Success Stories of Mathematics Saving Lives

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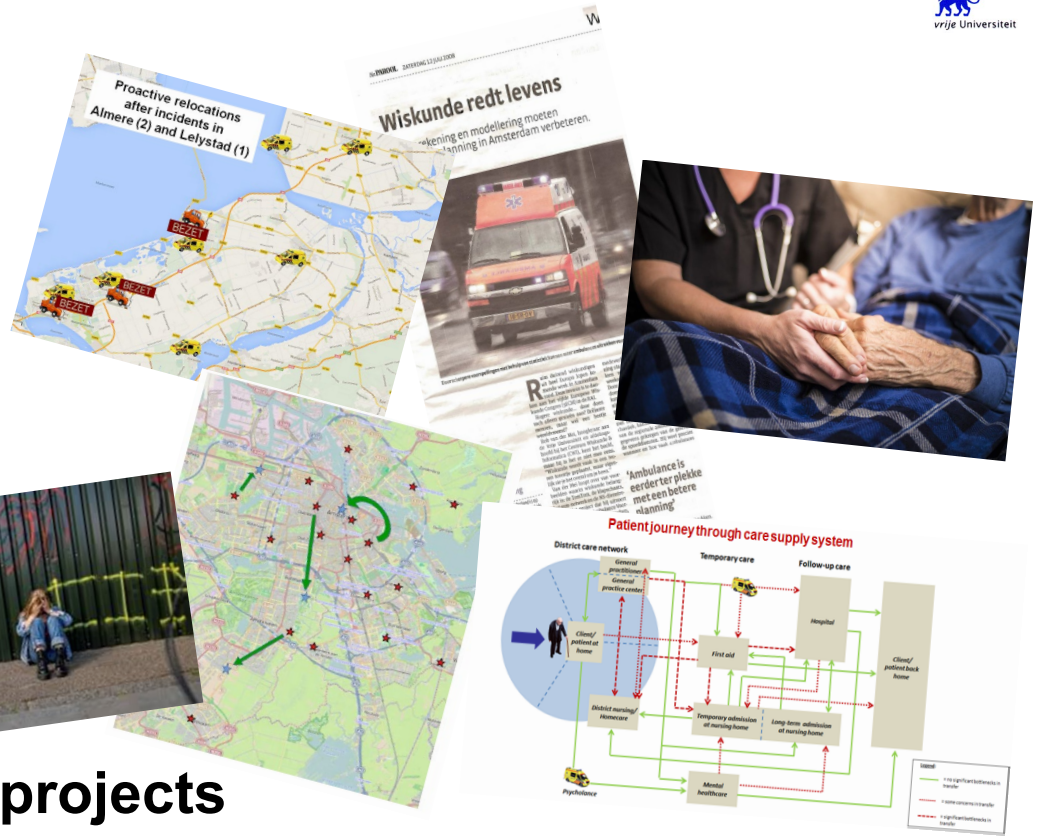
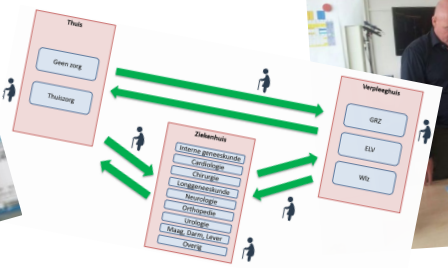
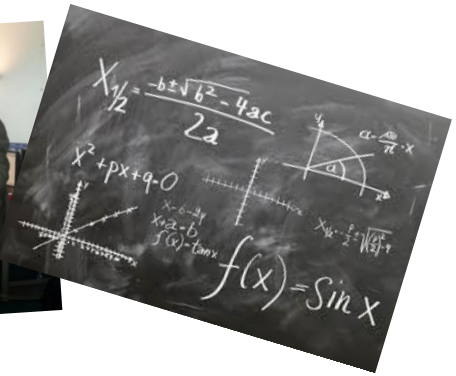


Overview:

1. **Perspective**
2. **Examples of successful projects**
   - Emergency services: “when every second counts”
   - COVID vaccination logistics
   - Acute elderly care
   - Mental healthcare
3. **Discussion**





“Zorgen over de Zorg”

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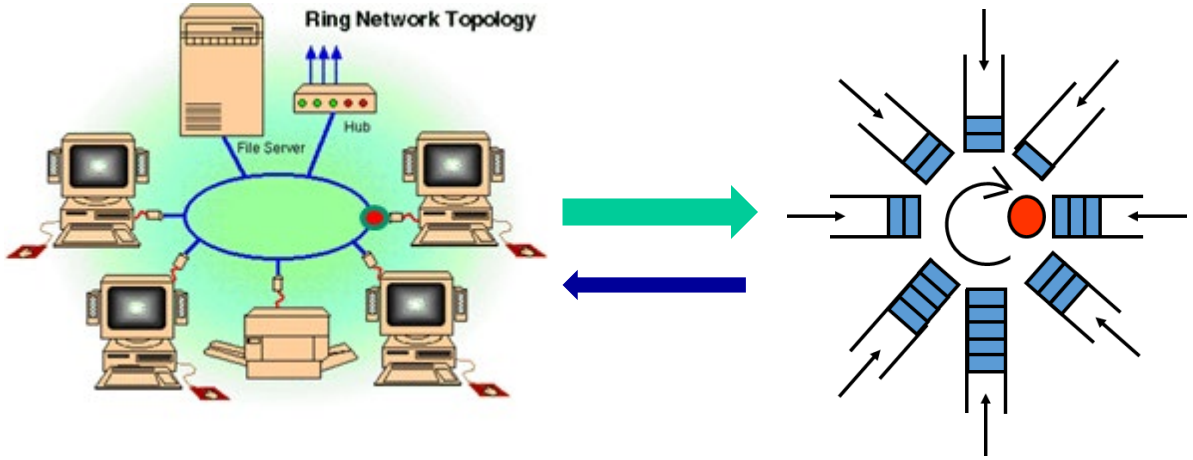
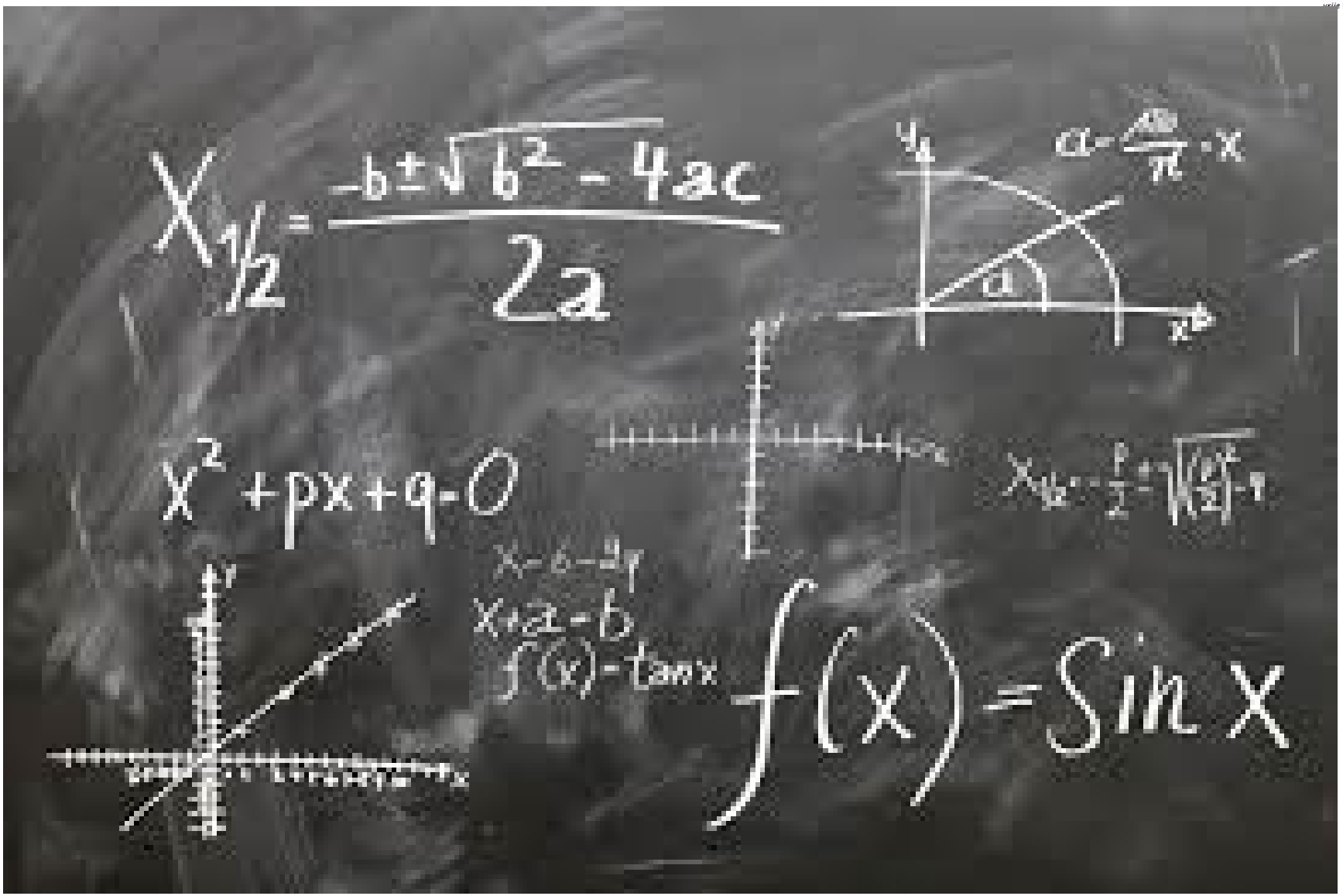
In hoeverre kan het gebruik van data analytics, AI, wiskundige modellering en optimalisatie bijdragen aan betere zorglogistiek?

My Background



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	VU (Full Professor in Applied Mathematics)
Since 2004	Centrum Wiskunde & Informatica

Maths In the Good-Old Days...



“Mathematics Inside”

“Mathematics is like oxygen: you do not see it, but you would miss it if it were is no longer there…”

Now It All Comes Together…

super-computers

"BigData"

