Developing Decision support systems for Traffic Control

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ProRail

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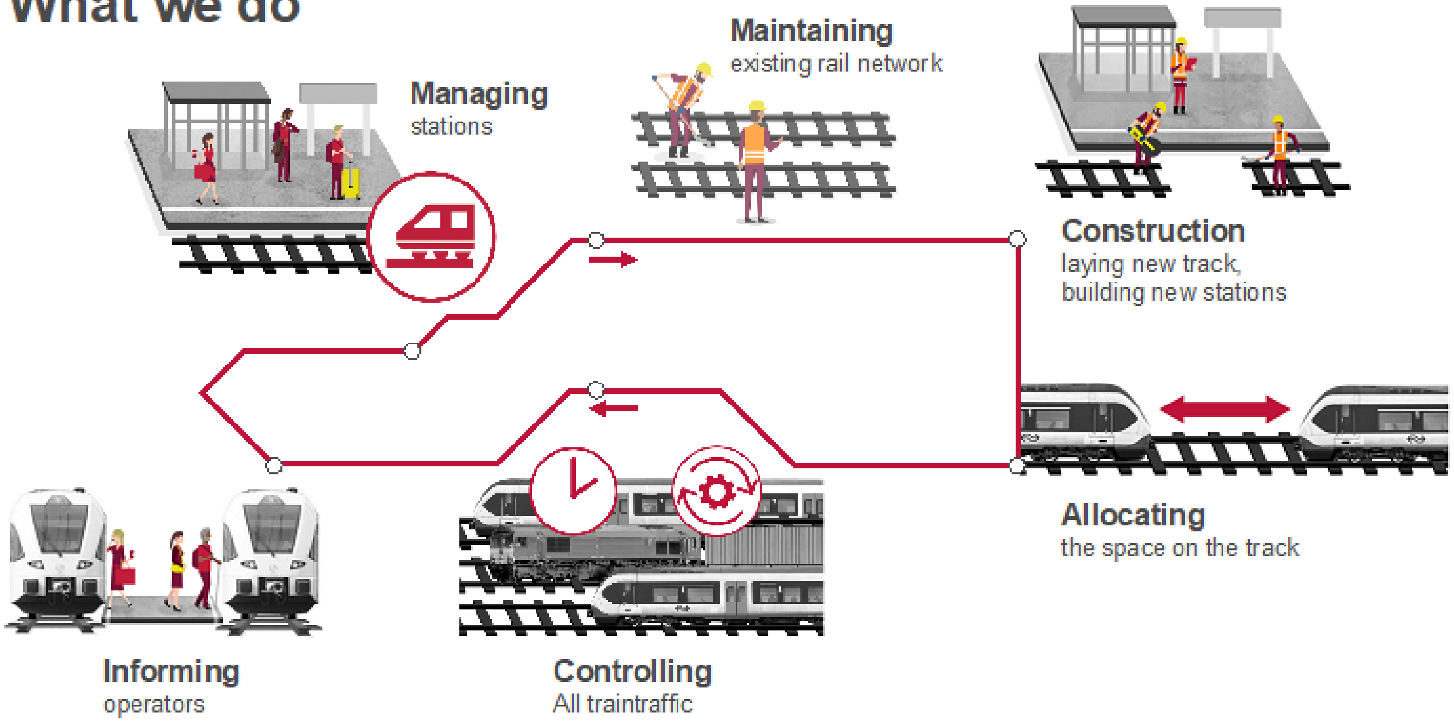
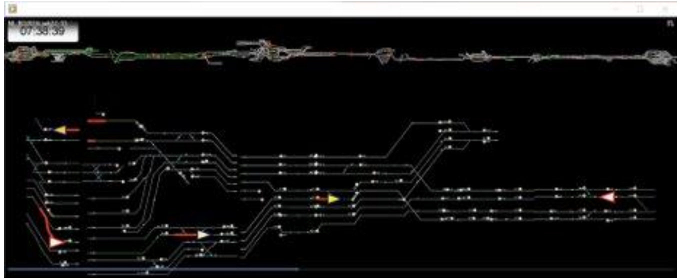
My aim for today is giving a brief overview of some decision support implementations, the challenges faced and our future plans.

