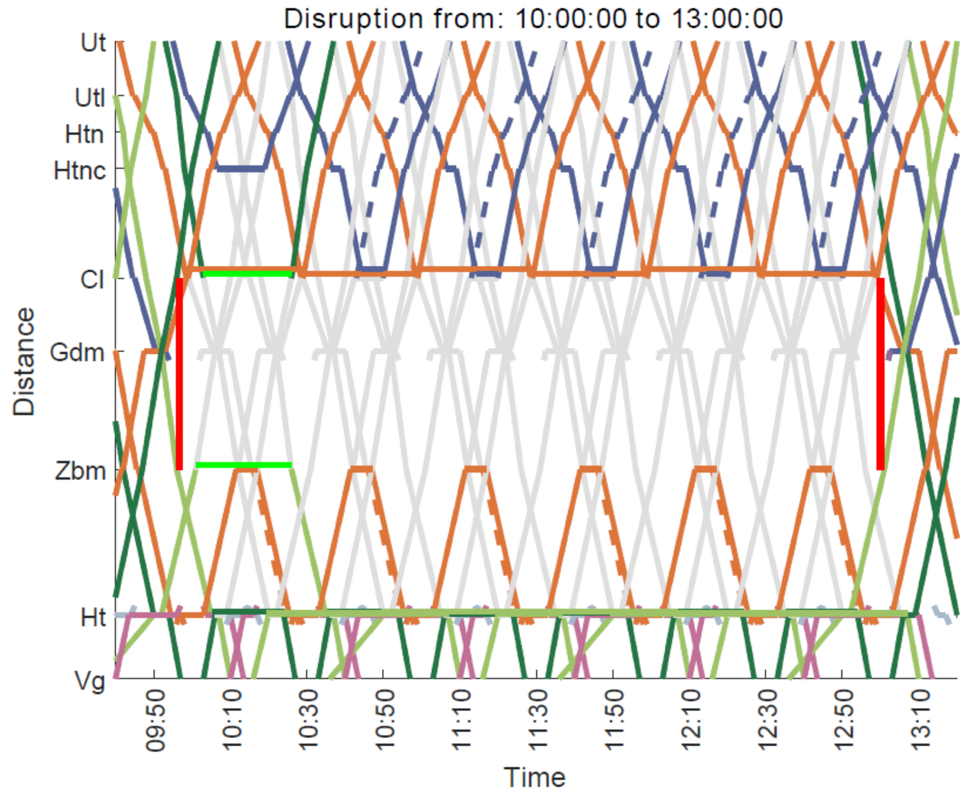
Smart disruption management

Outline

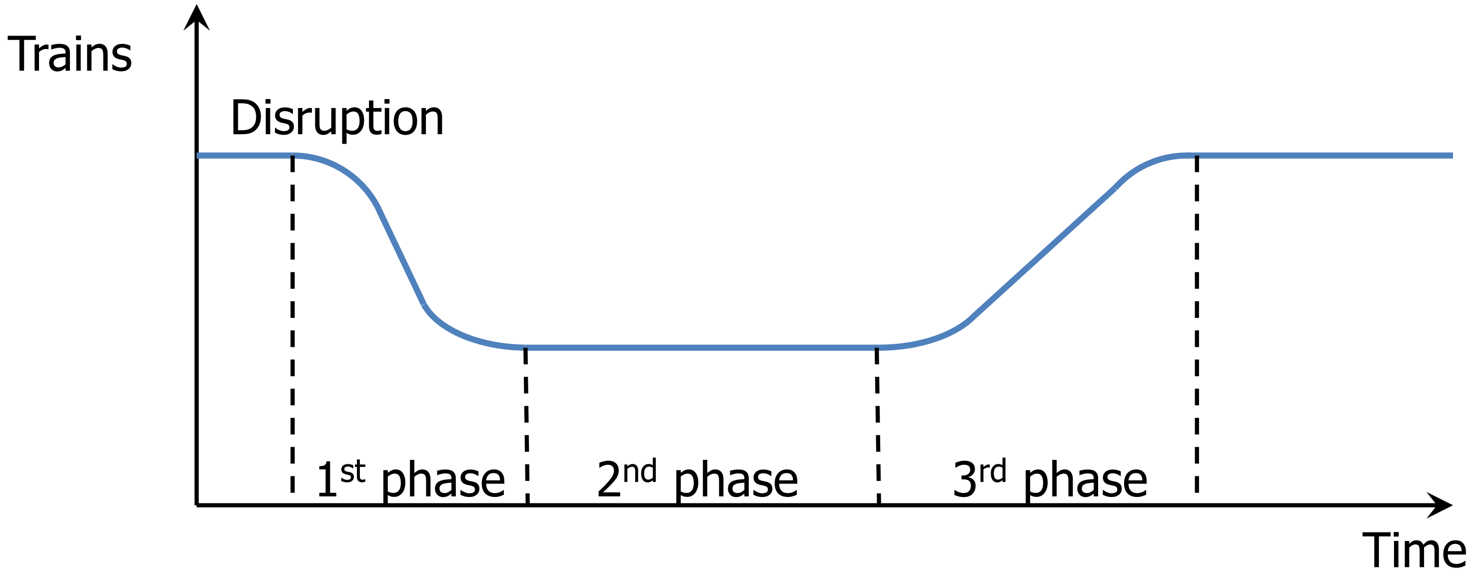
- Introduction
- Smart Disruption Information
- Smart Decision Support
- Example disruption estimate
- Conclusions



I.A. Hansen, Delft University of Technology

Disruption management process

Bathtub model



Disruption management: Situational Awareness, Decision, Execution

- 1st phase: Fast response, rapid new feasible plan, smooth transition
- 2nd phase: Operations according to new plan, prediction disruption end
- 3rd phase: Fast transition to normal situation

Smart disruption management

Introduction

✓ Integration

Smart Disruption Information	Smart Decision Support
❑ Availability disruption data	✓ Analysis disruption phases
❑ Analysis disruption types	✓ Analysis disruption measures
❑ Modelling disruption length	✓ Computation disruption timetable
❑ Prediction disruption length	✓ Computation transitions
Focus	**Focus**
• Track Circuit failures	• Full blockages