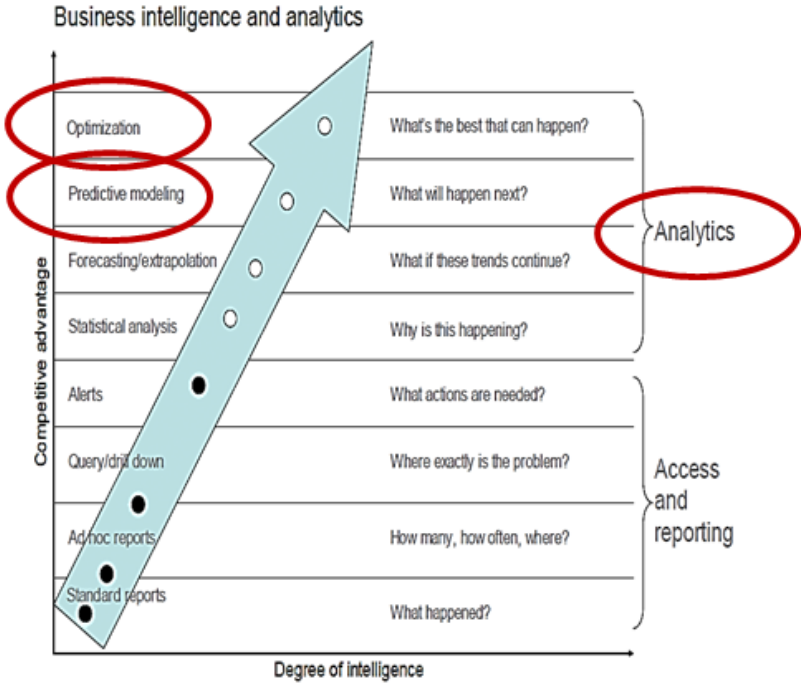
high-speed networks

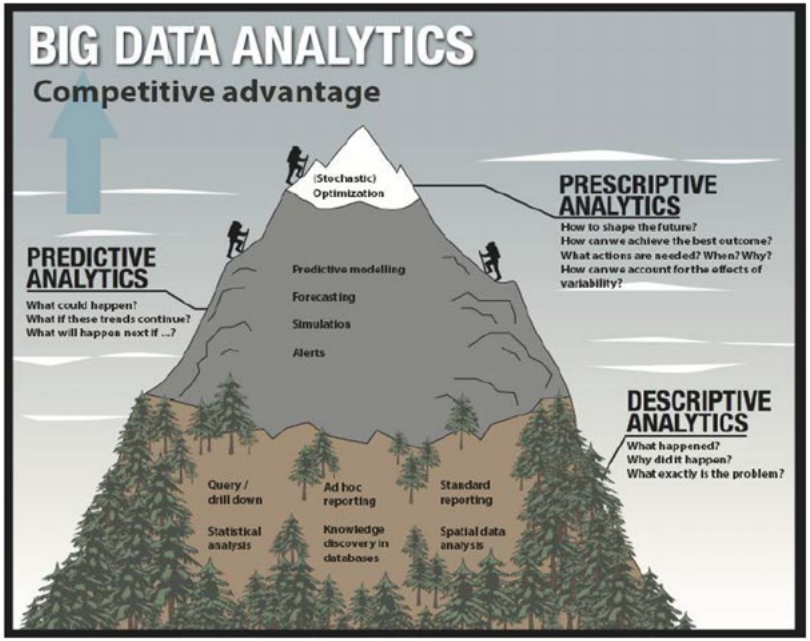
Artificial Intelligence

Data Analytics

Mathematics

Data Analytics en Optimalisatie





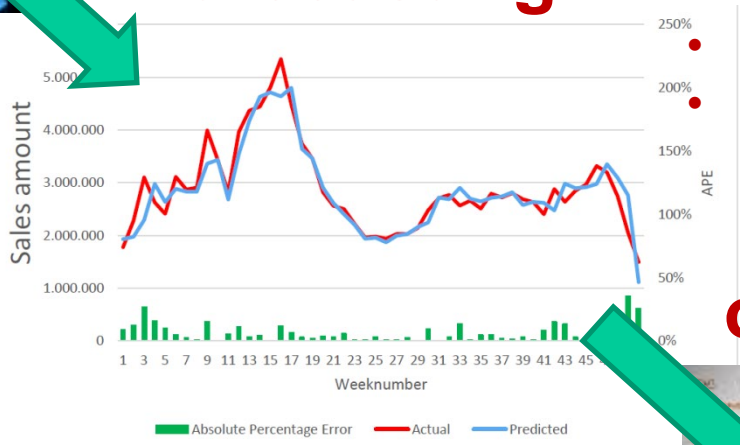
- **Data Analytics staat hoog op de management agenda**
- **Descriptive → Predictive → Prescriptive**
- **Organisaties die gebruik maken van data analytics en optimalisatie presteren aantoonbaar beter!**

Data Analytics and Optimization

data

data analytics

insights and forecasting



- Operations Research
- Stochastic Optimization

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

optimization models

optimization

Over the Past 25 Years...

Over the years:
100+ consultancy projects, 100+ R&D projects, 60+ Ph.D. students, 100+ M.Sc. students, 200+ publications

Conclusion: Data analytics, **mathematical modelling** and **optimization** can make a difference in virtually all application domains


Pictures from veiligheidsregio
Noord-Holland Noord
10-101
AMBULANCE
6-KKV-28

Ambulance Care in NL

A1-calls: Urgent and life threatening **< 15 min**

- severe incident

A2-calls: Urgent but not life-threatening

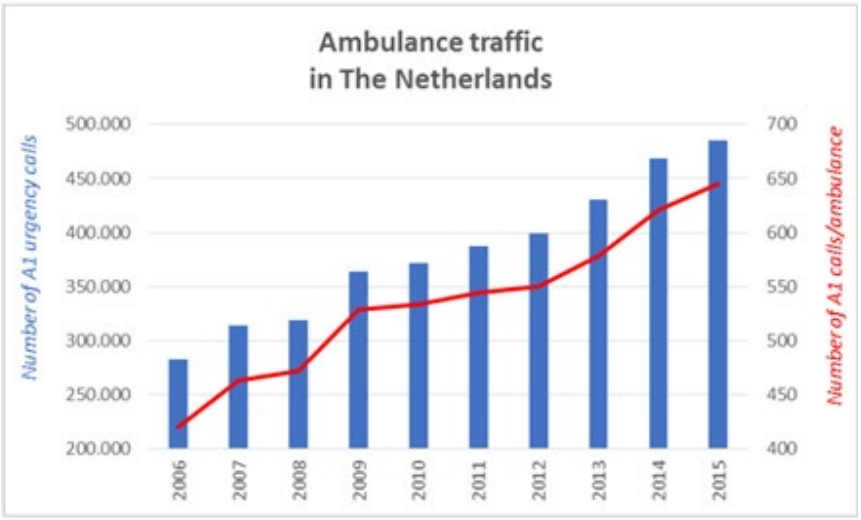
- broken leg **< 30 min**

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:

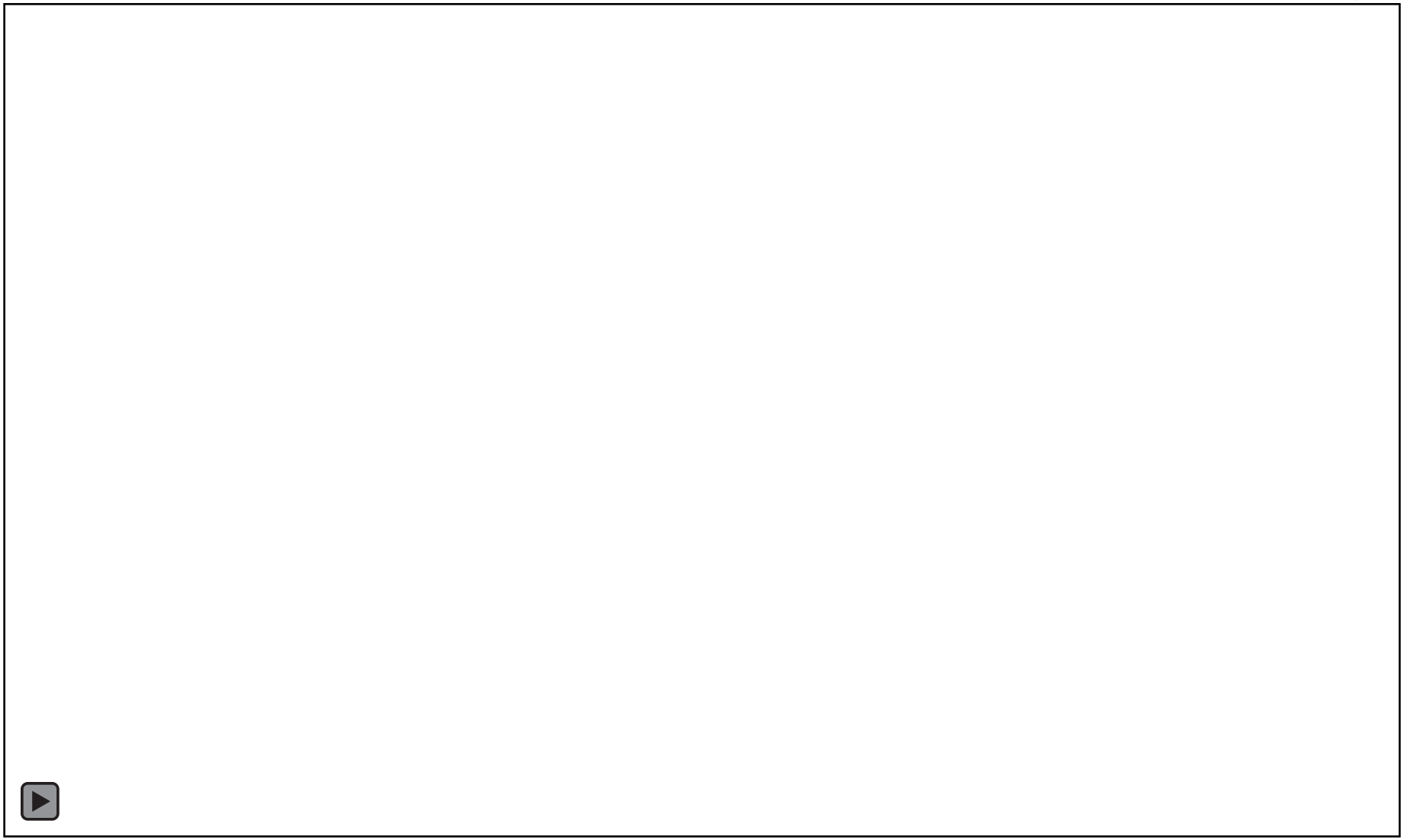
Dynamic Ambulance Management: proactive planning

REPRO : from Reactive to Proactive

Team Effort and Acknowledgments

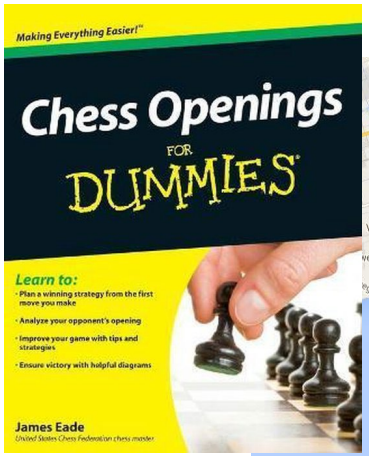
Thanks to: Karen Aardal, Caroline Jagtenberg, Pieter van den Berg, Thije van Barneveld, Theresia van Essen, Martin van Buuren, Sandjai Bhulai, Coen Huibers, Petra Vis, Lisette Sloof, Guido Legemaate, Rutger Kerkkamp, Peter Dwars, Maria Mahfoud, Melania Calinescu, and others

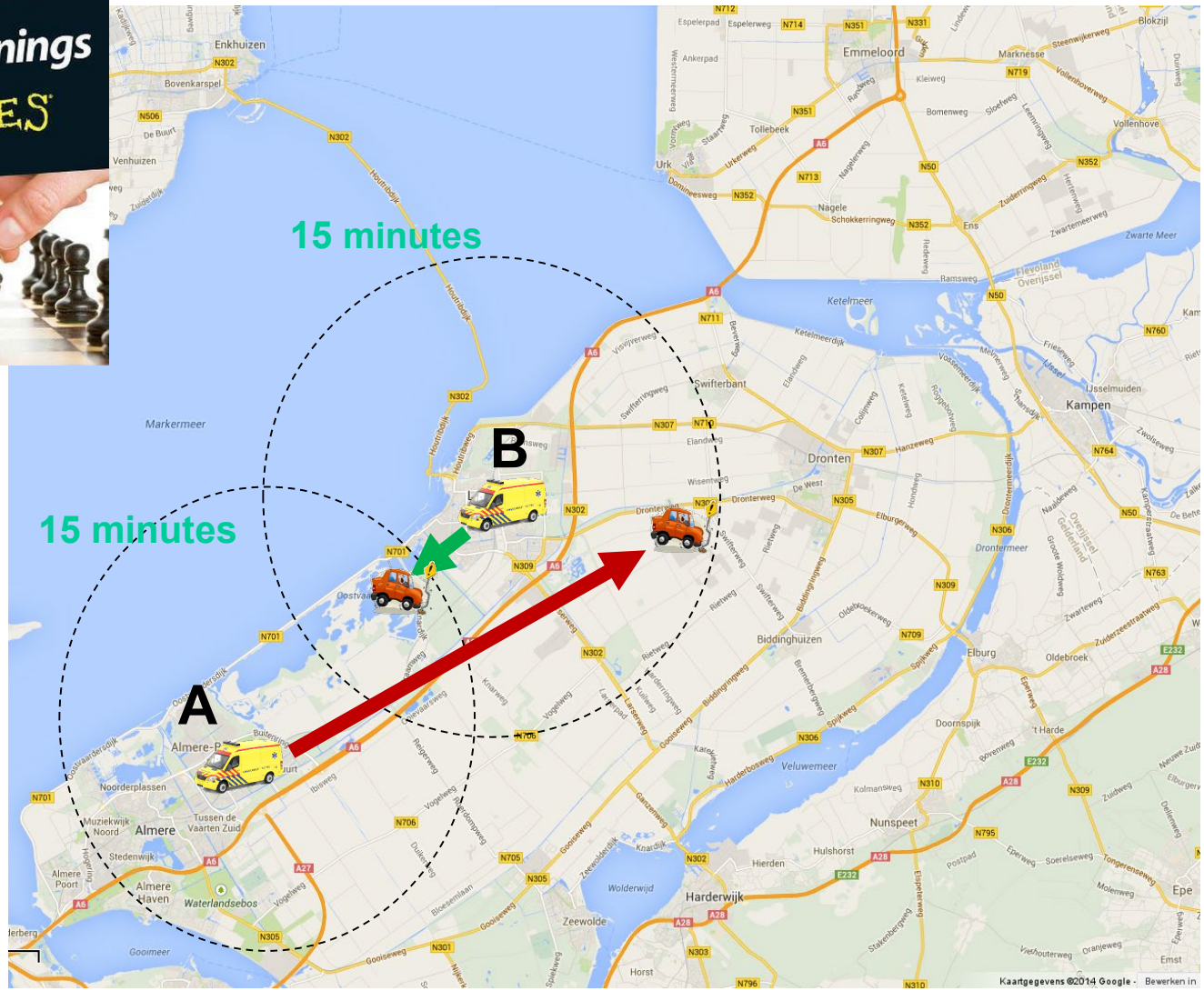
Mathematics in Action



Playing Chess

Chess for Dummies





?

