How to deal with imperfect failure predictions in after-sales services?

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Background

Education at University of Twente:

- MSc (ir.): Industrial Engineering & Management (1999 – 2004)
  Graduation: Keypoint Consultancy
- MSc (ir.): Computer Science (2000 – 2005)
  Graduation: Deutsches Forschungszentrum für Künstliche Intelligenz
- PhD: Operations Management (2005 – 2010)
  Visiting scholar: University of Texas at Austin

Working career:

- Postdoc at Eindhoven University of Technology (2010 – 2011)
- Consultant at Gordian Logistic Experts (2010 – 2011)
- Assistant professor at University of Twente (2011 – 2014)
- Assistant professor at Eindhoven University of Technology (2014 – 2017)
  Visiting professor: Rensselaer Polytechnic Institute
- Associate professor at Eindhoven University of Technology (2017 – now)
  Visiting professor: Dartmouth College

Research: New technologies in after-sales services

Research with:

- OEMs: ASML, Additive Industries, Canon Production Printing, Marel Poultry, Vanderlande, Thales Nederland, etc.
- Users: Netherlands Railways, Royal Netherlands Army, Royal Netherlands Navy, etc.

Most cited paper: Improving failure analysis efficiency by combining FTA and FMEA in a recursive manner (with Johnny Peeters & Tiedo Tinga)

Main focus in research on (predictive) maintenance optimization, spare parts inventory control (using additive manufacturing), and behavioral operations management

Overview

- Imperfect information
- Maintenance optimization
- Spare parts inventory control
- Conclusion

Perfect information

If we know for each part exactly when it will fail in the next few years, then maintenance and spare parts planning isn’t too difficult

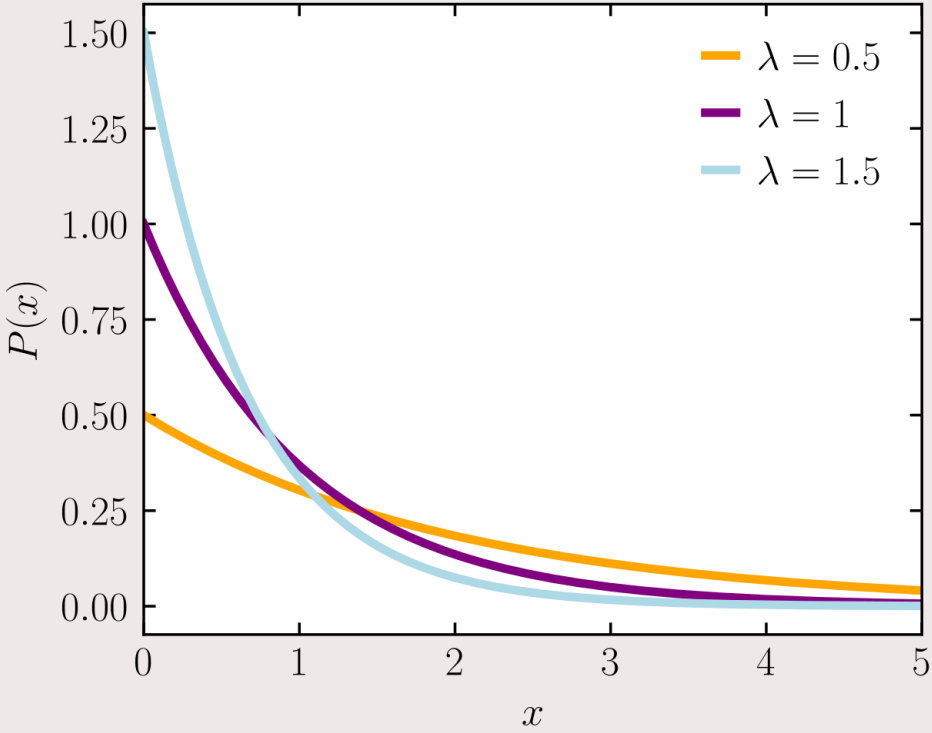
It’s still a big problem, but at least we know when we need to perform maintenance and have spare parts (and other resources) available

Exponentially distributed time to failure

A certain type of part fails:

