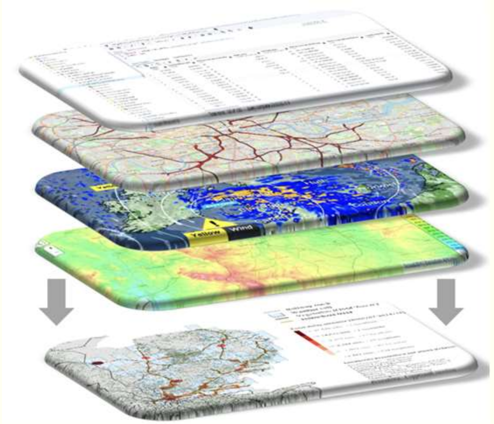


DAFNI Transport Sandpits 2024

Team: ClimaTrack Solutions

Forecasting resilience of railway network under propagating uncertainty

DAFNI Lunchtime seminar, 22 May 2024

UKRI Science and Technology Facilities Council

UKCRIC™ UK COLLABORATORIUM FOR RESEARCH ON INFRASTRUCTURE & CITIES

UKRI Engineering and Physical Sciences Research Council

DAFNI Data & Analytics Facility for National Infrastructure

Team composition

- Co-PI: **Ji-Eun Byun** (University of Glasgow)
- Co-PI: **Giuliano Punzo** (University of Sheffield)
- Researcher Co-I: **Qian Fu** (University of Birmingham)
- Co-I: **Iryna Yevseyeva** (De Montfort University)
- Co-I: **Tohid Erfani** (University College London)
- Co-I: **Konstantinos Nikolopoulos** (Durham University)






DAFNI
Data & Analytics Facility for National Infrastructure

Key challenges

Network Rail bears up to £100 million loss per year due to weather events:

- Can we better forecast **weather-related disruptions** of railway service?
- Can we identify **weak links** in a **network system**?

Key challenges

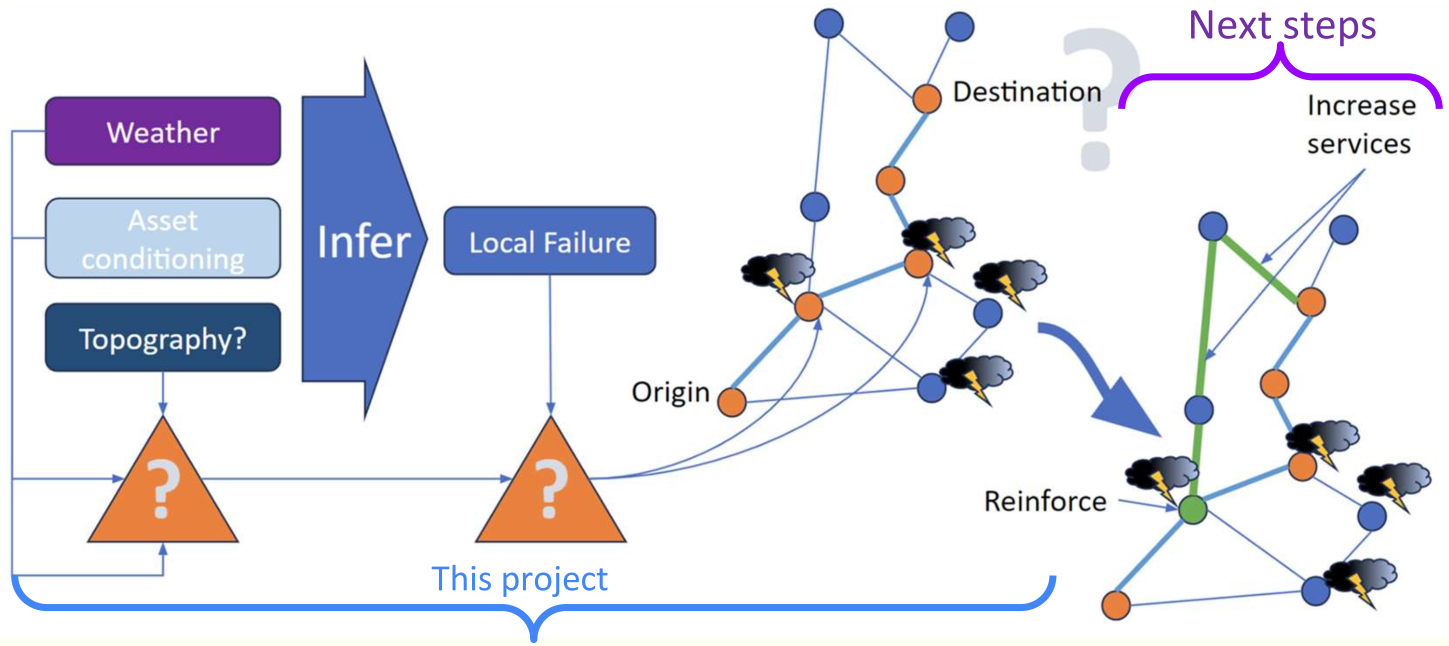
- **Data integration** across datasets with diverse codifications
- High **uncertainty** in weather events and asset failures
- **Uncertainty propagating** through jointly performing assets
- **Lack of ready-use computational tools** for decision-making

