

Real-time prediction of employee workload in digital railway control rooms

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The control room of the future: AI-empowered dashboards



- 1. Setting the stage
- 2. Research on workload
- 3. Implementation
- 4. Lessons learned
- 5. Future implications



1.Setting the stage

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Current trends

- Increasing heterogeneity, complexity and interconnectedness of many business processes (Vasconcelos & Ramirez, 2011)
- Digitization of business processes (Davenport & Ronanki, 2018)
- The adoption of machine/deep learning in industry is still in its infancy (Kraus et al., 2020)
- \rightarrow A need for data-driven decision support for management

Initiative

• European Commission: Industry 5.0



Control rooms

- The nerve center for real-time monitoring and intervention
- Manage and coordinate many environments: rail and air traffic, nuclear power plants, chemical production sites, ambulance, etc.

Characteristics

- 1. Real-time decision making
- 2. Highly variable workload
- 3. Safety-critical environment



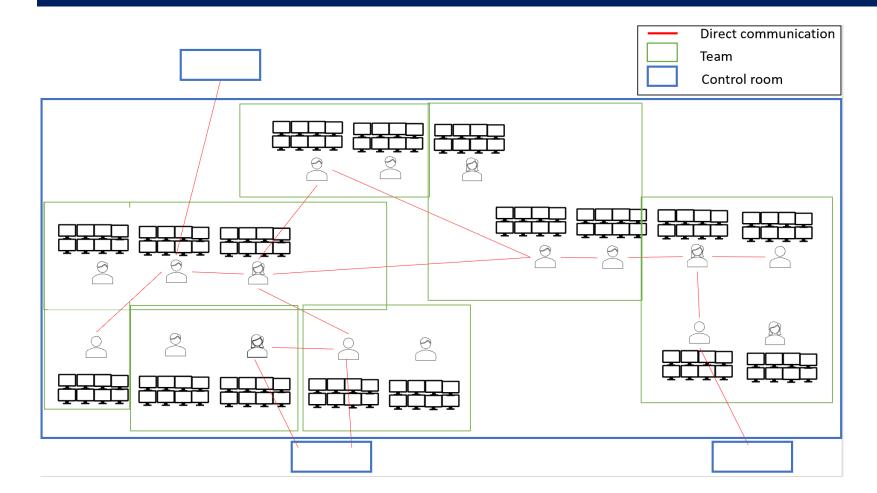




All Belgian railway traffic is managed in real-time by the control rooms of Infrabel

- Dense railway network
- Huge amount of events
 - Trains passing signals (50 million/year)
- All actions taken by operators in control rooms (150 million/year)

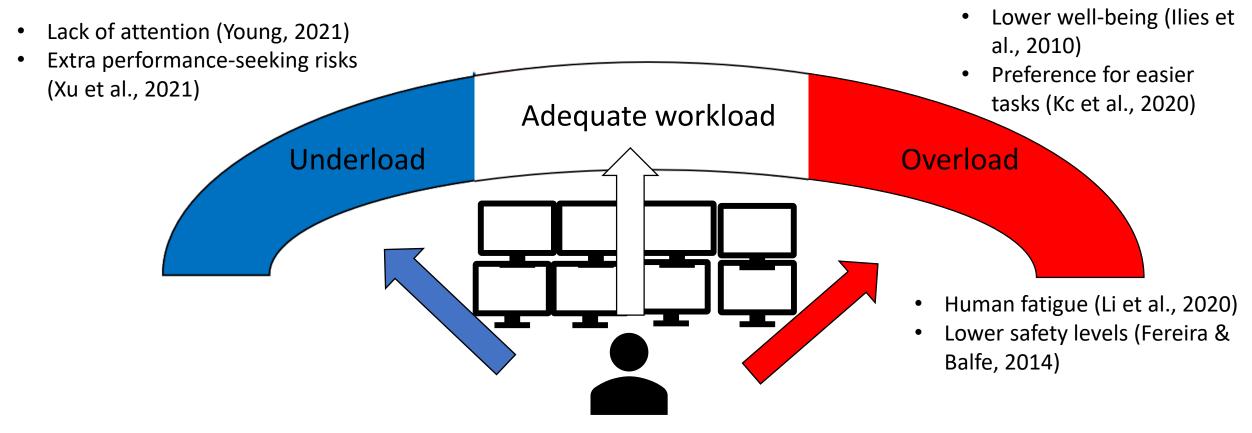




2. Control room operator workload







The importance of balanced workload within and between operators (Inegbedion et al., 2020)



