

“Success Stories of Mathematics in Real Life”

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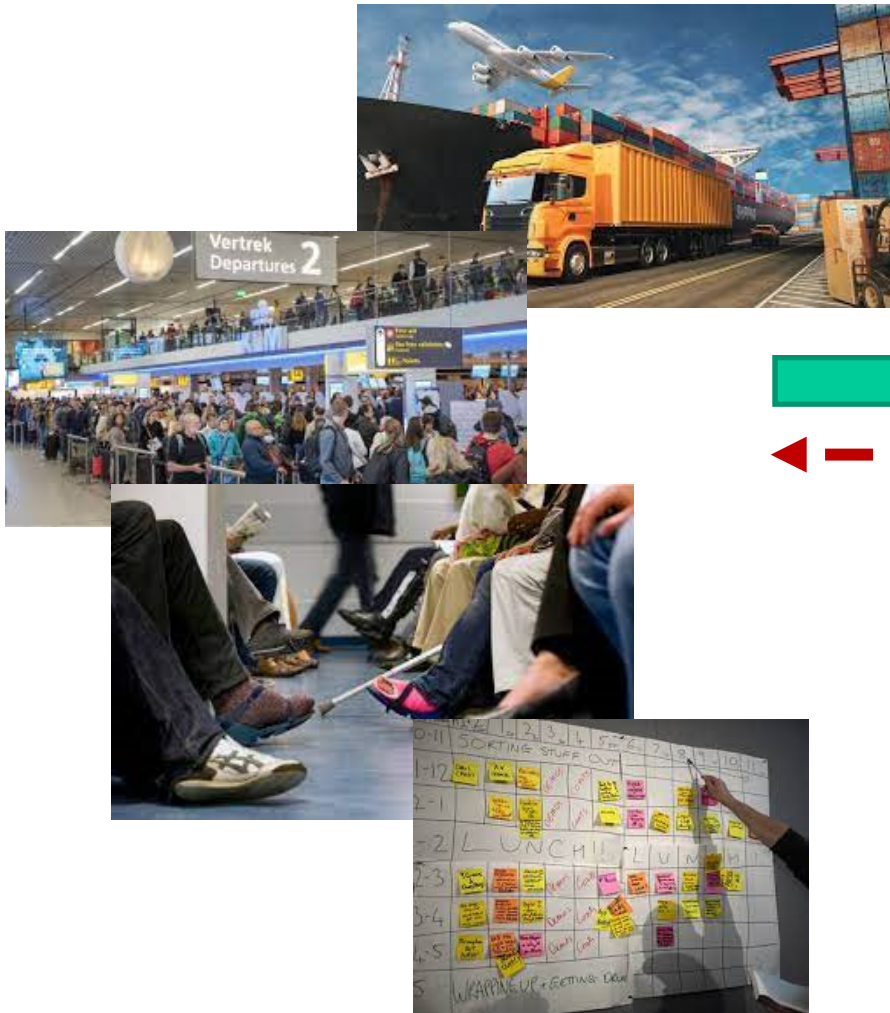
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Thanks to: Karen Aardal, Caroline Jagtenberg, Pieter van den Berg, Thije van Barneveld, Theresia van Essen, Martin van Buuren, Sandjai Bhulai, Coen Huibers, Lisette Sloof, Guido Legemaate, Rebekka Arntzen

Problem: Applied Mathematics too often Not Applied...

“practice”



“theory”



Success Stories of Mathematics in Real Life

Plan for today:

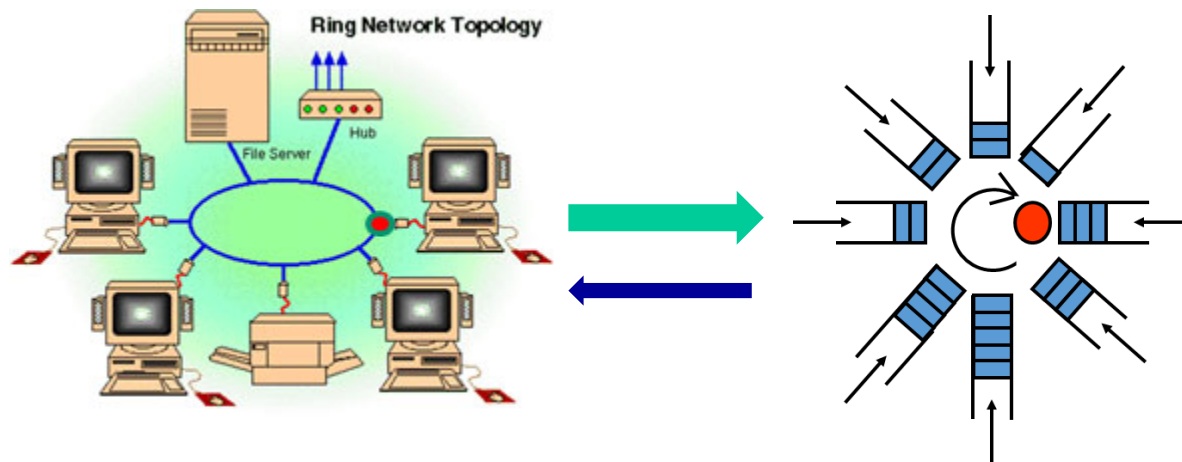
1. Examples of success stories

- Ambulance
- Firefighters
- Predictive policing
- Reducing waiting times in acute elderly care

2. Lessons learned and discussion



Short Resume



1991

M.Sc. in Mathematics and Econometrics

1995

Ph.D. in Queueing Theory

1996-2000

AT&T Bell Labs USA

2000-2002

KPN Research

2002-2004

TNO ICT

Since 2003

Full Professor in Applied Mathematics at VU A'dam

Since 2004

Centrum Wiskunde & Informatica

Over the years: shift from theory to application

Over the Past 25 Years...



Over the years:

100+ consultancy projects, 100+ R&D projects, 60+ Ph.D. students, 130+ M.Sc. students

Topics of interest: emergency logistics, healthcare logistics, RM & pricing, telecommunication networks, mobility, AI for suicide prevention, AI for cyber security and intelligence, defense

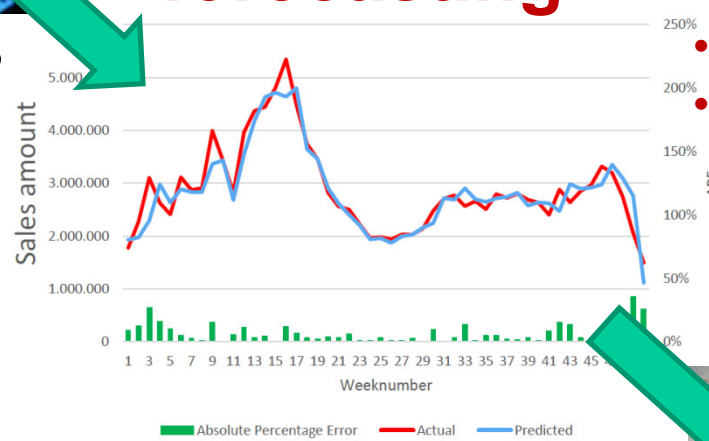
Data, Forecasting and Optimization

data



insights and forecasting

data analytics



- Operations Research
- Stochastic Optimization

optimization



optimization models

- Data mining
- Machine learning
- Neural networks
- Artificial intelligence
- Pattern recognition
- Predictive analytics
- Statistics

Pictures from veiligheidsregio
Noord-Holland Noord



IARIA Congress, Nice, July 24-28, 2022

Ambulance Care in NL



A1-calls: Urgent and life threatening

< 15 min

- severe incident

A2-calls: Urgent but not life-threatening

< 30 min

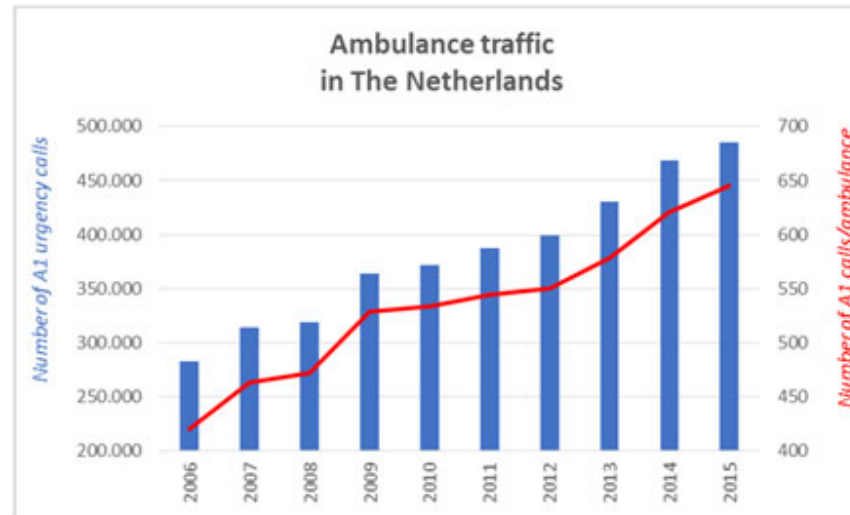
- broken leg

B-calls: Planned transport

- 'taxi' transport between hospital and care center or home

Requirement: 95% within response-time deadline

Ambulance Care in NL



Facts:

- 1 million calls per year, out of which 500,000 A1-calls
- 35,000 times (7%) the 15-minute target is not met
- Growing demand ('groeiende zorgvraag')

New and powerful concept:

Dynamic Ambulance Management: proactive planning

CWI



REPRO : from Reactive to Proactive



Wiskunde redt levens
Kansberekening en modellering moeten ambulanceplanning in Amsterdam verbeteren
JONNE ZANDHUIS

WETENSCHAP 'Incidentplanning werkt als een schaakspel'
Ambulance is vaker op tijd dankzij de wiskunde.
De ambulance die een te lange aarrnhdheid heeft om een leven te redden, het is een schrikbeeld. Rob van der Mei maakt met behulp van wiskundige modellen hulpdiensten met ambulancevoertuigen efficiënter.

