Capacity for Rail

Towards an affordable, resilient, innovative and high-capacity European Railway System for 2030/2050

Recommendations for a European standard for traffic management under large disruptions

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Executive Summary

The objectives of this deliverable are:

- The development of a set of recommendations for the management of large disruptions including extreme weather events;
- The definition of a roadmap for automation strategies of European disruption handling processes;
- The identification of the effect of different automation levels on disruption management as obtained from experiments and/or simulations.

To achieve these objectives, the first chapter of this document is devoted to the definition of the background and context of the study. Here, a summary of disruption management process as formalized in (CAPACITY4RAIL, 2016) and of its integration in the general emergency management procedures are provided. An analysis of the magnitude of large disruptions in Sweden concludes the chapter and shows the importance of effectively dealing with them.

The second chapter presents an analysis of the actual processes currently in place in different European countries (Spain and the UK) to cope with disruptions due to extreme weather events. For one of these countries (UK), the reports concerning the management of specific disruption events is analysed in detail. This allows the assessment of the degree of compatibility of the process implemented and the one previously formalised. Such an analysis shows the main criticalities in the process, often related to the lack of automation for what concerns, e.g., the communication, the resource allocation, the monitoring of the state of the system and the forecast of the future one. A set of lessons learned and recommendations are derived following the identification of these criticalities.

On the basis of these lessons learned, a roadmap for automation is provided in Chapter 3 and the impact on large disruption management is discussed. In this roadmap, we first focus on different individual aspects of the railway system, as the rolling stock and the command control and communication system. Then, we collect the relevant elements into a unified framework, for which we identify the main data requirements. Finally, we assess through simulation the validity of the roadmap. The results of the simulations show that no real capacity increase will follow any particular automation improvement, unless it is appropriately coupled with others. For example, a sole increase in train driving automation will not have a strong impact on capacity. However, this impact will be noticeable if driving automation is coupled with station platform management automation.

In Chapter 4, a specific instance of automation increase is studied. In particular, the focus is the development of an algorithm for delay prediction. This algorithm is based on an advanced data analytics procedure named Extreme Learning Machine and it allows the combination of the large amount of data generated by traveling trains to the large number of models to be managed. The

increase of automation represented by the used of this type of algorithm may bring four main advantages:

- Improved passenger information system, by increasing the perception of the reliability of train passenger services and, in case of service disruptions, providing valid alternatives to passengers looking for the best train connections;
- Improved freight tracking systems, estimating good's time to arrival correctly so to improve customers' decision-making processes;
- Improved timetable planning, providing the possibility of updating the train trip scheduling to cope with recurrent delays;
- Improved delay management, allowing traffic managers to reroute trains so to utilise the railway network in a better way.

Simulation experiments on real data show that the use of the method proposed may improve the prediction of delay of a factor two, with respect to the current practice. At the end of the chapter, we discuss the role that such a method for delay prediction may play for increasing the automation in large disruption management.

In Chapter 5 we analyse how the increase of automation in the capacity utilization planning process can be profitable when dealing with large disruption. In particular, this analysis links the work reported in this deliverable with the one performed in Work Package 3.2 of Capacity4Rail.

The conclusions are reported in Chapter 6, with a short summary of the main requirements, roadmap characteristics and possible impact of a specific instance of automation increase.

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Abbreviations and acronyms

Abbreviation / Accronym	Description
AAiC	Average Accuracy at i-th following Checkpoints
AAiCj	Average Accuracy at i-th following Checkpoint for train j
AACi	Average Accuracy at Checkpoint i
AACij	Average Accuracy at Checkpoint i for train j
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average Model
ATC	Automatic Train Control
ATO	Automatic Train Operation
ATP	Automatic Train Protection
AWS	Automatic Warning System
CCC	Command, Control and Communication
CCS	Command and Control System
CTC	Centralized Traffic Control
DAS	Driver Advisory System
DP	Differential Privacy
DTO	Driverless Train Operation
DWD	Deutscher Wetterdienst
ELM	Extreme Learning Machine
ELS	Extreme Learning System
ERTMS	European Railway Traffic Management System
ETCS	European Train Control System
EWAT	Extreme Weather Action Team
IM	Infrastructure Manager
k-NN	K Nearest Neighbour
KPI	Key Performance Indicator
LOA	Limit Of Authority
LPG	Liquefied Petroleum Gas
MOM	Mobile Operations Manager
MS	Model Selection
MTO	Manual Train Operation
NRCC	National Rail Communication Centre
NRL	Northern Rail Ltd
OCC	Operation Control Centre
PPM	Public Performance Measure
RBS	Radio Block System
RCM	Remote Condition Monitoring
RU	Railway Undertaker
SPIR	Significant Incident Performance Review
SSI	Solid State Interlocking
STO	Semi-automatic Train Operation
SVM	Support Vector Machine