ProRail

What we do



Multi-Agent Simulation
Background

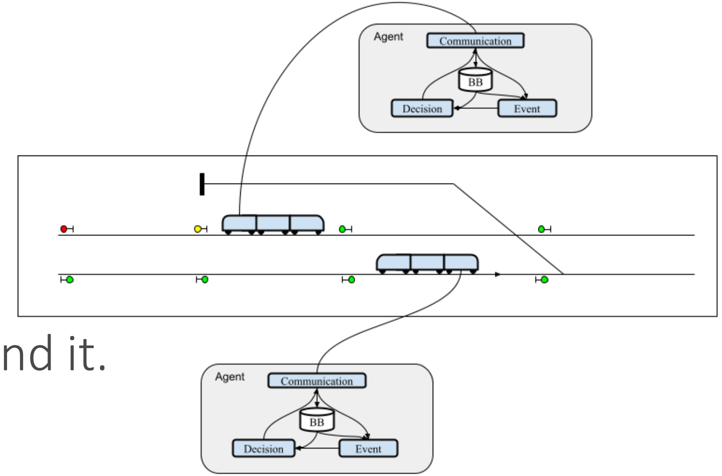


- **Simulation**: Microscopic simulation is used within ProRail to gain insight into the impact of infrastructure and timetable changes. Optionally done with Human in the loop simulation.
- **Innovation goal**: Improve the accuracy of this simulator. With a more accurate way to simulate the future, we can have better insights into the robustness & weak spots of the future timetable, which can be used as input for, amongst others, traffic control.

Multi-Agent Simulation
Background

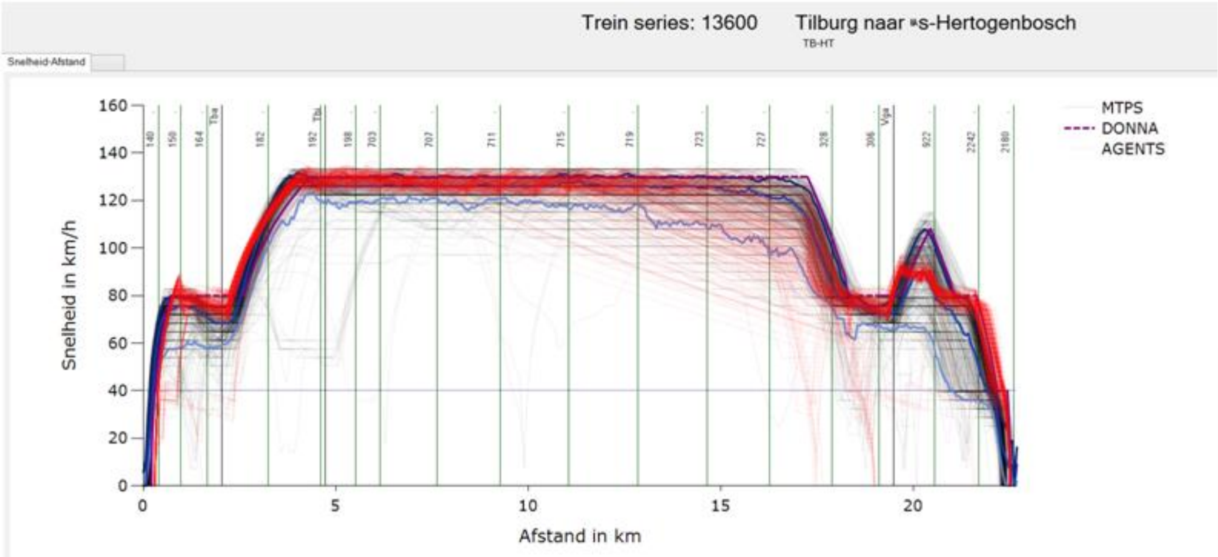
- **How**: Add realistic train driver behaviour to simulation software via Machine Learning and a Multi-Agent System.

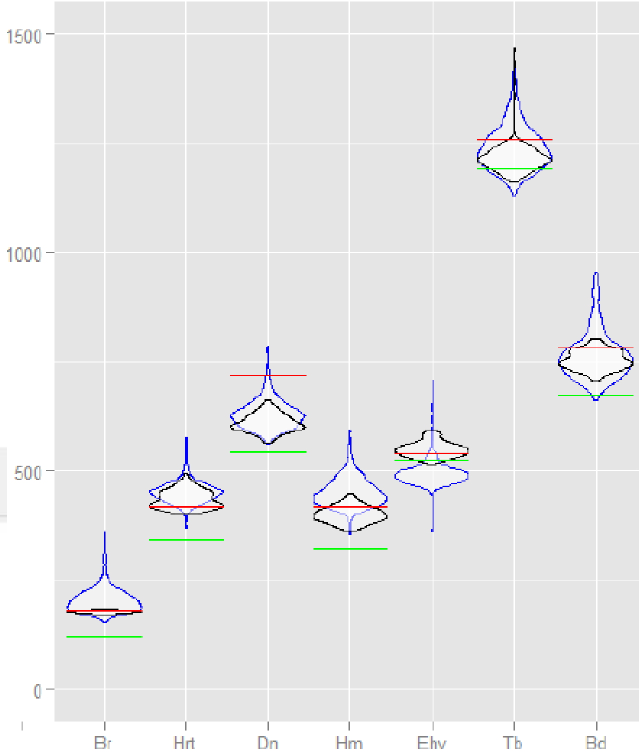
- **Idea:** Each train driver is simulated by its own agent. Making autonomous decisions based on what it believes to be the reality around it.