• Switch failures	• Infrastructure allocation

Smart Disruption Information

Approach

Copula: multivariate probability distribution for which the marginal probability distribution of each variable is uniform

- Nonparametric (Copula) Bayesian Network
  - Per disruption type
  - Determining influence factors (with available data)
  - Modelling dependencies
- Applied to track circuits and switches
- SAP data + additional data (weather data, geographical data)

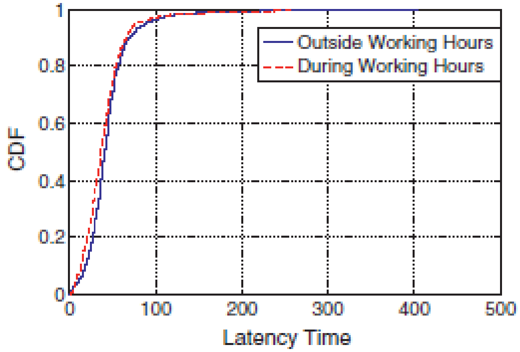
- Example data track circuits
  - Training data: 1920 failures (2½ year; 01-2011/06-2013)
  - Test data: 339 failures (½ year; 05-2014/10-2014)
- Time components disruption length
  - Latency time (time from start disruption to contractor at scene)
  - Repair time (contractor at scene to failure repaired)

Smart Disruption Information

Factors affecting the latency time

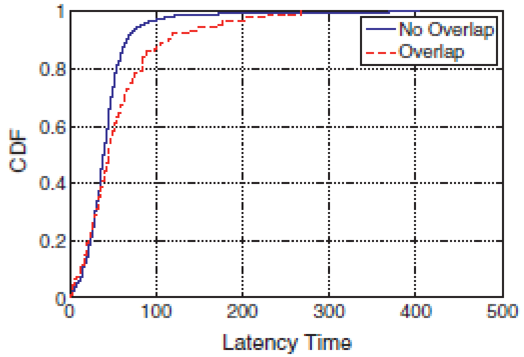
- Location

Fig. 4. The map of TC disruptions with latency time longer than 90 min.