(Credits: Network Rail)

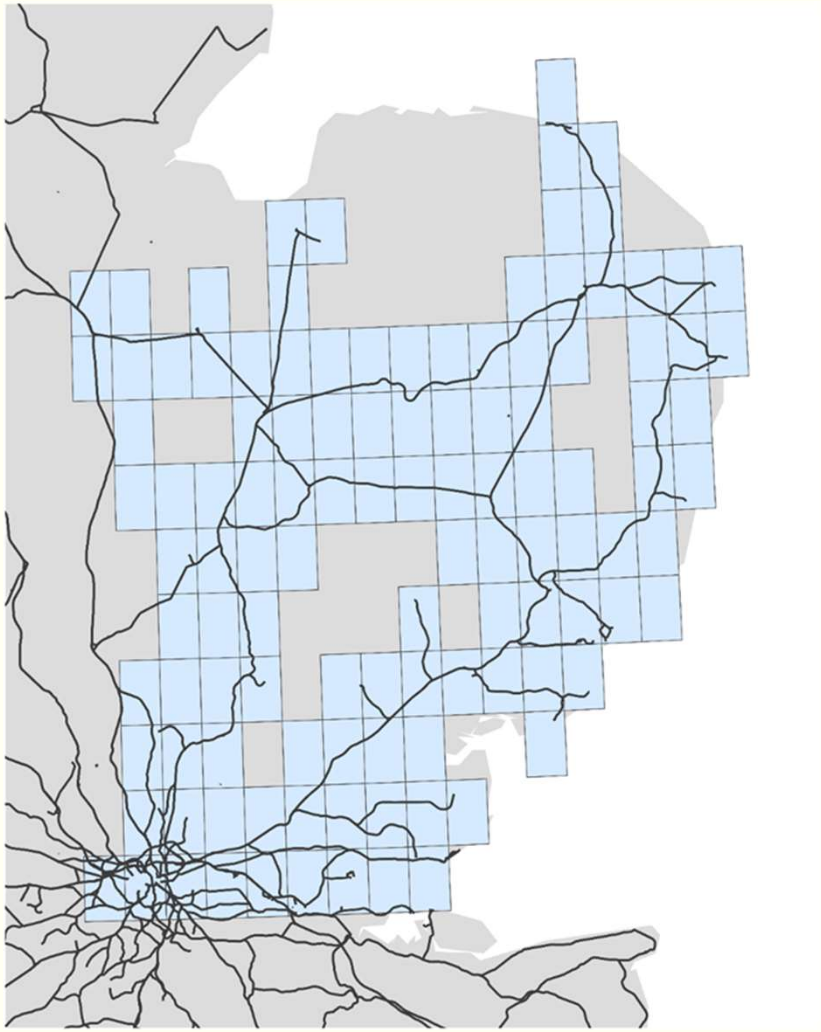
Proposed solution

Key challenges

- Data integration
- High uncertainty
- Uncertainty propagation
- Lack of ready-use computational tools



