Optimal strategies to manage major disturbances

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Paola PELLEGRINI
WP3.3 Lead

Objectives of WP3.3

Optimal Strategies (Extreme Situations)

Review of operational strategies in use or being developed and outcomes when different strategies are employed

- **D3.3.1: Analysis of European best practices and levels of automation for traffic management under large disruptions**
- **D3.3.2: Recommendations for a European standard for traffic management**

Source: theguardian.com

Source: DB Mediathek

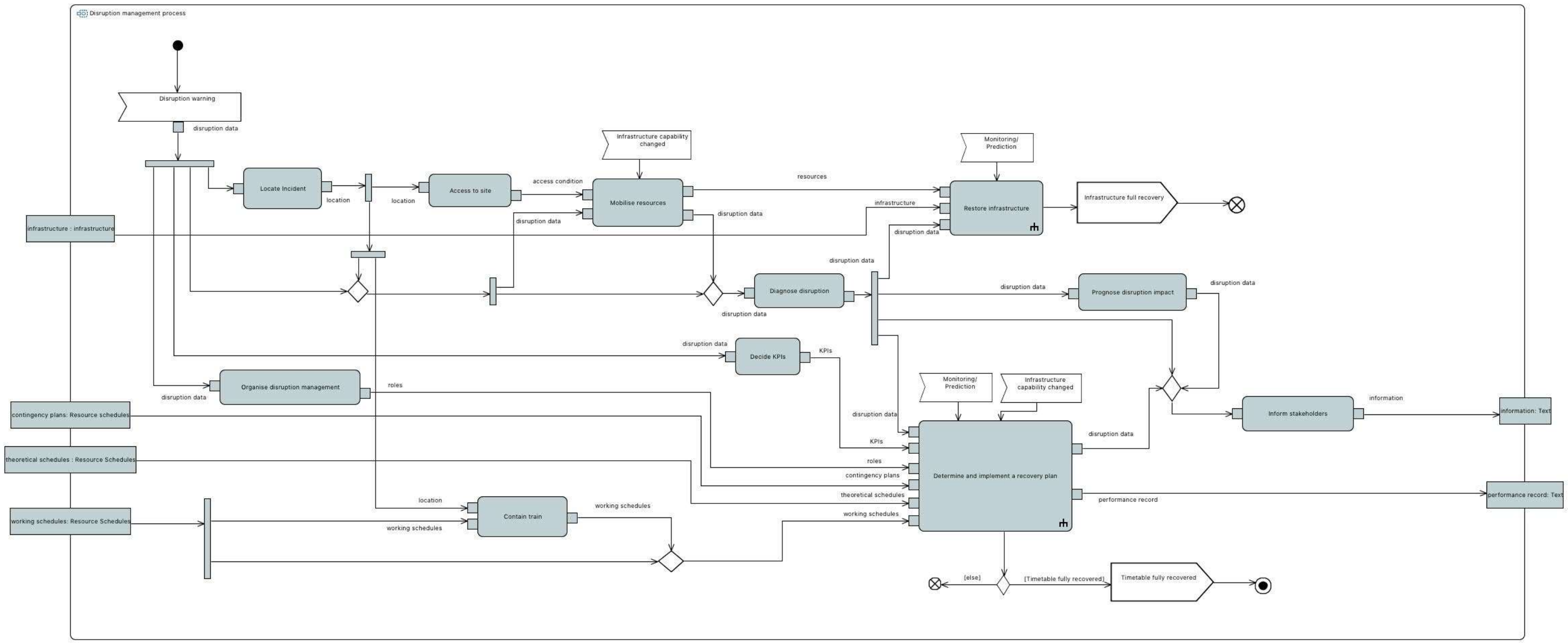
Disruption management process

The process has been formalised through **SysML activity diagrams**

SysML is a **standardised and open source** modelling language for system engineering

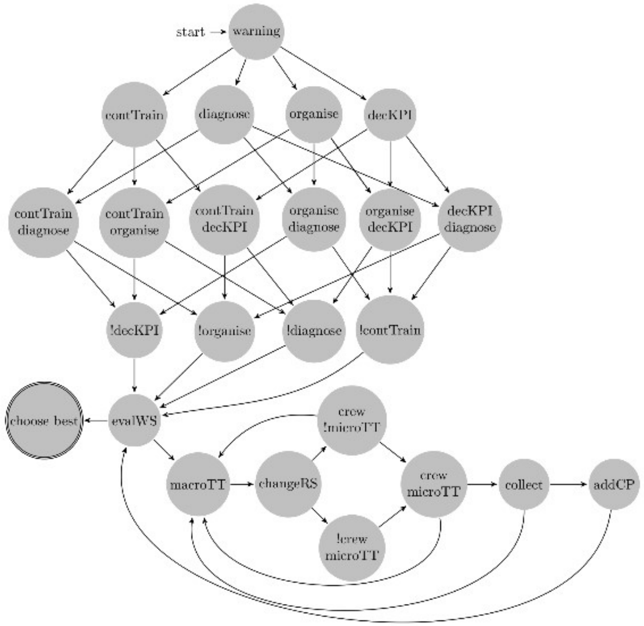
SysML allows specifying

- abstract system requirements
- main system's structures
- activity flows and data exchanges



Benefits of the SysML formalisation

Ease of translation of the activity diagrams into state graphs to check the main properties of the **system's behaviour**



Possibility of analysing the **level of automation** currently implemented and envisaged

Definition of a **unified framework** for the disruption management process throughout Europe

- Network Rail, Trafikverket, ADIF and SNCF could validate the model and specify country-specific procedures

Disruption management by ADIF

Analysis of the 2016 Network Statement

10 phase **general contingency plan**

Scheduled procedures	Phase 1	**Urgent security measures** and protection of traffic for incident prevention or minimisation
	Phase 2	**Identification** of the type of incident and gathering of information
	Phase 3	**Notice** to emergency services and to the internal and external security departments
	Phase 4	**Mobilising** the intervention resources
	Phase 5	**Information** to the RUs and bodies of the Railway Infrastructure Administration
	Phase 6	Information to the affected **passengers**
	Phase 7	**Report** on the status of victims in accidents
	Phase 8	**Control measures** about trains in transit
Coordinated efforts	Phase 9	**Coordination** in the place of the incident and between the incident point and the central level
	Phase 10	**Alternative Transportation Plan**

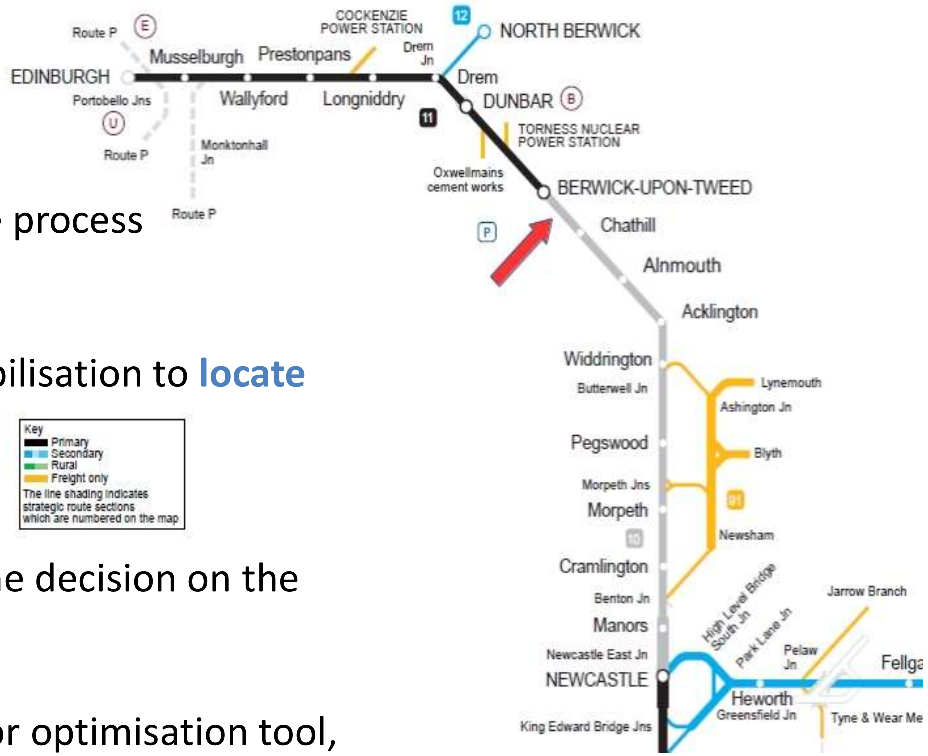
Disruption management by NR

Analysis of SPIRs: **Significant Incident Performance Reviews**

- Cause
- Prevention
- Incident response
- Detection, diagnosis & repair
- Train service management & recovery
- Service to Passengers
- What went well?
- Transferable lessons
- Urgent performance advice