The empirical distribution of latency time during and outside working hours.

- Weather and overlapping disruptions

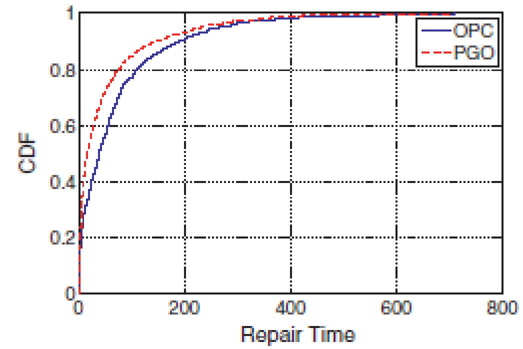


The empirical distribution of latency time with respect to the presence of an overlapping incident.

Smart Disruption Information

Factors affecting the time to repair

- Type of maintenance contract
  - ❖ Usual contract (OPC)
  - ❖ Performance governed (PGO)
  - ❖ (inhouse service)

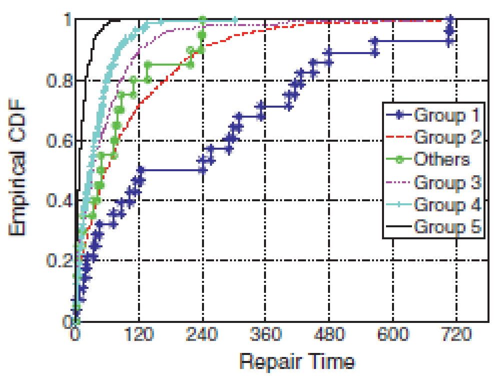


The empirical distribution of repair time between TC with OPC and PGO contracts.

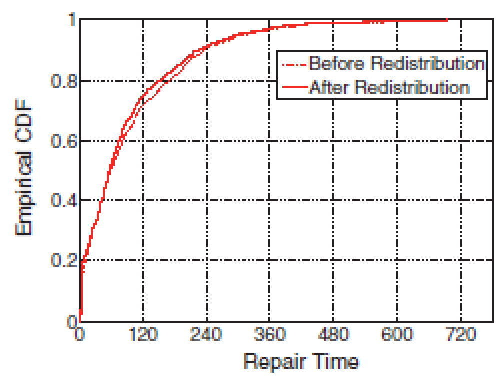
- Cause

1. Group 1: impedance bond failure.
2. Group 2: the relay cabinet failure, cable problem, track-side electrical junction box problem, and arrestor problem.
3. Group 3: external reasons.
4. Group 4: splinter/grinding chips and insulator problem.
5. Group 5: coins.
6. Others.

Source: Zilko, Kurowicka & Goverde, 2016



(a) The empirical repair time distribution of all six groups before redistribution



(b) The empirical repair time distribution of Group 2 before and after redistribution

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Copula Bayesian Network

Track circuit Bayesian Network

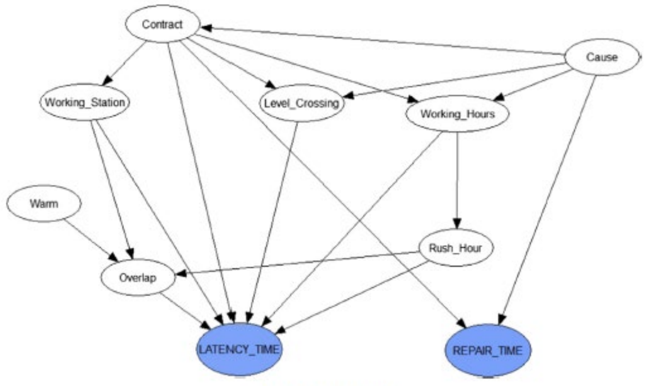


Fig. 9. The track circuit BN.