TAA	Total Average Accuracy
TAAj	Total Average Accuracy for train j
TM	Traffic Management
TMS	Traffic Management System
TPE	TransPennine Express
TPS	Train Protection System
TPWS	Train Protection Warning System
TSI	Technical Specifications for Interoperability
UTO	Unattended Train Operation

1. Background and context

Based on the findings of (CAPACITY4RAIL, 2016), we recall here the main procedures implemented by European Infrastructure Managers to cope with disruptions, with particular attention to the ones due to extreme weather. When the disruption management process concerns extreme weather events, it can be included in the more general emergency management process, which is detailed later in this chapter. Then, we summarise the main weather-specific guidelines which were delivered by the "Management of Weather Events in the Transport System" (MOWE-IT) project and we report the results of an analysis of the magnitude of large disruptions in Sweden, to underline the importance of the disruption management process studied.

1.1 Disruption management process

Disruption management in railway operation describes the (re-)actions that are performed to return the system back in its initial operational state, after an unexpected event affected the system lastingly. (Yu & Qi, 2004) describes disruption management as "*a real-time dynamic revision of an operational plan when disruptions occur*". They characterize several sources for internal and external factors that cause disruptions in general:

- *Changes in system environment* for example due to weather conditions.
- *Unpredictable events* for example in case of terrorist attacks, union strikes, power outages, etc.
- *Changes in system parameters*.
- *Changes in availability of resources* for example due to machine failures, resign of key personnel, etc.
- *New restrictions* for example arising from new government laws, new union contracts, new industry regulations, etc.
- *Uncertainties in system performance* often caused by a limited understanding of the system.
- *New considerations* which were not present in the planning phase.

The challenge of disruption management in railway operation is to get back to regular operation after an unexpected event occurs and to minimize loss and negative impacts on the whole railway system. Disruption management for railway operations includes:

- Consideration of constrains (e.g., connection information, resource dependencies);
- Determination of optimization criteria (e.g., recovering capacity);
- Optimization of the process with the coordination of individual measures.

In particular, the process considered in this work aims to cope with large disruptions, which require changes of the originally planned resources utilization through the coordinated action of infrastructure managers (IMs) and railway undertakers (RUs). In general, the scope of large scale disruption covers:

- Crew delay or unavailability;
- Train failure (limiting the access to a line section or station platform);
- Infrastructure degradation, e.g., track or line section closure;
- Extreme weather events;
- Other cases due to external factors.

The following sections describe the process of disruption management as introduced in the (ON-TIME, 2013) and refined in (CAPACITY4RAIL, 2016). Within the latter, the described process has been validated for different European Countries: UK, France, Spain and Sweden. The formalization of the process is done using the graphical modelling language SysML (Object Management Group, 2016). It provides the needed concepts and structures to model the parameters, methods and constraints of the disruption management process as well as the rules of the involved stakeholders.

1.1.1 Disruption management processes throughout Europe

The organisation of disruption management varies across Europe, and sometimes even within a country, depending on locations and physical layouts. However, some fundamental similarities exist.

First of all, disruption management relies on several actors who ensure railway operations, as controllers and resource planners from both IMs and RUs. The variety of the involved actors and their requirements explains why a successful disruption management depends on unambiguous communication between all parties.

Moreover, disruption management is a highly interconnected process: any aspect of decision-making is linked to several other aspects and to the progress achieved within one's own organisation and cross-organisation. Location, timing, type of incident and severity of incident will all influence the capacity to deliver an alternative timetable, and therefore influence alternative solutions.

Indeed, different solutions come along with different benefits and require different considerations and constraints. So far, there is only little technical support especially designed for disruption management. Contingency plans (if available) only cover strategies within the scope of one organisation. This is rather the case for the infrastructure part. Resilient contingency plans for crew and rolling-stock are often non-existent.

1.1.2 SysML Model

Within this section, we summarise the formalisation of the disruption management process detailed in (CAPACITY4RAIL, 2016). The process is modelled in SysML, a standardised and open source modelling language for system engineering.