Analysis of incident records

SPITTAL (TWEEDMOUTH) FLOODING ON FRIDAY 10TH DECEMBER 2010 - London North Eastern route G



The management of this disruption follows the process formalized in the SysML diagrams

In the SPIR, details are given on the teams mobilisation to **locate the incident** and **restore the infrastructure**

The intervention of the experts allowed the **diagnosis of the disruption**, which triggered the decision on the recovery plan

The **recovery plan** was set with no automatic or optimisation tool, but based on personal agreements among the several stakeholders

No automatic sensors were used to **detect** the start, the duration or the end of the disruption

The **communication** was mostly phone-based

Lessons learned

- Generic contingency plans are not appropriate: **specific** responses must be provided for each incident
- **Coordination** of disruption management and emergency management is necessary
- The **implementation** of disruption management strategies is a sovereign task of the IMs
- Oral **coordination and communication** are highly important

Recommendations on automation improvements

The level of human-automation interaction is generally quite low in case of disruption

Possible improvements:

- Automatic **integration** of weather forecast models in the preparation for extreme weather events
- Automatic **information** sharing: communication across organizations
- Automatic **decision support tools**: quick and optimized
- Automatic state **monitoring**

Roadmap for automation increase

On the basis of the lessons learned, a **roadmap** for automation is provided.

We first focus on different **individual aspects** of the railway system.

Then, we collect the relevant elements into a **unified framework**.

Finally, we assess through **simulation** the validity of the roadmap.

Rolling stock

Driving	Description
Manual	The **driver** is **completely** in **control**
Semi-Automatic	The **driver** is in **control** and the train is equipped with an **interventionist computer** that enforces movement authority instructions (LOA)
Driverless	The **driver is a supervisor** and only intervenes when the system is in a faulty condition
Unattended	An ATO equivalent system is integrated into ETCS system and drives the train **without any need for supervision**

Command, control and communication (CCC) system and Platform

C4R Capacity for Rail

Command, control and communication (CCC) system

Train Detection	Train Protection	Traffic Management
Manual	Train stops	Junction box based TM
Track circuits and axle counters	Induction based	Manual TM
Radio based detection	Radio based	Rule based-TM
	Autonomous	Autonomous

Platform

Platform Management	Passenger Guidance	Train Dispatch	Passenger Management
Manual	Manual door operation	Manual	Platform staff
Automatic	Automatic door operation	Automatic	Active monitoring

Infrastructure

Level of Automation	Human	Machines
Manual	Primary **identifiers** of critical areas based on experience	Used to **measure and quantify** the area under investigation, also used to rectify issues under human control
Semi-Automatic	Primary analysis of fault labelled areas **using metrics provided by the machines**	Processor based machines that can **measure** areas for current condition **and predict** failures
Automatic	**Operate** the machines, such as dedicated infrastructure measurement trains. The human task is then limited to **planning** for maintenance activity	Intelligent machines that can **identify and analyse** a fault for possible root causes and provide recommendations for intervention criteria
Autonomous	Operational trains regularly **measure** infrastructure and create a rich database that can be mined for **identifying** critical areas autonomously With the introduction of robotics and autonomous systems it is possible to schedule a maintenance period with respect to an operational timetable	

Roadmap

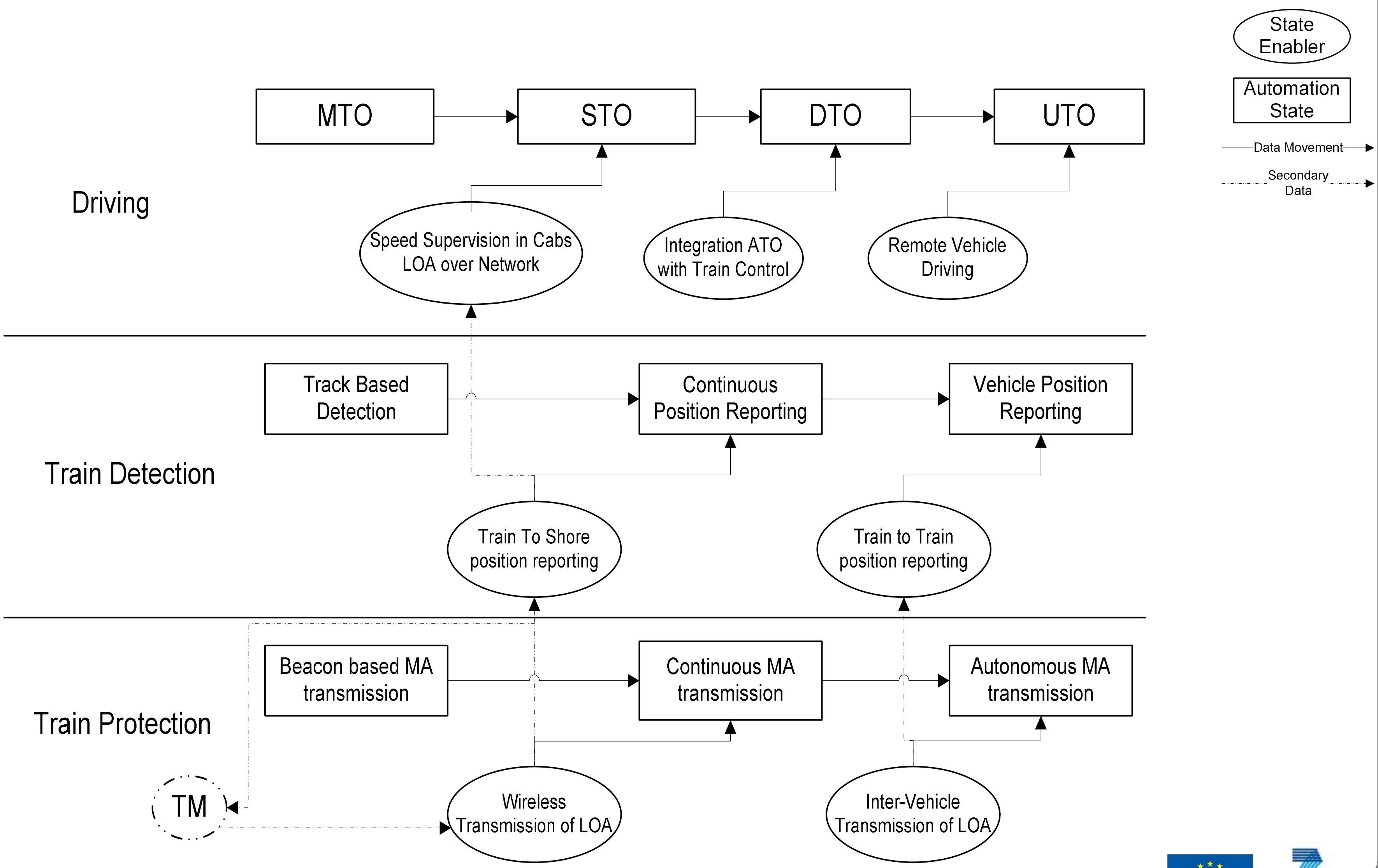
A roadmap helps to **visualise** all of the individual changes into a **single table** to show the progression of the railway system

