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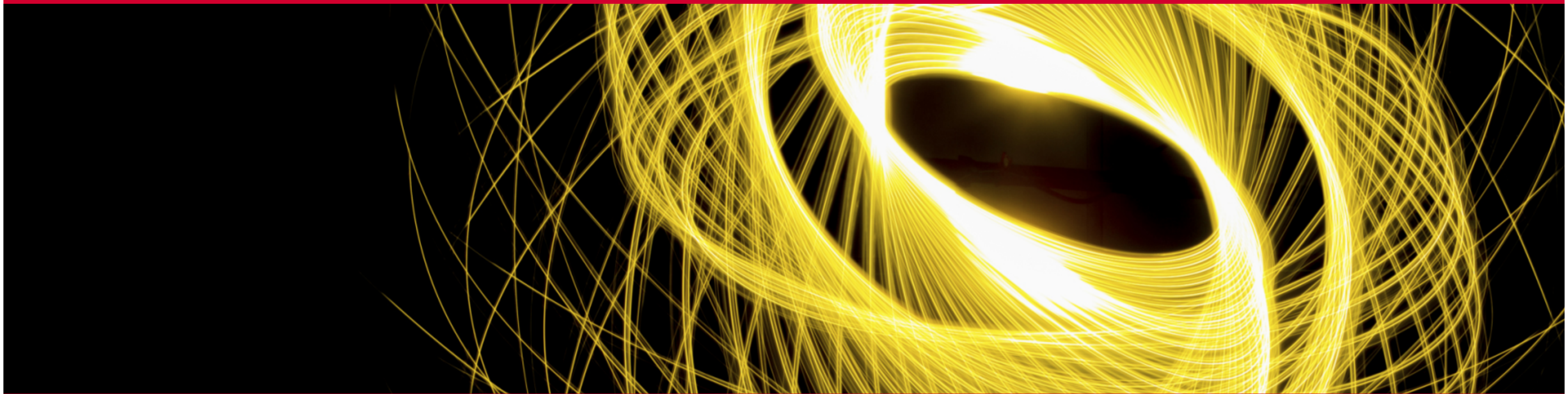
Subseasonal forecasting: Managing telecommunications fault risk



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[2] NCAS, University of Reading

[3] BT research

Introduction

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- Telecommunications
  - UK £33bn/year or ~1.5% GDP net economic contribution (Kelly, 2015)
  - BT / Openreach responsible for ~90% of fixed line infrastructure

- Weather highlighted as a contributor to increased fault rates
  - BT annual reports each year from 2013-2018
  - Associated with service delays, disruptions and challenging conditions

- Initial goal: skillful forecasts of fault rates ~weeks ahead
  - Enables Openreach to prepare for, e.g., fault rate spikes

- But ***does this solve the underlying challenge?***
  - Difficult to assign an economic value to fault rate forecast improvement, instead:
    - Penalties if fail to hit regulated targets for ***fixing*** faults ('RD3') ➔ ***target failures***
    - Avoid retaining excess fault repair capacity ➔ ***avoidable costs***

- Implications for forecast assessment
  - Limitations of static "cost-loss" models (c.f., Richardson, 2000; Murphy 1985)

This talk

Part 1: Establishing a skillful ***fault rate forecast (national- and weekly- mean)***

- Long-term climatology
- Weeks-ahead forecasting

Part 2: Estimating ***forecast value***

- Avoiding unnecessary costs and performance failures

Aside: data normalization for commercial sensitivity

- 1.0 week^{-1} = long term average weekly fault rate
- Repair capacity (# engineers) similarly scaled