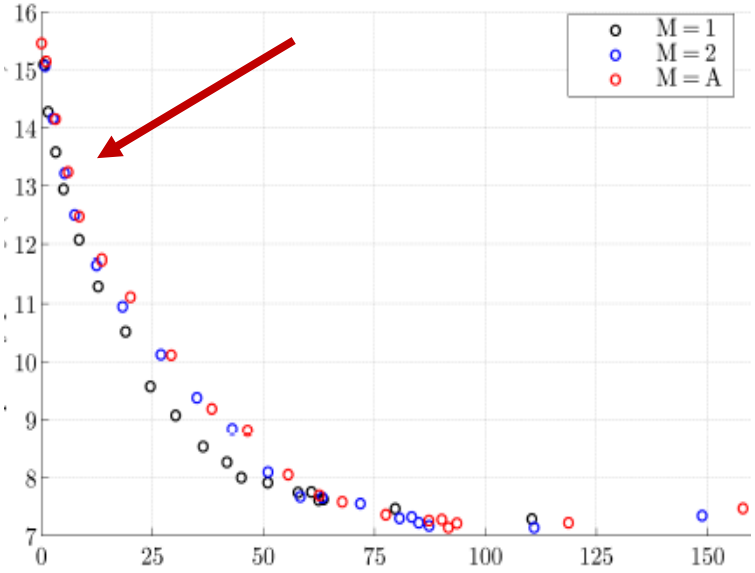
Chess for Professionals

Basic situation (no incidents)

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

Effectiveness of Relocations

late arrivals



relocations per day

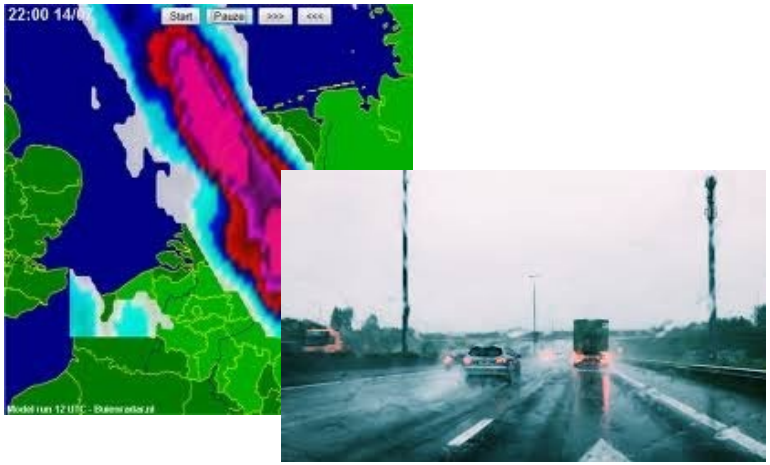
Good news:

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

Under the Hood...

Basic idea: maximize preparedness for next indicent

Real-Time Decision Making

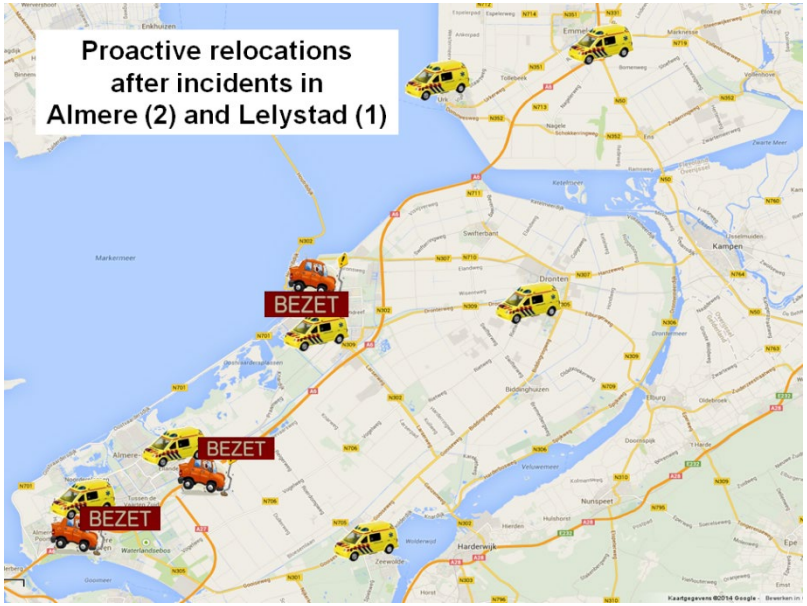


weather circumstances

real-time traffic information

mass events

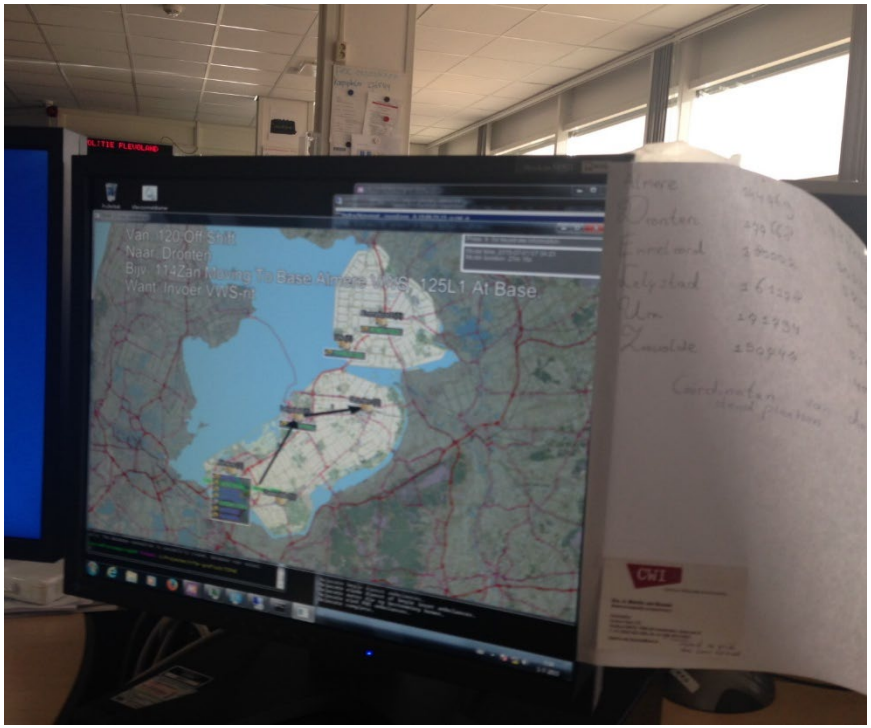
Acceptance in Practice?



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

Unboxing Logistics event, Arnhem, September 22, 2022

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 of Fire Stations

coverage

# wijzigingen	Dekking TS	RV	HV	WO	Totaal
0	87,68	98,23	96,84	88,6	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	94,76
4	94,38	99,64	96,84	90,6	95,53
Ongelimiteerd	98,62	99,86	98,10	93,37	98,53

4 modifications

Observation

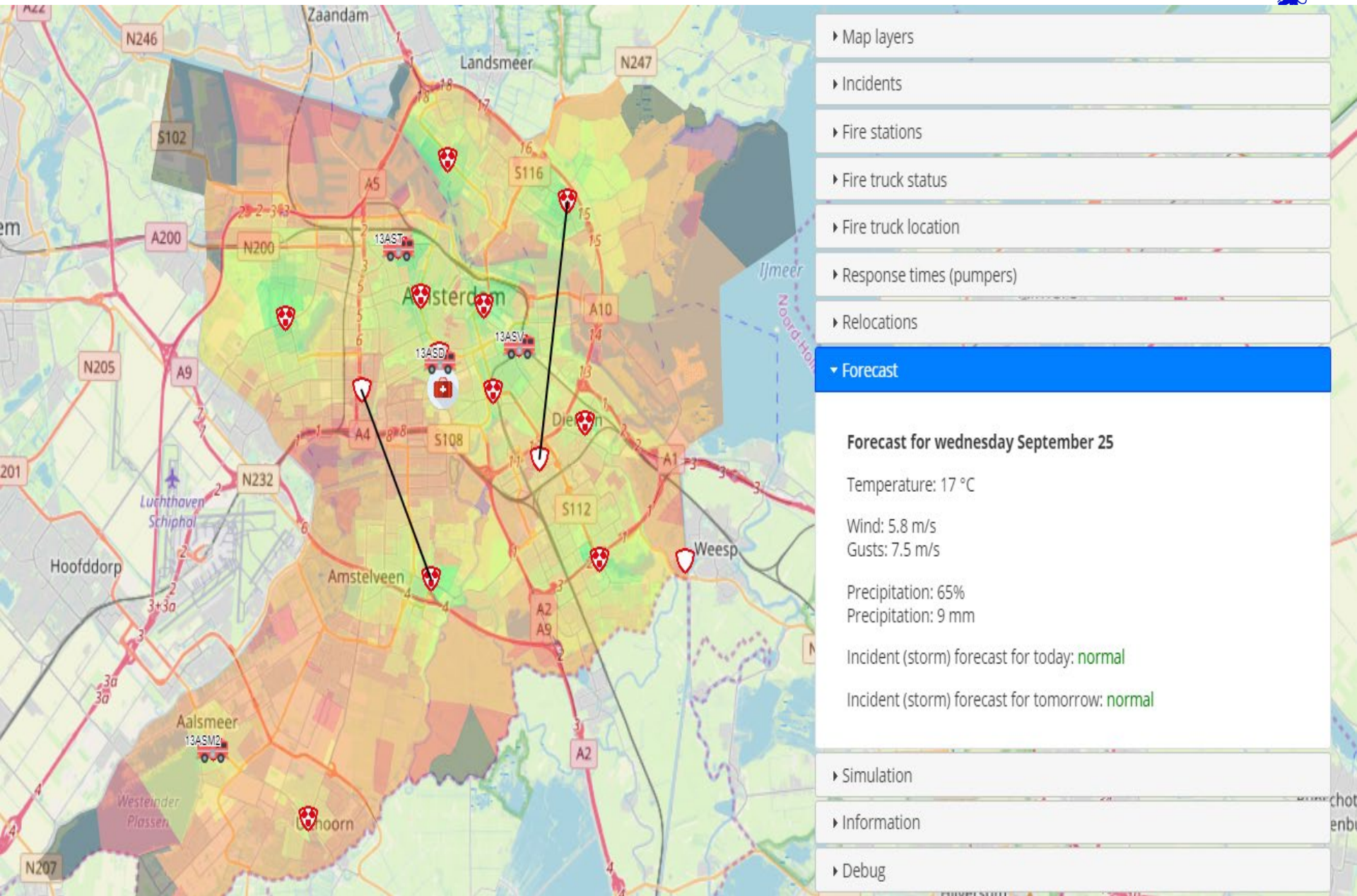
% late arrivals can be reduced by > 50% by relocating only 4 stations!

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.