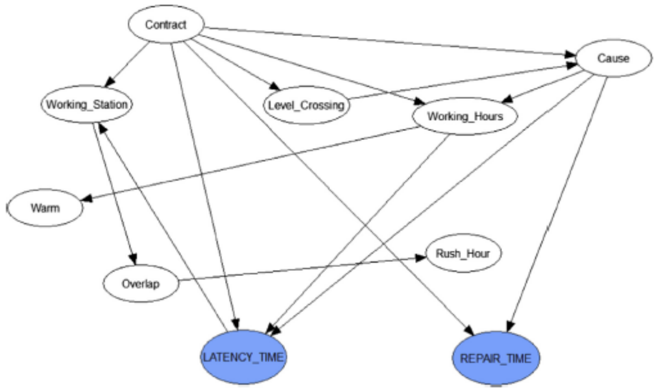
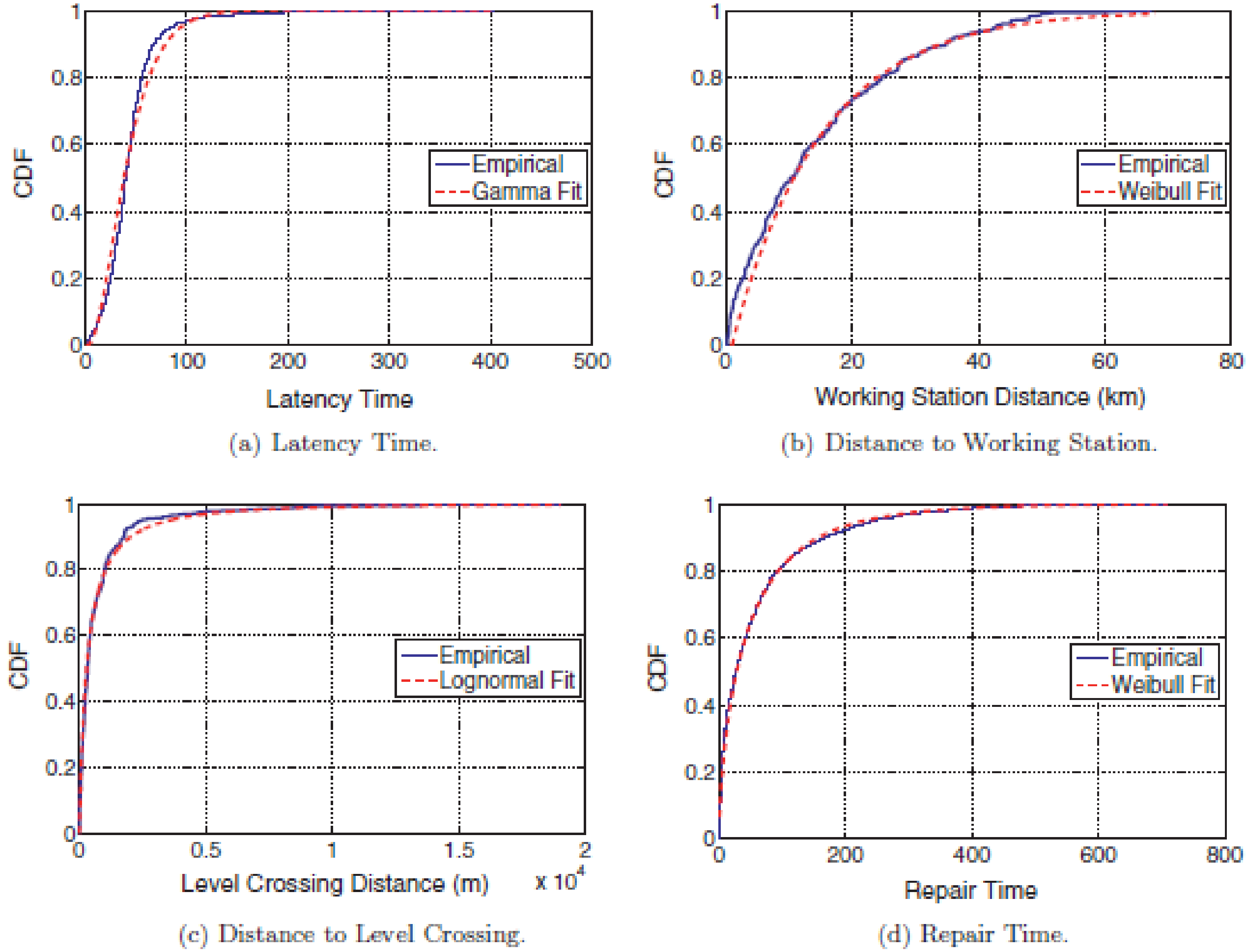