'Ambulances kunnen veel tijdwinst boeken'
efficiënt inzetten van hun wagens. De inefficiency leidt volgens hem tot omroede kosten. Het centrum wil op basis van voorbeeld verkeersdrukte in brengen hoe lang het duurt ambulances op van A naar B van de dag van A worden Ook kan worden groot de kans is dat lancee nodig is. Op rekeningen kun de regio stand- lances moete netwerk te Van de kele maan- lingen te kum-

'Big Data' helpt politie
PvdD: vragen over rioolwet

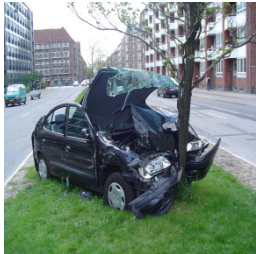
Amsterdam
'Ambulances kunnen veel sneller'
AMSTERDAM - De inzet van ambulancevoertuigen kan veel beter worden georganiseerd. Er kan veel tijdwinst worden geboekt. Wiskunde en informatiekunde worden gebruikt om de efficiëntie van de ambulancedienst te verbeteren. De organisatie gaat samen met de TU Delft, de gemeente Amsterdam en de Nederlandse Organisatie voor Wetenschappelijk Onderzoek (NWO). De organisatie gaat samen met de TU Delft, de gemeente Amsterdam en de Nederlandse Organisatie voor Wetenschappelijk Onderzoek (NWO). Volgens prof. dr. Rob van der Mei van het instituut, zijn er grote verschillen in de inzet van ambulances op een bepaald moment van de dag van A naar B te krijgen. Ook kan worden groot de kans is dat lancee nodig is. Op rekeningen kun de regio stand- lances moete netwerk te Van de kele maan- lingen te kum-

amst'lyv IEDERE ZONDAG SHOPPEN
www.stadsforumamstelveen.nl

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Ambulance Service Process

112!



New incident happens

call center

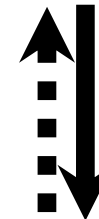


'Closest' available ambulance allocated

base station



Ambulance departs



Medical treatment On-scene



hospital



Patient handed over

To closest base location

To closest hospital

Mathematics in Action

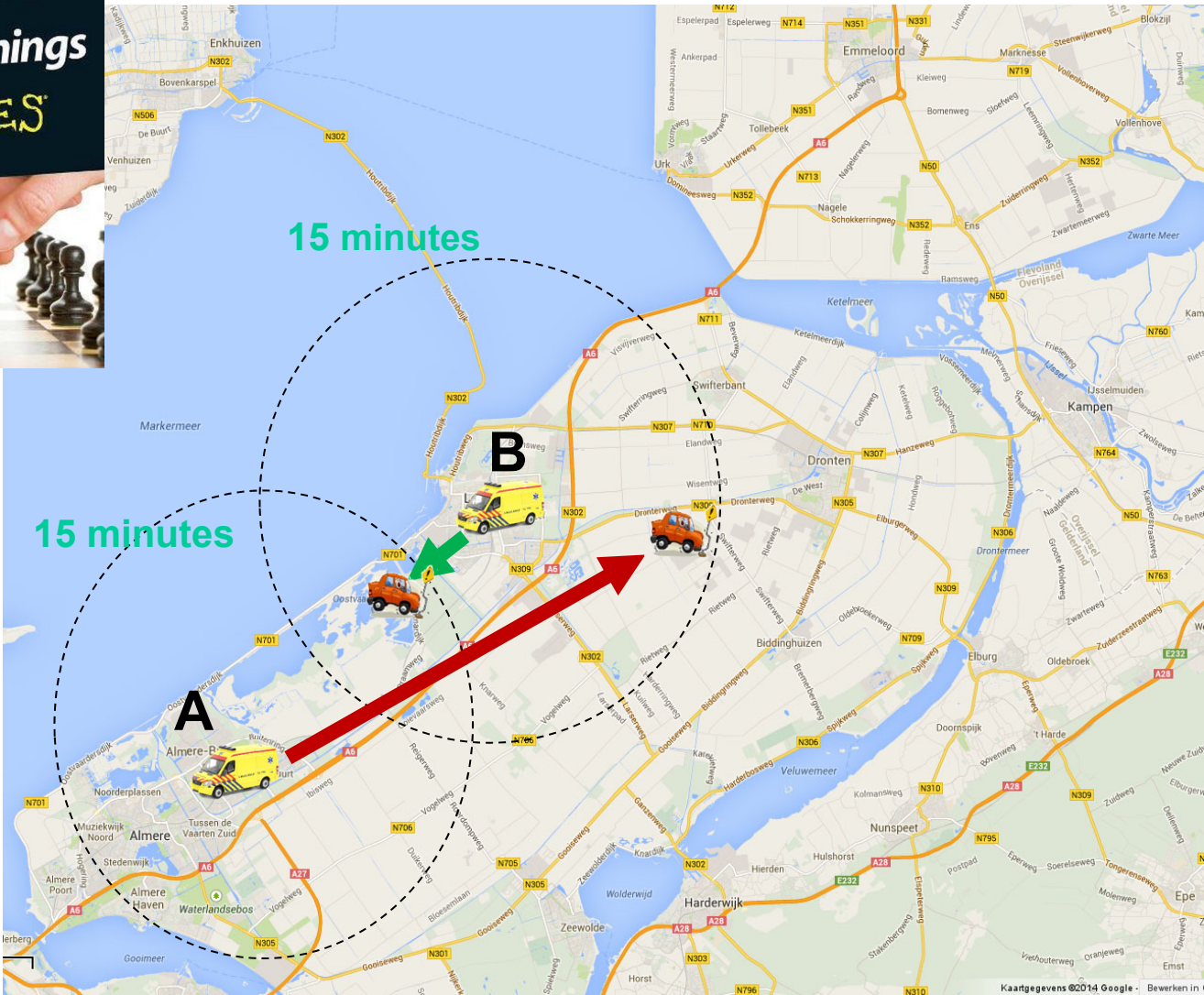
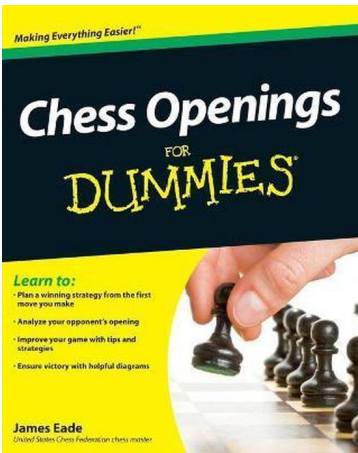


Playing Chess



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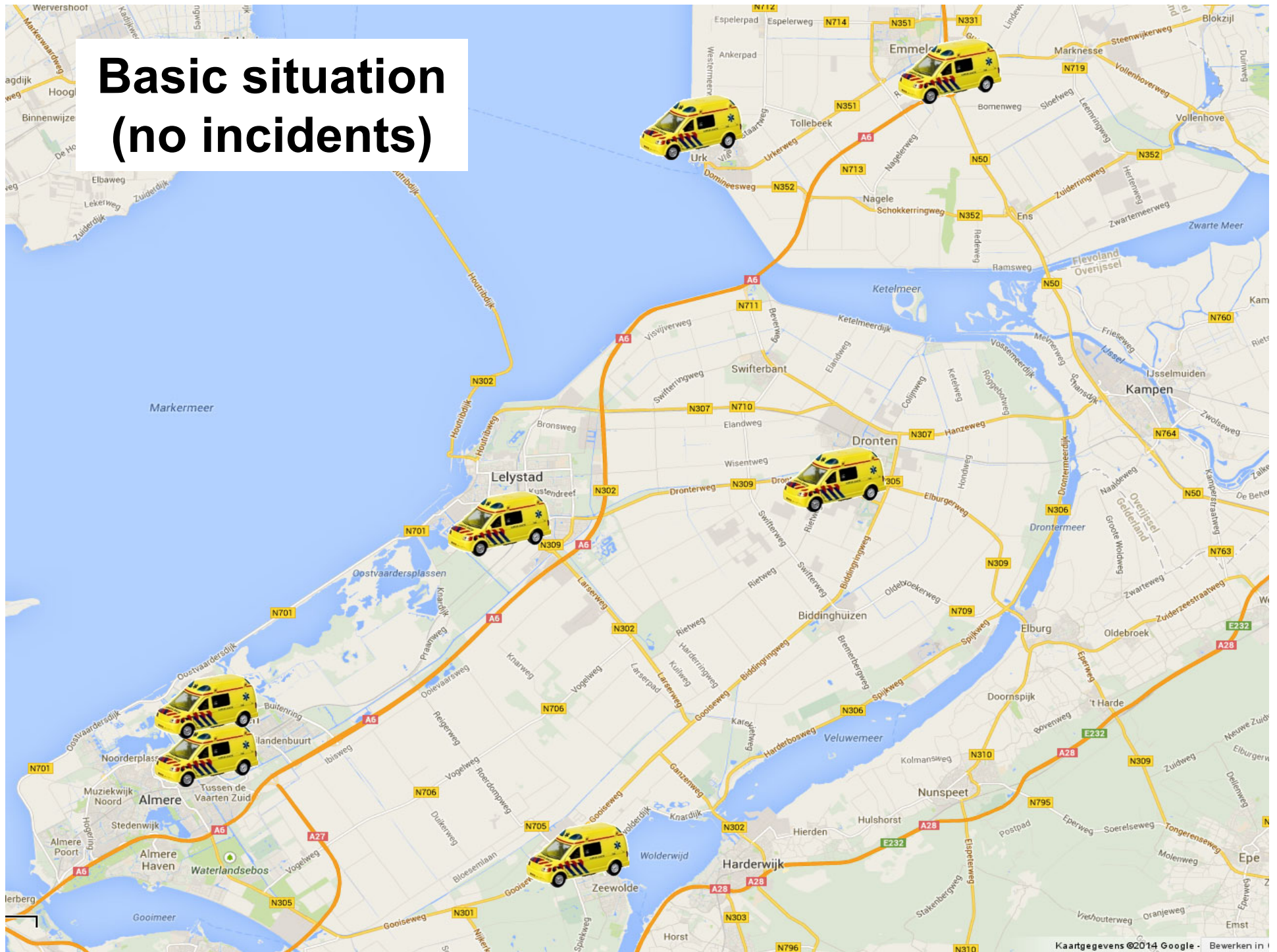
Chess for Dummies