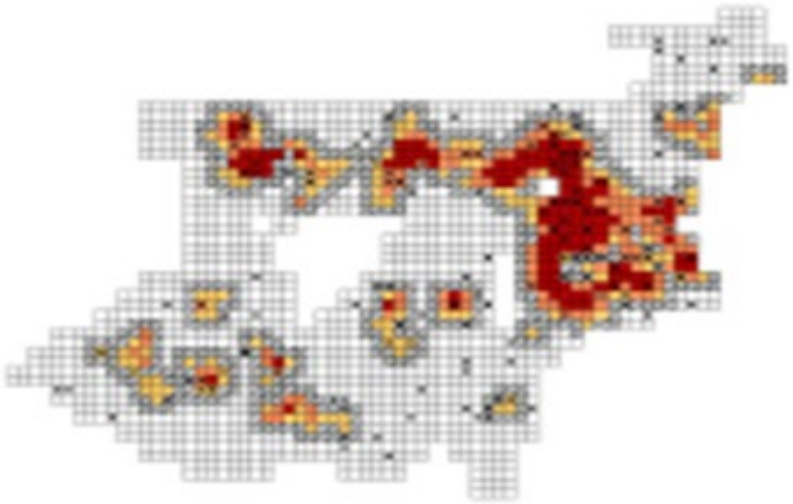
"Furthermore, we have identified another process which can greatly benefit from optimizations the model provides. When during a large scale incident multiple base stations are being called upon, we are now able to.re-allocate remaining resources (vehicles) to better positions to regain optimal overall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

Tool ("fireSCore")



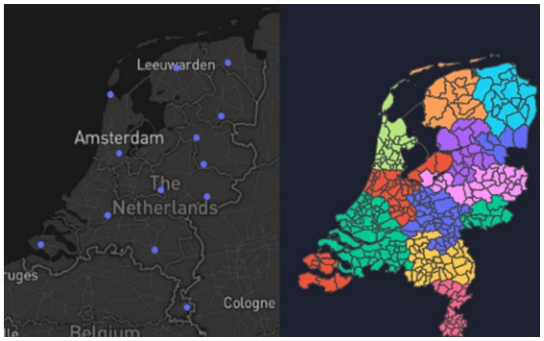
Fighting Crime with Maths!

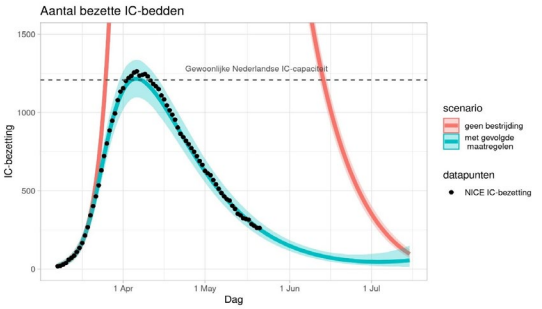
Predictive Policing



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

Mathematics during COVID





- Forecasting number of patients
- **Proper locations** of the vaccination hubs?
- Optimal **distribution of patients** over hospitals
- Waiting times of the different age and priority groups?
- What are the implications of uncertainty in **vaccine availability**?

- Collaboration with GGD GHOR, RIVM and LCPS
- Decision support system

- What combination of “factors” leads to high-risk profile?
- NLP to support the quality of service during chats or calls

Waiting Lists in Elderly Care

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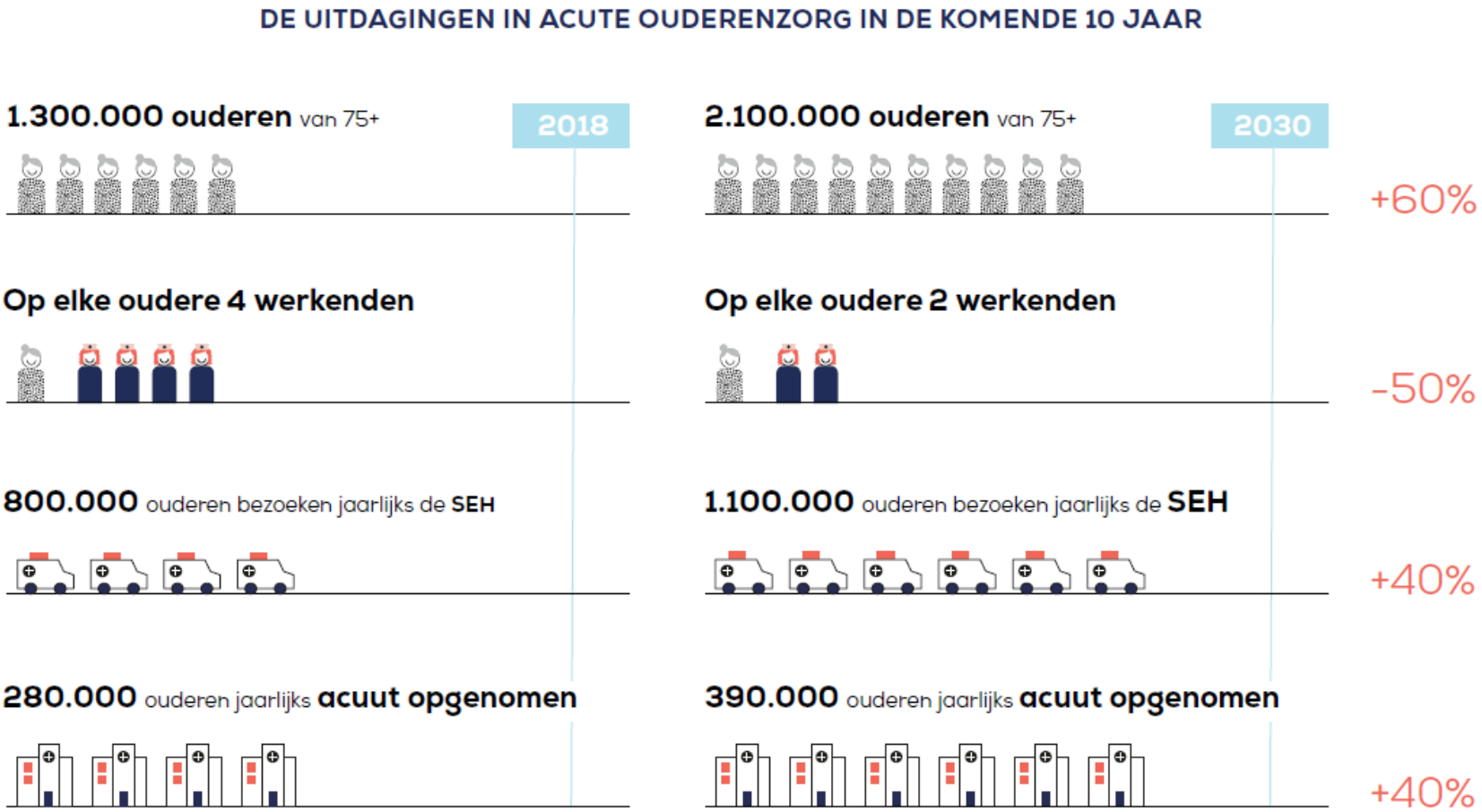
Amsterdam UMC Universitair Medische Centra

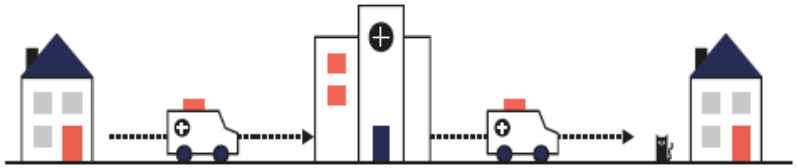
VU

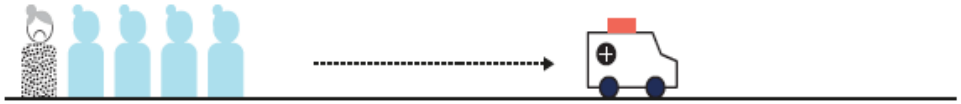
"DOLCE VITA": Challenges in Acute Elderly Care



Current System Creates Demand

ONS HUIDIGE SYSTEEM CREËERT ZORGVRAAG



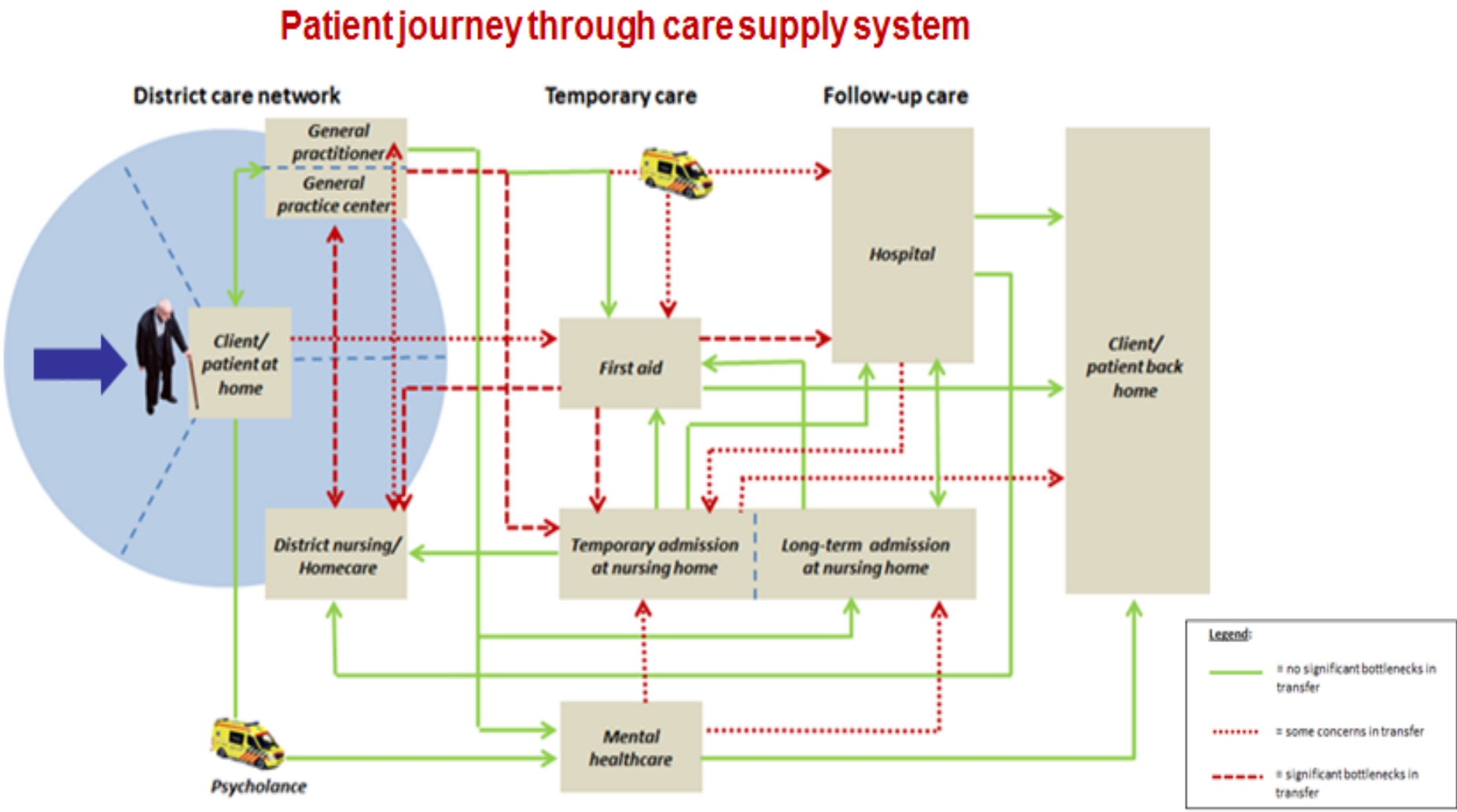


1 op de 5 ouderen (57.000) is **binnen een maand terug op SEH**.

1 op de 3 ouderen (85.000) is **blijvend achteruit gegaan** in functioneren.