Fig. 11. The learned track circuit BN structure from data.

Fig. 10. The location of the observed TC disruptions caused by coins.

Fitting parametric distributions to the continuous variables



(a) Latency Time.

(b) Distance to Working Station.

(c) Distance to Level Crossing.

(d) Repair Time.

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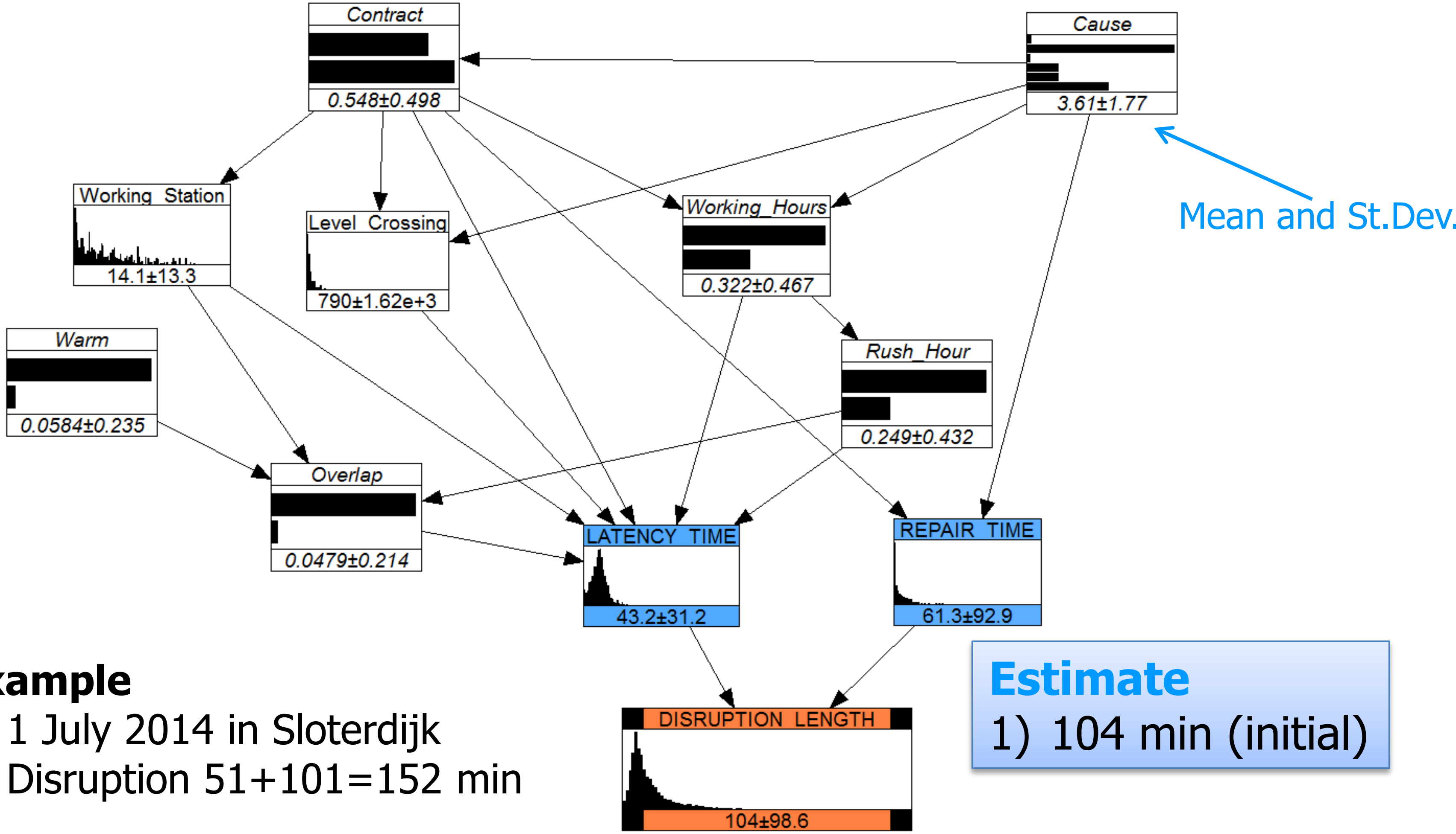
Model use and validation