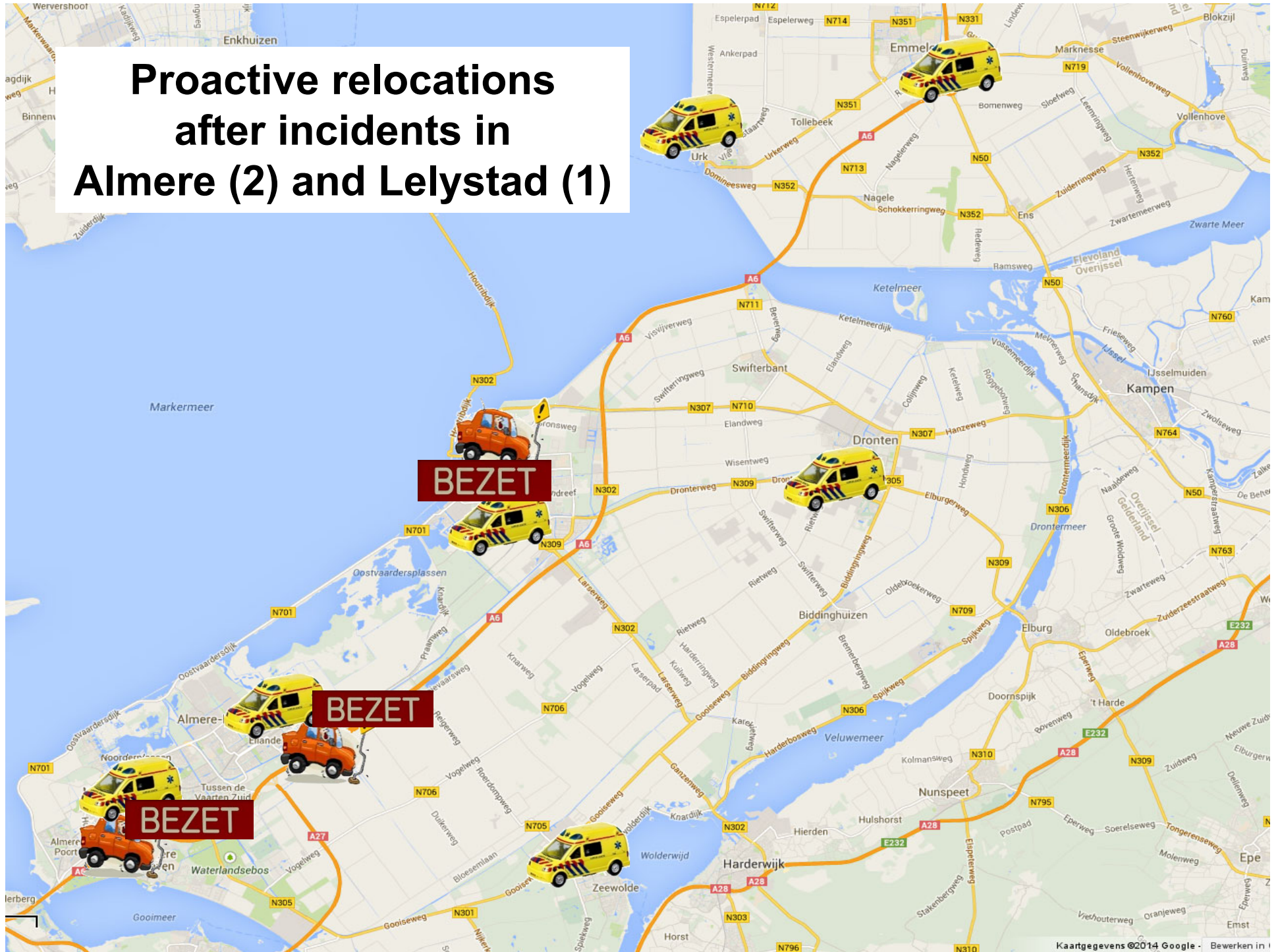
Chess for Professionals



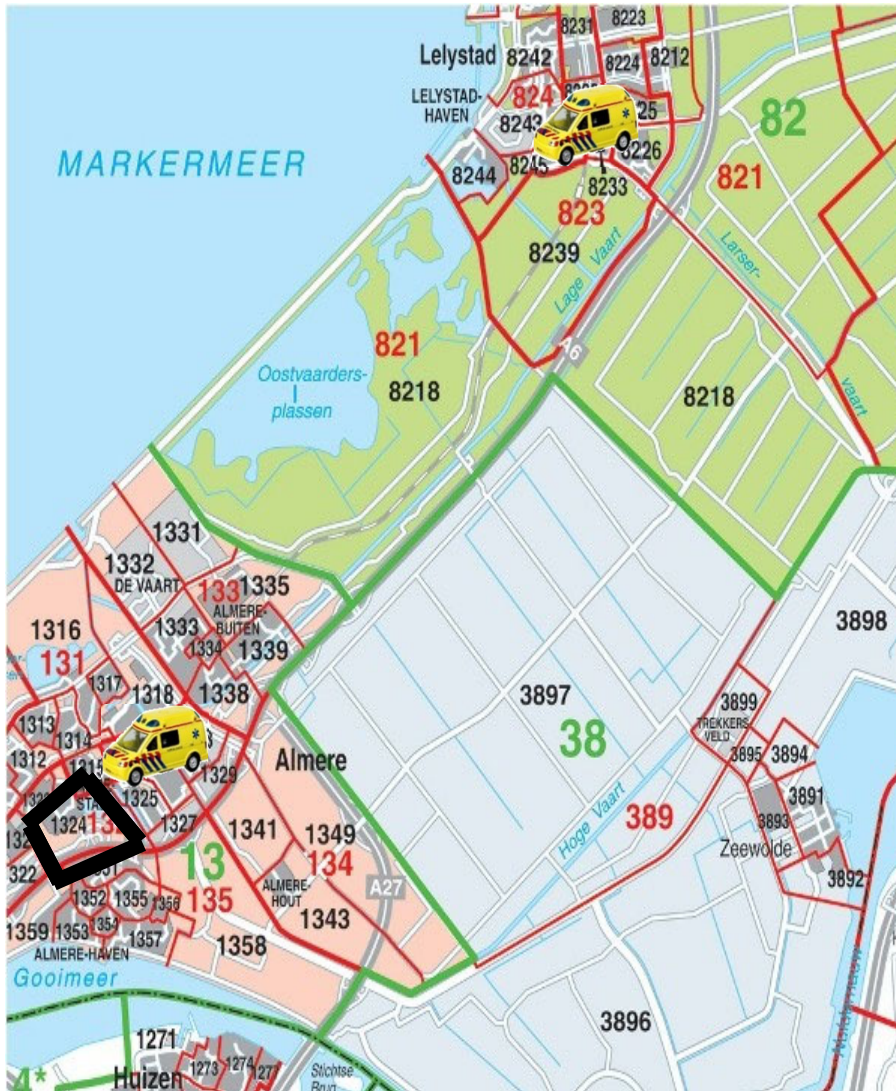
Basic situation (no incidents)



Proactive relocations after incidents in Almere (2) and Lelystad (1)

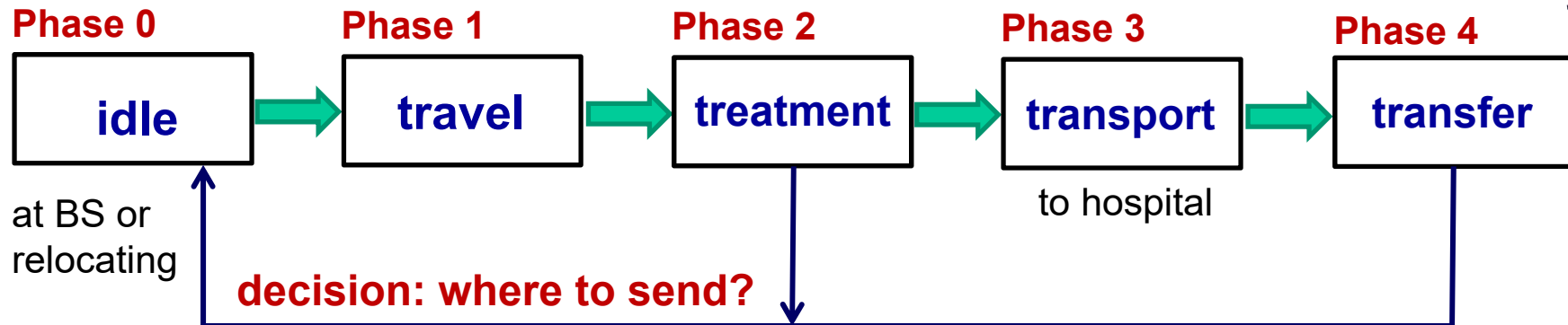


Simple Model



- Region subdivided in N nodes (postal areas)
- Base locations
- Locations of hospitals
- **Next incident:** at node i with probability p_i
- **Arrivals:** Poisson
- All incidents of highest urgency
- Travel distance matrix R (fixed)

Simple Model



Relocation decision moments:

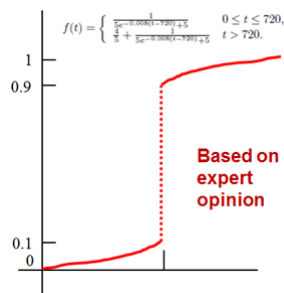
- **1:** when ambulance is dispatched to **newly** incoming incident
- **2:** when ambulance **becomes idle** → **where to go?**

Single-Coverage Heuristic

Basic idea: minimize ‘unpreparedness’

- **System state:**
for each ambu: (location/destination, phase)
- **Unpreparedness:**

$$U(s) := \sum_{i=1}^N f(\min\{r_i^0(s), r_i^4(s)\}) p_i$$



driving time from
destination of
closest phase-0
ambu to node i

expected time till
closest phase-4
ambu is present
at node i

Single-Coverage Heuristic (ct'd)