from a manual system to a fully automated one

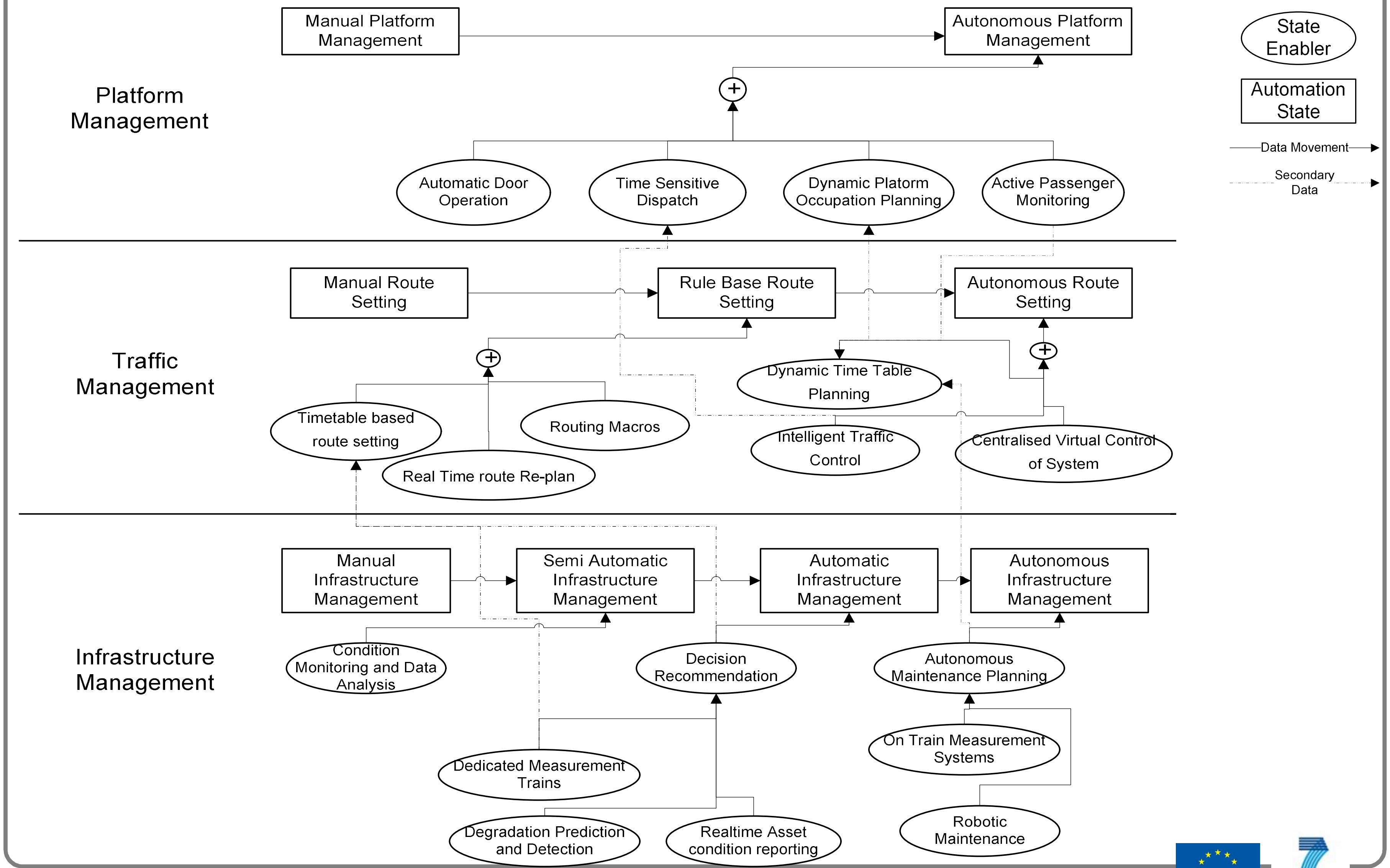
The overall improvement of capacity and reliability will be achieved only when the **whole system** will have reached a maturity level

Infrastructure	Manual	Semi-Automatic	Semi-Automatic	Automatic	Automatic	Autonomous
Platform Management	Manual	Manual	Manual	Automatic	Automatic	Automatic
Traffic Management	Manual TM	Manual TM	Manual TM	Rule Based TM	Rule Based TM	Autonomous TM
Train Protection	Induction Based	Induction Based	Radio Based	Autonomous	Autonomous	Autonomous
Train Detection	Track Circuits & Axle Counters	Augmented Train Detection	Augmented Train Detection	Autonomous	Autonomous	Autonomous
Driving	Manual	Semi-Automatic	Driverless	Driverless	Unattended	Unattended
Grade of Automation	**GoA 0**	**GoA 1**	**GoA 2**	**GoA 3**	**GoA 4**	**GoA 5**

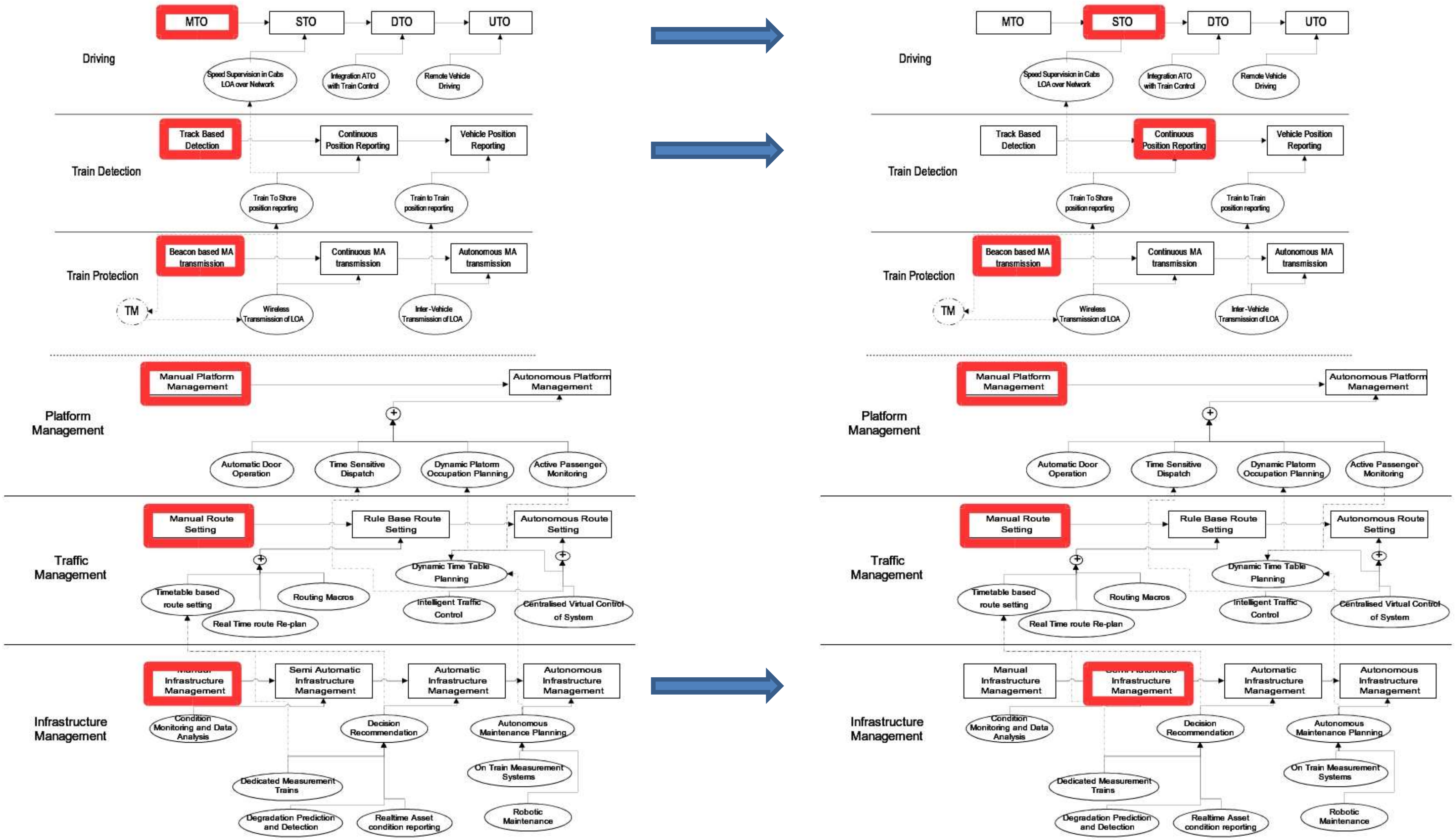
Roadmap: graphical representation (1)