- on average once every so many years at random, i.e.,
- with exponential time to failure,
- generating a Poisson demand process

We have stochasticity, which complicates spare parts planning; preventive maintenance makes no sense



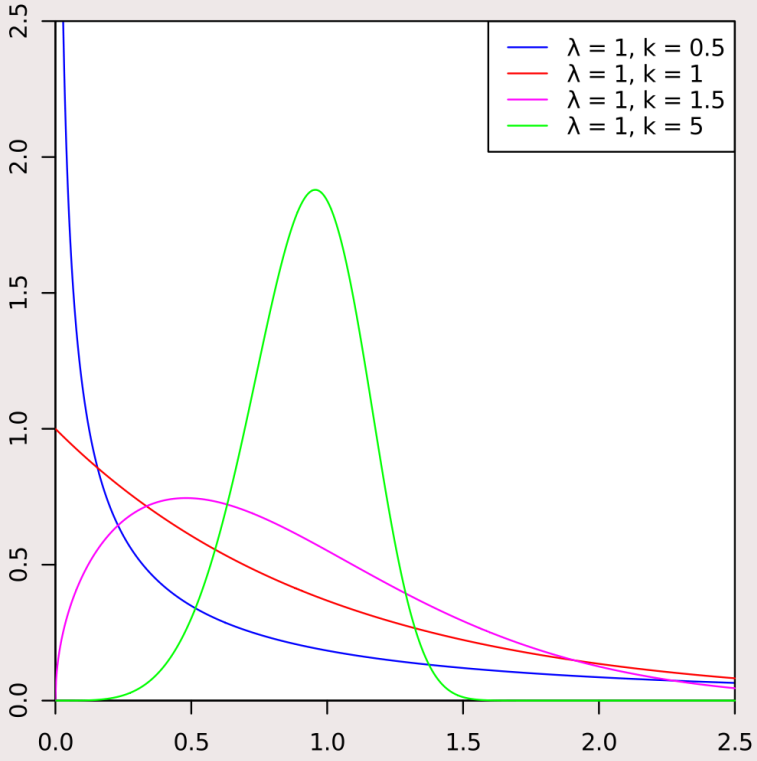
Weibull distributed time to failure

A certain type of part fails:

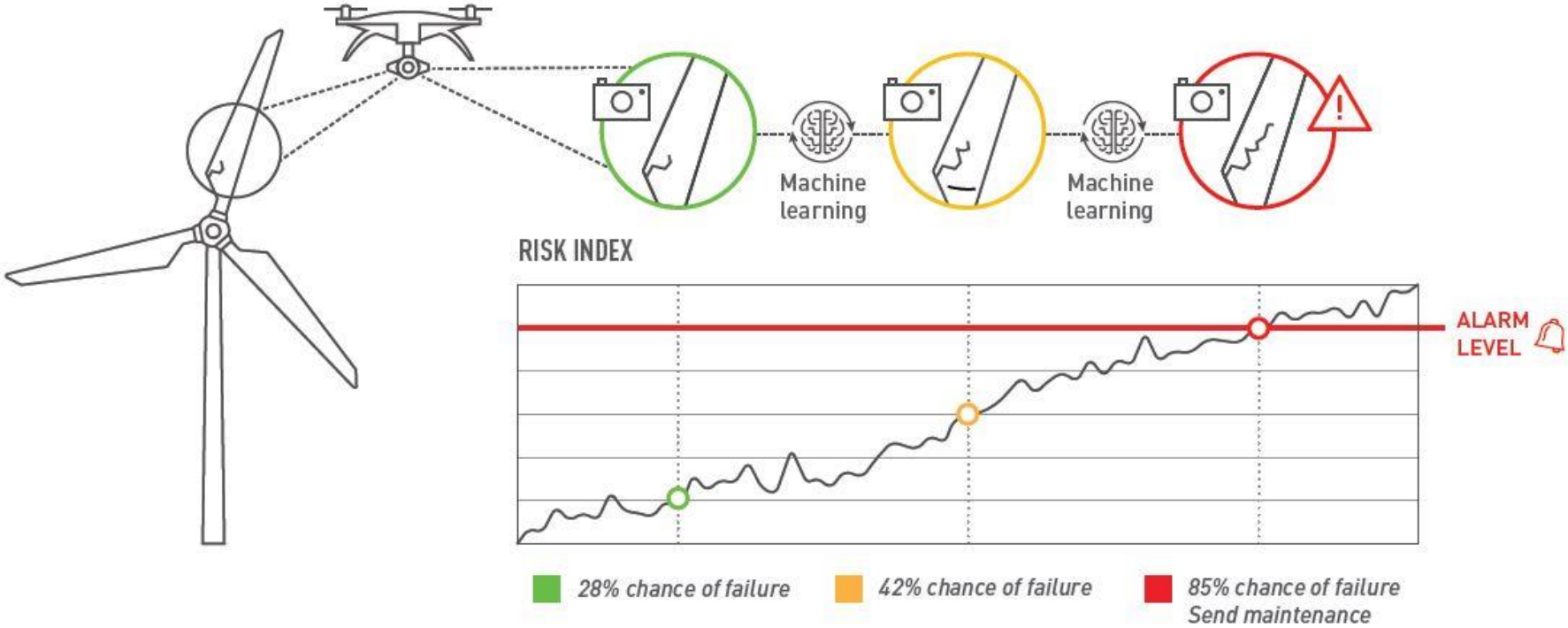
- with a Weibull distributed time to failure with shape parameter β>1