Requirements of the disruption management process

The SysML language allows specifying abstract system requirements. They describe the characteristics of the actors' needs as well as their expectations. In the formalisation proposed, the top-level requirement *Decision making* describes the overall goal of the system. The technical system (and its interfaces) for disruption management as a whole is aimed to satisfy this requirement. The top-level requirement contains detailed requirements based on a prioritised list of capability requirements (ON-TIME, 2012).

Requirement "Decision making"

The *Decision making* requirement indicates the need for the system to be able to make decisions during disruption management. Moreover, it shall be able to support both IM's and RU's controller actions. As specifications to this requirement, the system must be able to make decisions on the need for resource reallocation, and in case the need is detected, to make decisions on the actual reschedule by resources reallocation. Furthermore, *Communication* activities between stakeholders are to be assured. These requirements are described more in detail in the remainder of this section.

Requirement "Decision on resource reallocation need"

The *Decision on resource reallocation need* requirement indicates the capability of the system to decide when the start of reallocation is needed during disruption management. It is supported by the *Monitoring* and *Prediction* of the infrastructure and traffic state. The former concerns the observation of the infrastructure and the traffic state. The latter concerns the analysis of the result of this observation, to obtain a prediction on the infrastructure and traffic future state. Beside the system immanent monitoring equipment, also external data, e.g., weather forecast, can be considered for *Monitoring* and *Prediction*. While the current state will be mainly based on own monitoring results, the future state of infrastructure and traffic state can be predicted by integrating external data, e.g., wind speeds that can lead to temporary speed restrictions. These data are to be analysed in terms of their impact on the railway infrastructure and traffic state.

Requirement "Decision on how to reallocate resources"

This requirement states that the system shall be able to

- rapidly produce a feasible schedule;
- optimise train recovery plans;
- optimise platforming and
- integrate rolling-stock and crew schedule rostering.

A system fulfilling these requirements will be able to handle quickly and effectively all parties and assets directly involved in a disruption, as customers, crew, trains, tracks and station infrastructures.

Requirement "Communication"

The *Communication* requirement supports the integration of IMs' and RUs' decisions. *Communication* consists in the ability of the system to perform all the necessary communication activities during a disruption.

SYSTEM STRUCTURE DEFINITION WITH BLOCK DIAGRAMS

In SysML models, blocks are used to define a system's structure. Block characteristics can be described using properties, operations or references. By compositions and references among blocks, both structural and virtual dependencies can be modelled. Here, block diagrams are used for modelling the disruption management process. They define the relevant properties of the infrastructure, the train definition, the overall schedule, the trips, the events, and the human resources (drivers, conductors and crew). The behaviour of the system components is not explicitly modelled in this formalisation: they are considered black-box systems. This allows the modelling of different systems through the same structure: blocks simply act as interfaces between possibly different implementations. By doing so, we can represent through a unique model the disruption management processes implemented in several European countries.

RESOURCE SCHEDULE

The most critical block definition is the one describing the *Resource schedules*. It defines relevant properties, constraints, and values that characterize a whole schedule:

- *Timetable*;
- *Rolling-stock schedule*;
- *Crew schedule*.

The *Resource Schedules* block is related to a *Timetable* block by a composite association with cardinality one to one. Hence, a *Resource Schedules* block contains exactly one *Timetable*, and one *Timetable* belongs to exactly one *Resource Schedules* block. A *Timetable* is composed by a set of tasks, so called *Train Services*. It can be represented at either the macroscopic (stations and lines traversed) or the microscopic level (tracks and switches used, signals passed).

In addition to the composite association between the *Resource Schedules* and the *Timetable* block, another composite association links the *Resource Schedules* and the *Rolling-Stock Schedule* block. This association has a multiplicity one to many, to model the fact that a *Resource Schedules* block may contain several rolling-stock schedules. This may be necessary if the schedules must be distinguished by RUs or depots.

Similarly to the *Timetable* and the *Rolling-Stock Schedule*, in the SysML block definition diagram, the *Crew Schedule* block has a composition relationship with the *Resource Schedules* block. The *Crew Schedule* is organised as sequences of *Trips* per day. Some breaks and other activities are added in between. As it contains *Trips*, the *Crew Schedule* block has a composition relationship with the *Trip* block.

TRAIN SERVICE BLOCK

To detail the tasks composing a *Timetable,* a composite association links the *Timetable* block to the *Train Service* block. To represent the fact that a Timetable may contain several trains and it surely contains at least one, the multiplicity of the terminal part of this association is one to many. A *Train Service* block represents a train mission that starts from a station and arrives at a destination station indicated respectively by the *origin* and *destination* reference properties. The turning connections are specified by the *successor* reference property.