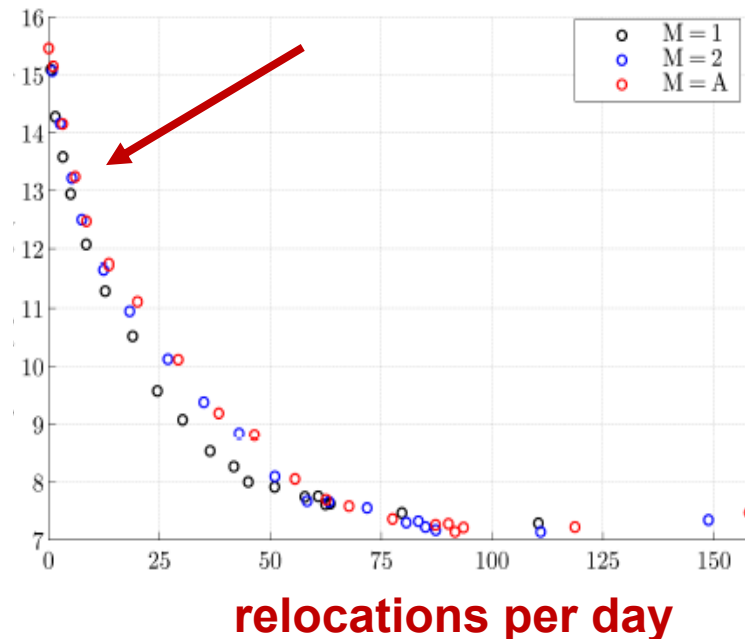
	A	L	Z	D	E	U
A	0.49201	0.71491	0.95077	0.8746	0.80672	0.82788
Z	0.52587	0.29001	0.49201	0.44969	0.38181	0.40297

Example: unpreparedness in given situation = 0.49201

Sending an ambulance from Zeewolde to Lelystad reduces unpreparedness by from 0.49 to 0.29

Effectiveness of Relocations

late arrivals



Good news:

1. Only a few relocations really do matter
2. Doing ‘at least something’ already makes the difference (“80/20-rule”)

Real-Time Decision Making



weather circumstances

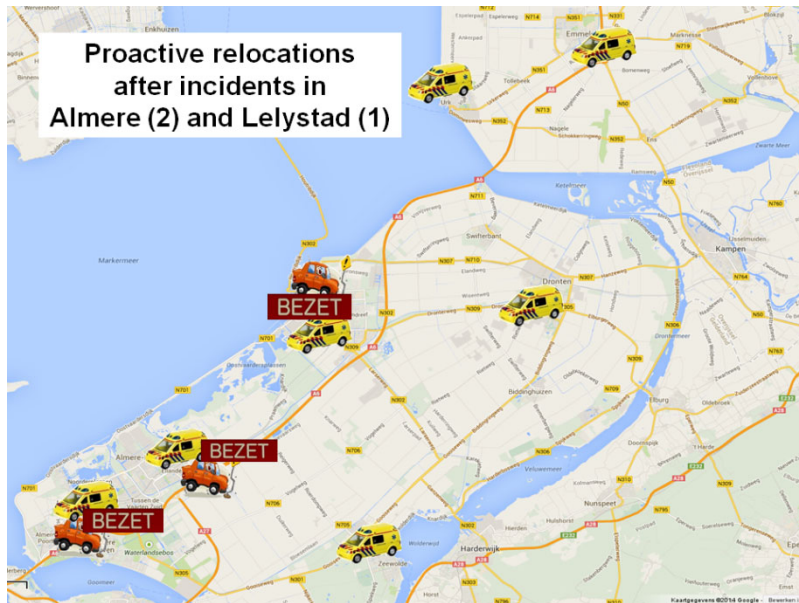


real-time traffic information



mass events

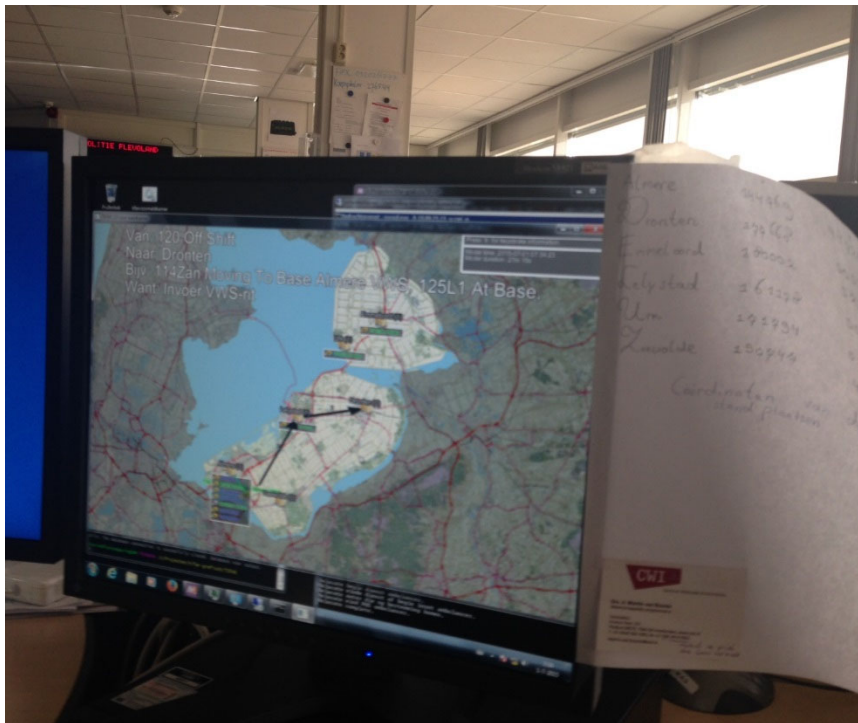
Acceptance in Practice?



Acceptance of new concept only if

1. not too many relocations!
2. only at specific time epochs (e.g., departure from hospital)
3. performance is really better than 'static' solution

Proof of the Pudding...



Pilot with tool implementation

1. Our algorithms are well accepted and really used
2. More reliable / predictable performance
3. Strong reduction in late arrivals, while many more 112-calls!



Operational Setting

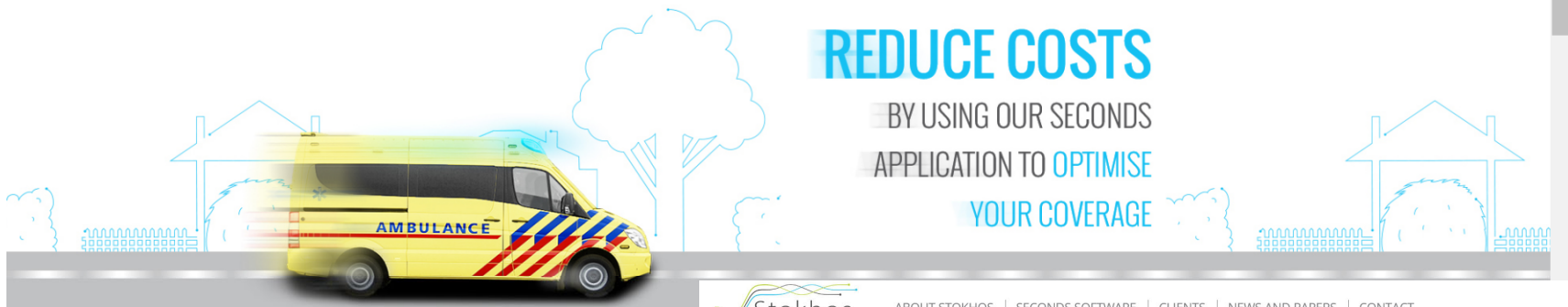
Computer zet ambulances slimmer in



Stokhos Emergency Mathematics



ABOUT STOKHOS | SECONDS SOFTWARE | CLIENTS | NEWS AND PAPERS | CONTACT



REDUCE COSTS
 BY USING OUR SECONDS
 APPLICATION TO OPTIMISE
 YOUR COVERAGE



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Op vrijdag 20 november besteedde actualiteitenprogramma EenVandaag aandacht aan de slimme innovaties van Stokhos en aan hoe deze succesvol worden ingezet in de veiligheidsregio's Flevoland, Gooi en Vechtstreek en Zuid-Holland Zuid. Mooie samenwerkingen die levens redden, hersteltijden bekorten, kwaliteit van leven na een incident op een hoger niveau weten te houden en zorgkosten besparen.



Voor het volledige artikel kunt u [hier](#) klikken.

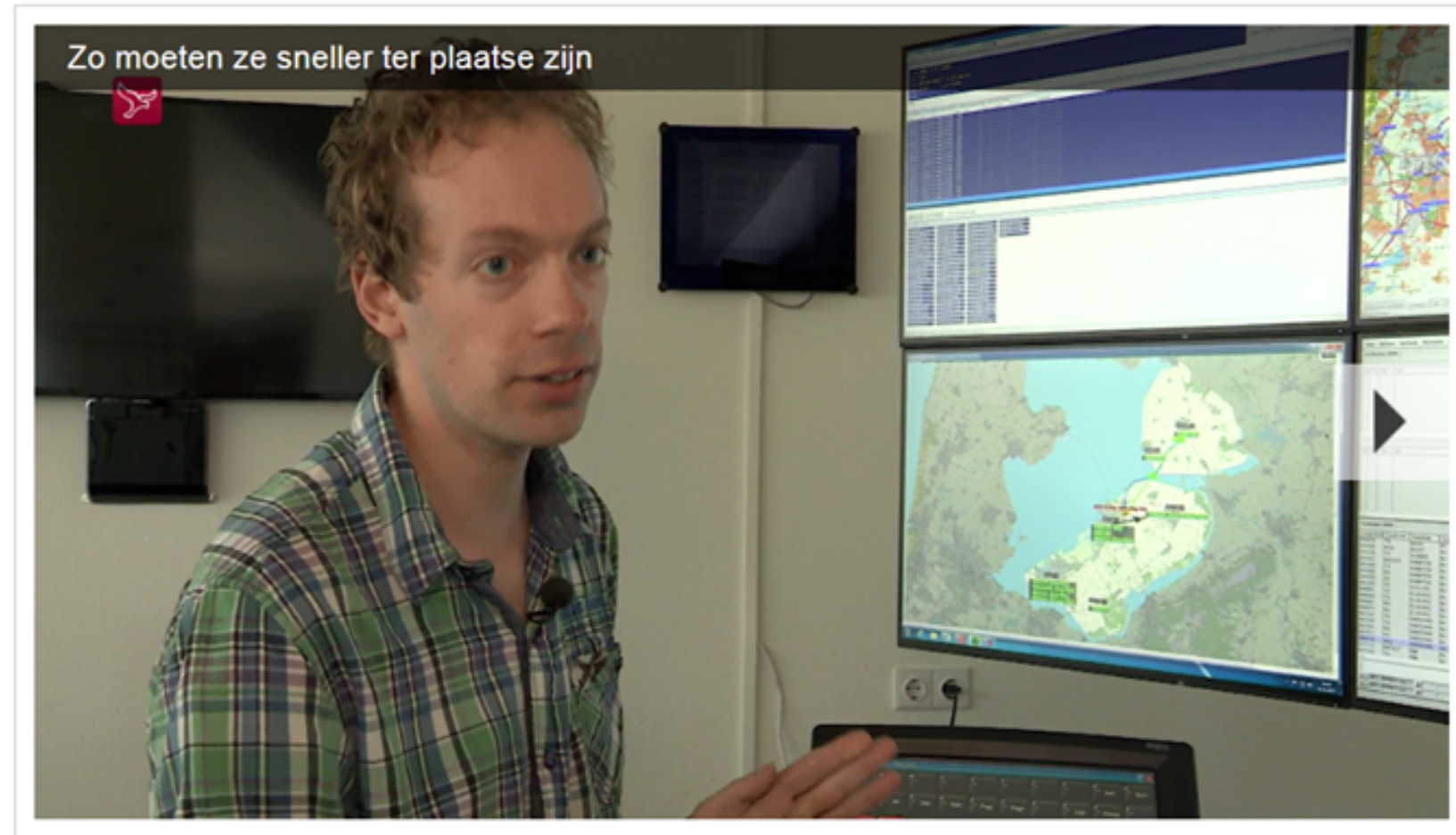
Our Seconds Application calculates the coverage of a that future incidents are reached within the set resp

FEATURES

What Made the Difference?