We still have stochasticity,
now with an increasing failure rate

Preventive maintenance makes sense;
most spare parts models assume
Poisson demand



Predictive maintenance (1/2)



Predictive maintenance (2/2)

Predictive maintenance: Monitor certain conditions and predict the remaining useful life or the probability of failure over a certain time period, e.g., until the next maintenance moment.

This improves usage of components, but makes maintenance and spare parts planning more difficult than with time-based / usage-based maintenance

Many types of imperfections in the information

Especially with new product introductions, we may not know:

- What type of distribution the time to failure has
- Let alone the values of its parameters
- What conditions to monitor
- Let alone how the conditions change over time, and when they indicate imminent failure

I'll discuss

- maintenance optimization with partial observation of degradation, and
- spare parts inventory control using only initial reliability estimates

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Maintenance optimization when information is incomplete and environment-dependent

Ongoing research with:

- Ragnar Eggertsson (PhD student at TU/e)
- Geert-Jan van Houtum (TU/e)

Problem

- Heating, Ventilation and Air Conditioning units (HVACs); we focus on the AC
- One or two per carriage
- Too many failures lead to limited trains (in the summer)
- Degradation status of the HVAC is not known exactly

Problem: Degradation information

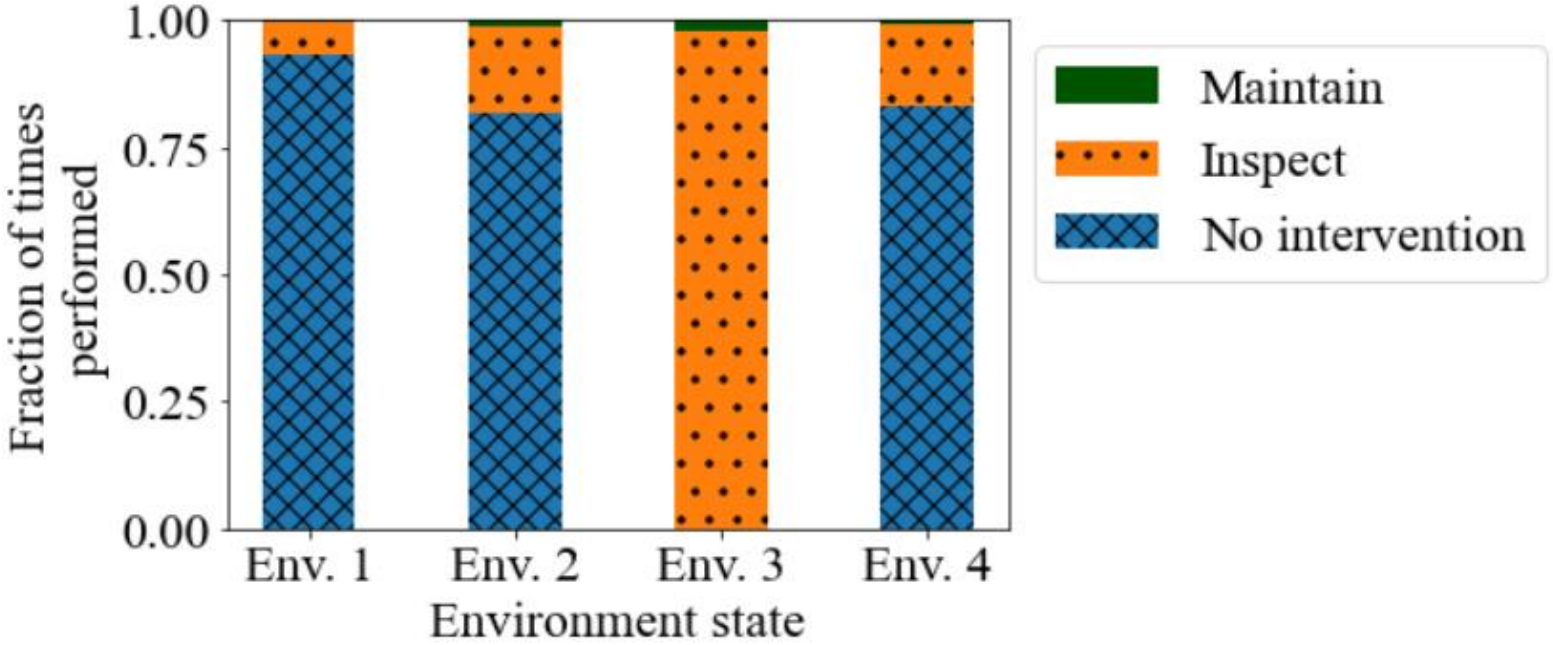
Observations and costs:

- AC failures are obvious in summer