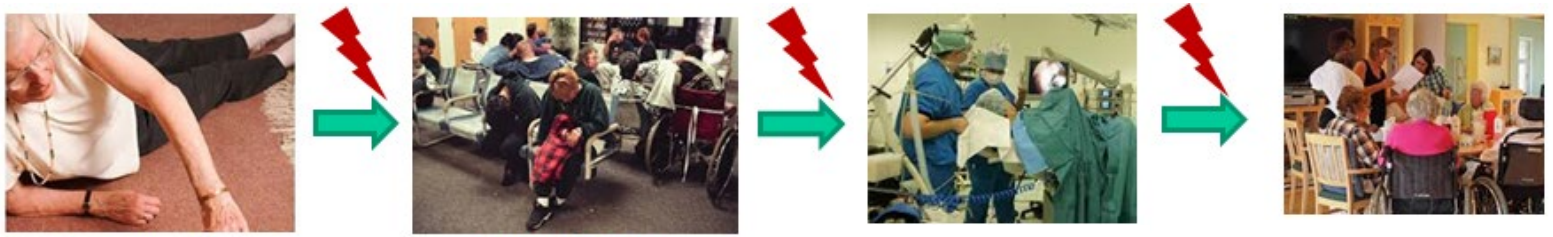
1 op de 3 ouderen (85.000) is **binnen een jaar** na opname **overleden**.

Patient Journey



- **"Waterbed model"**

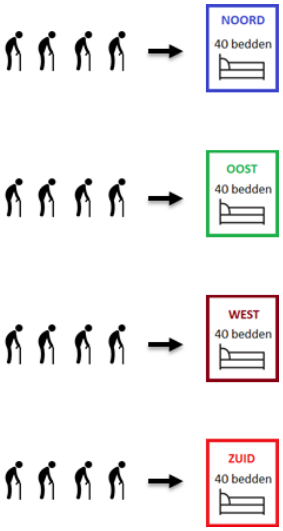
Excessive Waiting Times

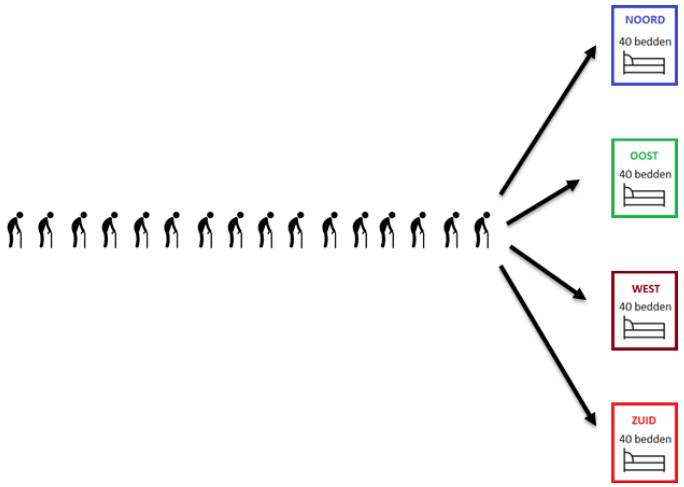


1. **High fractions** of older people in need of institutional care that are currently on a waiting list
   - 16% in the Netherlands
   - 30% in Slovakia
   - 47% in Lithuania
2. 16% of older adults in Spain die on the waiting list
3. Regional shortages: Copenhagen, waiting time > 3.5 years