Bayesian Netwerk



Example

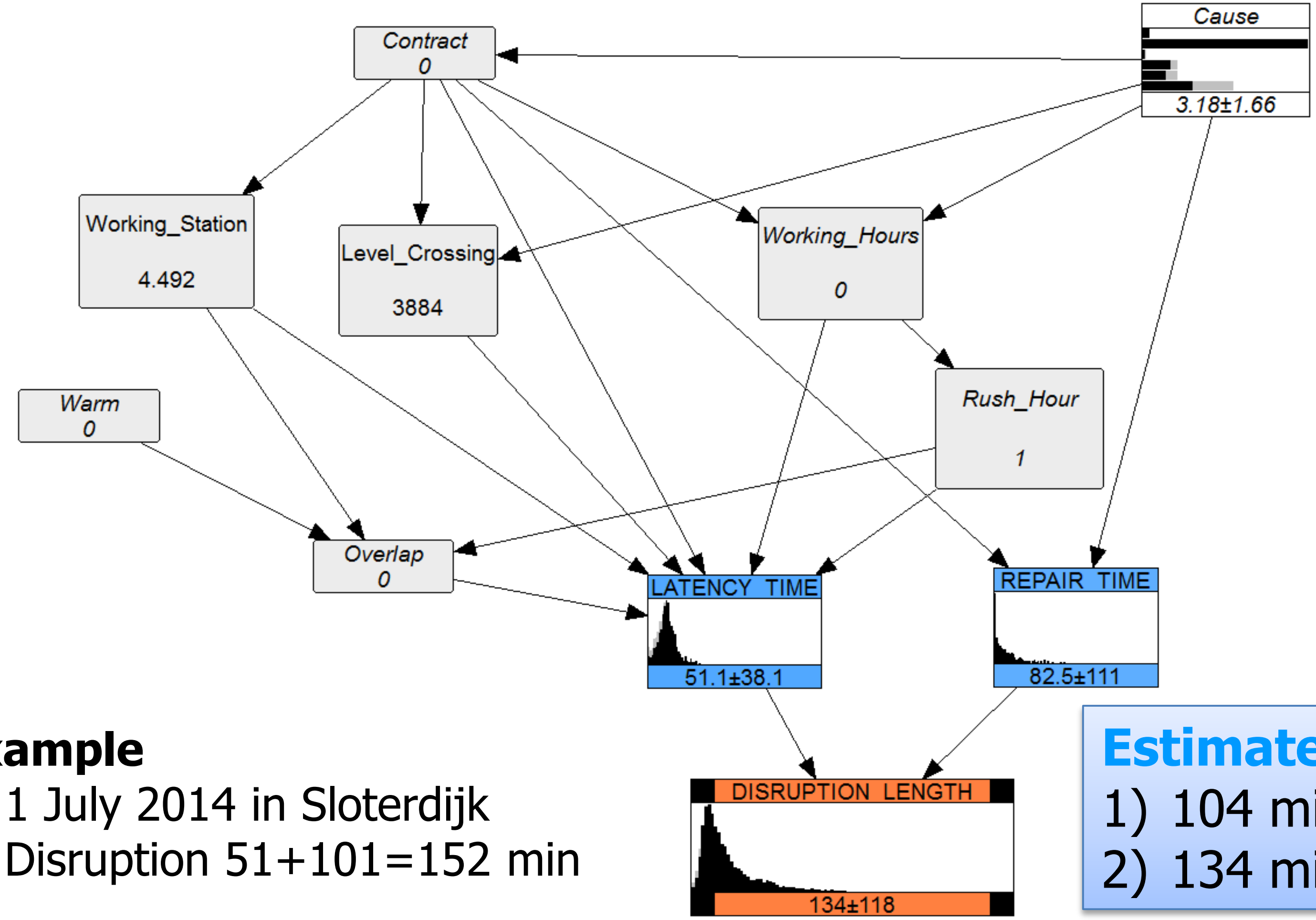
- 1 July 2014 in Sloterdijk
- Disruption 51+101=152 min