Multi-Agent Simulation
Background

- **Results**: A better fit for approaching driving time distributions.





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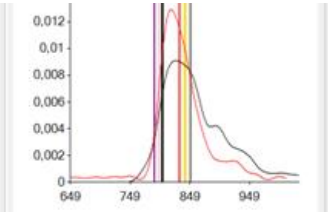
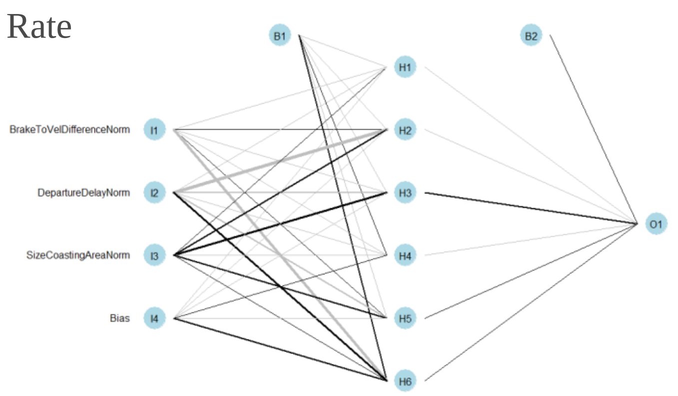
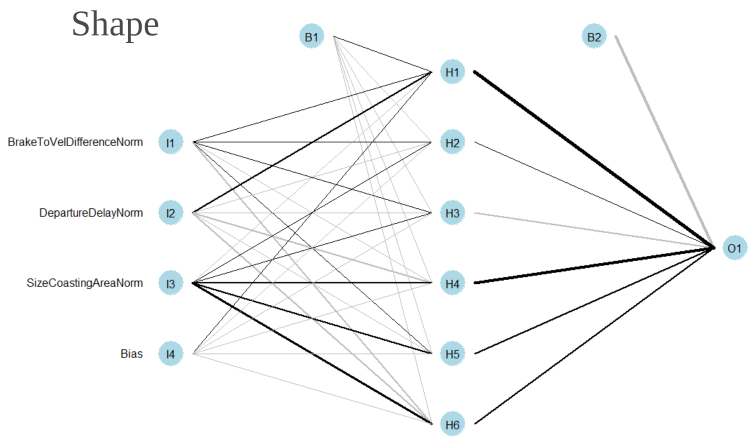


Multi-Agent Simulation
Challenges

- Goal is not to make them drive optimally, but realistically
  - Approach: Use Machine Learning methods such that they express a range of behaviours





Multi-Agent Simulation
Challenges

- Machine Learning has difficulties dealing with edge cases, combined with no room for true errors.
  - Approach: Combine Machine Learning methods with statistical fitting and rule based reasoning.
    - Rule based: Which action to take
    - When & how: Machine learning + statistical fits and hard limits.

Multi-Agent Simulation
Challenges

- Driver model needs to be updated every time there is a significant change to outside operations.
  - Solution approach: Verify & validate the model over time and only make changes when needed.

Predicting train delays
Background

- **Predicting delays, current approach:**
  - Travel information:

$$Delay_{20minLater} = Delay_{Now} - StoppingBuffer\ - 1$$

  - Traffic control:

$$Delay_{20minLater} = Delay_{Now}$$

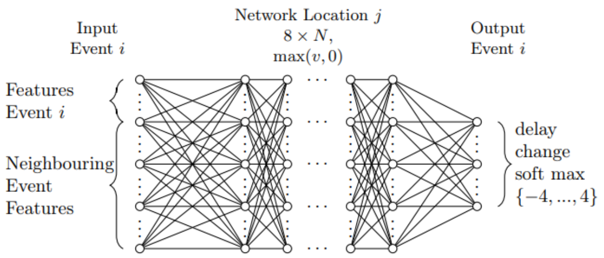
- **Innovation goal**: Give decision makers a windows into the future of 20+ minutes, so that they can pre-emptively act to minimize the impact of delays, conflicts, etc.