Cause for long waiting times: preferences for nursing homes

Balancing Trade-off



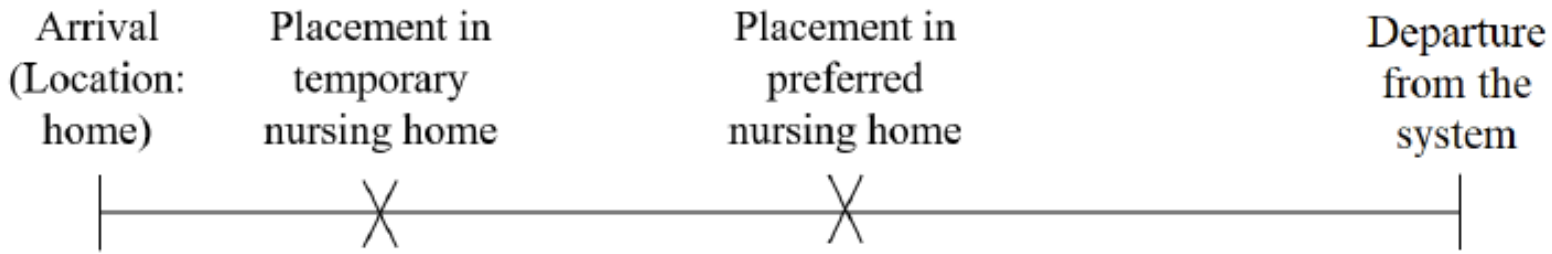


individual preferences ? efficient use of beds

+ include personal preferences
– inefficient use of beds

+ efficient of use beds
– no individual preferences

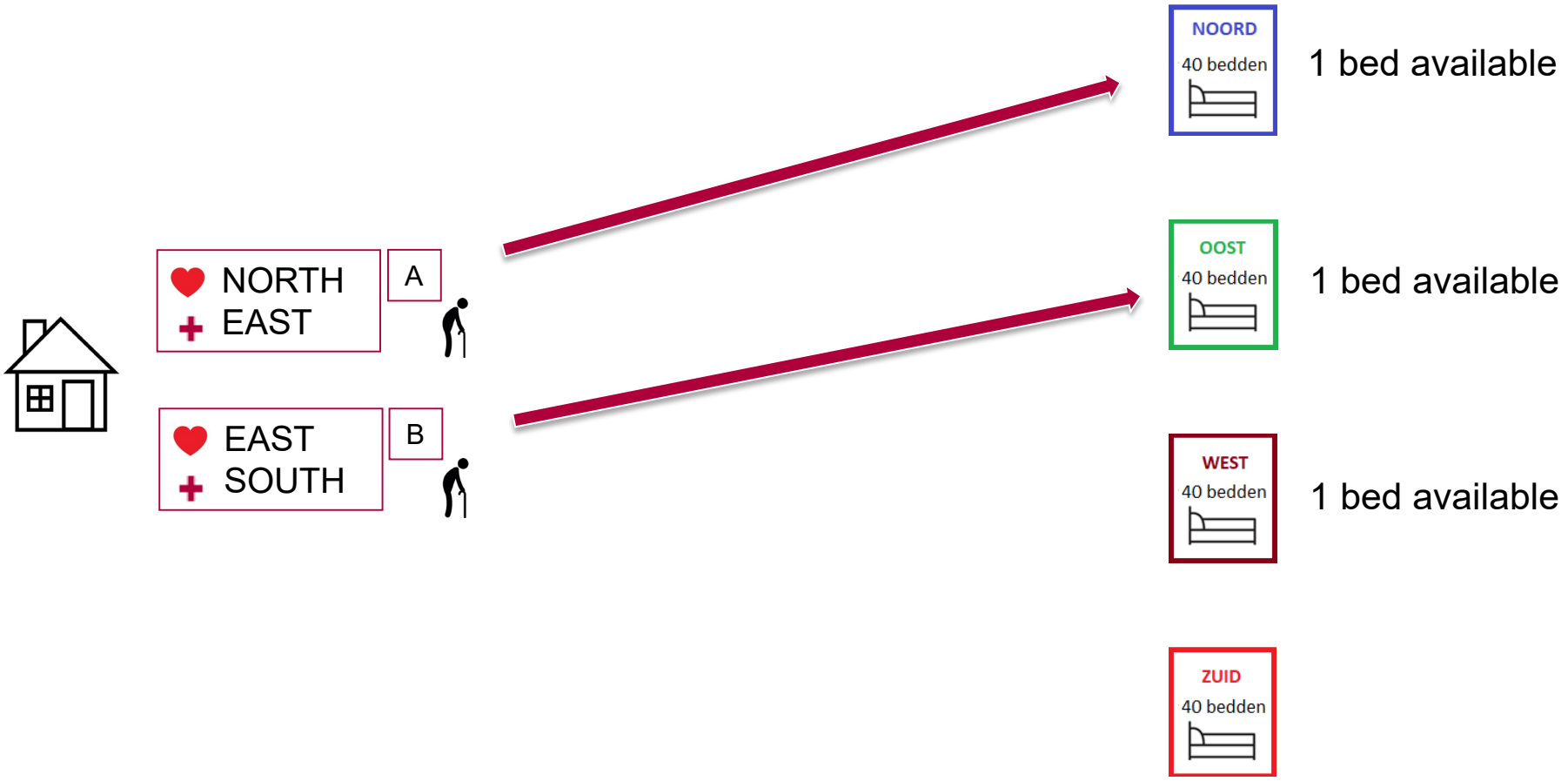
Common Way of Working



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

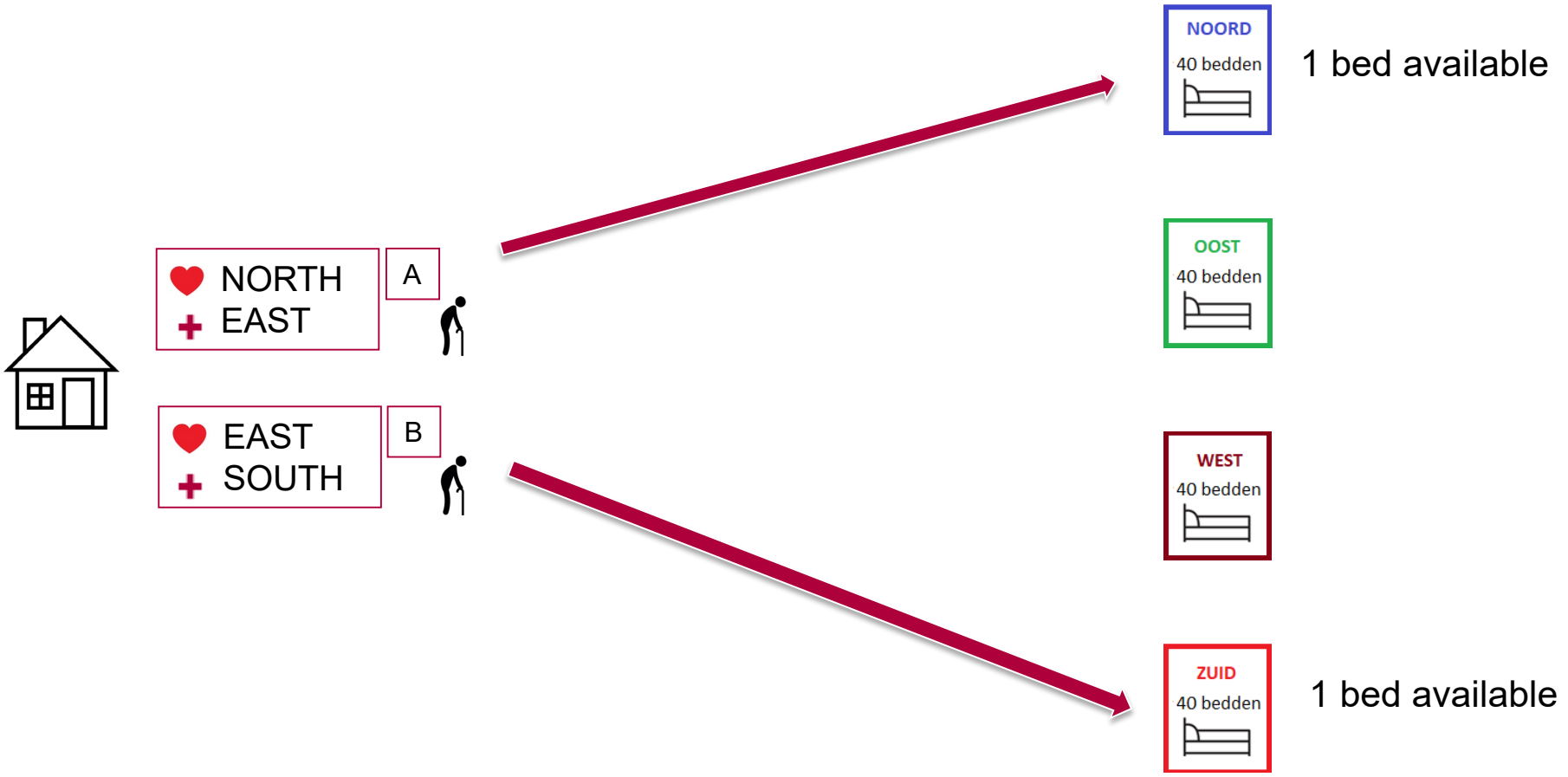
Toy Example

(1) Preferences of patients



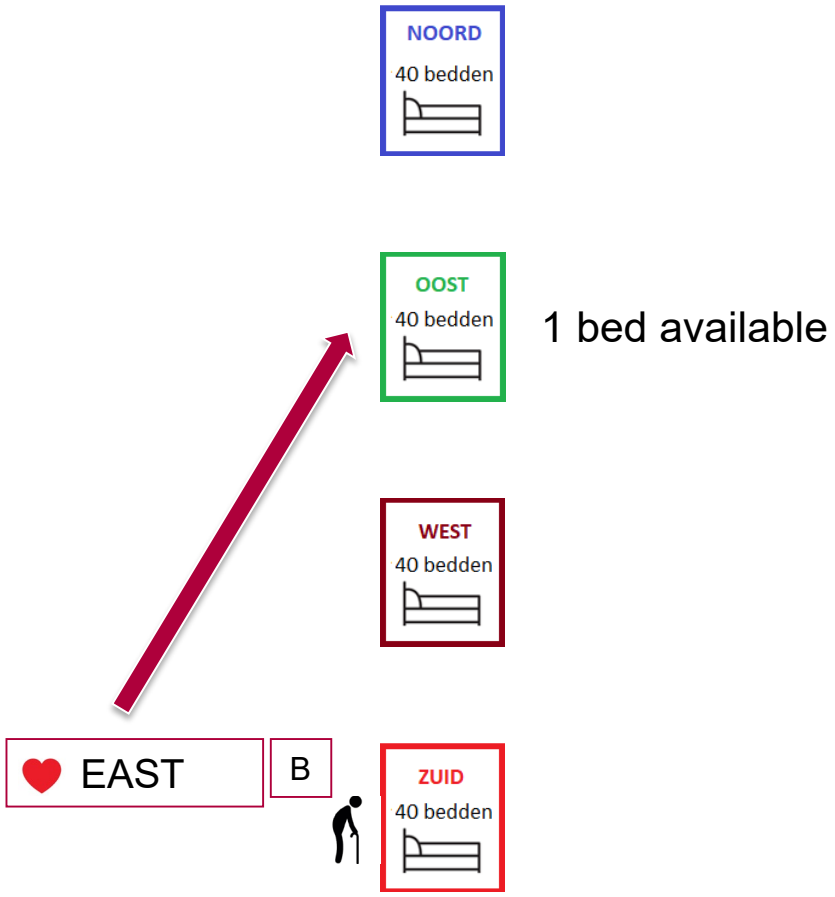
Toy Example

(2) Transitions between care centers



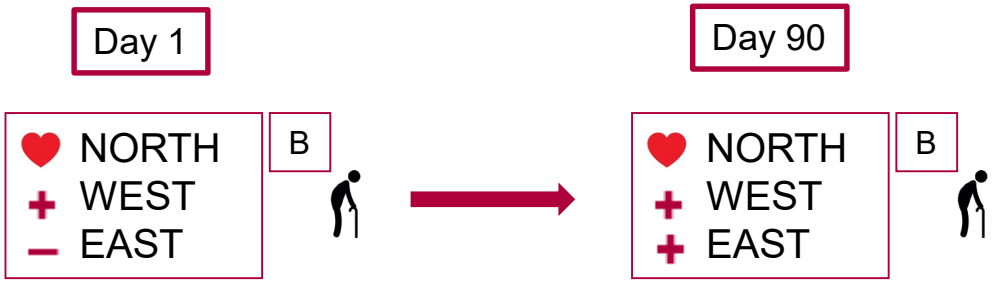
Toy Example

(2) Transitions between care centers



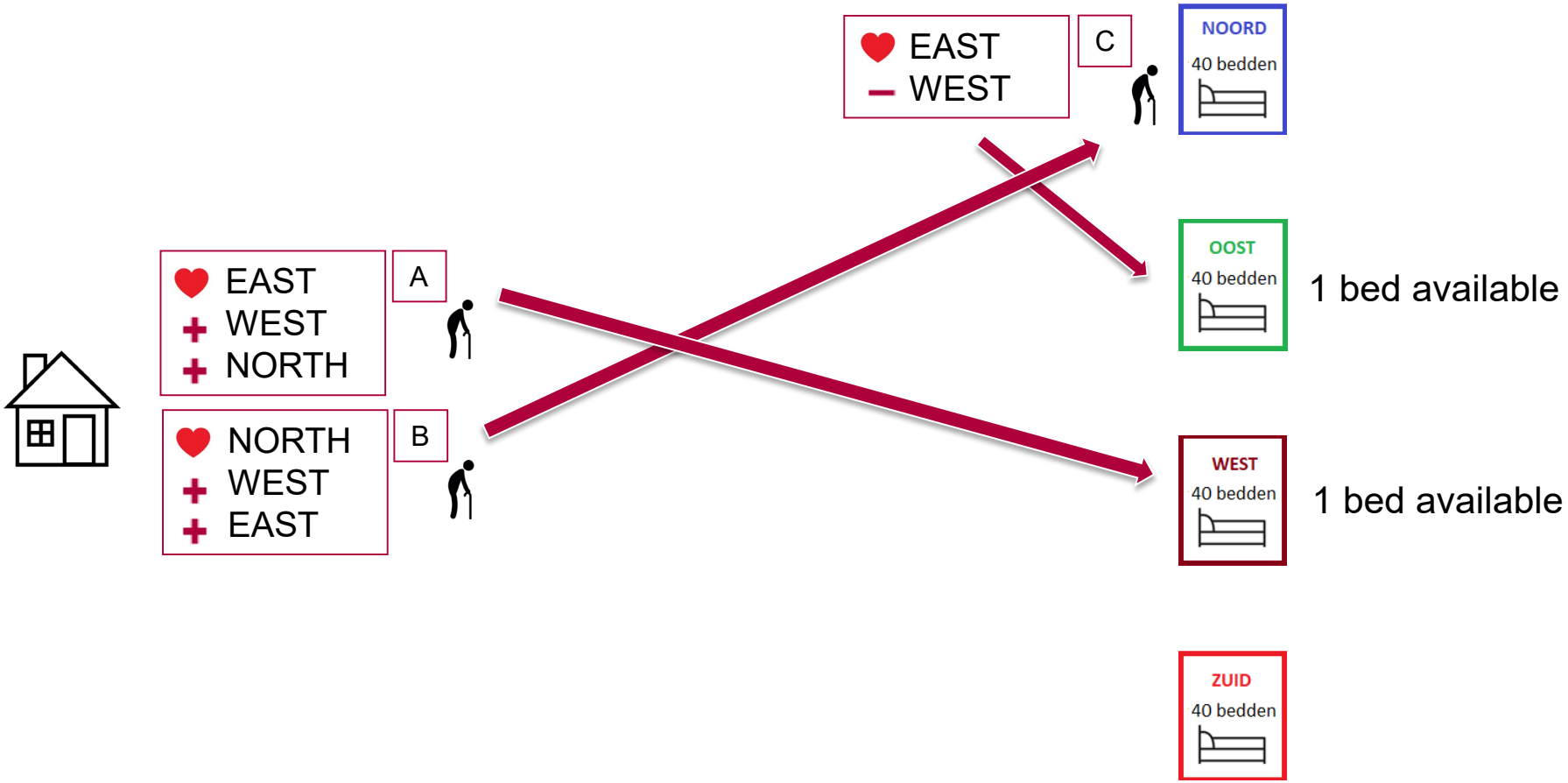
Toy Example

(3) Increase in urgency



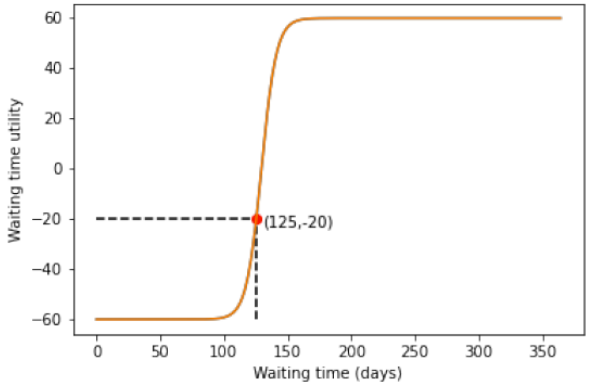
Toy Example

(4) Transition to preferred nursing home



"Bed" Allocation Model

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



Mathematical optimization model

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

maximize "happiness"

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

$$\sum_{n \in N} x_{pn} = 1 \qquad \forall p \in P$$

$$x_{pn} \in \{0, 1\} \qquad \forall p \in P, n \in N.$$

Case Study for Amsterdam

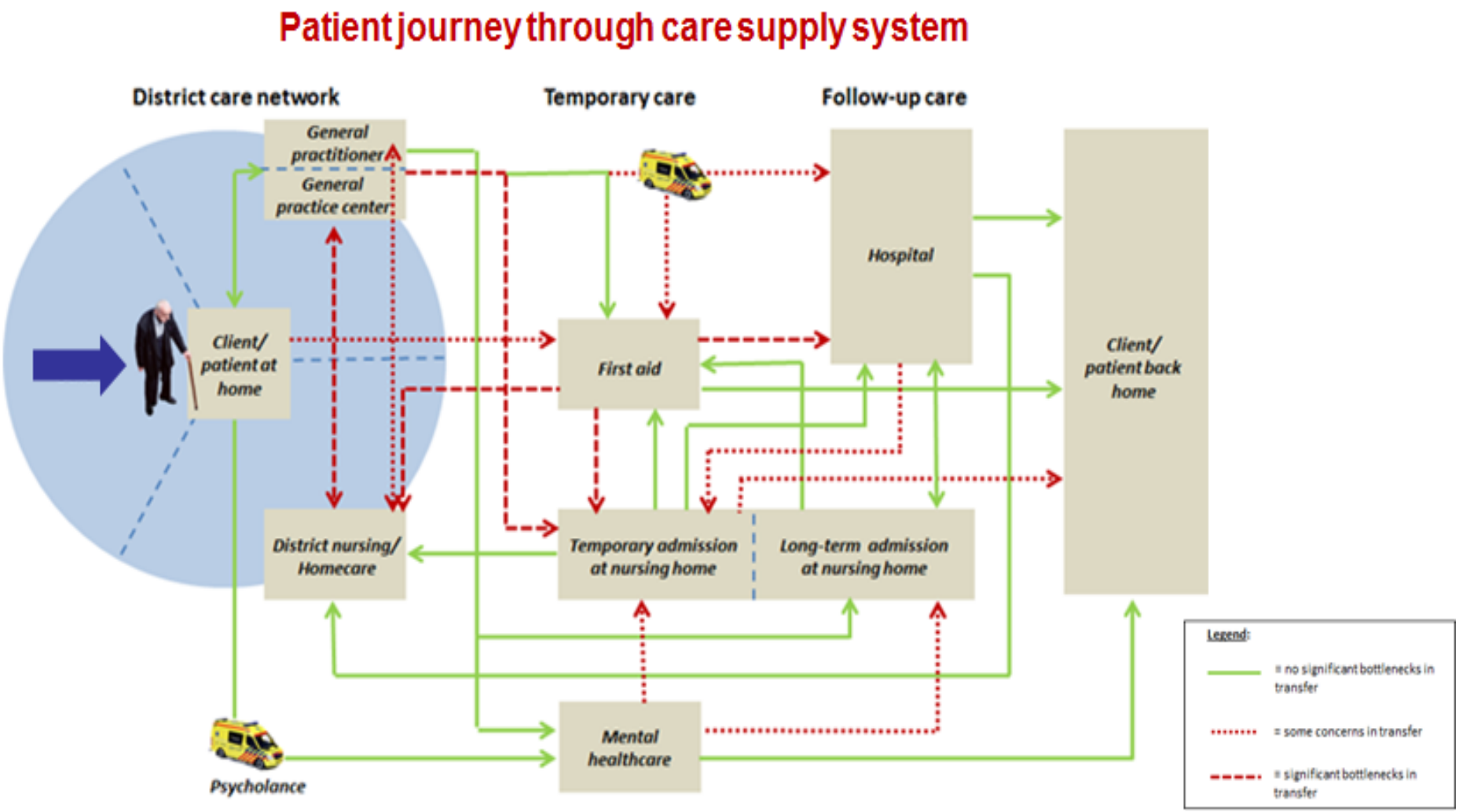
- **Current practice:**
  - Waiting time till placement 211 days (232 till preferred)
- **Assignment model with 1 preferred care center:**
  - Waiting time till placement 51 days (177 till preferred)
- **Assignment model with 2 preferred care centers:**
  - Waiting time till placement 33 days (105 till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