Estimate

1) 104 min (initial)

Model use and validation

Bayesian Netwerk: conditionalized (basic info)



Example

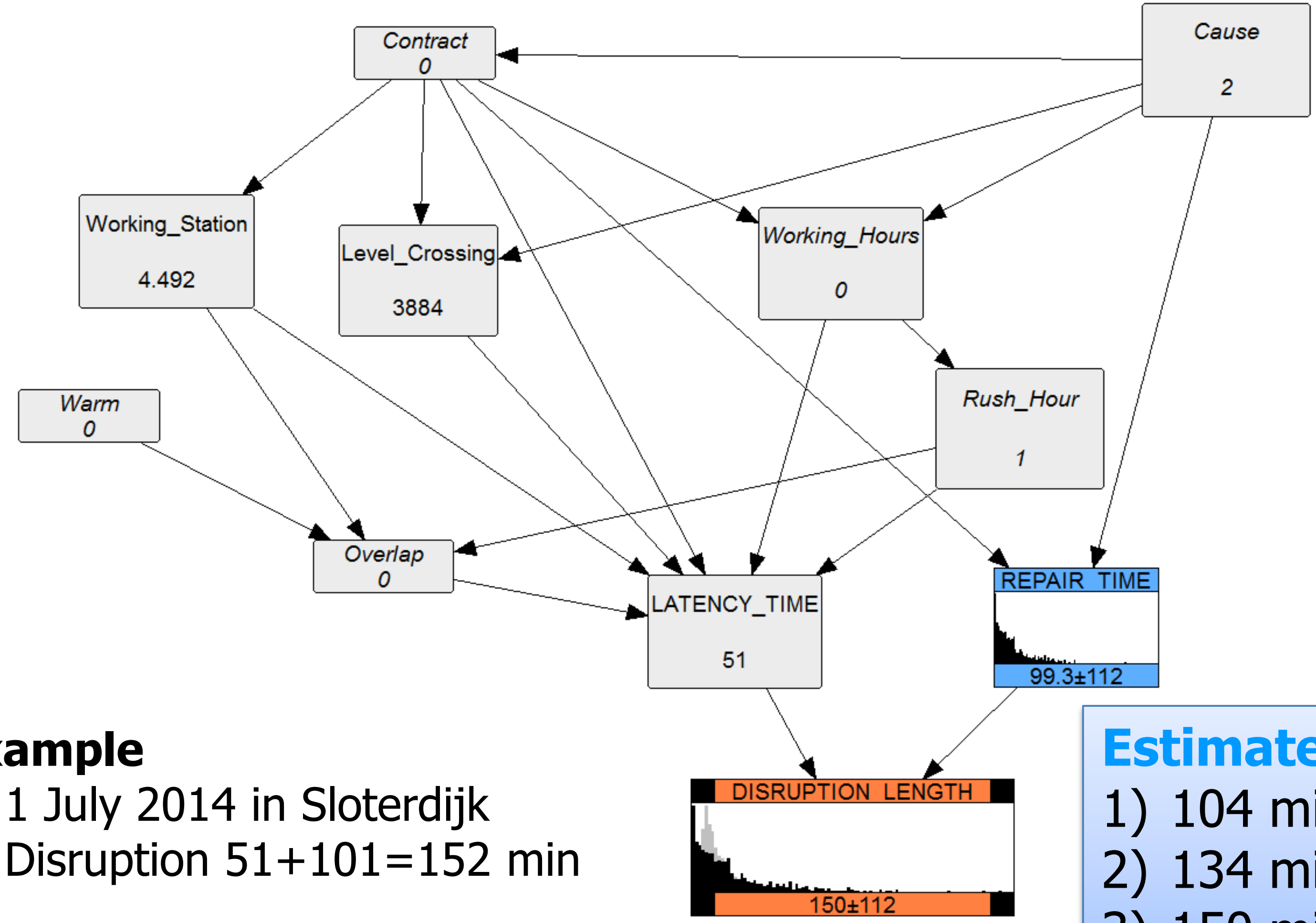
- 1 July 2014 in Sloterdijk
- Disruption 51+101=152 min