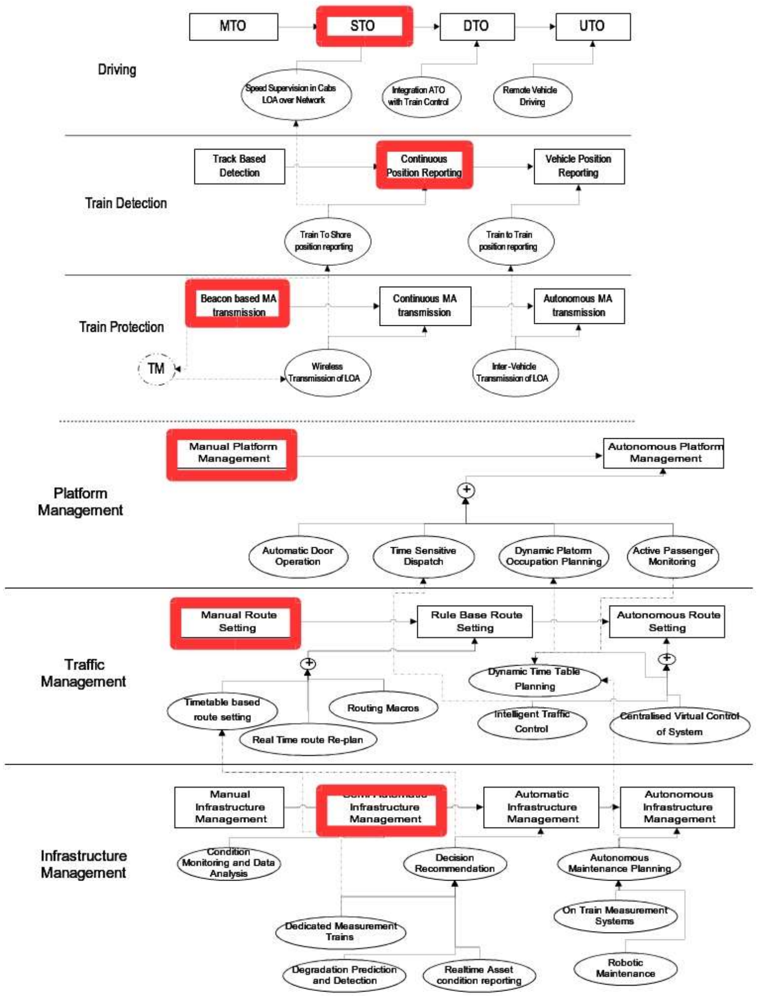
Roadmap: graphical representation (2)