Strategy (1): Fragility/weather data



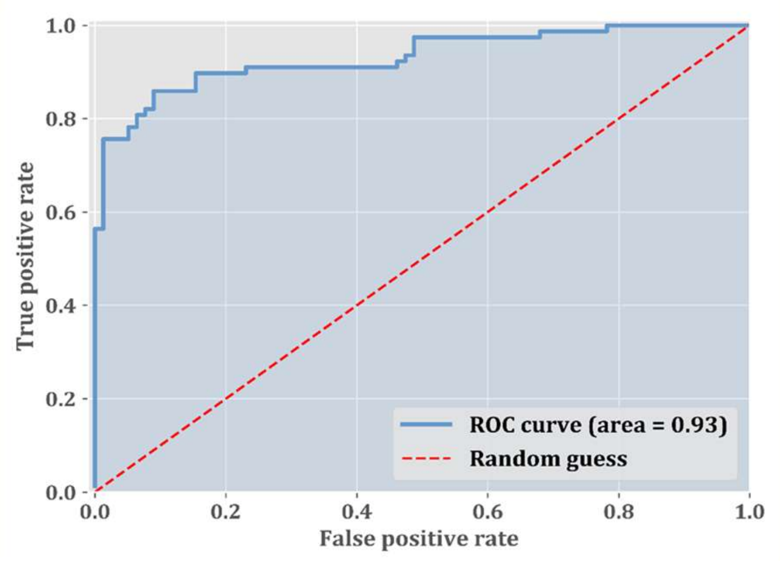
Data on Anglia region

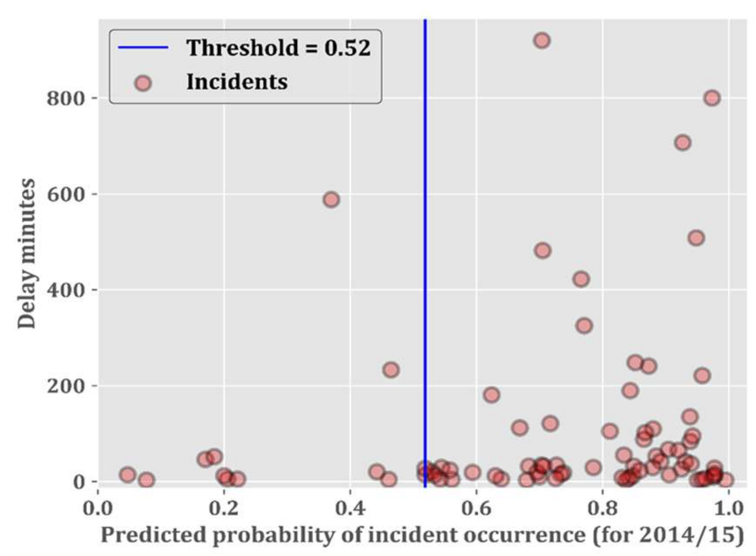
- **Historical rail delays** (04/2006 – 03/2015)
  - Network Rail TRUST data (incl. time, location, incident, causation reasons and delay minutes)
- **Asset** (railway tracks ———)
- **Lineside vegetation coverage (15 species)**
- **Weather** (5 × 5 km grids ▢)
  - Temperature
  - Wind speed/direction
  - Precipitation
  - Relative humidity
  - Solar radiation

Strategy (1): Fragility/weather data

Logistic regression (No. of records in the test set: 156)

Incidents captured: ~85%





Weather-related

- **Max. gust speed** (×10 mph)
- **Avg. wind direction** [90°, 180°)
- **Avg. wind direction** [180°, 270°)
- **Avg. wind direction** [270°, 360°)
- **Temperature deviation** (°C)
- **Max. relative humidity** (%)
- **Max. snowfall** (mm)
- **Max. total precipitation** (mm)

Vegetation cover fraction (×10%)

- **Alder**
- **Ash**
- **Beech**
- **Birch**
- **Conifer**
- **Elm**
- **Horse chestnut**
- **Lime**
- **Oak**
- **Poplar**
- **Shrub**
- **Sweet chestnut**
- **Sycamore**
- **Willow**
- **Others**

Fu, Q., & Easton, J. M. (2018). Prediction of weather-related incidents on the rail network: prototype data model for wind-related delays in Great Britain. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *4*(3), 04018027.