- Insights from a granular data structure containing all anonymized operator events
- 2. Empirical usefulness of the proposed model and insights into the importance of the different organizational & operational characteristics
- 3. Development of an application to provide decision-support for the control room manager

Input: operational and organizational characteristics

- Operational features
 - Experience
 - Railway operations
 - Time
 - Current workload



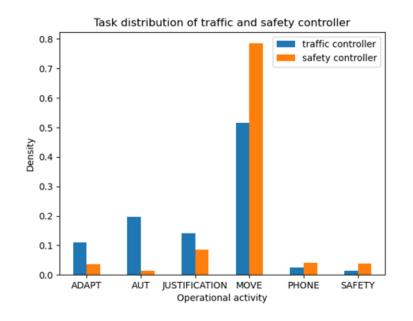
- Organizational features
 - Control room characteristics
 - Partner interactions



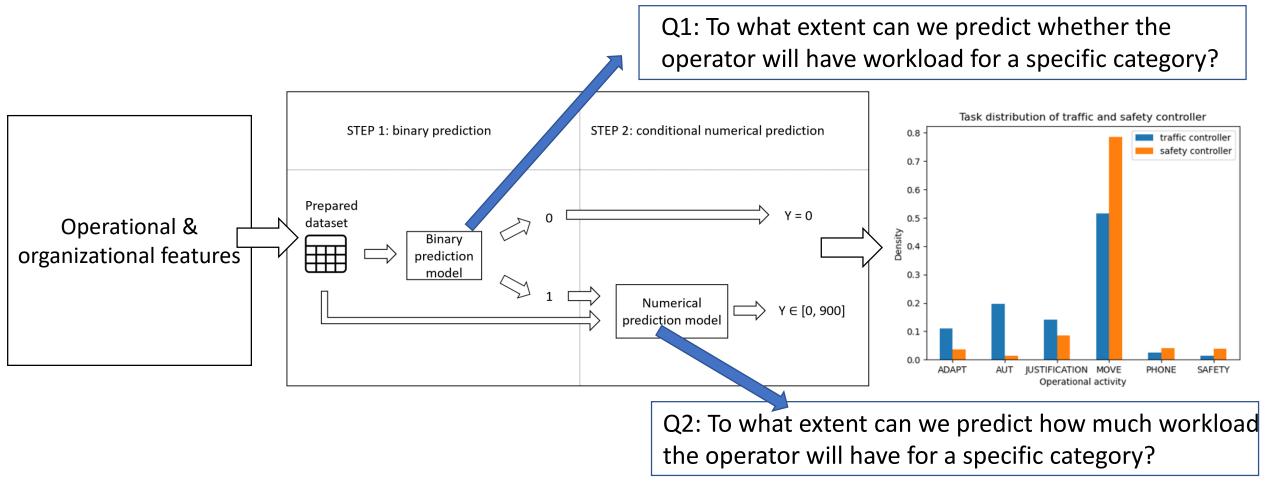
Output: Operational workload categories

 In line with the multi-attribute task battery for human operator workload (Comstock & Arnegard, 1992) = communication, resource management, automation, scheduling, monitoring and tracking

category	content
MOVE	proactively monitoring of railway traffic
ADAPT	changing tracks and station platforms
AUT	changing the automation
SAFETY	safety interventions
PHONE	phone calls between operator and driver
JUSTIF	justification of train delays