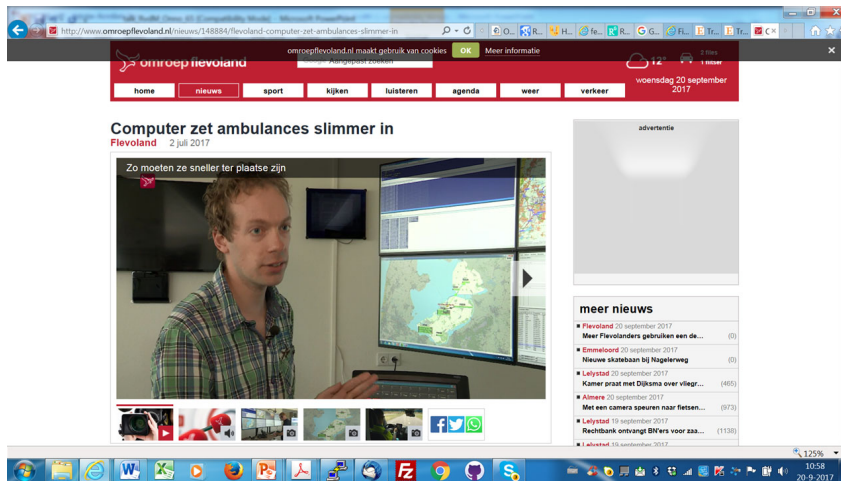
Computer zet ambulances slimmer in

Flevoland 2 juli 2017



Martin van Buuren

Lessons Learned



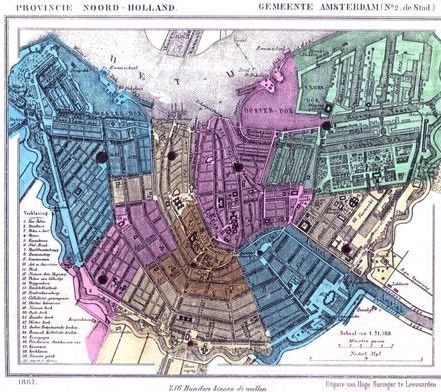
1. Not every researcher is a good entrepreneur!
2. Include software engineering expertise from the beginning
3. **Presence of the research team during pilot phase** crucial



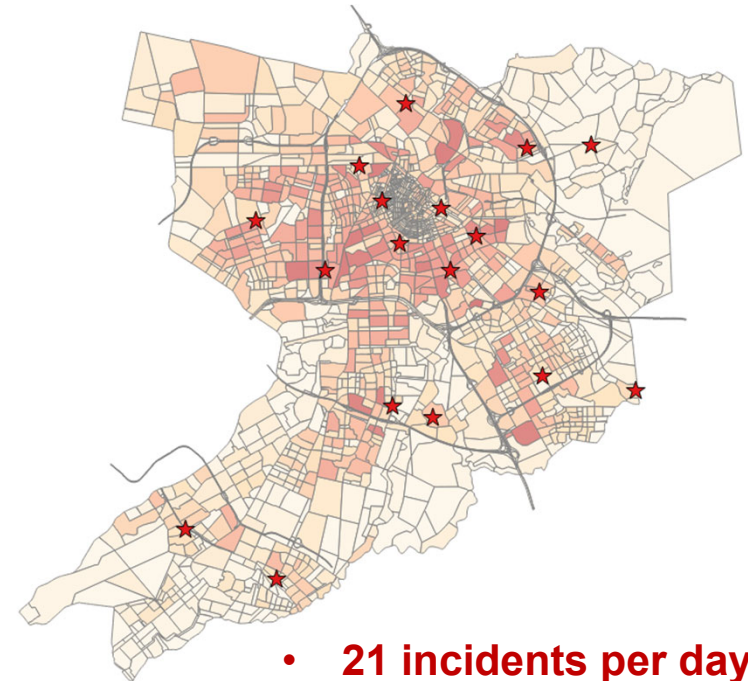
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Demand Changing over Time

Amsterdam in 1600



Service region Amsterdam/Amstelland



- 21 incidents per day
- duration 1 hour

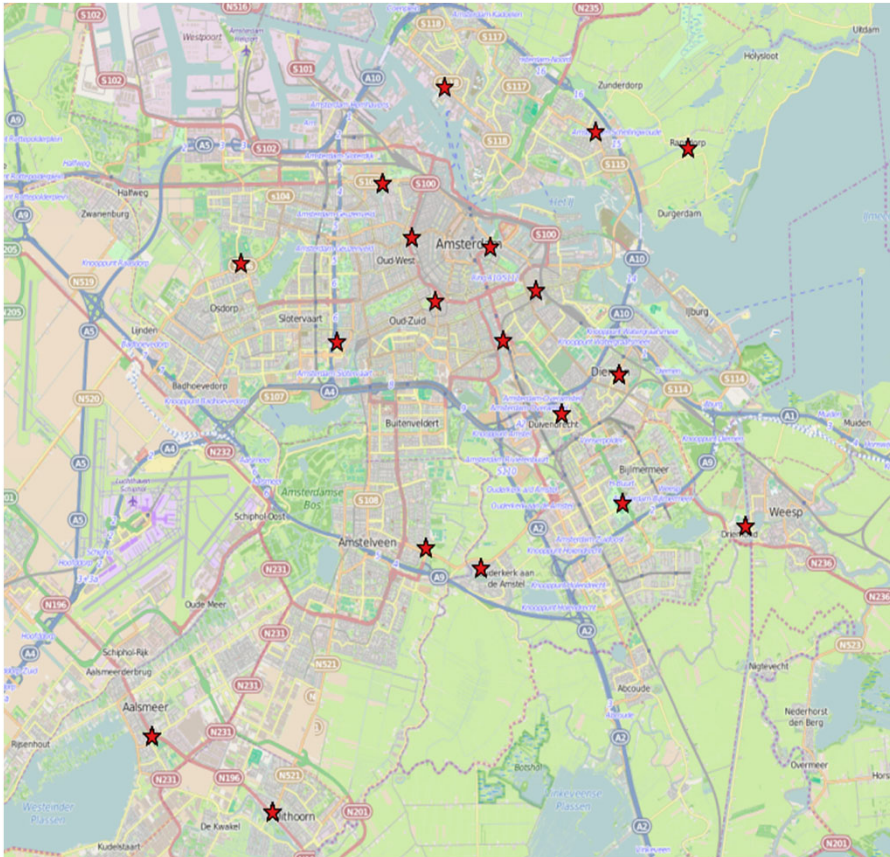
Amsterdam in 2020



Response time target: 5, 6, 8 or 10 minutes

Question: are base locations still properly located?

Mathematical Model



Assumptions

- set of demand locations (DL's)
- multiple vehicle types k
- relative demand $d_{i,k}$ for DL i for type- k vehicles
- distance matrix
- set of potential locations for base stations
- number of available vehicles per type
- professional or volunteer stations
- response time targets: 5, 6, 8, 10
- option to 'veto' relocation at specific stations

- Relocation of base locations

Optimization Model

demand at demand point i for vehicle type k

1 if demand point i is covered by vehicle of type k

1 if at least 1 vehicle located at location j

$$\max \left\{ \sum_{i \in N} \sum_{k \in K} d_{ik} y_{ik} - \beta \sum_{j \in M} z_j \right\}$$

Decision variables:

x_{jk} = #type- k vehicles at location j

$$\sum_{j \in M_{ik}} x_{jk} \geq y_{ik} \quad \forall i \in N, k \in K$$

coverage constraint for demand point i for type- k vehicles

$$\sum_{j \in M} x_{jk} \leq c_k \quad \forall k \in K$$

capacity constraint of type- k vehicles

$$x_{jk} \leq z_j \quad \forall j \in M, k \in K$$

no vehicles at unused station j

$$y_{ik}, z_j, x_{jk} \in \{0, 1\} \quad \forall i \in N, j \in M, k \in K.$$

Goal: Maximize expected coverage subject to constraints

Easy extension: inclusion volunteering stations

Optimization Results

coverage

4 modifications

# wijzigingen	Dekking				Totaal
	TS	RV	HV	WO	
0	87,68	98,23	96,84	88,64	90,83
1	89,99	98,23	96,84	88,64	92,29
2	91,76	99,64	96,84	88,64	93,74
3	93,20	99,64	97,27	89,78	94,70
4	94,38	99,64	96,84	90,68	95,53
Ongelimiteerd	98,62	99,86	98,10	93,37	98,53

Observation

% late arrivals can be reduced by > 50% by relocating only 4 stations!

Letter by Commander in Chief:

“The results convincingly show that—and how—significant improvements of our service quality can be realized by easily implementable re-allocation of our resources. While pro-actively re-allocating current base stations is costly and time-consuming, we recognize the benefits improved coverage provides. We have successfully integrated results from the model into our decision making process, and will continue to do so.