Model estimation result

Variable	Coef. est.	Std. err.	z-statistic	P>|z|	[95% conf. interval]	Odds ratio
(Intercept)	–14.7823	0.976	–15.153	0.000	[–16.694, –12.870]	
Weather-related						
Max. gust speed (×10 mph)	0.9248	0.057	16.169	0.000	[0.813, 1.037]	2.521
Avg. wind direction [90°, 180°)	–0.9495	0.289	–3.280	0.001	[–1.517, –0.382]	0.387
Avg. wind direction [180°, 270°)	–0.9476	0.223	–4.240	0.000	[–1.386, –0.510]	0.388
Avg. wind direction [270°, 360°)	–0.3964	0.245	–1.617	0.106	[–0.877, 0.084]	0.673
Temperature deviation (°C)	0.6358	0.031	20.654	0.000	[0.576, 0.696]	1.889
Max. relative humidity (%)	0.9735	0.093	10.445	0.000	[0.791, 1.156]	2.647
Max. snowfall (mm)	0.3235	0.287	1.128	0.259	[–0.239, 0.886]	1.382
Max. total precipitation (mm)	–0.0366	0.033	–1.097	0.273	[–0.102, 0.029]	0.964
Vegetation cover fraction (×10%)						
Alder	0.1813	0.857	0.212	0.832	[–1.498, 1.860]	1.199
Ash	0.1860	0.227	0.821	0.412	[–0.258, 0.630]	1.204
Beech	–1.3831	1.182	–1.170	0.242	[–3.700, 0.933]	0.251
Birch	–0.2200	0.304	–0.724	0.469	[–0.815, 0.375]	0.803
Conifer	0.1994	0.797	0.250	0.802	[–1.362, 1.761]	1.221
Elm	0.9973	0.910	1.096	0.273	[–0.786, 2.780]	2.711
Horse chestnut	–1.6999	2.333	–0.729	0.466	[–6.272, 2.873]	0.183
Lime	–0.7794	1.189	–0.656	0.512	[–3.109, 1.550]	0.459
Oak	0.0329	0.233	0.141	0.888	[–0.424, 0.490]	1.033
Poplar	–0.5946	0.563	–1.056	0.291	[–1.699, 0.509]	0.552
Shrub	–0.0462	0.119	–0.39	0.697	[–0.279, 0.186]	0.955
Sweet chestnut	0.8613	0.949	0.908	0.364	[–0.998, 2.721]	2.366
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Strategy (2): Rail network simulation

Simulation of rerouting and unmet demand

- Input:
  - R, residual network, (copy of the partially functioning network), with edge attributes:
    - re-assigned flow, $f^r_{u,v} = 0$
    - capacity, c_{uv} = 50% of the steady state traffic
  - $\boldsymbol{D}^{re} = \{D^{re}_{od}, \dots\}$, set of OD trips that need to be distributed in R,
- initiate: i=0,
- repeat
  - For all OD pair that $D^{re}_{od} > 0$:
    - if there is no path in R from o to d with capacity:
      - $T'^{re}_{od} = 0$
    - if there is a path, $P^r_{od} = \{e_{ou}, e_{uv}, \dots, e_{wd}\}$, from o to d with capacity that is both the shortest and the geographical length of which is within twice the original path,
      - $T'^{re}_{od} = \min(c_{ou}, c_{uv}, \dots, c_{wd})$, where c_{uv} is the available capacity of edge e_{uv}
      - For all edges in P^r_{od}: $f^r_{u,v} += T'^{r}_{od}$
  - For all edges in R:
    - if $f^r_{u,v} > c_{uv}$,
      - reduction factor $\varphi_{uv} = c_{uv}/f^r_{u,v}$
      - $c_{uv} = 0$
    - if $f^r_{u,v} \leq c_{uv}$,
      - reduction factor $\varphi_{uv} = 1$
      - $c_{uv} -= f^r_{u,v}$
  - For all OD pairs,
    - $\varphi_{od} = \min(\varphi_{ou}, \varphi_{uv}, \dots, \varphi_{wd})$
    - $T^{re}_{od} += T'^{r}_{od} * \varphi_{od}$,
    - $D^{re}_{od} -= T'^{r}_{od} * \varphi_{od}$
  - remove edges that $c_{uv} = 0$ from R
  - i+=1
- until i=multi-search cut-off
- Return $\boldsymbol{T}^{re}$, trips get delivered via rerouting