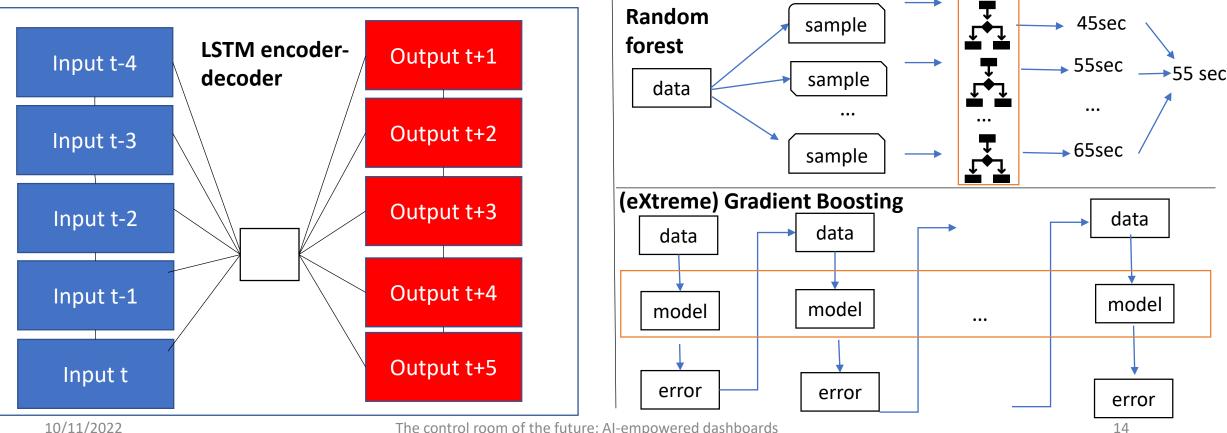
Model: linking characteristics with workload categories



Model: linking characteristics with workload categories On Track Lab

Q1: To what extent can we predict whether the operator will have workload for a specific category?

Q2: To what extent can we predict how much workload the operator will have for a specific category?



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The control room of the future: AI-empowered dashboards



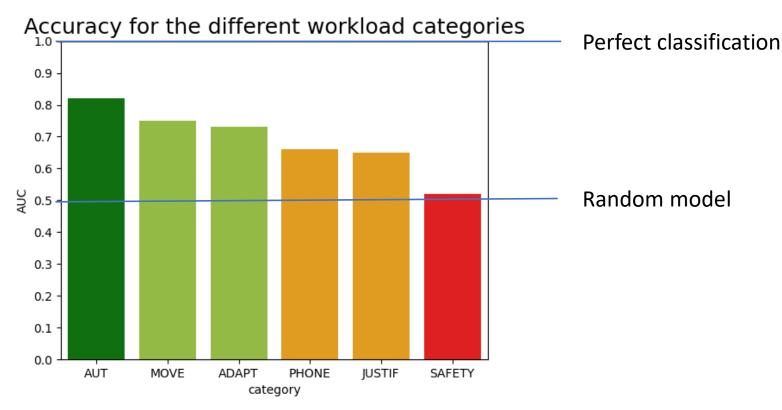
- Different types of risk to be managed when modeling
 - 1. Data
 - 2. Specification
 - 3. Development
 - 4. Validation
 - 5. Operational
 - 6. Security
 - 7. Managerial



Source: 'Managing model risk' by Seppe Vanden Broucke & Bart Baesens



• Q1: To what extent can we predict whether the operator will have workload for a specific category in the next 15 minutes?