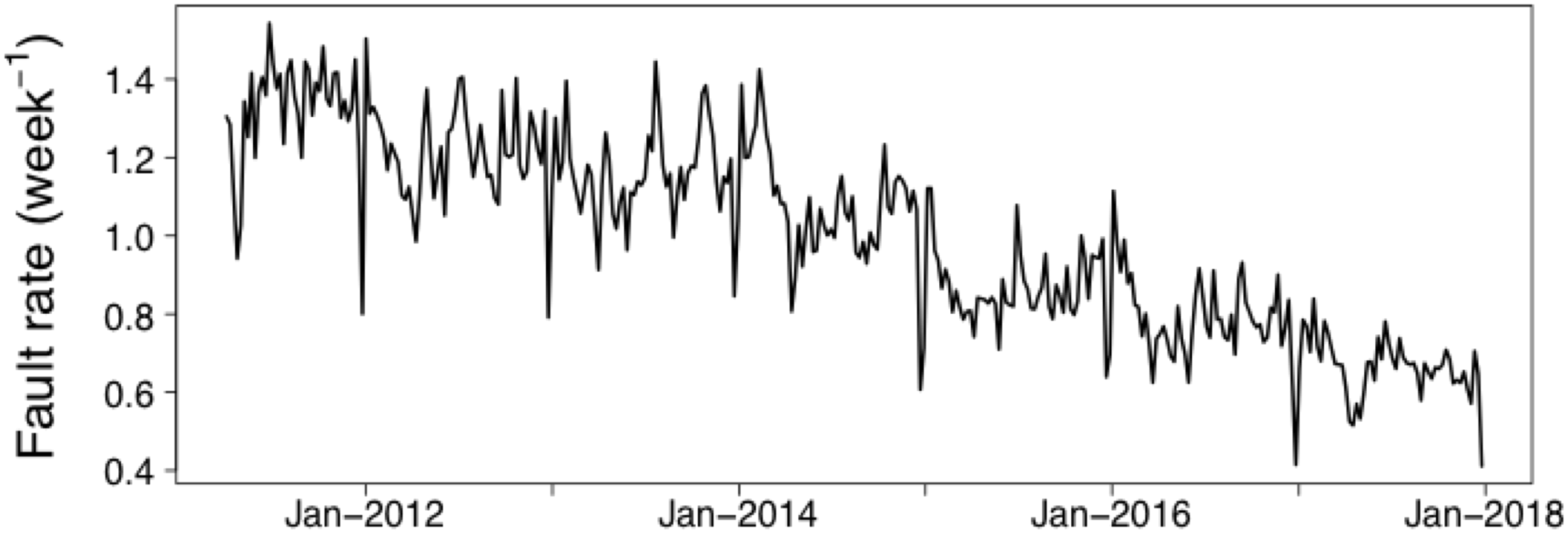
Paper: Brayshaw, Halford, Smith, Jensen (in review, Met Apps)

Part 1a - Fault rate climatology

- As with many weather/climate impact problems, the impacted system is changing rapidly
- Total number of lines (~25M) lines fairly constant but…
  - Four main line types: VOICE, VOICE_BB, MPF, NGA
    - Different types ➔ different technologies ➔ different weather sensitivities
  - System evolving rapidly (mix of line types, network hardening)
    - Relevant observational data available late 2011 to end 2017
    - Weekly resolution

➔Want long homogeneous “synthetic” historic record (c.f., Cannon et al 2015 for wind power)

National weekly total VOICE fault rate, normalized by 2012-2017 mean



Part 1a - Fault rate climatology

- Construct multiple linear regression (fault rate against ERAInt UK-land area) by line type:

$$FRA_i^{VOICE} = \alpha_0 + \alpha_1 PS + \alpha_2 PT + \alpha_3 T + \alpha_4 W + \alpha_5 WT + \alpha_6 RHT + \alpha_7 HOL + \varepsilon_i(0, \sigma)$$

3-week-running-mean precip

Weekly precip over threshold (binary)

2m Temperature

10m windspeed squared

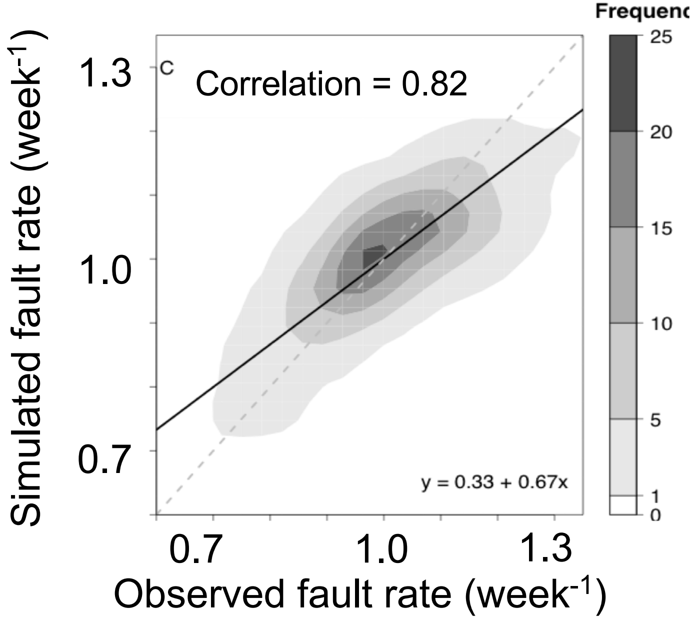
10m windspeed over threshold (binary)