- AC failures are expensive in summer
- AC failures go largely unnoticed in fall, winter and spring
- AC failures are usually not important in fall, winter and spring

So: Both costs and (partial) information are environment-dependent

We add the environment to the model of Ohnishi et al. (1986)

Numerical example



Numerical experiment: Not using the optimal policy

	Optimal policy		Aggregate policy	Myopic policy
	value (€)	bound	rel. value	rel. value
$\mathcal{M}_{\text{base}}$	162,795	0.93%	$112.2 \pm 1.4\%$	$101.0 \pm 1.2\%$
$P^{\text{E}}_{4,\text{fast}}$	166,493	0.92%	$107.3 \pm 1.4\%$	$101.5 \pm 1.2\%$
$P^{\text{E}}_{4,\text{equal}}$	158,702	0.92%	$100.7 \pm 1.3\%$	$111.8 \pm 1.2\%$
$P^{\text{E}}_{3,\text{slow}}$	183,955	0.94%	$114.4 \pm 1.4\%$	$100.6 \pm 1.2\%$
$P^{\text{E}}_{3,\text{fast}}$	188,354	0.93%	$109.3 \pm 1.4\%$	$100.6 \pm 1.2\%$
$P^{\text{E}}_{3,\text{equal}}$	170,996	0.93%	$100.4 \pm 1.3\%$	$120.3 \pm 1.1\%$
L_{low}	128,108	0.86%	$100.8 \pm 1.2\%$	$100.6 \pm 1.1\%$
L_{high}	194,136	0.92%	$122.6 \pm 1.5\%$	$101.0 \pm 1.2\%$

Numerical experiment: Value of information

	$\mathcal{E}'$	value (€)	bound (€)	$I(\mathcal{E}', (1,1))$
$\mathcal{M}_{\text{base}}$	$\emptyset$	162,795	1,513	0
Ω_1	$\{1\}$	158,550	1,460	4,245
Ω_2	$\{2\}$	150,638	1,373	12,158
Ω_3	$\{3\}$	136,341	1,238	26,454
Ω_4	$\{4\}$	155,001	1,445	7,795
Ω_{f}	$\{1,2,3,4\}$	111,748	987	51,047

Further research

- Making the algorithms faster and less memory consuming
- Allowing for multiple components
- Making algorithms that give understandable solutions
- Actual case study on NS data