The *Event* structured value type captures event features of a *Train Service*, as the arrival at a station or the passing of a signal. The *type* property gives information of the category of events which is to occur and the *position* one locates where the event occurs.

Another important property is the sequence of stops, which is typed as a sequence of *Stop Position* blocks. The *Stop Position* block is defined to manage the state (Boolean parameter *cancelled*) of the commercial and non-commercial stops.

TRIP BLOCK

The *Trip* block constitutes the link of the Timetable (via the *Train Services*), the *Rolling-Stock Schedule* and the *Crew Schedule* blocks. The *Trip* block is an association block: it describes the structural properties of an association. A *Trip* is the association between a *Train Service* and a resource to perform it. The assignment of resources is internally managed within the *Trip* block which offers an operation *hasResource()* that returns false if and only if all the required resources for the *Train Service* are not assigned.

RESOURCE BLOCK, TRAIN UNIT BLOCK, CREW BLOCK

These blocks correspond to the *Resource* (*Train Units* and *Crew*) affected to the *Train Service*. Hence, the *Train Unit* and *Crew* blocks are subclasses of the *Resource* block. The subclass relation allows the block to reuse the features of the superclass blocks and to add its own features.

A *Train Unit* is a self-propelled railway vehicle. It is the basic rolling-stock element to operate trains; the case of operating with carriages and a locomotive will not be considered here for the sake of simplicity, but the modelling constructs used can also incorporate these elements. *Train Units* can be coupled and uncoupled to form trains of different length, called train compositions. With respect to the *Rolling-Stock Schedule*, *Train Units* are assigned to a sequence of *Trips*. Along this sequence, the departure station of a *Trip* must be the same as the arrival station of the predecessor *Trip*. Each day, the first and last *Trip* of the sequence must respectively start and end at a depot. The number of *Train Units* available at a depot is called the rolling-stock inventory. A *Trip* sequence is “balanced” if the inventory of the depots at the end of the day is sufficient to cover the required rolling-stock inventory for the beginning of the next day. An important goal during operations is to avoid off-balance at the end of the day. In a *Rolling-Stock Schedule*, each *Train Unit* follows a coherent *Trip Schedule*, starting from a depot. Moreover, its definition includes information as the number of carriages, the seating capacity and the length of the *Train Units*.

The *Crew* block has two subclasses: the *Driver* block and the *Conductor* block.

ACTIVITY DIAGRAMS OF DISRUPTION MANAGEMENT PROCESS

In the proposed activity diagrams, the process is described as sequences of actions that transform input to output tokens. The input/output pins of actions are connected to enable the flow of inputs/outputs. In addition, the execution of the actions is enabled by control tokens.

The activity diagram of the Disruption Management Process detailed in (CAPACITY4RAIL, 2016) shows the connection of the actions and the activities composing the disruption management process. In a SysML activity diagram, the activity starts at the initial node shown as a solid black circle. A token is placed on that node and triggers the execution of one or more actions via the outgoing control tokens.

DISRUPTION WARNING

The process starts as soon as a *Disruption warning* signal is received. In a traffic monitoring process, an activity detects a disruption and communicates a signal event of a *Disruption Warning* with a send signal action. Furthermore, preventive suspension of railway operation, e.g., due to warnings from weather forecast institutes, can also be handled as disruption warnings. At this level of description of the process, there is no specification of the SysML block which owns the activity that will send the *Disruption warning* signal. More specifically, this means that the signal can be sent by an activity performed either by a technical system or by a human operator through any communication support.

A signal defines a message with a set of attributes. The definition of the signal *Disruption warning* includes *Disruption Data* block that in turn contains system immanent *causes* (e.g., *Crew delay*, *Section line closure*) as well as external *causes* (e.g., *Weather events*). An *accept signal* action transforms the received signal in an output pin to carry the properties of the signal, in this case the *Disruption data*. Remark that the *accept signal* actions and the *send signal* actions allow asynchronous communications between activities: the sender activity does not wait for a response from the receiver to proceed to the next action.

Following the acceptance of the *Disruption warning* signal, a fork node duplicates the token object *disruption data* and enables the execution of the four following actions:

- Locate incident;
- Organise disruption management;
- Diagnose disruption;

- Decide KPI's.