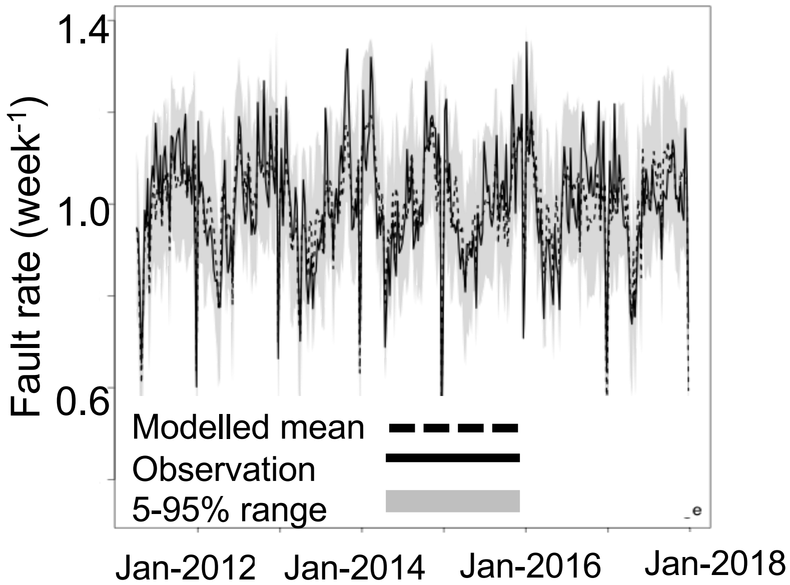
3-day relative humidity over threshold

public holidays

Normal residual

- Adjust to a "reference" system state in late 2017
- Sum over 3 line types: VOICE, VOICE_BB, MPF
  - Good quality reconstruction (including residual)
  - Simplify to meteorology-only problem (drop blue terms) ➔ 'synthetic' record 1979-2017