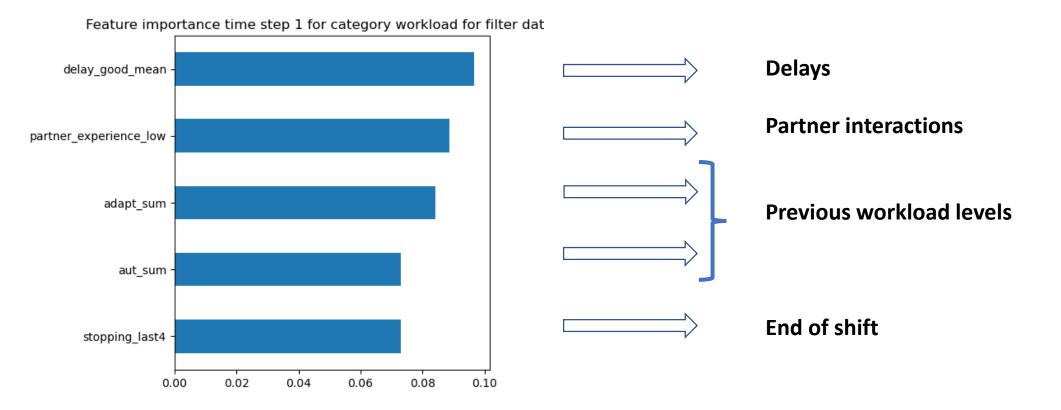


• Q2: To what extent can we predict how much workload the operator will have for a specific category in the next 15 minutes?

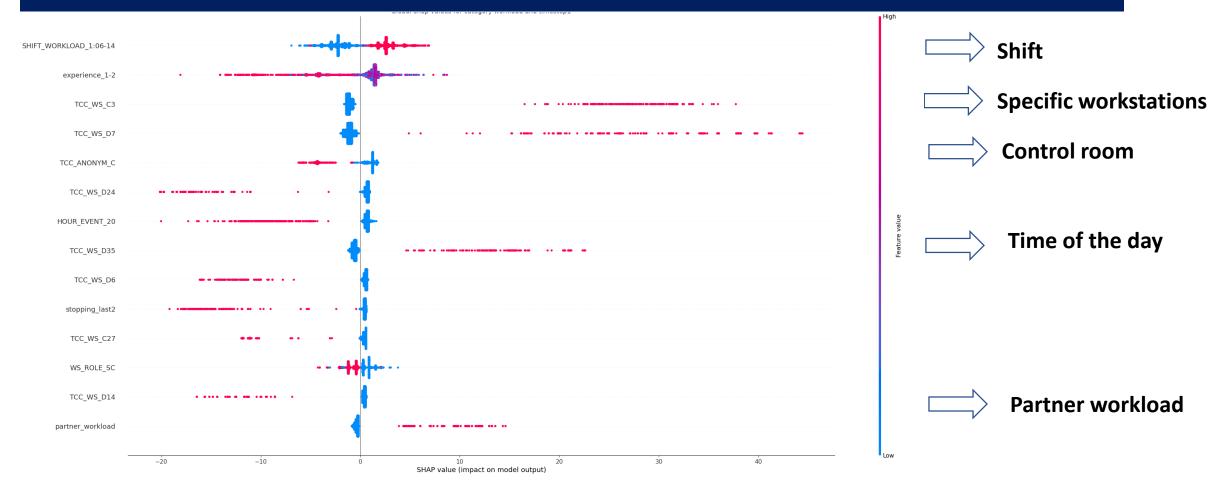
category	RF	XGB	
MOVE	23s	22s	
AUT	22s	20s	
ADAPT	60s	54s	$RMSE = \left \frac{\sum_{i=1}^{N} (yi - \hat{yi})^2}{N} \right $
SAFETY	18s	18s	\sqrt{N}
PHONE	70s	70s	
JUSTIF	57s	57s	