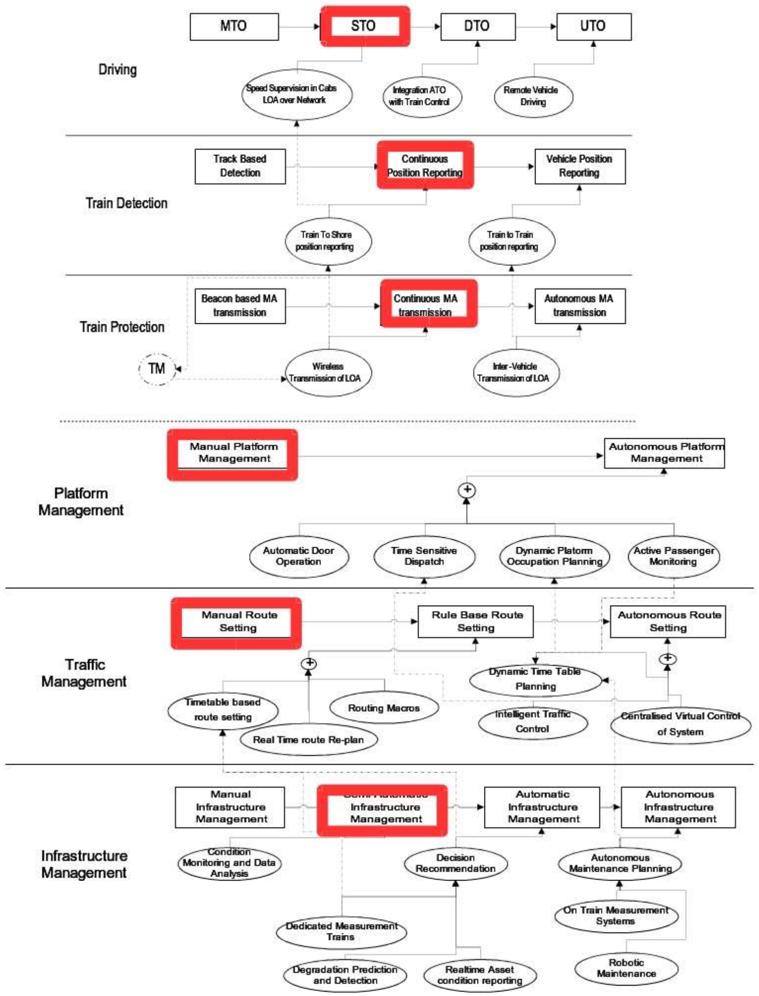


Roadmap: GOA 0 and GOA 1

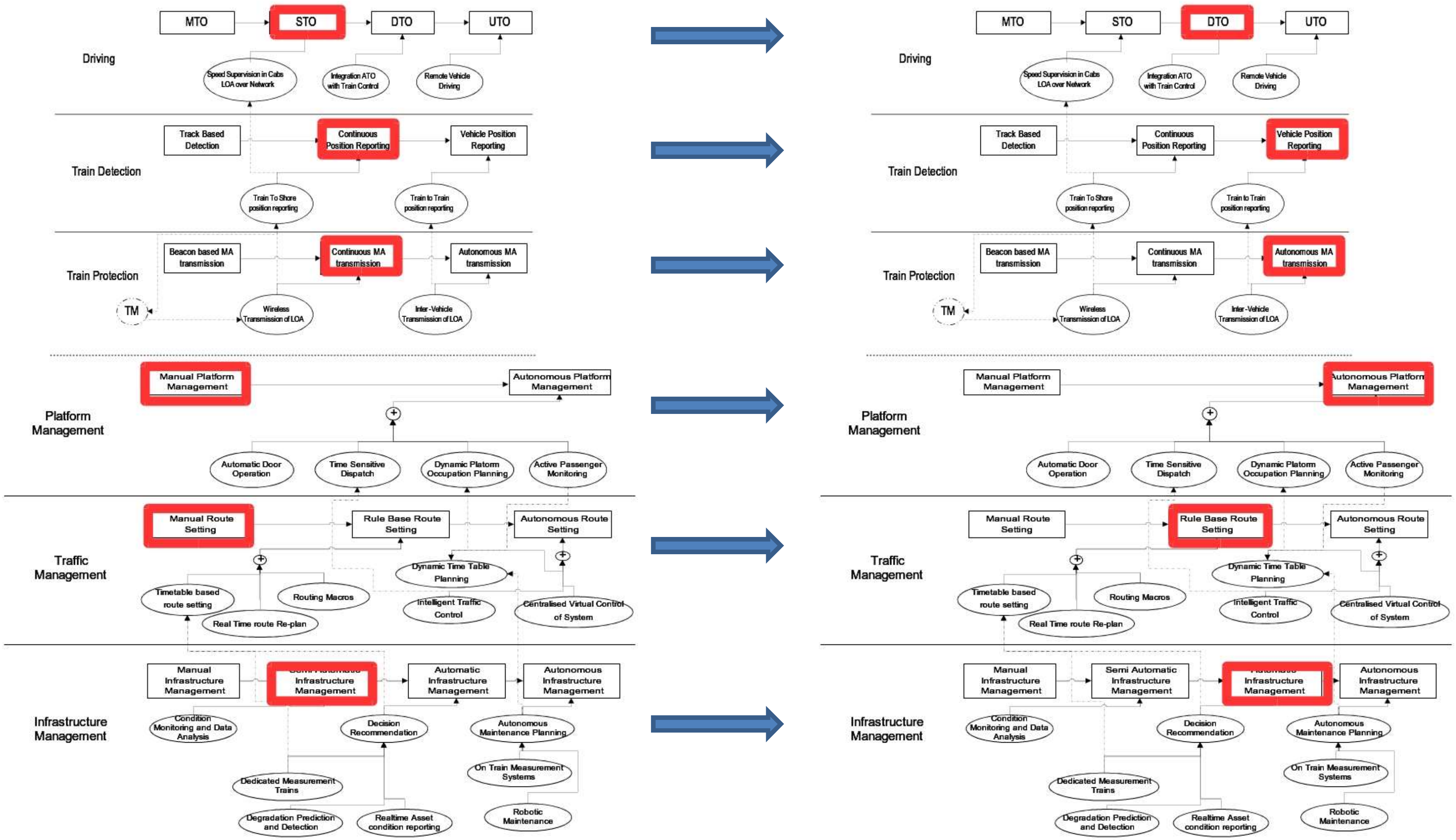


Roadmap: GOA 1 and GOA 2

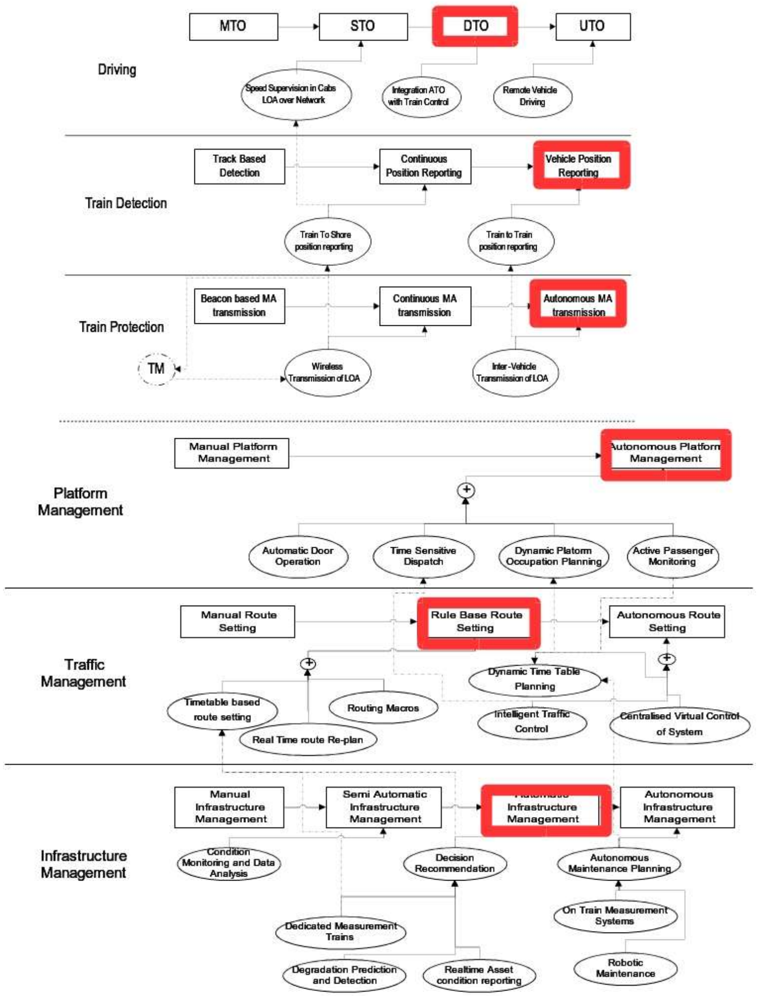


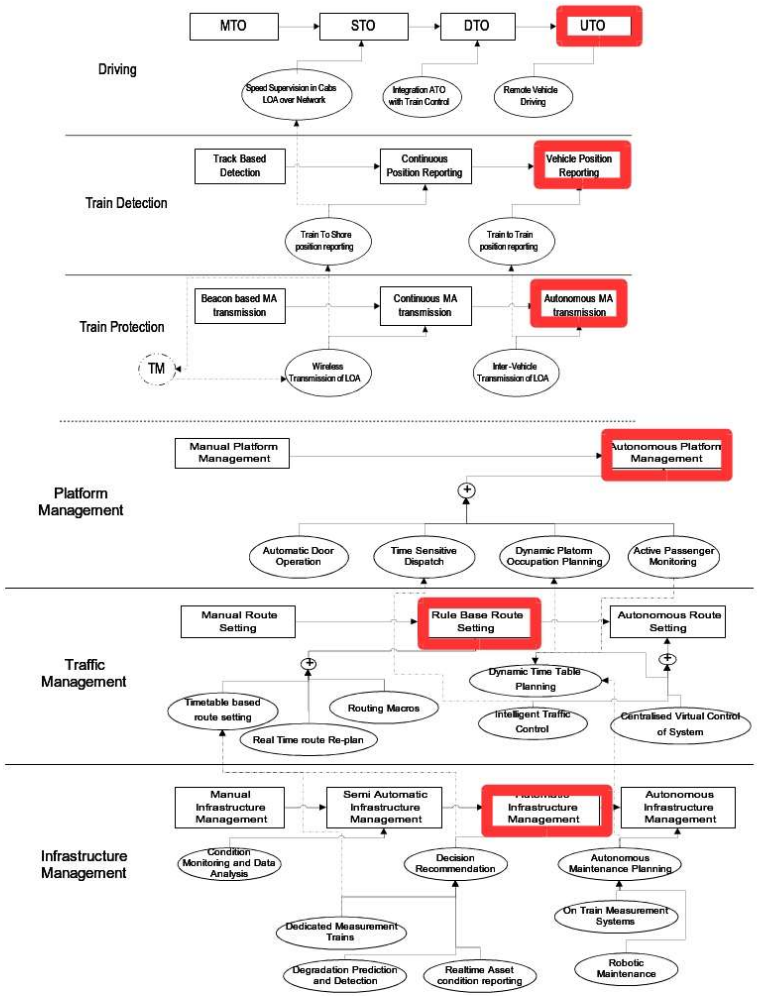


Roadmap: GOA 2 and GOA 3

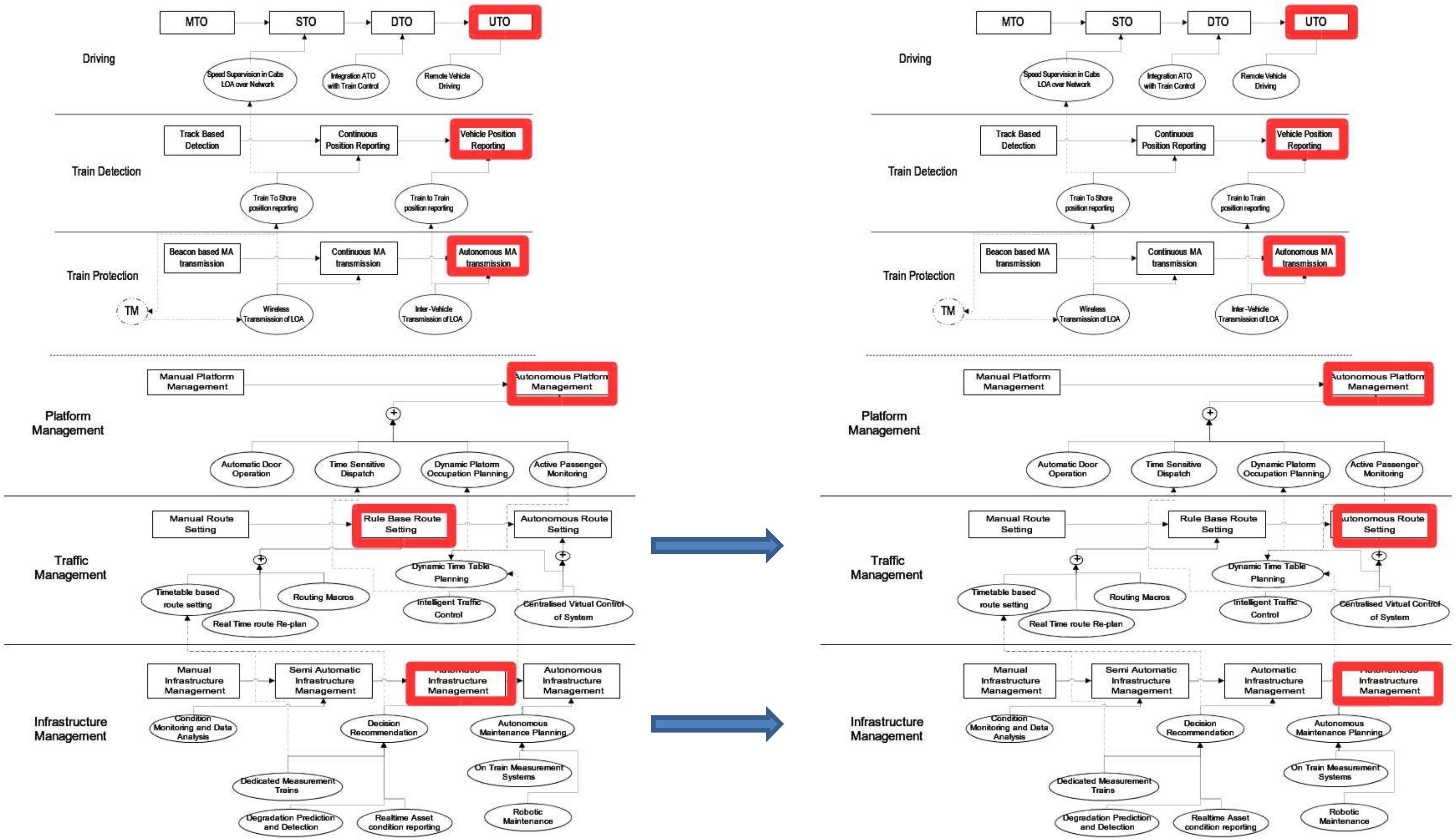


Roadmap: GOA 3 and GOA 4



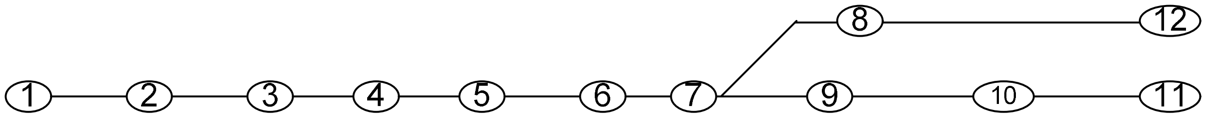


Roadmap: GOA 4 and GOA 5



Validation of the roadmap through simulation

Capacity for Rail



Simulation with BRaVE

Assessment of journey times (proxy of capacity) with increasing levels of automation:

- Four types of signalling (4 Aspect, ETCS 1, ETCS 2 and ETCS 3)

Automation

Automation

- level1: Manual Driving + Train Staff Supervised Platform Departures;
- level2: Manual Driving + Station Staff Supervised Platform Departures;