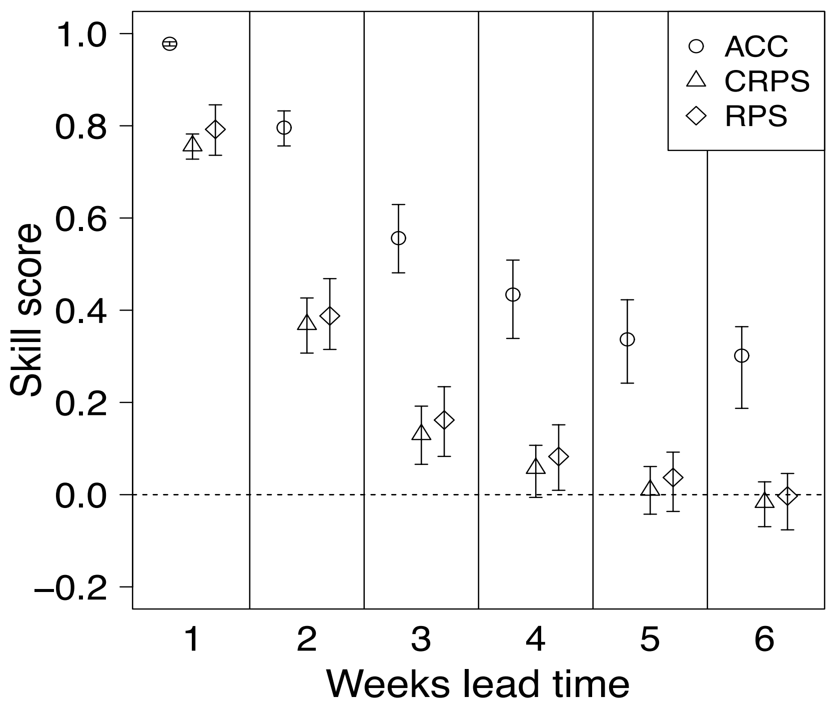




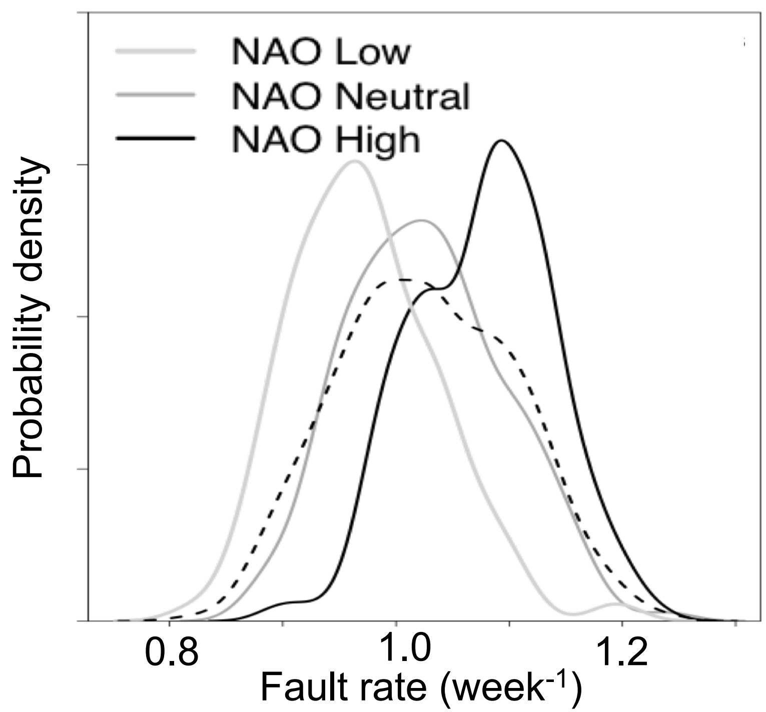
Part 1b - Fault rate forecast

- Focus on winter: higher fault rates and likely greater meteorological predictability
- ECMWF subseasonal forecast
  - 20yr 11-member hindcast out to week 6
  - Corresponds to forecasts launched Dec 2016 – Feb 2017 (model Cy43r1)
  - Lead-time dependent mean bias correction
- Simple strategy:
  - Predict NAO then use climatological NAO-faults relationship ➔ estimate weekly fault rates

NAO forecast skill (w.r.t. climatology)