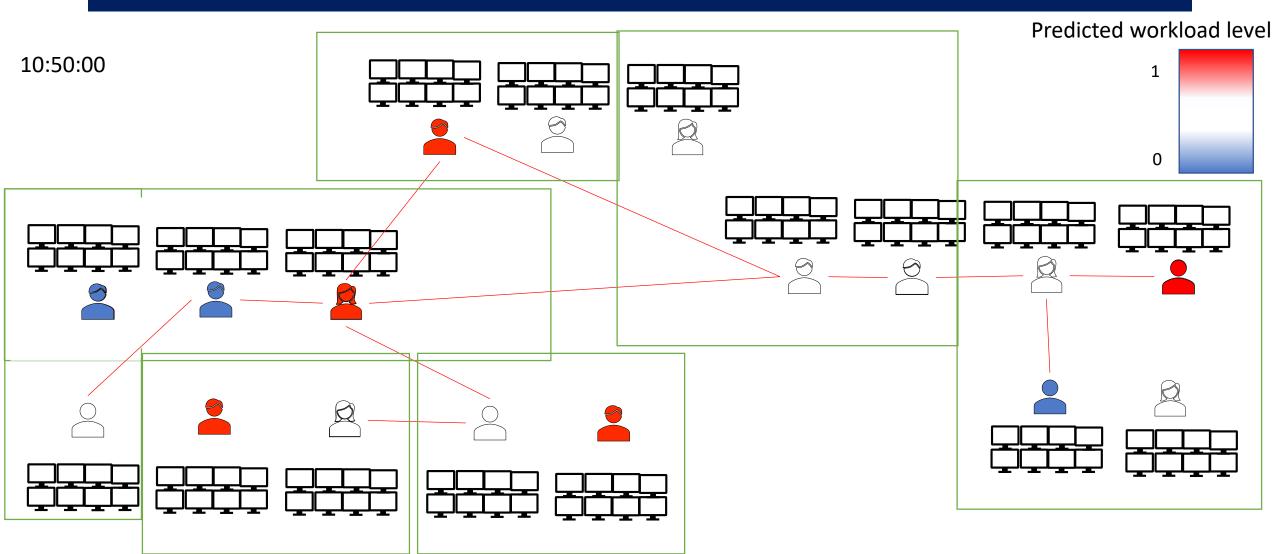
Insights in the importance of features of random forest model













3. Implementation

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Technology readiness level (TRL)

A compass for assessing how ready the technology is for the real-world (developed by NASA, originates from '70s)

2 stage approach

- \rightarrow using proofs of concepts
- Replay real-time simulation
 - Face validity
 - Flexibility
- Real-time implementation

- R Shiny

TRL 9	System proven in operational environment	
TRL 8	System complete & qualified	
TRL 7	Integrated pilot system demonstrated	
TRL 6	Prototype system verified	
TRL 5	Laboratory testing of integrated system	
TRL 4	Laboratory testing of prototype	
TRL 3	Proof of concept established	
TRL 2	Technology concept/ application formulated	
TRL 1	Basic principles are observed	



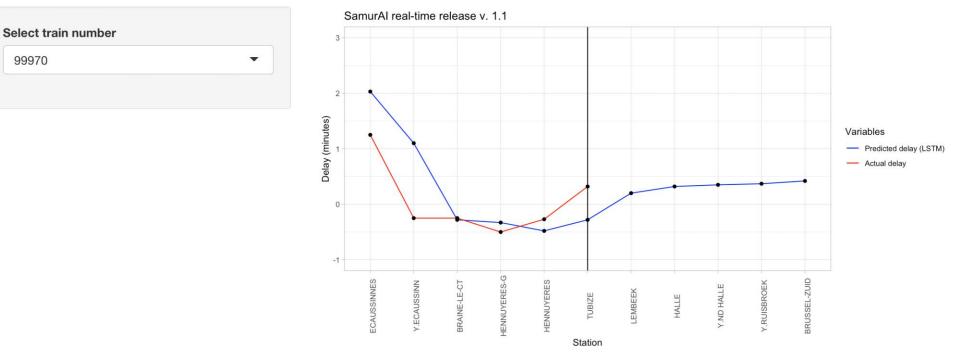
Implementation for management





Sobrie, Verschelde, Hennebel & Roets (2022) – Capturing complexity over space and time: An application to real-time delay prediction in railways

DL model predictions







- There is untapped potential for machine learning in control rooms
 - Multidisciplinary approach required
 - Close collaboration between academia and practice
 - Learning iteratively: FAIL = first attempt in learning
- A roadmap towards implementation requires
 - Focus a practical issue
 - Construction of a real-time data flow
 - Model validation by operational testing

5. Future implications

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- Balancing the workload within and between operators
 - Research done in the BALANCE project of the On Track Lab
- Estimating the evolution of workload thresholds within a shift
 - Research done by the System Dynamics Lab of Virginia Tech
- More granular insights on the relationship between workload, delays, human errors and fatigue

Any questions?

Stay on track at https://ontracklab.com

Contact me at leon.sobrie@ugent.be



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