Estimate

1) 104 min (initial)
2) 134 min (basic info)

Smart Disruption Information

Bayesian Netwerk: conditionalized (after diagnosis)



Example

- 1 July 2014 in Sloterdijk
- Disruption 51+101=152 min

Estimate

1) 104 min (initial)
2) 134 min (basic info)
3) 150 min (diagnosis)

Smart Decision Support

Approach

- Computation of feasible disruption timetable with optimal short-turning stations for all relevant trains for full blockages

- Conceptual framework
  - Isolate disruption area with minimal impact to adjacent areas
  - Schedule short-turned trains to opposite train paths
  - Prevent shunting and big delays by short-turning on earlier station
  - Integrate transitions in computation of disruption timetable for 2nd phase

- Multi-station multi-phase short-turning model
  - Assuming scheduled train paths at start disruption

See for more details:
Zilko, AA, Kurowicka, D, Goverde, RMP (2016) , Modeling railway disruption lengths with Copula Bayesian Networks, Transportation Research Part C 68:350–368

Conclusions

Smart Disruption Length

- General results
  - Disruption data lack detail (failing element, repair details)
  - Relatively small effect of each variable
  - Strong effect of joint variables
  - Still big uncertainty (range) by rough data
  - The more information about a disruption, the better the prediction
- Recommendations
  - Improve registration (by contractors) of details about failure and repair for better understanding and prediction of disruption length
- Future research
  - Point estimate from (wide) disruption length distribution & updates
  - Impact optimistic and pessimistic estimates on operations and travellers
  - Application to other disruptions (signals, rolling stock, etc.) with experts

Conclusions

Smart Decision Support

- General results
  - Rapid decision after disruption occurrence decreases transitions
  - Process times change with route, platform track, and short-turning
  - Microscopic model computes adapted running and dwell/short-turn times
  - Conflict-free disrupted timetable improves performance and information
  - Short-turning stations are optimized per train line
- Recommendations
  - Make available validated standardized data (infrastructure, routes, signalling logic, timetable) for quick configuration of models
- Future research
  - Partial obstructions of corridors and stations
  - Impact on travellers and evaluation of priorities (weight factors)
  - Automated decision support of disruption measures
  - Dynamic (real-time) computation of disruption measures