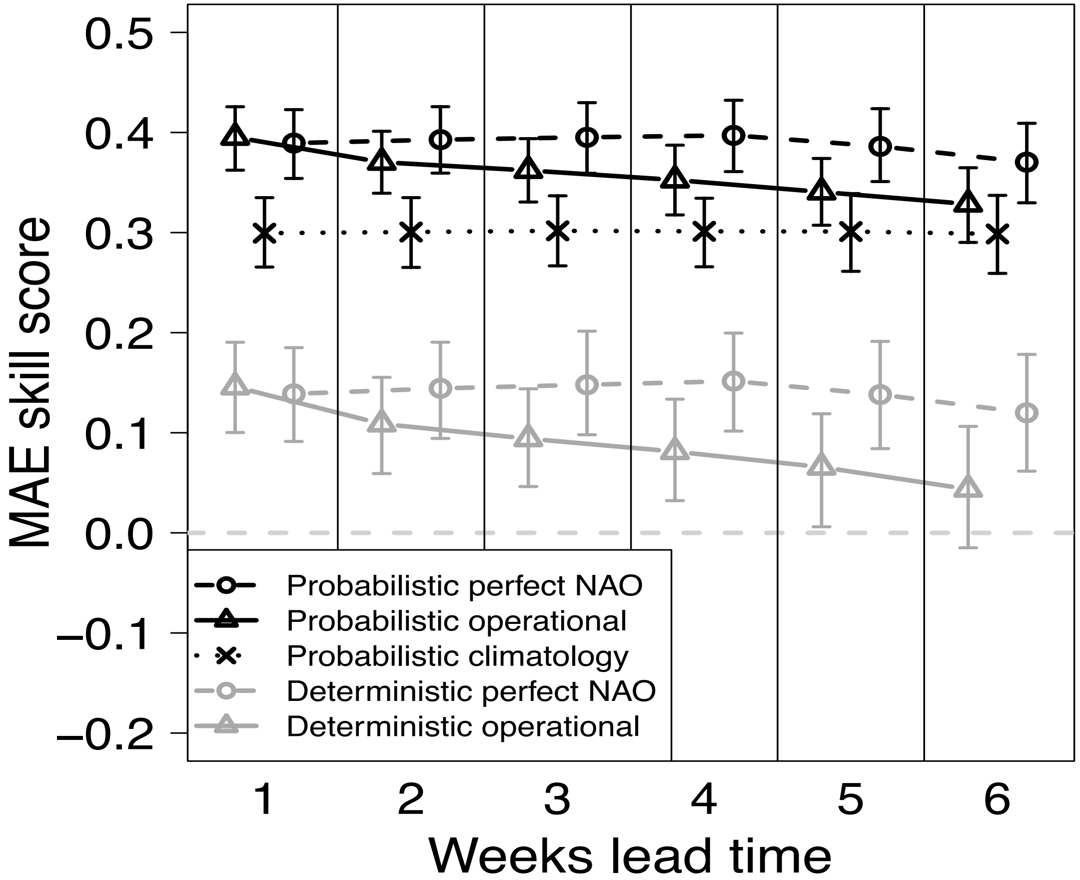


NAO impact on fault rate



Part 1b - Fault rate forecast

- Toy fault rate forecast model:
  - Each ECMWF ensemble member classified high/neutral/low NAO (weekly)
  - Corresponding NAO-based fault rate anomaly added to weekly climatological fault rate
    - Deterministic = fault rate anomaly is a single value
    - [Semi-]probabilistic = fault rate anomaly is a distribution
  - Average over ensemble members



MAE/CPRS forecast skill relative to deterministic climatology

➔ Evidence for skill weeks 3-5

- Probabilistic perfect NAO
- Probabilistic operational
- Probabilistic climatology
- Deterministic perfect NAO
- Deterministic operational

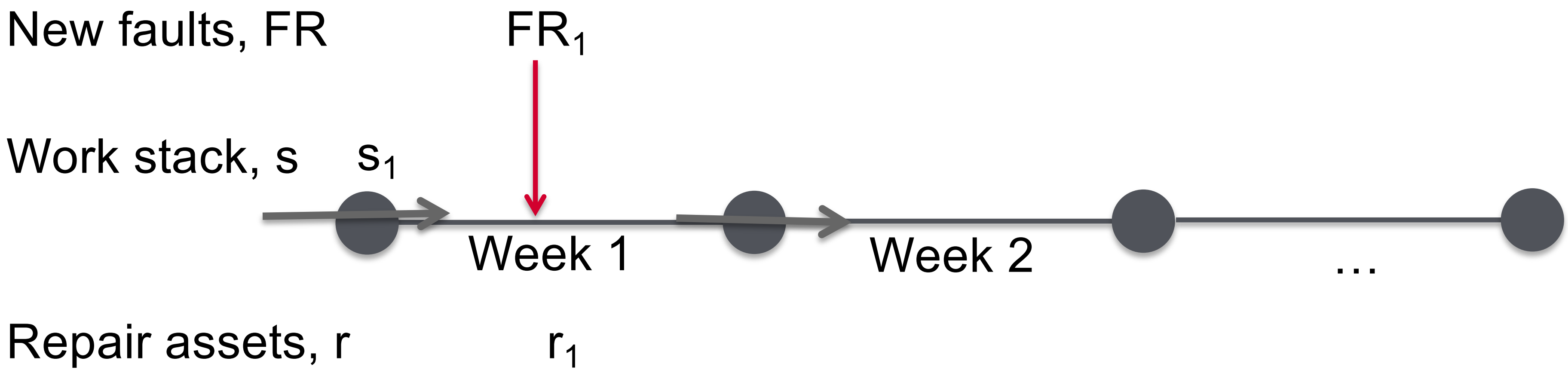
Part 2 – Decisions and value

- Recall: concern is *fixing faults promptly*, not just predicting faults

- Toy model of decision process
  - Target: fix a fraction ($1-\lambda$) of incoming faults during any week
  - Assume engineers only fix faults (“repair capacity”)
  - Unfixed faults carryover into next week and must be fixed before new work
  - Can employ ‘extra’ engineers (increase repair capacity) but with 1-week lead

- Aside - real decision is far more complex:
  - Daily resolution
  - Multi-objective (e.g., same engineers install new lines, with associated targets)
  - Decisions on multiple time-horizons from ~week-4 to near real time