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Robust spare parts inventory control

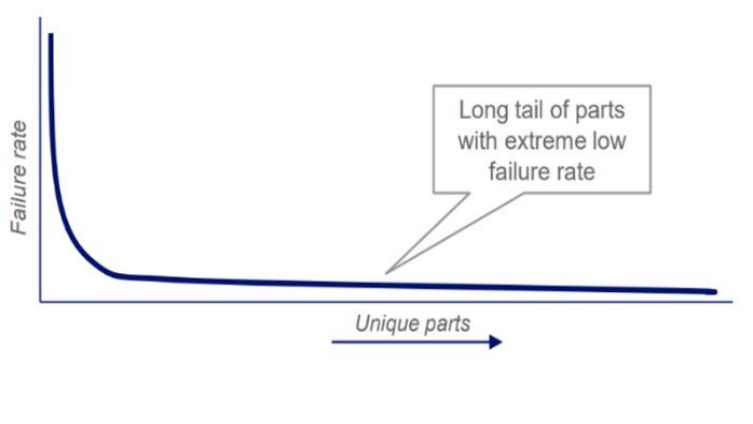
Ongoing research with:

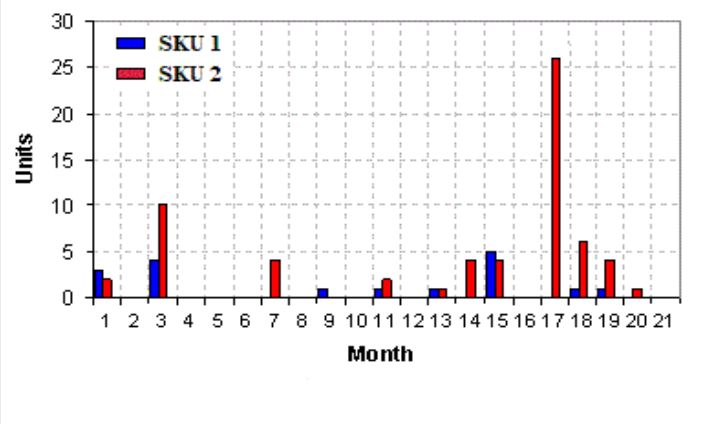
- Zhao Kang (PhD student at TU/e)
- Ahmadreza Marandi (TU/e)
- Ton de Kok (CWI & TU/e)
- Joan Stip (ASML & TU/e)

Problem (1/2)

New product introduction (NPI): Demand rate is hard to estimate:

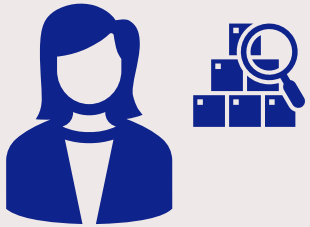
- Mainly dependent on estimates of reliability engineers
- Historical demand data is very limited
- Demand is intermittent

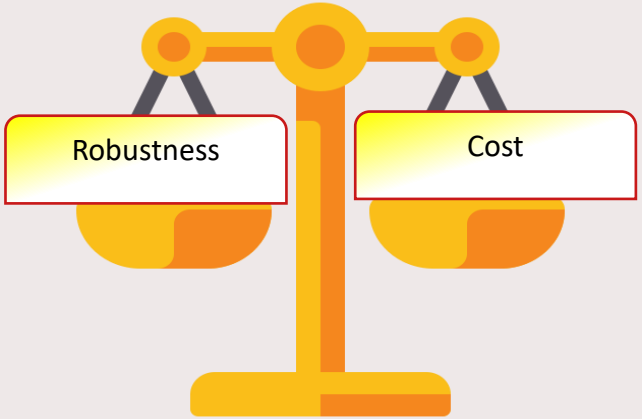




Problem (2/2)