- level3: Automatic Driving + Train Staff Supervised Platform Departures;
- level4: Automatic Driving + Station Staff Supervised Platform Departures;
- level5: Automatic Driving + Automatic Platform Departures

Three test cases:

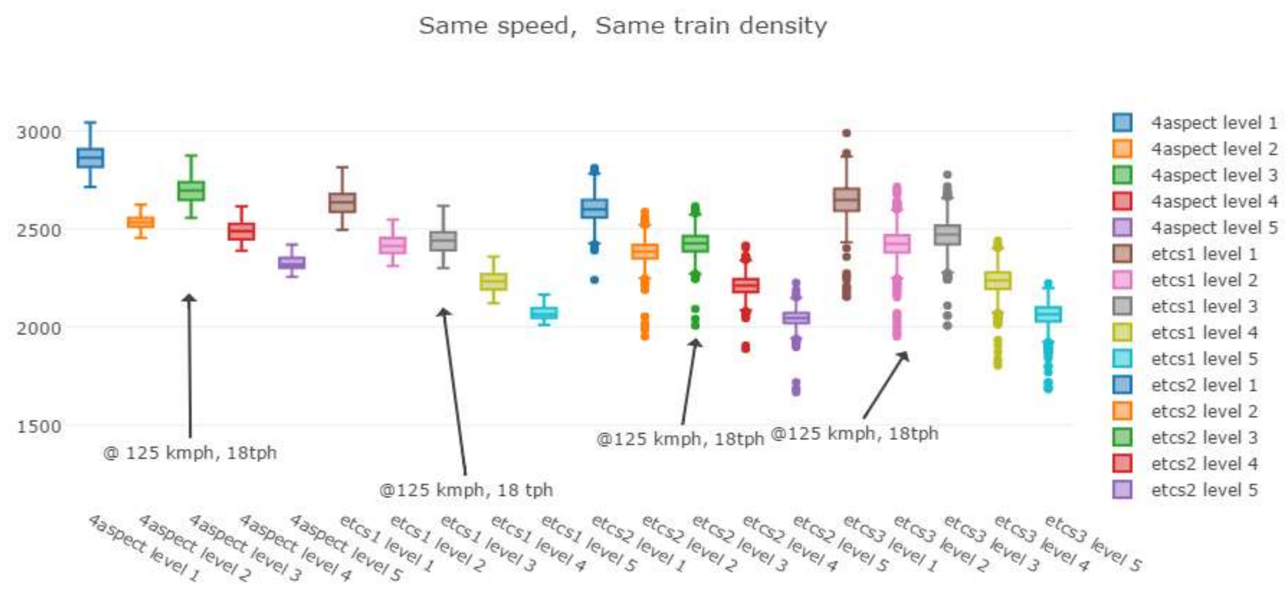
1. Same speed, same traffic density
2. Different speed, same traffic density
3. Different speed, different traffic density

Simulation results for validation

Capacity for Rail

The results show that incremental improvements do not necessarily show capacity improvements

Automation when applied in groups, such as the one proposed in the roadmap above, yields better results



Analysis of an instance of automation increase: delay prediction

C4R
Capacity for Rail

A specific **instance of automation increase** is studied.

