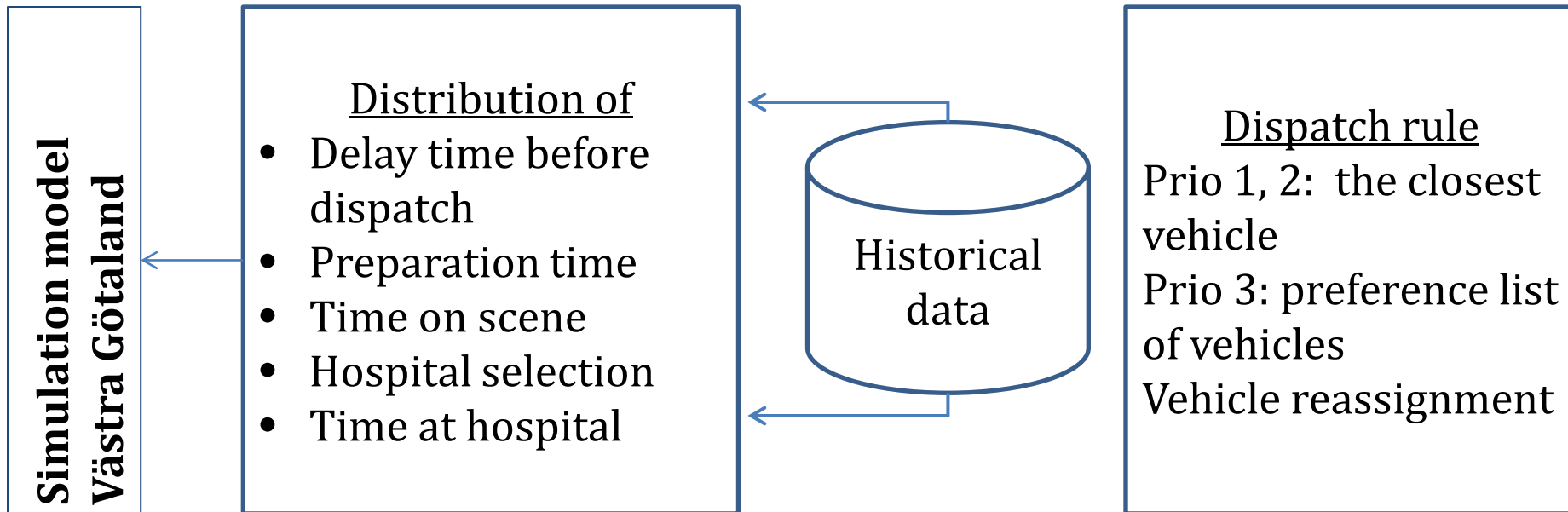
• Application to Västra Götaland County, Sweden



Call generator
Emergency calls of priority 1, 2, 3
Call intervals follow an exponential distribution

Travelling model
Ratios for travel speeds
Pre-computed shortest routes

• Application to Västra Götaland County, Sweden



A test case/an input snapshot

100 replications

Measures:

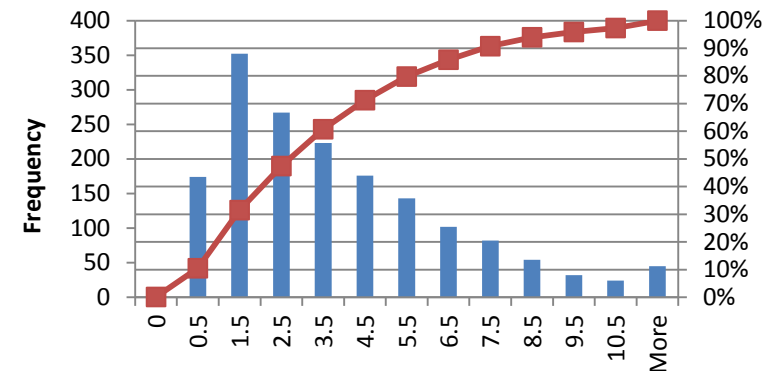
- #available vehicles
- Region-wide response time
- Mean response time for high-demand zones (150 zones)

Average value of 100
replications**Absolute difference**Corresponding real
system stateThe relevant real
measure**95% prediction
interval**

- Prediction of #available vehicle

95%PI	30min simulation	60min simulation
TRUE	80% (5.7-11-15.5)	73% (7.4-13.7-19.5)
FALSE	20% (6.0-11-16.2)	27% (7.8-14.8-21.0)

Abs. dif. (vehicles)	30min	60min
<3.5 ~ 3	61%	44%
<4.5 ~ 4	71%	53%



- Prediction of response time

95%PI		30min simulation	60min simulation
Region-wide response time	TRUE	87% (1.0-3.6-19.5)	88% (1.6-4.6-14.0)
	FALSE	13% (1.2-3.4-11.6)	12% (2.2-4.3-8.0)

- Prediction of response time

Response time	Abs. dif. (minute)	30min simulation	60min simulation
Region-wide	<1.5	81%	72%
	<2	90%	83%
High-demand zones	<1.5	77%	71%
	<2	84%	79%

- The better accuracy of shorter duration prediction is expected.
- Using the average response time to assess the EMS state prediction shows remarkable validity.
- The proposed prediction model with simulation engine can support dispatch and relocation by artificially including the decisions in the input snapshot given to the simulation.

Thank you!