High service target + initial demand rate

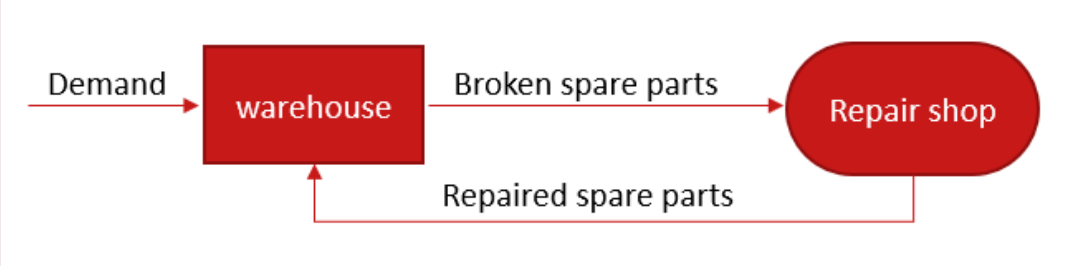




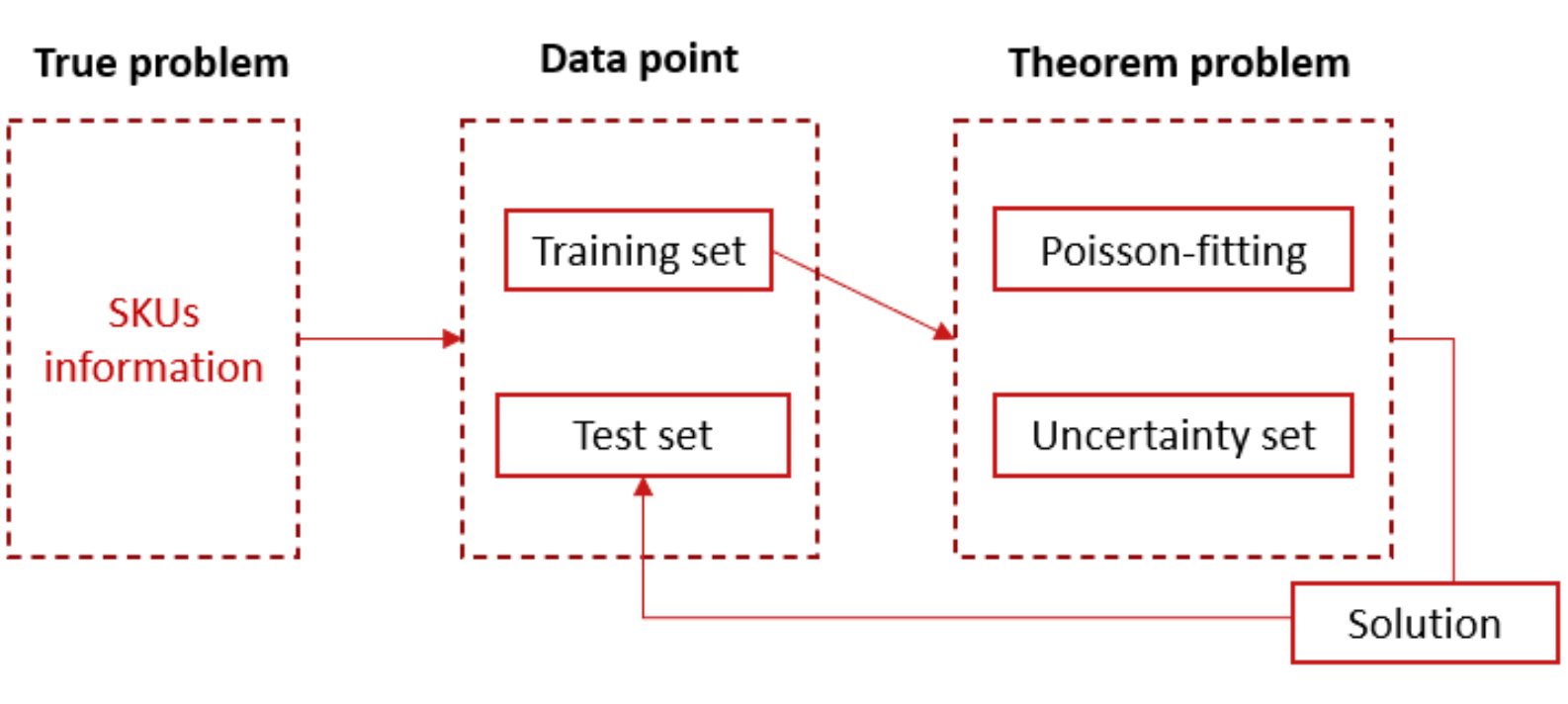
Stock more	or	Stock less
+ Excellent service performance		− Poor service performance
− High investment cost		+ Low investment cost
+ Low penalty cost		− High penalty cost
− More inefficient stock (not used in 5 years)		+ Less inefficient stock