Centralized approach:

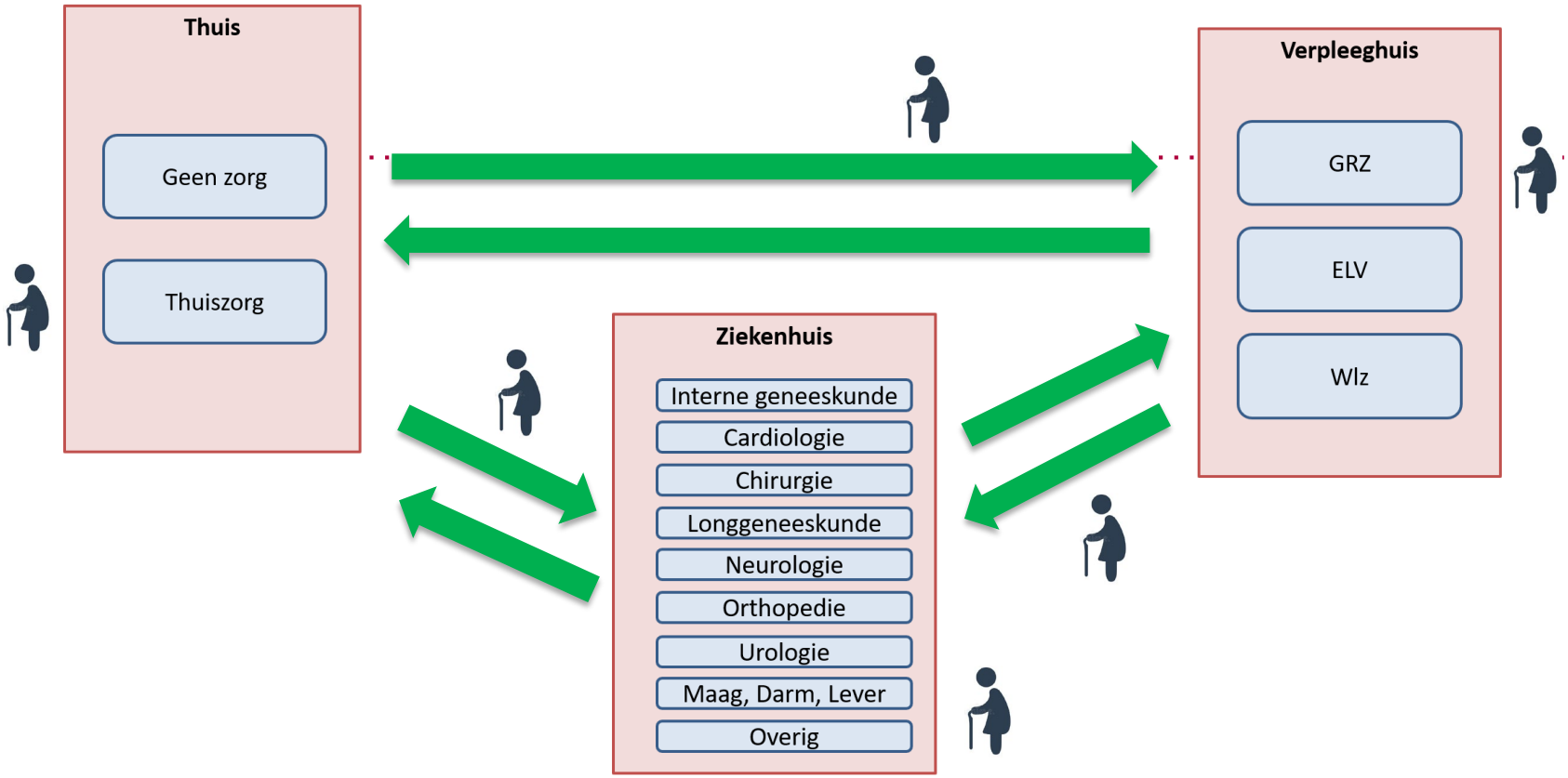
1. Includes individual preferences
2. Dramatic reduction in waiting time

also psychiatry, youth care,…

Waterbed model



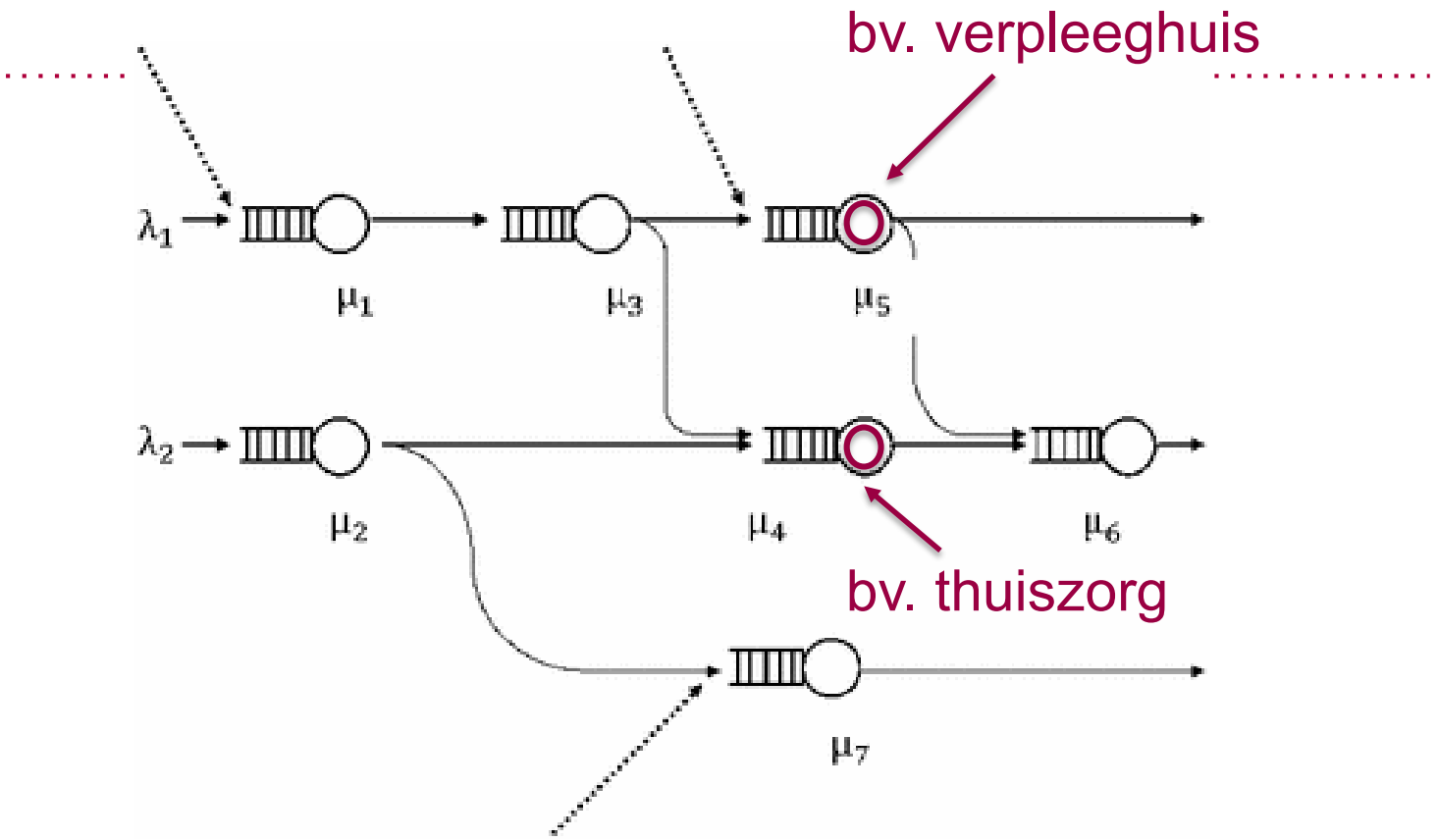
Acute Elderly Care Network



Typische vragen

- Waar zitten de bottlenecks?
- Hoe effectief zijn maatregelen voor reductie wachttijden?

Wiskundig Macro-Model

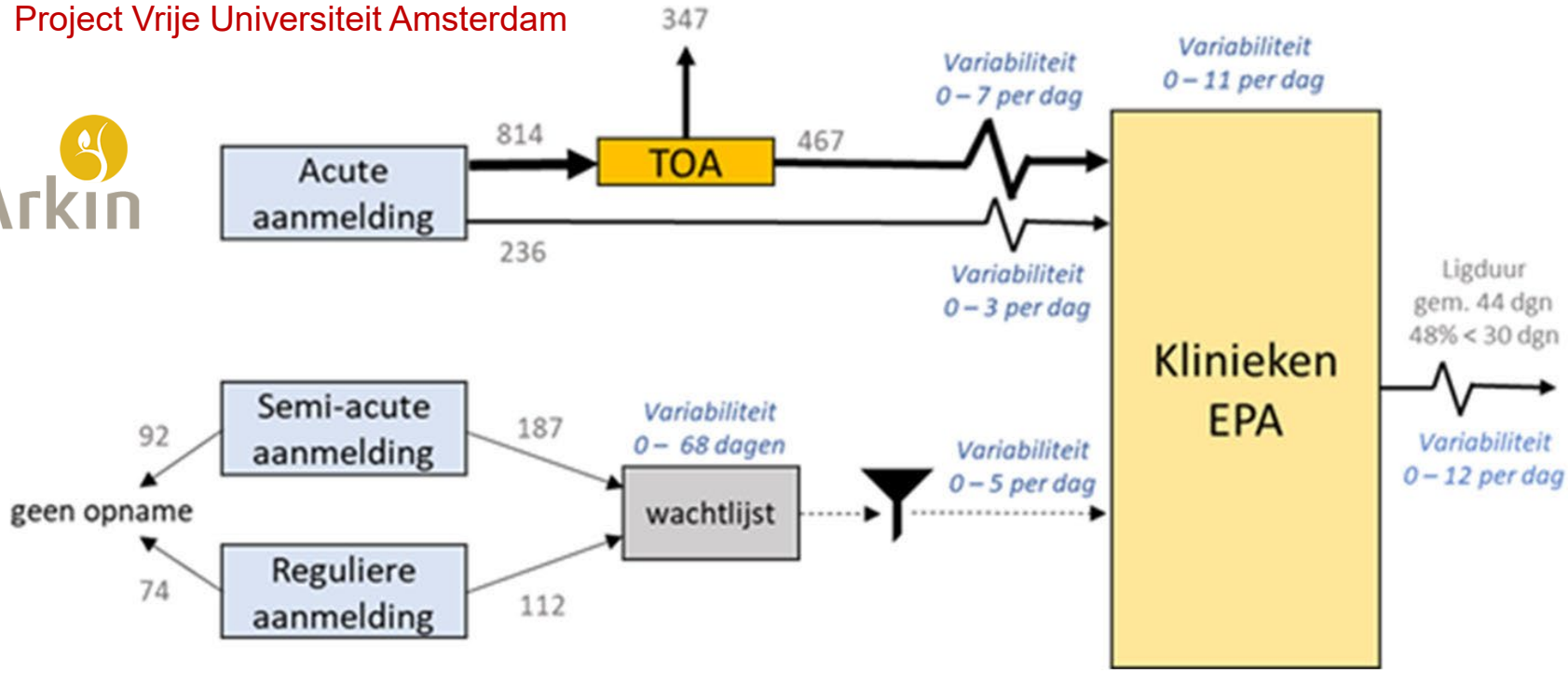


- Stochastische netwerk van zorgaanbieders (onzekerheid)
- Doorlooptijden, wachttijden