The focus is the development of an algorithm for **delay prediction**.

An experimental analysis shows the validity of the algorithm.

Identification of the requirements

C4R
Capacity for Rail

Four different delay categories should be addressed:

1. **Structural (systemic) delay**: a delay th
   due to small errors in the calibration c

2. **Meaningful statistical recurrent delay**
   number of times on the same train an
   line;

3. **Delay caused by known, recurrent exogenous ev**
   to recurrent exogenous events (e.g., rainy days, c
   which can be known in advance);

4. **Unpredictable delay**: a delay due to unknown non-recurrent events that result in a delay over the line (e.g., train disruptions, natural disasters or, in general, sudden exogenous events that are not known in advance).

Current and histori
related to all the
the target ra
infrastruct

Analysis and forecasting of time series

Exogen

SEVENTH FRAMEWORK PROGRAMME

Analysis and forecasting of time series: state of the art

Capacity for Rail

Three main families of models have been identified:

- **Autoregressive** models
  - sample autocorrelation function which allow inference
- **Data mining** models
  - computational processes for discovering patterns in data sets
  - involve methods at the intersection of
    - artificial intelligence,
    - machine learning, and
    - statistics
- **Feature selection and rank** models
  - process of selecting a subset of relevant variables for the model construction

Data sources identification and formal definition of data characteristics

Two principal data sources have been analyzed:

- Railway information systems - traffic management system *(case study for RFI)*
  - Data about train movements
    - including precise time and position references
  - Theoretical timetables
    - including planning of exceptional train movements

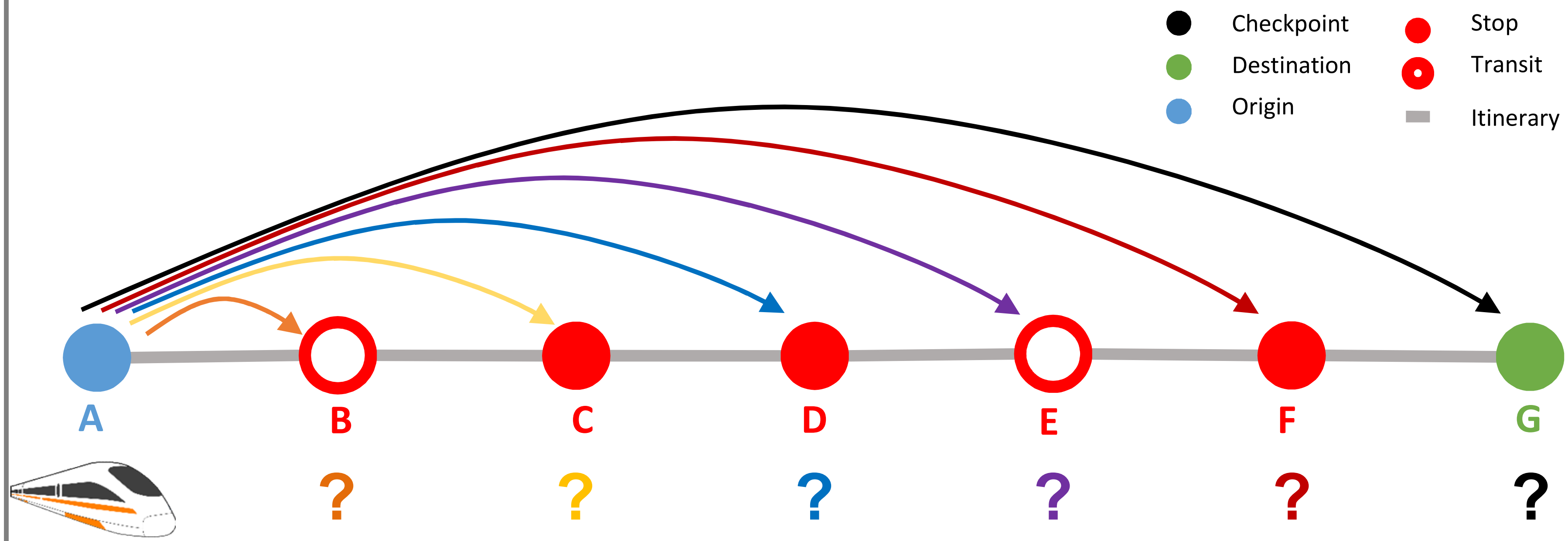
Data retained: 4 tables	
list of stations	list of trains
minutes that can be regained in each section of the network	information that characterizes each train movement

- Exogenous data sources
  - Information about the tourists' presence
  - Information about the number of passengers on each train
  - Information about weather conditions
  - *These exogenous variables are only theoretically introduced*

Proposed modeling solution

For each train and for each of the successive checkpoints composing its trip a **data-driven multivariate regression model** is built

It outputs **delay predictions** for arrival and departures for the corresponding checkpoint

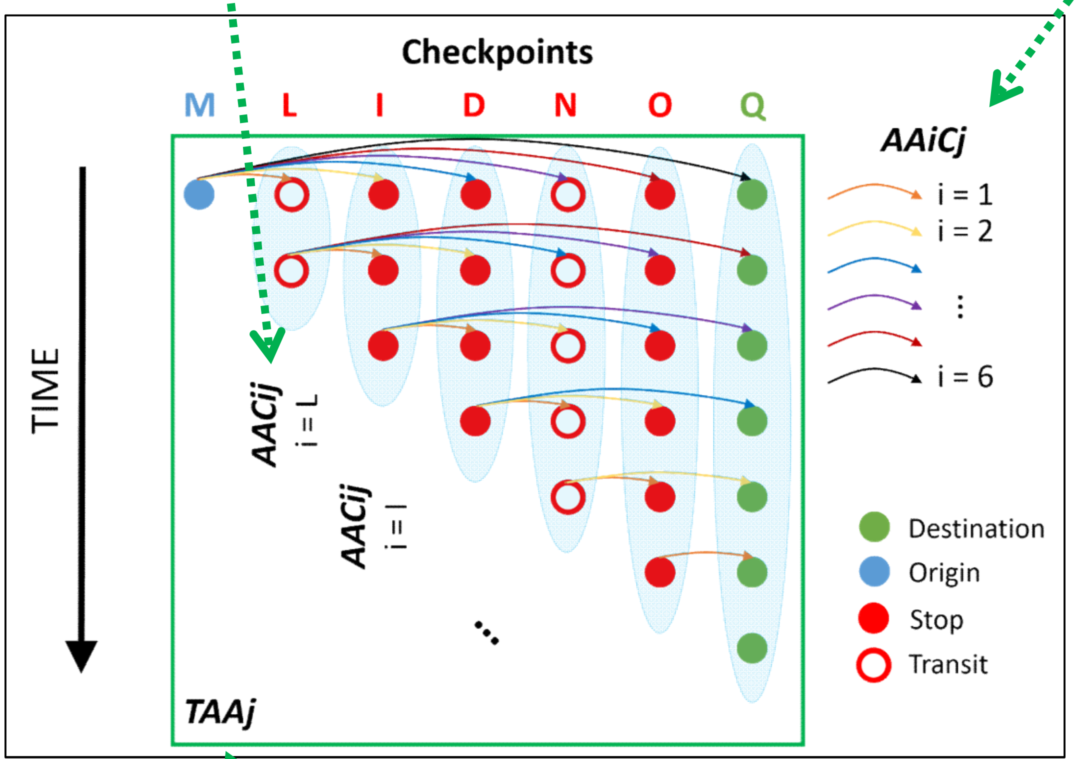


Each arrow represents a data-driven model

KPI's

for train *j* and checkpoint *i*: average of |predicted delay - actual delay|

for train *j* and the *i*-th following checkpoint with respect to the prediction position: average of |predicted delay - actual delay|