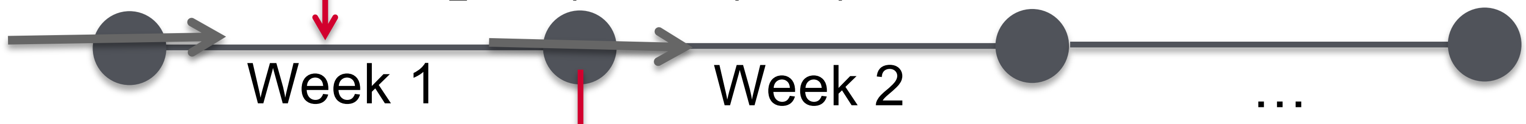
Part 2 – Decisions model



Part 2 – Decisions model

New faults, FR FR_1

Work stack, s s_1 $s_2 = s_1 + FR_1 - r_1$



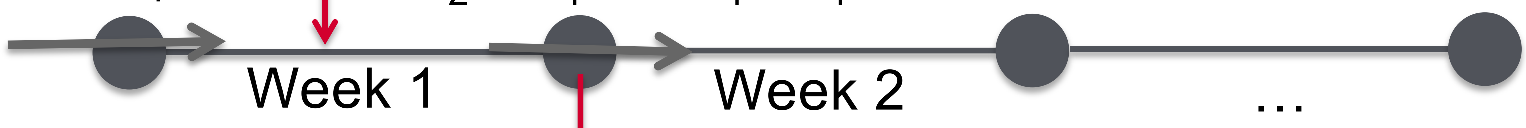
Repair assets, r r_1

Target failures, α $\alpha_1 = \mathrm{Max}(0, s_1 + FR_1\,(1-\lambda) - r_1)$

Part 2 – Decisions model

New faults, FR FR_1

Work stack, s s_1 $s_2 = s_1 + FR_1 - r_1$



Repair assets, r r_1 r_2

Target failures, α $\alpha_1 = \mathrm{Max}(0, s_1 + FR_1 (1-\lambda) - r_1)$

Need to decide r_2 during week 1

➔ locks in decision of repair assets one-week in advance

Part 2 – Decisions model

Forecast fault rate

New faults, FR $\quad FR_1 \quad FR_2^f$

Work stack, s $\quad s_1 \quad s_2 = s_1 + FR_1 - r_1$

Week 1 $\quad$ Week 2 $\quad$ …

Repair assets, r $\quad r_1 \quad r_2$

Target failures, α $\quad \alpha_1 = \mathrm{Max}(0, s_1 + FR_1 (1-\lambda) - r_1)$ $\quad \alpha_2^f = \mathrm{Max}(0, s_2 + FR_2^f (1-\lambda) - r_2)$

Forecast failure rate

Part 2 – Decisions model

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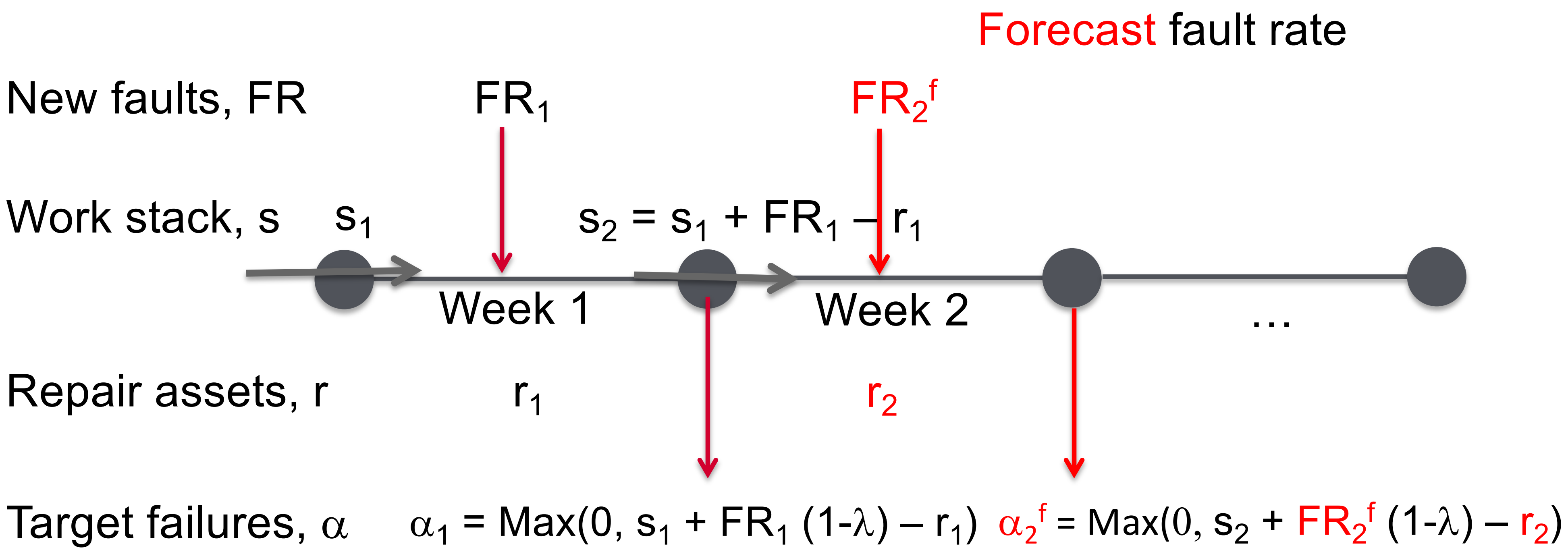