Assumptions

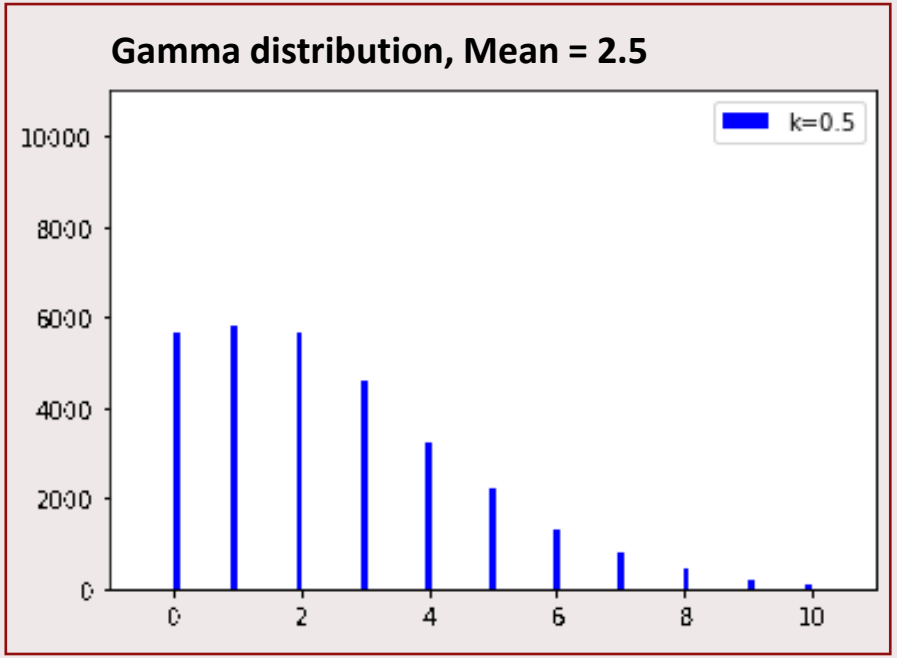
- One warehouse, with emergency shipments
- Multiple (critical) components in the warehouse
- For each component, we use one-for-one replenishments, i.e., a base stock policy