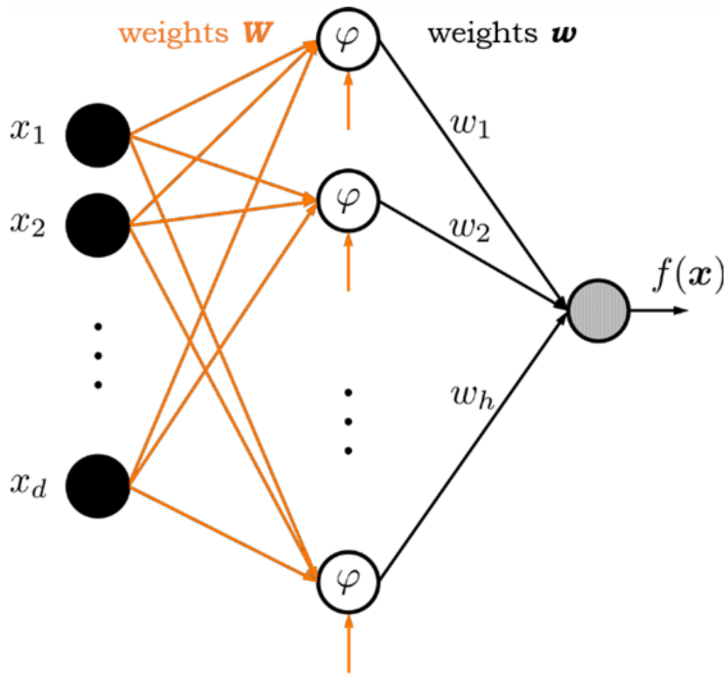


for train *j*: average over i of AACij

Model building

The selected state-of-the-art Machine Learning algorithm able to solve multivariate regression problems is the **Extreme Learning Machines (ELM)** algorithm

It builds a particular type of **artificial neural network** model



Model assessment

The **performance assessment** is based on state-of-the-art statistical tools (e.g., hold out, cross-validation, etc.)

The general idea behind these tools is to use part of the available data to **build models**, and then to **assess their performance** using the rest of the data.

Data used to build data-driven models

Data used to assess the generalization ability of a model

Experimental analysis: setup

We use **real data**, provided by RFI

The available data refers to

- **6 months** of movements in the area of **Milan** and
- **1 year** in the area of **Genoa**

We adopt an online-approach: it updates the predictive models every day

We compare the model with the **current technique used by RFI**

Experimental analysis: simulation steps

The simulation includes several steps, which are repeated for each day:

- **build the model** for each train based on training set
- tune the models' **hyperparameters** through Cross Validation
- consider the **next test day**
- **consider** each train and all the passed **checkpoints**
- for each train and for each checkpoint, **predict the delay** of the train at each of its subsequent checkpoint
- **validate the models** in terms of performance based on what had really happened at a future instant
- take out the data related to the current day from the test set, and add them to the **training set**
- **repeat** the procedure until the test set is empty

Test of the performance on a part of the training set

Example of results (1)

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Capacity for Rail

for train *j* and the *i*-th following checkpoint with respect to the prediction position: average of |predicted delay - actual delay|

AAiCj	RFI	ELM	RFI	ELM	RFI	ELM	RFI	ELM
j \ i	1st		2nd		3rd		4th	
1	1.8	1.6	2.1	1.8	2.3	2.1	2.5	2.3
2	3.2	1.8	3.4	1.9	3.8	2.2	4.2	2.4
3	1.9	1.4	2.0	1.6	2.3	1.8	2.6	1.9
4	2.0	1.5	2.2	1.6	2.6	1.9	3.0	2.1
5	1.4	0.9	1.7	1.0	2.0	1.2	2.3	1.4
6	1.4	1.3	1.7	1.5	2.0	1.8	2.3	2.1
7	1.3	1.0	1.4	1.1	1.6	1.3	1.8	1.5
8	1.3	1.0	1.6	1.3	1.9	1.4	2.1	1.6
9	1.2	0.8	1.2	0.9	1.4	1.0	1.5	1.1
10	1.5	1.0	1.6	1.1	2.0	1.3	2.3	1.5
11	1.4	1.2	1.5	1.3	1.7	1.5	1.9	1.6
12	2.1	1.6	2.6	1.9	3.1	2.1	3.5	2.3
13	1.2	0.9	1.3	1.0	1.4	1.1	1.6	1.3
14	3.1	2.1	2.2	2.0	-	-	-	-
15	2.0	1.3	2.4	1.5	2.9	1.7	3.4	1.9
16	[illegible]	[illegible]	2.0	1.3	2.4	1.5	2.8	1.6
17	1.9	1.3	2.2	1.4	2.7	1.6	3.1	1.8
18	1.3	0.4	1.3	0.4	1.5	0.5	1.7	0.6
19	1.5	0.7	1.6	0.7	1.8	0.8	1.9	0.9
20	1.5	0.3	1.7	0.4	1.8	0.5	1.8	0.6
21	1.1	0.5	1.2	0.6	1.2	0.7	1.2	0.8
22	1.2	0.4	1.2	0.5	1.3	0.6	1.3	0.7
23	1.9	0.7	2.0	0.8	2.4	1.0	2.6	1.1
24	1.0	0.4	1.1	0.5	1.1	0.6	1.1	0.7
25	1.0	0.4	1.1	0.4	1.2	0.5	1.1	0.6
26	1.9	0.7	2.0	0.8	2.3	0.9	2.6	1.0
27	1.0	0.4	1.1	0.4	1.2	0.5	1.1	0.7
28	1.0	0.4	1.0	0.5	1.2	0.6	1.4	0.7
29	1.1	0.3	1.1	0.4	1.2	0.5	1.1	0.6
30	2.0	0.6	2.1	0.7	2.4	0.9	2.7	0.9

. . .

ELM improves **up to x5**

accuracy ↓ as *i* ↑: the forecast refers to an event further in the future

SEVENTH FRAMEWORK PROGRAMME

Example of results (2)

for train *j*: average over i of AACij

ELM improves **for all the trains**

ELM improves **up to more than x3**

j	TAAj RFI	TAAj ELM
1	2.2	2.0
2	4.3	2.2
3	2.3	1.6
4	2.4	**1.7**
5	1.7	1.1
6	1.9	1.7
7	1.5	**1.2**
8	1.9	1.5
9	1.4	**0.9**
10	1.8	1.2
11	1.8	1.5
12	2.8	2.0
13	1.4	1.1
14	3.1	**2.1**
15	[illegible]	[illegible]
16	3.9	1.0
17	[illegible]	[illegible]
18	6.7	4.3
19	[illegible]	[illegible]
20	3.7	1.0
21	[illegible]	[illegible]
22	4.9	**2.2**
23	6.5	3.6
24	5.1	2.3
25	4.6	**1.8**
26	5.6	2.9
27	6.2	**2.8**
28	5.5	2.8
29	4.2	1.1
30	4.7	1.8
	..	

Results: summary

The results over the testing data have shown a promising result:

for the specific train considered, the data-driven models outperform the current technique by a factor of ≈2x (on total average)

Future works will consider also **exogenous information**

- weather information,
- passenger flows
- railway assets conditions
- …

The team

C4R
Capacity for Rail

IFSTTAR
UIC
NetworkRail
TRAFIKVERKET
oltis group
SYSTRA
adif
THE UNIVERSITY OF BIRMINGHAM
LiU LINKÖPING UNIVERSITY
TECHNISCHE UNIVERSITÄT DRESDEN
IK INSTYTUT KOLEJNICTWA
AnsaldoSTS
DB
TRL
Newcastle University

Thank you for your kind attention

Paola PELLEGRINI

WP3,3 Lead

IFSTTAR

paola.pellegrini@ifsttar.fr