Rerouting: Edmonds-Karp algorithm

Demand and Supply:
Averaged Data from Network Rail

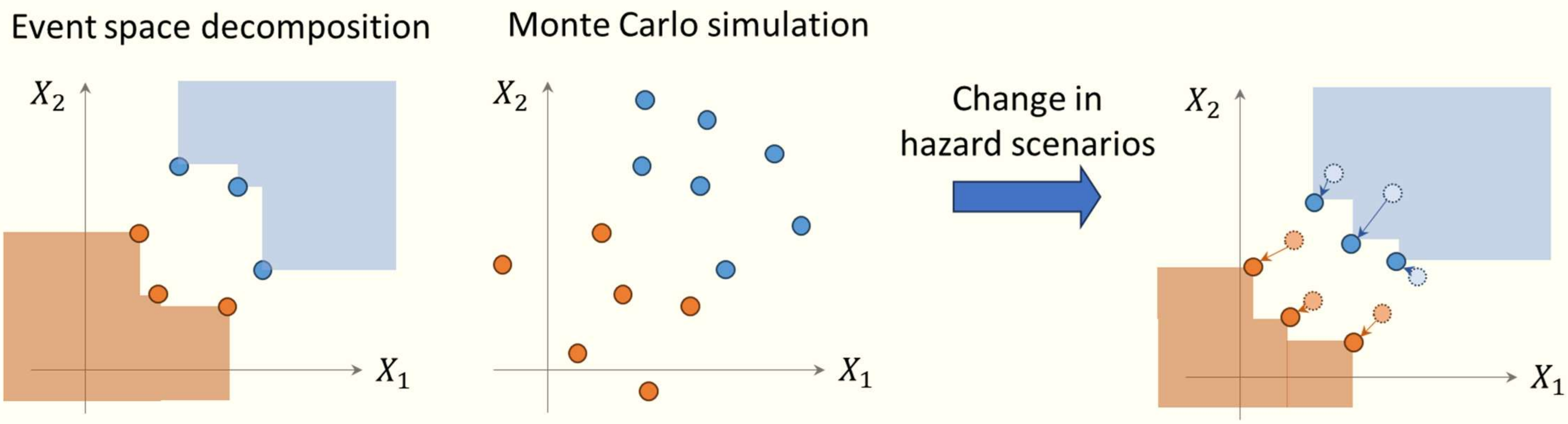
Residual demand =
Total original demand -
demand using damaged/removed edges +
demand rerouted to not use damaged edges

Li, Q., Punzo, G., Robson, C., Arbabi, H., & Mayfield, M. (2022). A Novel Approach to Climate Resilience of Infrastructure Networks. *arXiv preprint arXiv:2211.10132*.

Strategy (3): System reliability methods

Event decomposition algorithm for coherent systems

- Better component states do not worsen a system state.
- Less time and memory than brute-force MCS or AI methods.