Waterbed "What-if"-tool

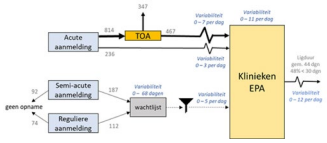
Use case Mental Healthcare

Project Vrije Universiteit Amsterdam

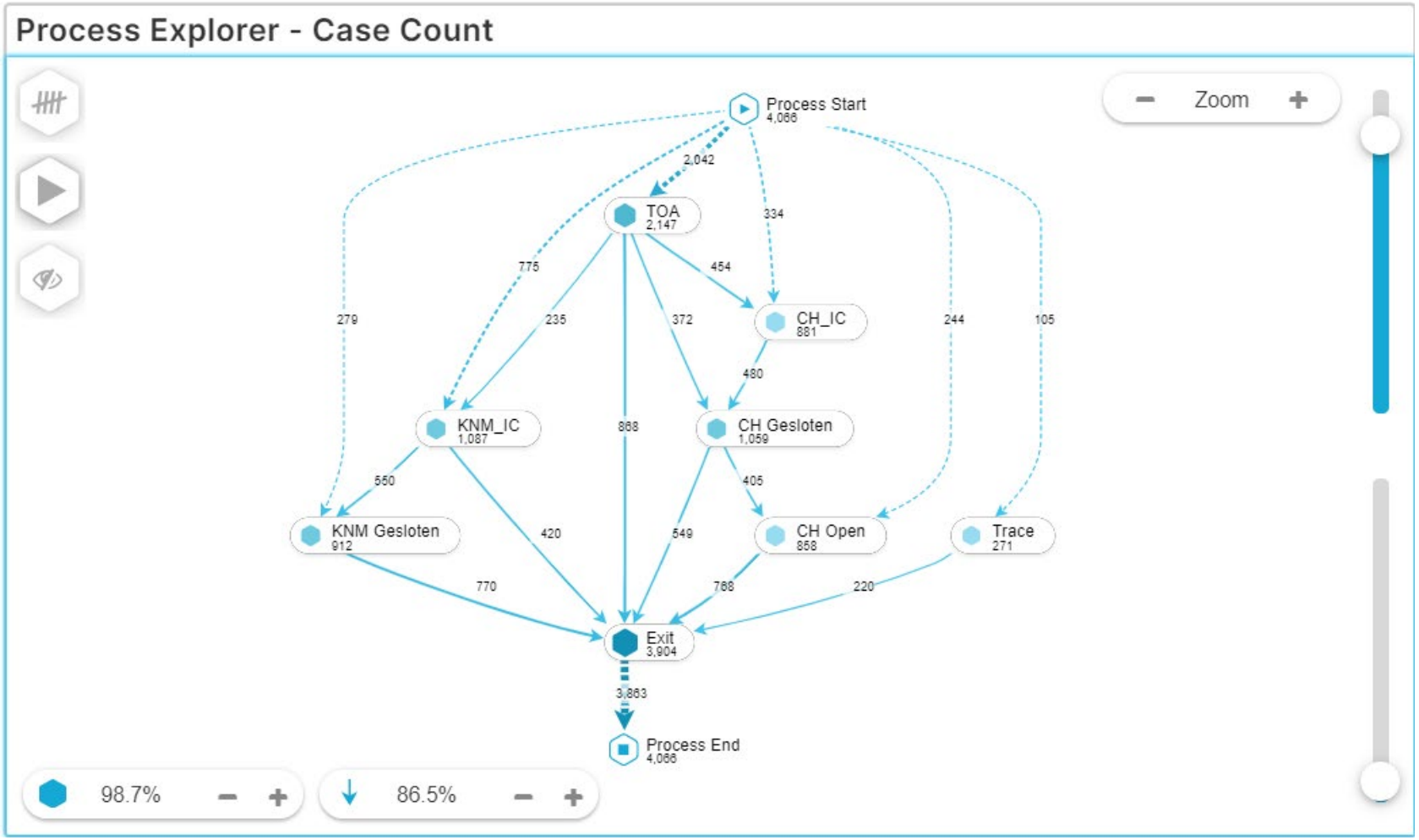


Typische “what-if”-vragen:

1. Hoe presteren we nu eigenlijk?
2. Wat zijn de capaciteitsbottlenecks?
3. Hoe effectief zijn maatregelen in capaciteitsmanagement?
   - wachttijden, doorstroom, …
4. Wat als instroom van clienten met 10% toeneemt?



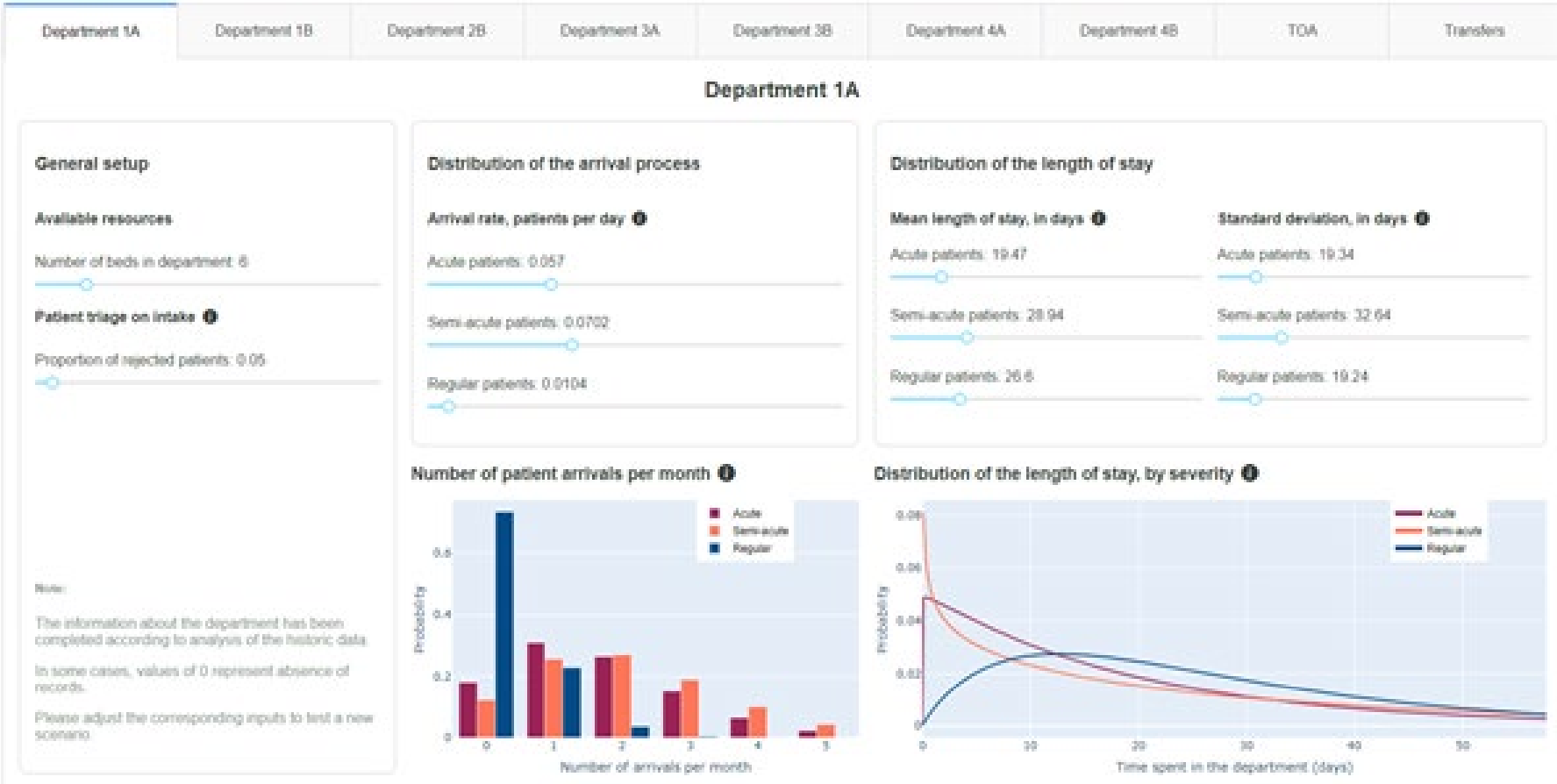
Process Mining



Vraag: Hoe ziet onze process-flow er eigenlijk uit?

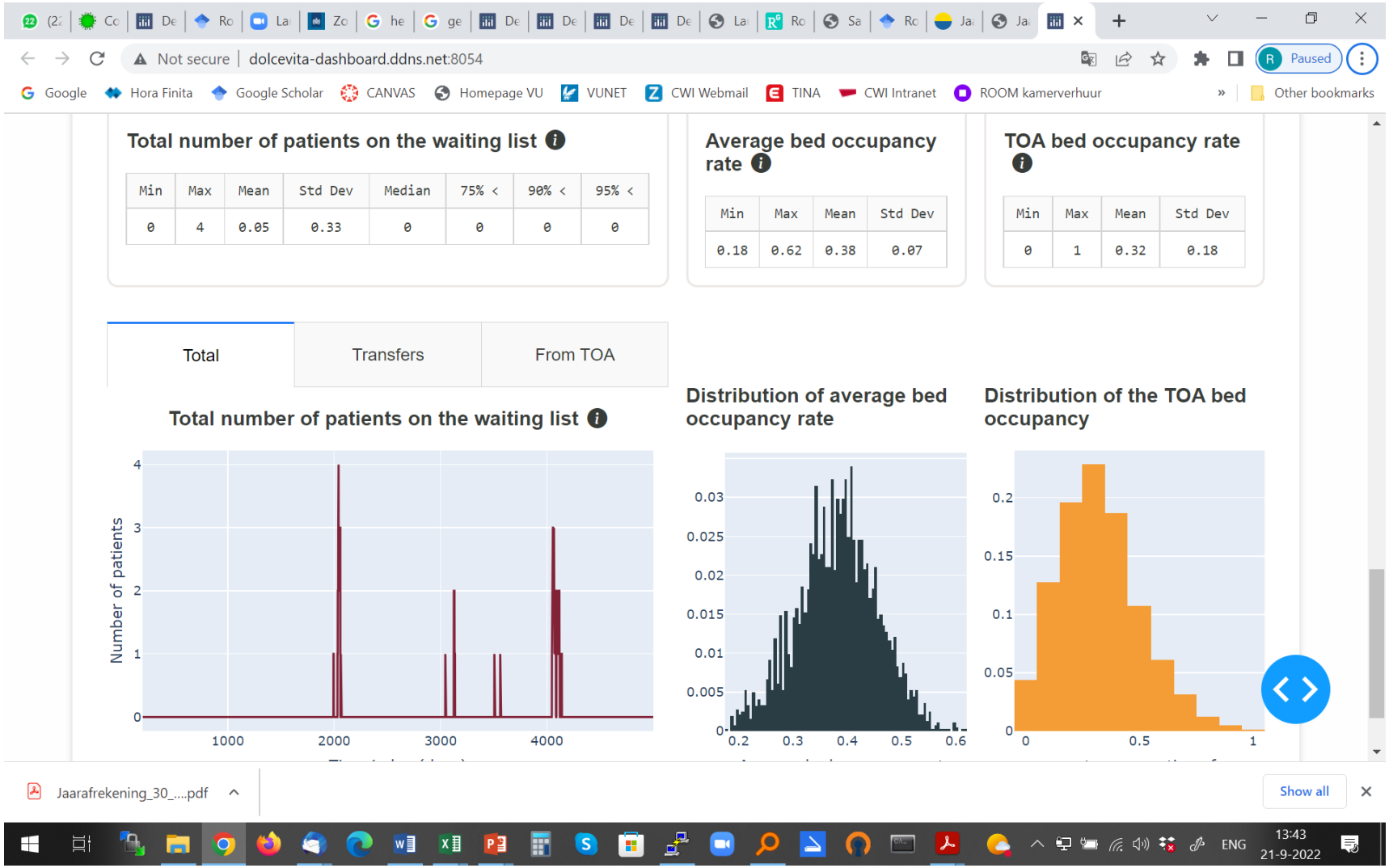
“What-if” Planning Tool

Input



"What-if" Planning Tool

Output



Discussion

Question 1:

What limitations and obstacles do you see in using Mathematics and analytics in improving healthcare logistics?

Question 2:

What are new possibilities for improving healthcare logistics have not yet been fully explored?

Success Stories of Mathematics Saving Lives

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