Choose r_2 as: $\underset{r_2}{Min}(c_{fail}\alpha_2 + c_{repair}r_2)$

$$r_{\min} \leq r_2 \leq r_{\max}$$

Part 2 – Decisions model

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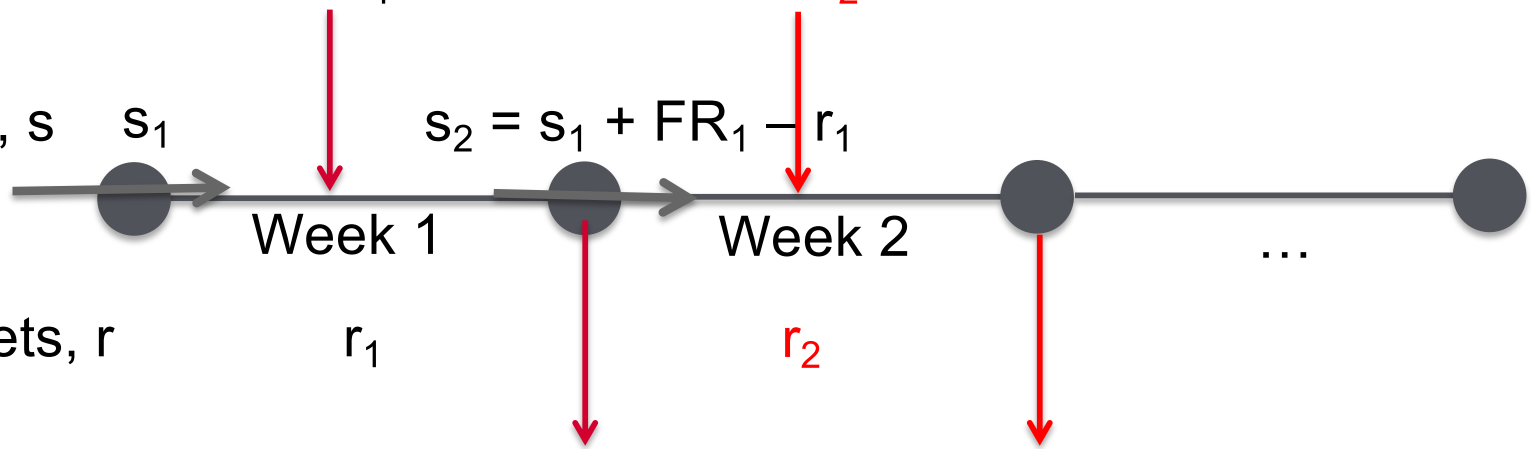
Forecast fault rate

New faults, FR FR_1 FR_2^f

Work stack, s s_1 $s_2 = s_1 + FR_1 - r_1$



Repair assets, r r_1 r_2

Target failures, α $\alpha_1 = \mathrm{Max}(0, s_1 + FR_1 (1-\lambda) - r_1)$ $\alpha_2^f = \mathrm{Max}(0, s_2 + FR_2^f (1-\lambda) - r_2)$