Predicting train delays

Background

- **Approach**:

1. Two internships:
   - Both resulting in a better accuracy
2. RAS competition predicting:
   - Delay Jumps >4min
   - Delay direction changes
   - Precise delay

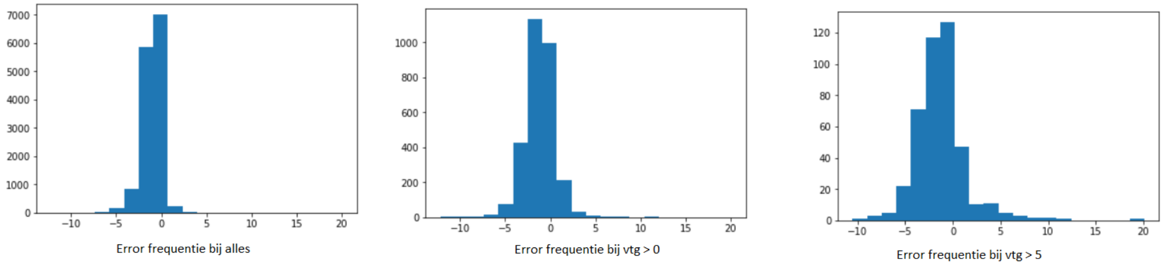


Haahr, Jørgen Thorlund, Erik Orm Hellsten, and Evelien van der Hurk. "Train delay prediction in the netherlands through neural networks." (2019).

3. Prototype

Predicting train delays
Challenges

- Machine Learning challenges:
  - Heavily unbalanced dataset
  - ‘Natural’ delay decay predictions are good, but not the interesting part
  - Predicting delay jumps is difficult



Predicting train delays
Challenges

- Even if the Machine Learning model performs ‘better’, it was not deemed an improvement.

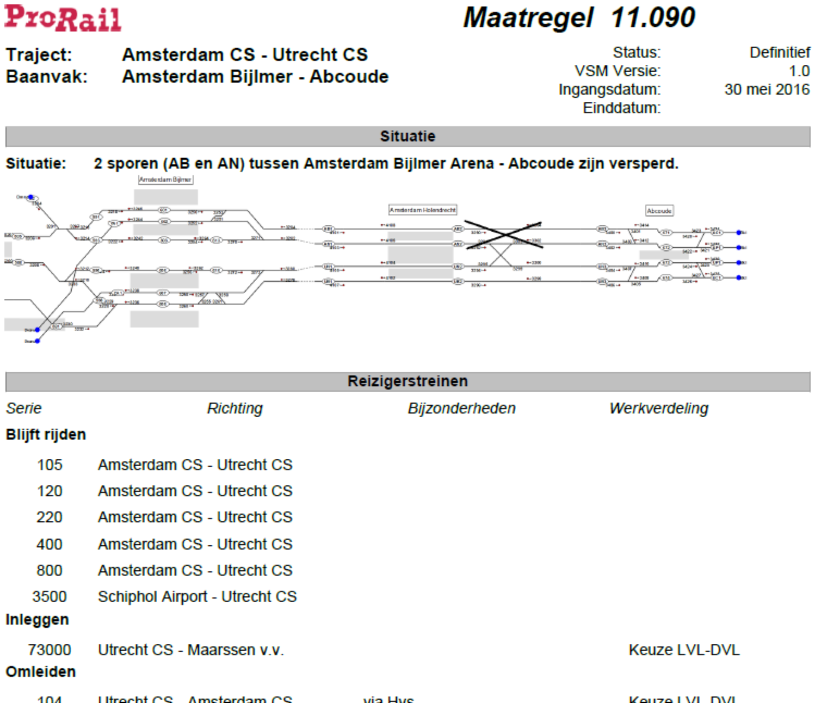
- Error type matters a lot to decision makers
  - The current approaches never give a False Positive.
  - The higher the delay jump, the more important it is, but the higher the error rate is as well.

- Taking into account train-train interactions

Generating contingency plans
Background

- **Contingency plans:**
  - >3500 pre-designed plans to deal with disruptions
  - Manually designed

- **Innovation goal:**
  - Implement a decision support system to speed up this design process



ProRail — **Maatregel 11.090**

Traject: Amsterdam CS - Utrecht CS
Baanvak: Amsterdam Bijlmer - Abcoude

Status: Definitief
VSM Versie: 1.0
Ingangsdatum: 30 mei 2016
Einddatum:

Situatie

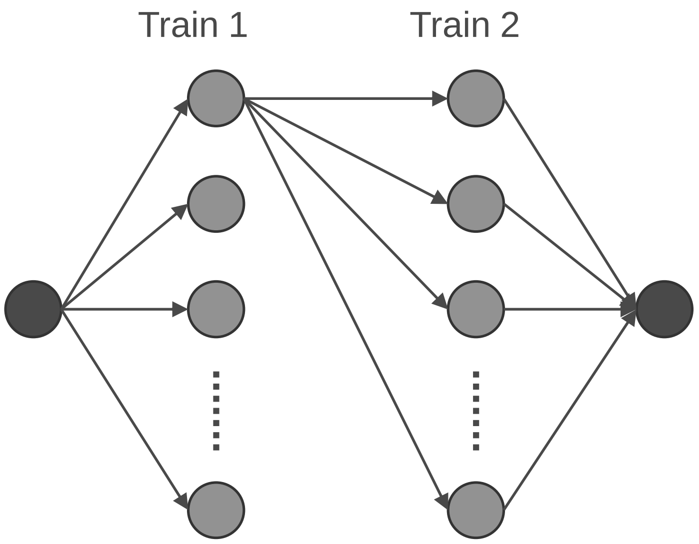
Situatie: 2 sporen (AB en AN) tussen Amsterdam Bijlmer Arena - Abcoude zijn versperd.

Reizigerstreinen

Serie	Richting	Bijzonderheden	Werkverdeling
Blijft rijden			
105	Amsterdam CS - Utrecht CS		
120	Amsterdam CS - Utrecht CS		
220	Amsterdam CS - Utrecht CS		
400	Amsterdam CS - Utrecht CS		
800	Amsterdam CS - Utrecht CS		
3500	Schiphol Airport - Utrecht CS		
Inleggen			
73000	Utrecht CS - Maarssen v.v.		Keuze LVL-DVL
Omleiden			
104	Utrecht CS - Amsterdam CS	via Hvs	Keuze LVL-DVL

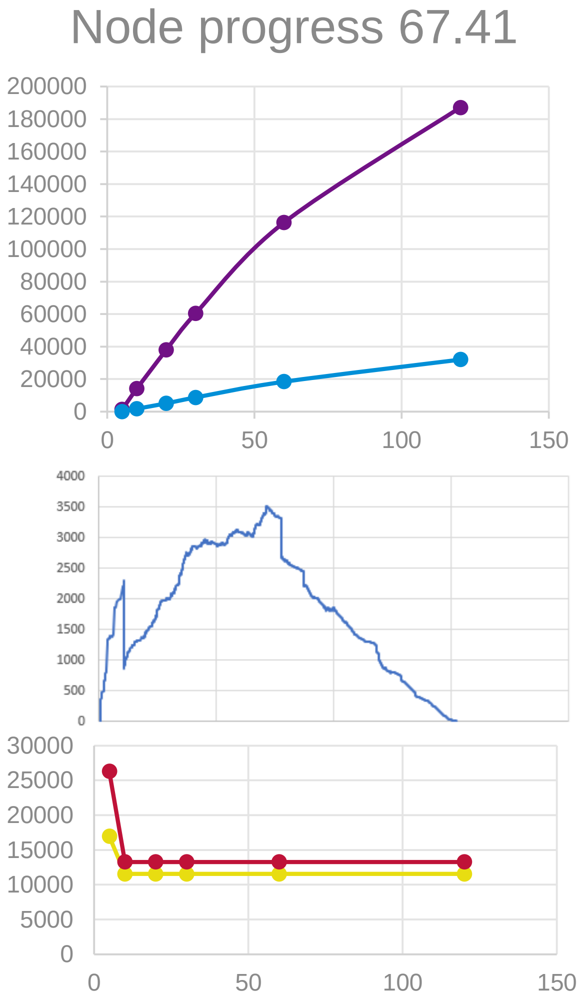
Generating contingency plans
Background

- Approach:
  - Model it as a search tree
  - Search via a form of Branch and Bound
  - Steps:
    1. Pick a disrupted train to adjust
    2. Determine ‘all’ relevant possible plan adjustments
    3. Check for new conflicts for each possible plan adjustment
    4. Pick ‘best’ option, and go back to step 1



Generating contingency plans
Challenges

- Optimization challenges:
  - Problem size & business rules
  - Not spending too much time on non-relevant / equivalent solutions
  - Getting the heuristic to always ‘quickly’ find a first solution



Generating contingency plans
Challenges

- Implementation Process challenges:
  - Domain size
  - IT department unfamiliar working with innovative techniques
  - Giving guarantees up-front is difficult

Surprisingly the users are not the challenge here

Future of Traffic Control
General

- More flexible control area sizes – adjustable as needed
- Adjusting roles into a safety controller and traffic controller
- IT that supports this change in communication and information needs
- More automation and decision support for routine tasks

Questions?