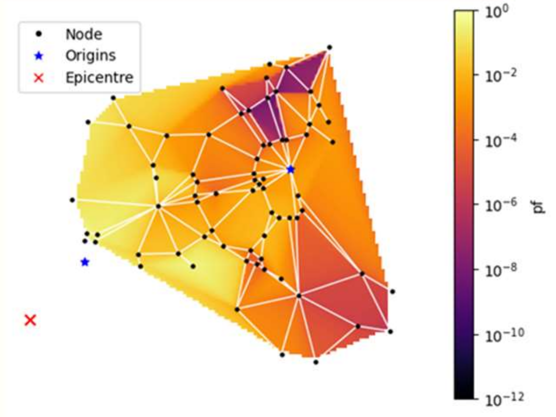
Illustrative event spaces

Strategy (3): System reliability methods

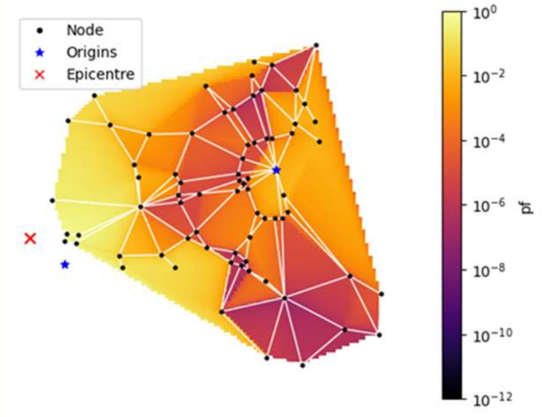
MBNpy toolkit

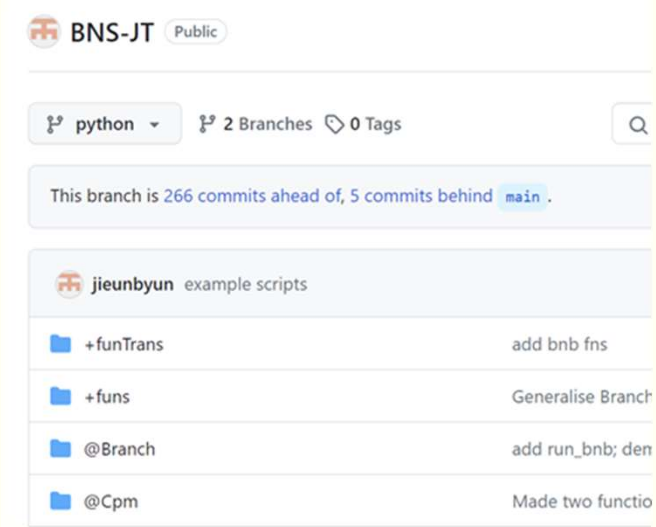
- A general, open-source tool for system reliability methods
- Example: Highway network & seismic risks

A-priori decomp. 24 hours



Real-time updating: 10 mins





Outputs on DAFNI platform

National infrastructure database (NID)

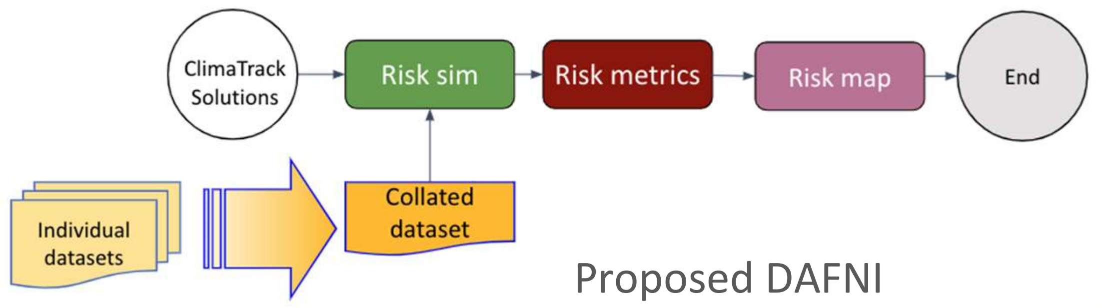
Focus on **strong wind** and **heatwaves**

D1- Aggregated datasets of **weather-related disruptions**

D2 - A weather-related **risk map** of the railway network in the Anglia region

National infrastructure modelling service (NIMS)

D3 - A risk mapping **software** (in Python)



Proposed DAFNI workflow

Impact

Risk-informed forecasting of weather-related disruptions

Exploitation of regional data and network topology

Collaborative, continuous model calibration via DAFNI platform towards ever more reliable railway service.

Capitalising on the project findings for a full-nation scale project in partnership with Network Rail

Conclusion

Problem: Increasing weather-related disruptions on railway services

Objective: Risk assessment tools and data compilation on railway network, with a particular focus on system-level performance

Strategy: Probabilistic models of weather + Fragility models of railway assets
+ Simulation of railway operation + System reliability engineering tool
= Ready-use risk assessment tool of a railway network

Significance:
[Public] Resilient operation on railway network
[R&I community] A collaborative risk assessment tool applicable for general railway networks