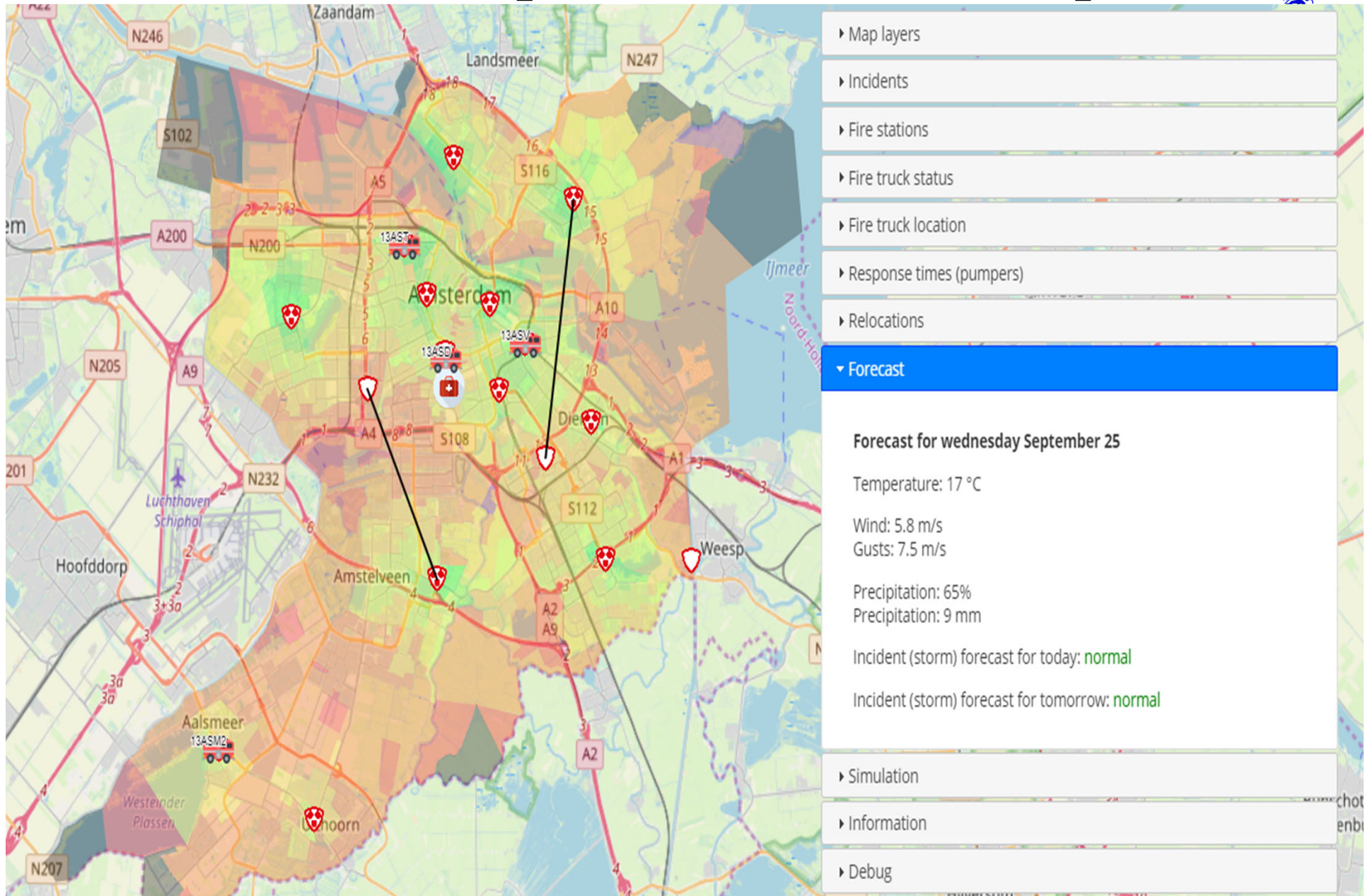
“Furthermore, we have identified another process which can greatly benefit from optimizations the model provides. When during a large scale incident multiple base stations are being called upon, we are now able to re-allocate remaining resources (vehicles) to better positions to regain optimal overall coverage. Results from this project are to be implemented in the Spring of 2016.”



→ next step: relocations during major incidents



Tool ("fireScore")



Fighting Crime with Maths!



Predictive Policing



- **Goal:** reduction of **high-impact crimes**
- **Idea:** Allocation of man-power at 'hot' places
- Cross-correlation with demo- and geographic factors
- 'Near-repeat' phenomenon

Waiting Lists Health Care

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Kamer ontstemd: wachtlijsten verpleeghuizen flink langer dan verwacht

NOS, 15-01-2020

Wachtlijst verpleeghuiszorg groeit opnieuw: 'Druk op mantelzorgers'

Nu.nl, 14-12-2019

Maanden wachten op de juiste zorg: 'Mijn patiënt overleed op de wachtlijst'

Nieuwsuur, 26-11-2019

Challenges in Acute Elderly Care

DE UITDAGINGEN IN ACUTE OUDERENZORG IN DE KOMENDE 10 JAAR

1.300.000 ouderen van 75+

2018



2.100.000 ouderen van 75+

2030



+60%

Op elke oudere 4 werkenden



Op elke oudere 2 werkenden



-50%

800.000 ouderen bezoeken jaarlijks de SEH



1.100.000 ouderen bezoeken jaarlijks de SEH

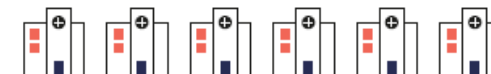


+40%

280.000 ouderen jaarlijks acuut opgenomen



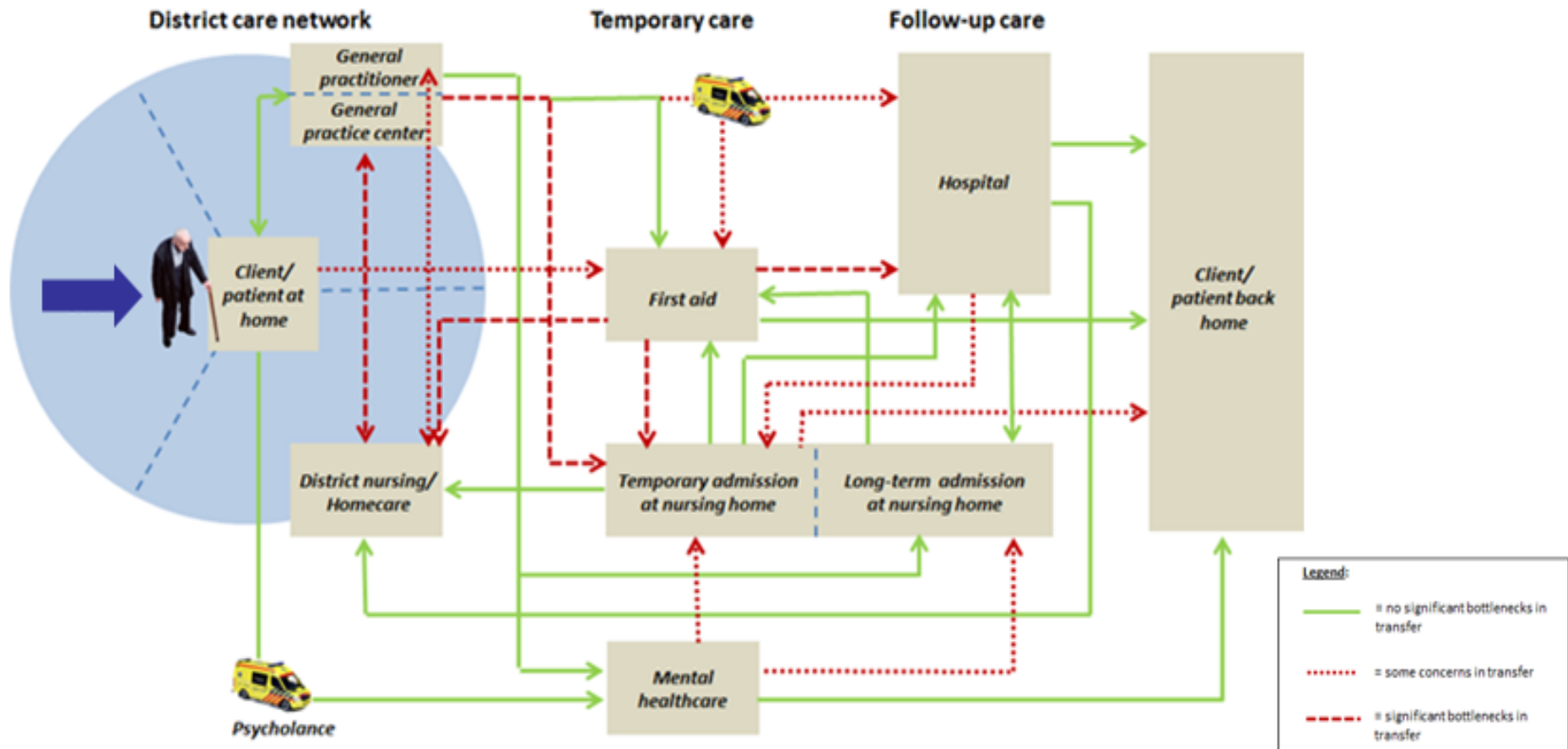
390.000 ouderen jaarlijks acuut opgenomen



+40%

Patient Journey

Patient journey through care supply system



Excessive Waiting Times



incident



overload



surgery (after
14 days)



nursing home

CWI



Amsterdam UMC
Universitair Medisch Centrum



1. **High fractions** of older people in need of institutional care that are currently on a waiting list