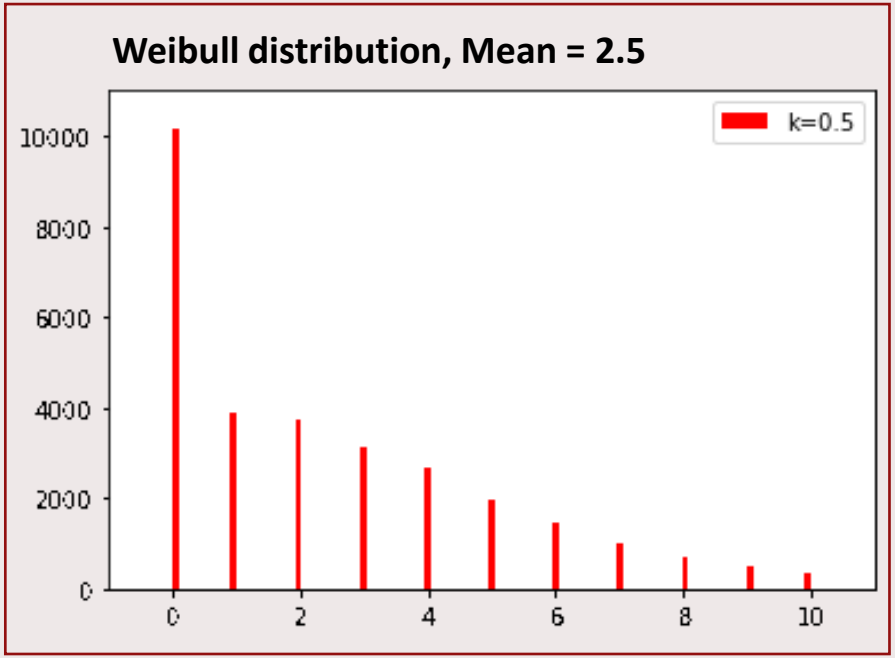


Simulation study: Setup



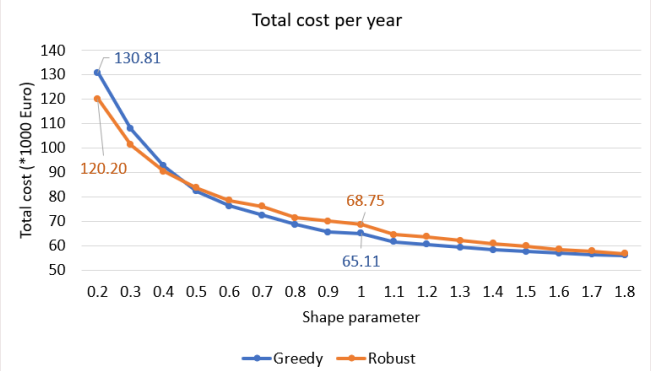
Simulation study: Demand

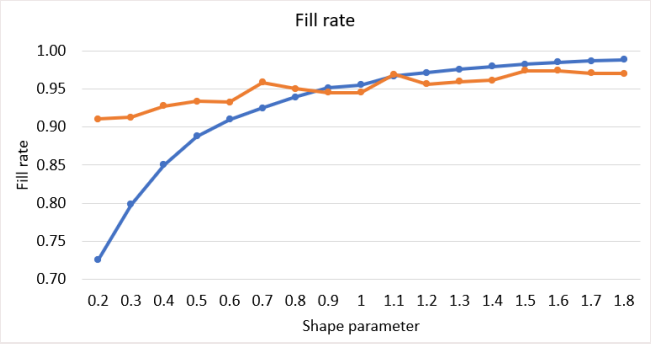




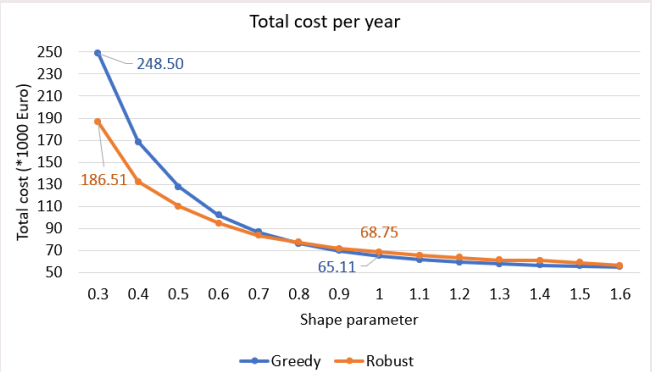
Simulation study: Results

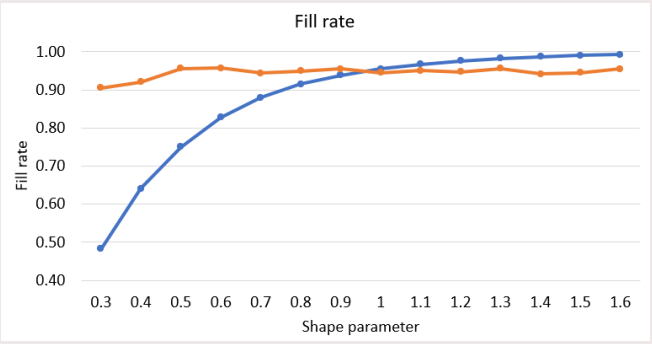
Gamma distribution





Weibull distribution





Further research

- Improving the algorithms and proving they are optimal
- Simulation studies on data without an underlying demand distribution
- Actual case study on ASML data

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Conclusion

- With perfect information, providing after-sales services isn’t difficult
- With imperfect information, we can still do a lot
- I hope to have given you some idea of what’s possible

- We are always looking for data sets to learn and improve algorithms
- Feel free to contact me if you have questions and interesting problems

Questions & discussion

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Contact me at r.j.i.basten@tue.nl