Forecast failure rate

Choose r_2 as: $\underset{r_2}{Min}(c_{fail}\alpha_2 + c_{repair}r_2)$

$$r_{\min} \leq r_2 \leq r_{\max}$$

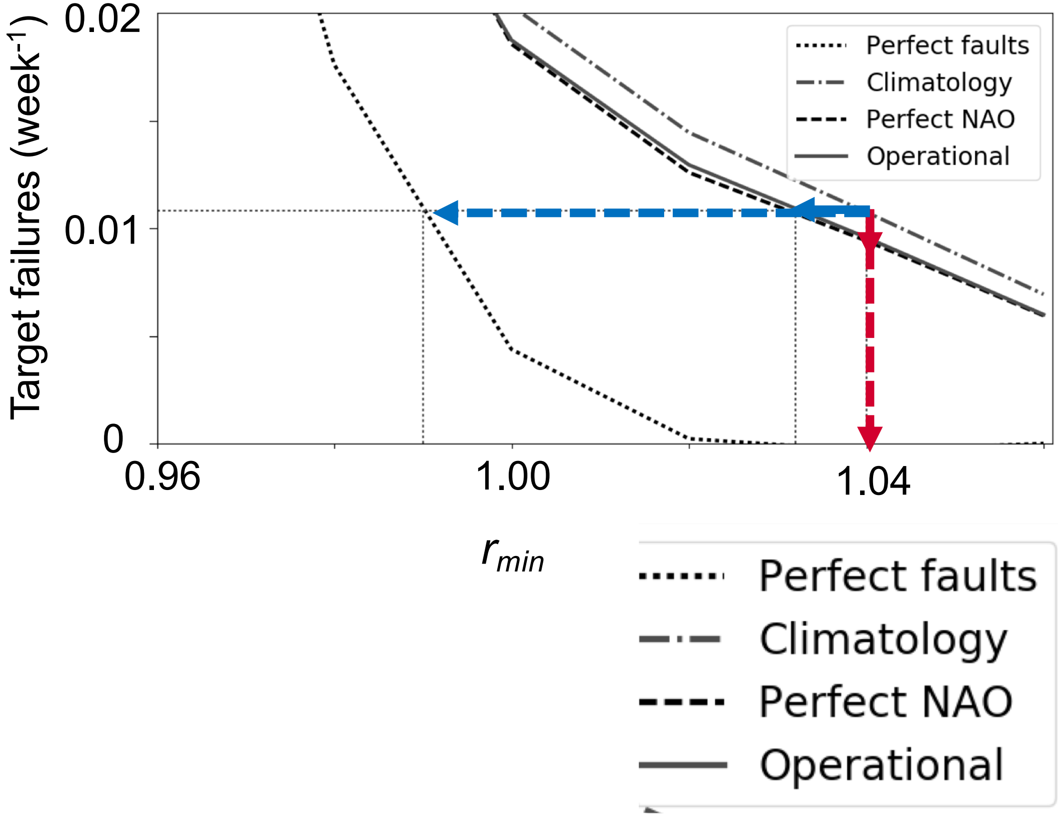
Then step forward to calculate **actual** α_2 using r_2 and the **actual** fault rate FR_2

Iterate over 'perpetual winter' from ECMWF hindcasts (neglect end years)

Part 2 – Decisions and value

Fixed contingency

- Two parameter decision model: r_{max}, r_{min}
- If user has insufficient ability to respond, forecast has no added value (not shown)
- Experiment: constant contingency
  - (r_{max}-r_{min} = 0.15 week^{-1})
  - Vary minimum repair capacity (r_{min})



- **Operational**:
  - For a given repair capacity, improved forecasts reduce target failure rate (~10%, up to 100%?)
  - ➔ "Better" performance with given resources

- **Planning**:
  - For a given target failure rate, improved forecasts reduce required repair capacity (~1%, up to 5%?)
  - ➔ "Reduced cost" for same performance level

Context: Annual staffing cost ~£500M, max penalty for failures up to ~£1M/day

Conclusions

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- Long term fault rate climatology
  - "Zeroth order" prediction - possible and valuable
- Fault rate forecast
  - Simple scheme demonstrates skill possible in weeks 3-5 (for winter)
- Value for decisions
  - Improved operations (fewer fails with same repair capacity)
  - Improved planning (smaller repair capacity needed for same performance)
- Wider implications
  - Value depends on ability of decision maker to respond and their objectives
  - Integrated decision-forecast evaluation
  - Errors linked: cost/loss model limitations

		Event occurs	
		No	Yes
Take action	No	0	L
	Yes	C	C - γL

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Brayshaw, Halford, Smith, Jensen (in review, Met Apps)

Cannon et al (2015 Rene Energy)