16% in the Netherlands

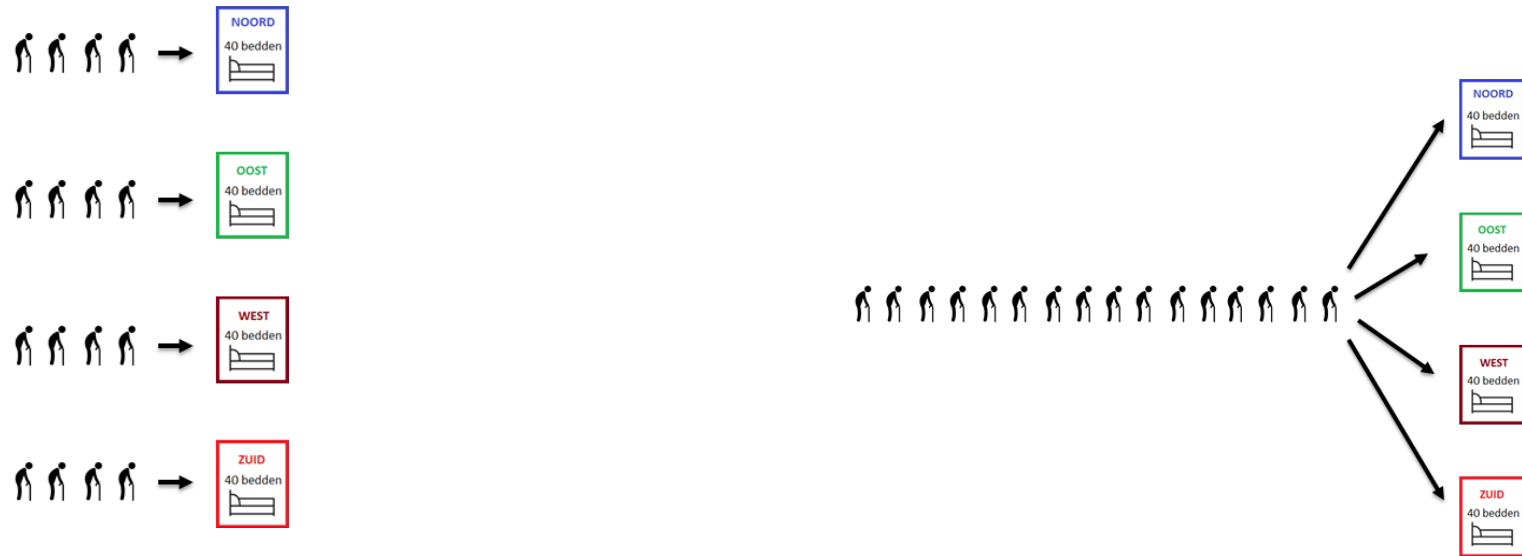
30% in Slovakia

47% in Lithuania

2. 16% of older adults in Spain die on the waiting list
3. Regional shortages: Copenhagen, waiting time > 3.5 years

Cause for long waiting times: preferences for nursing homes

Balancing Trade-off



individual preferences

efficient use of beds

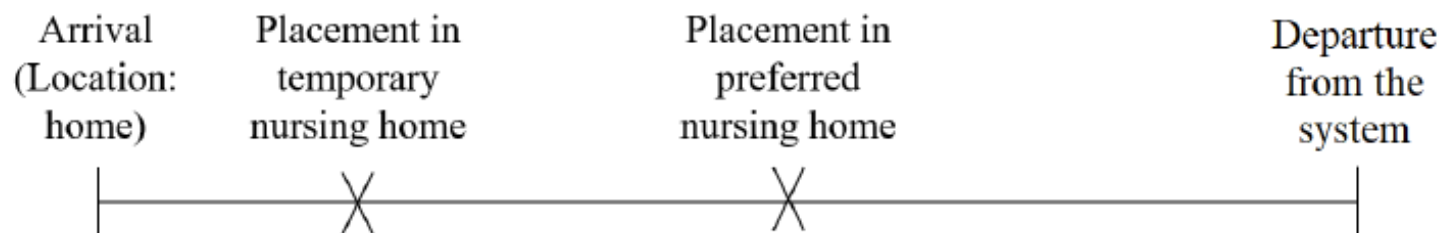
- + include personal preferences
- inefficient use of beds



- + efficient of use beds
- no individual preferences

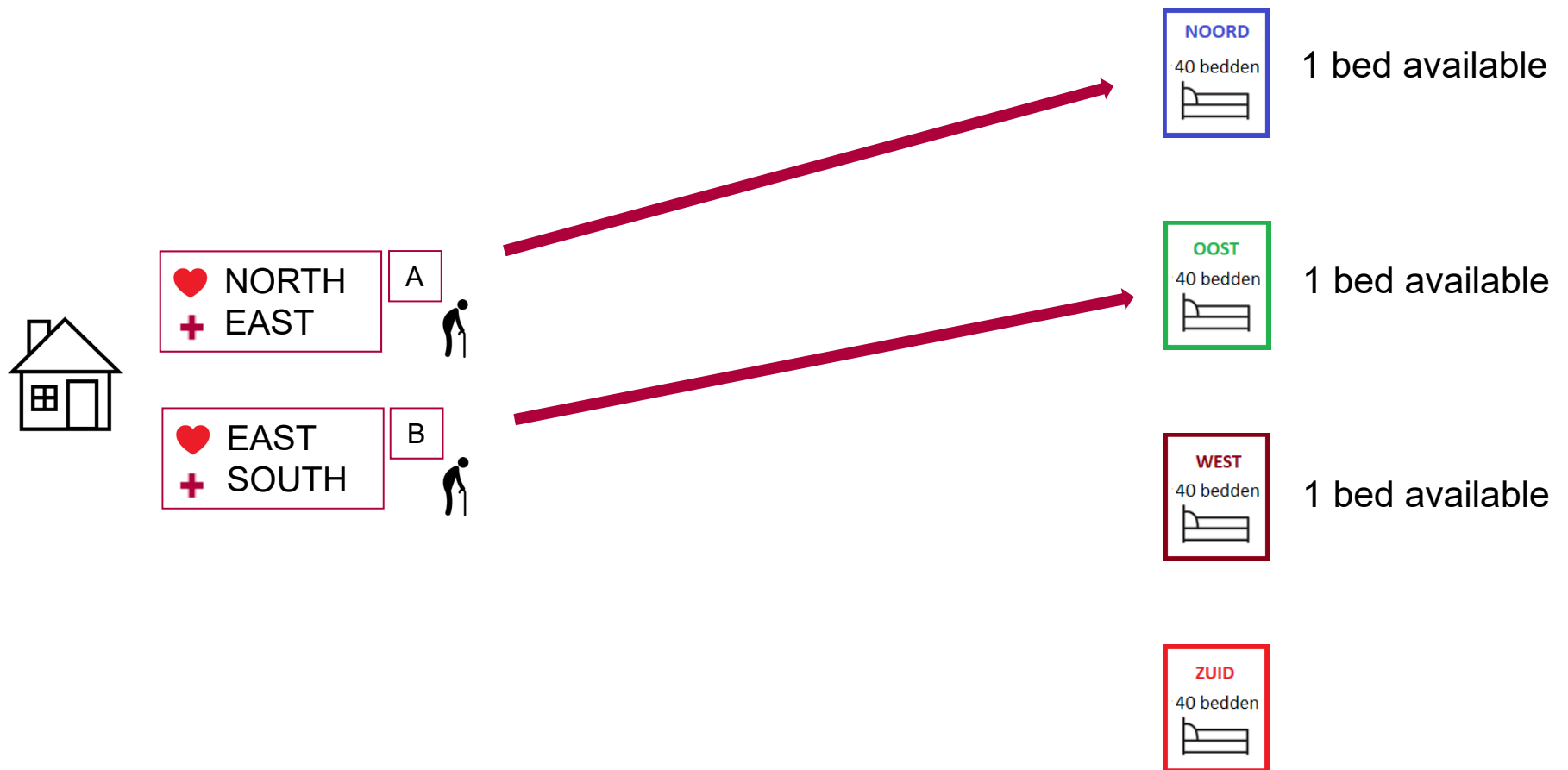
Current Way of Working

- Older adults typically apply for one nursing home
- They **wait at home** until a bed becomes available
→ probably placed in a temporary nursing home
- **Hardly any coordination!**
- **Our approach:** centralized approach using allocation model



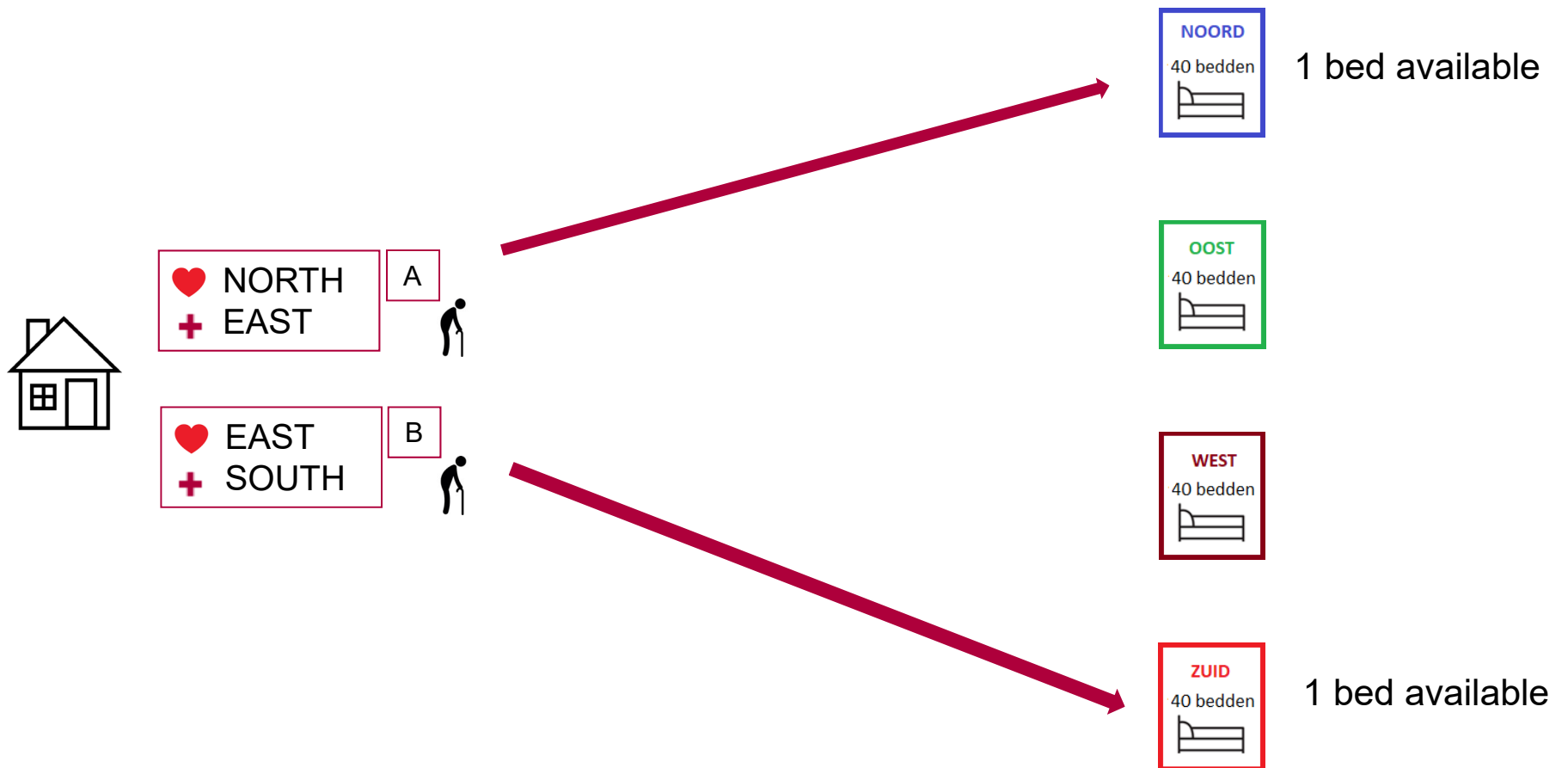
Toy Example

(1) Preferences of patients



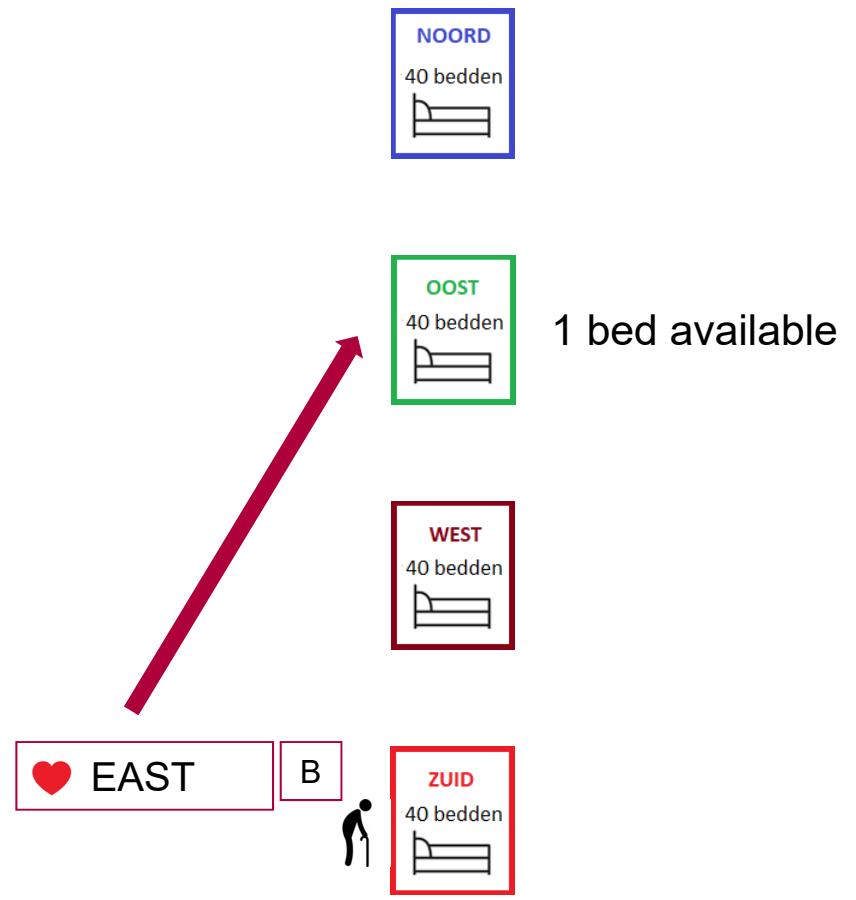
Toy Example

(2) Transitions between care centers



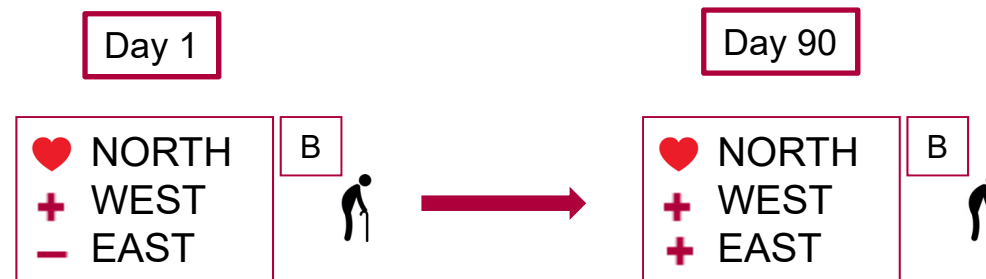
Toy Example

(2) Transitions between care centers



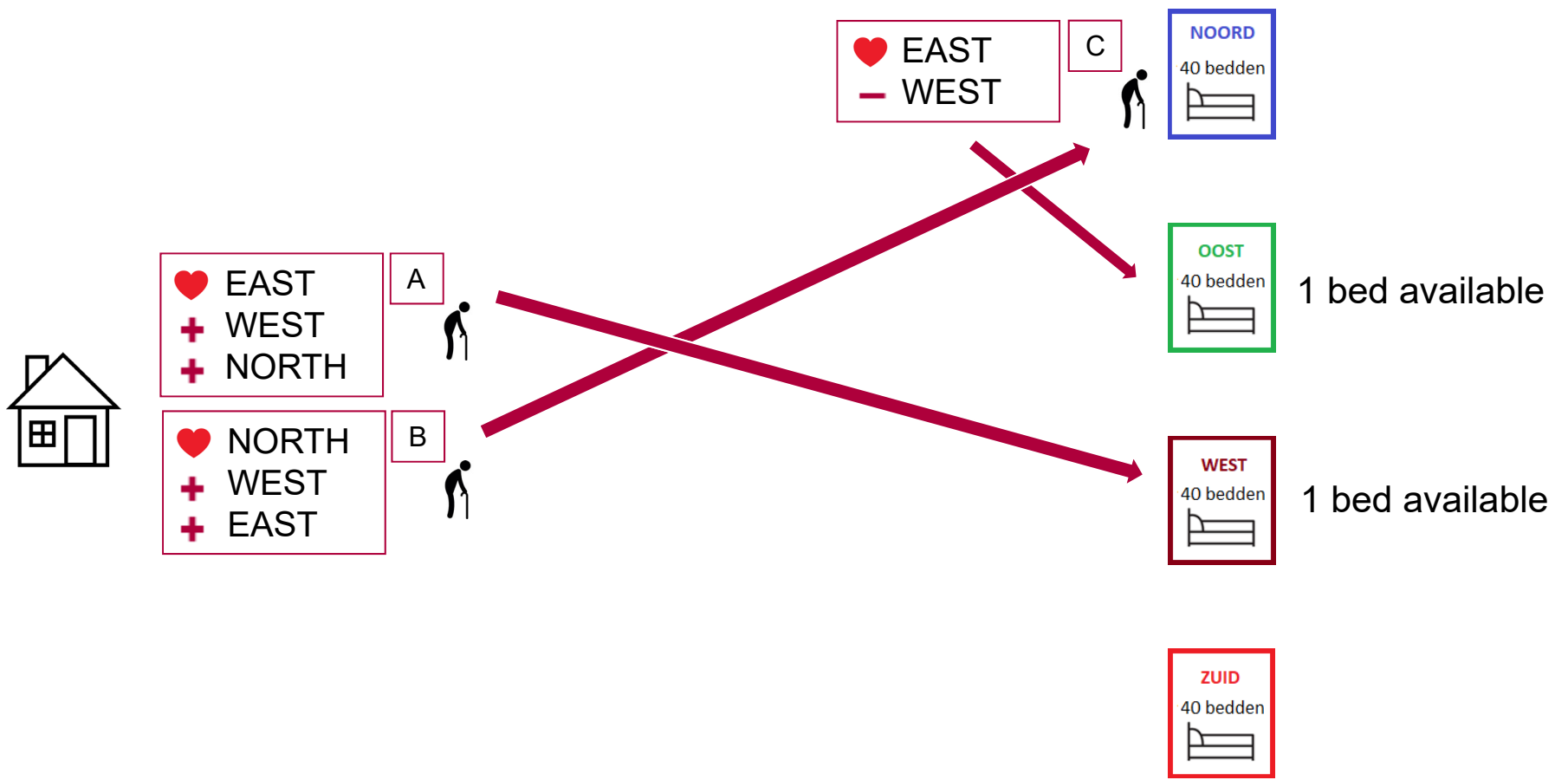
Toy Example

(3) Increase in urgency



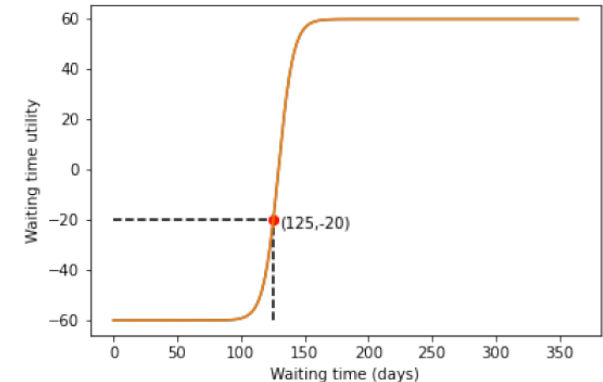
Toy Example

(4) Transition to preferred nursing home



Allocation Model

- Patient preferences are defined as utility functions
- Allocation model maximizes the utility of all patients
- Simulation model to test quality of outcomes



Optimization model

$$\max \sum_{p \in P} \sum_{n \in N} u_{pn}(l_p, w_p) x_{pn}$$

$$\text{s.t. } \sum_{p \in P} x_{pn} \leq c_n$$

$$\sum_{n \in N} x_{pn} = 1$$

$$x_{pn} \in \{0, 1\}$$

$$\forall n \in N$$

$$\forall p \in P$$

$$\forall p \in P, n \in N.$$

maximize utility

Results for Amsterdam

- **Current practice:**
 - Waiting time till placement 211 days (232 till preferred)
- **Assignment model with 1 preferred care center:**
 - Waiting time till placement 51 days (177 till preferred)
- **Assignment model with 2 preferred care centers:**
 - Waiting time till placement 33 days (105 till preferred)

Centralized approach:

1. Includes individual preferences
2. Dramatic reduction in waiting time

also psychiatry, youth care,...

Success Stories of Mathematics in Real Life

Rob van der Mei

Contact: mei@cw.nl



Proactive relocations after incidents in Almere (2) and Lelystad (1)