These four actions invoke activities that refine *location*, *scope*, *causes* of the disruption, roles within the organisation and Key Performance Indicators (KPIs) to be used to monitor or control the process. In particular, *Locate incident* is the action in charge of determining the location of the incident and the scope of the affected area based on the currently available information; in case of a disruption due to a flood, for example, the area threatened by the flood is identified. *Organise disruption management* consists in assigning people to specific roles for the duration of the incident (e.g., specifying the name and contact details of the person in charge of a process). In the action *Diagnose disruption*, after receiving a signal of a *disruption warning* and *disruption data*, the aim is to determine the cause and the amplitude of an incident; e.g., receiving extreme weather warnings may lead to the detection of a flooding situation or risk. The causes will typically include the heavy rain, but may also concern, for example, the overflow of a river. Finally, *Decide KPI's* involves the definition of the key performance indicators which will be used to assess the evolution of the situation and the quality of the proposed *Resource Reschedules*.

Location, *scope* and *causes* are attributes of the *disruption data* token put in the input/output pins of the actions. These data will be filled as soon as the information becomes available within one of the mentioned activities.

BRANCH FOLLOWING THE LOCATE INCIDENT ACTION

After having invoked *Locate incident*, the process can proceed with the action *Contain trains* as the location is known and the trains to hold to prevent escalation can be determined. The holding of trains is recorded in the timetable of the input parameter *working schedules*. The changed *working schedules* is placed on the output flow to be input to *Determine and implement a recovery plan*, to make a decision on the hold trains.

The action *Access to site* is invoked simultaneously. It requires the plan, execution or handback of track or electrical isolation to allow access to the site of the incident (e.g., setting signals to red so that track-workers can access the failed point). Once the access conditions are met the action *Mobilise resources* is invoked to move resources (people or plant) to the site of the incident. To do so, the *disruption data* are also required, which explains the further transmission of this token from the initial fork. When the action *Mobilise resources* is completed, the resources on site can provide new information about the incident. This information updates the *disruption data* and invokes the action *Diagnose disruption*, the output of which is the cause of the disruption.

Depending on the nature of the incident (e.g., for some kind of weather events as strong winds), the activities *Access to site*, *Mobilise resources* and the subsequent *Restore Infrastructure* may not imply any actual action.

BRANCH FOLLOWING THE DIAGNOSE DISRUPTION ACTION

In the Diagnose Disruption action, the identified cause of the incident is stored on the corresponding attribute of the output token *disruption data*. The token is then replicated to enable the execution of four actions:

- Restore Infrastructure;
- Inform stakeholders;
- Prognose disruption impact;
- Determine and implement recovery plan.

RESTORE INFRASTRUCTURE

Restore infrastructure consists in performing all the activities necessary to restore the infrastructure capability. The execution starts with the action *Design a restore plan*, which depends on the actually mobilized *resources*, on the *Infrastructure* characteristics, and on the latest version of the *disruption data*. The restore plan may be composed of different phases. Each phase is dealt with sequentially, through the action *Perform restoration phase*s. The output of this action is an *Infrastructure capability changed* signal, which communicates the current phase achieved. This signal is received by the *Mobilise resources* action, in which the current resource mobilisation may be changed depending on the new capabilities. If necessary, the *Restore Infrastructure* activity is reiterated with the new *resources*. Concurrently to the re-assessment of the mobilized resources, the next phase of the restore plan is performed, until the last phase is completed and the *Infrastructure full recovery* signal is sent. When the capability is fully recovered the flow stops.

INFORM STAKEHOLDERS

Simultaneously to the invocation of *Restore Infrastructure*, the action *Inform stakeholders* is executed. It consists in the communication to the stakeholders of the cause and the estimations of major delays (e.g., putting information on screens at all affected station platforms). This action provides the output parameter *Information* of the overall activity.

PROGNOSE DISRUPTION IMPACT

Concurrently, also the *Prognose disruption impact* action is executed: it estimates the delay caused by the disruption and updates the *disruption data*. The updated disruption data are then transmitted again to the *Inform stakeholders* action.

DETERMINE AND IMPLEMENT A RECOVERY PLAN

The last token sent by the *Diagnose disruption* action triggers one of the most important activities of the process: *Determine and implement a recovery plan*. This complex activity which takes as input all the known information on traffic (*theoretical schedules, working schedules, Monitoring/Prediction signal* which keeps constant track of traffic conditions), on existing *contingency plans (*e.g., the implementation of special trains to deal with the demand mode-transfer due to ash clouds, or the temporary speed restrictions due to strong winds), on current *infrastructure* capabilities (signal *Infrastructure capability changed*), and on *KPI's* and *roles* defined for dealing with the disruption. The action performed here is the iterative performance of *Evaluate working schedules and emergency schedules quality*, comparing the current *working timetable* and the *emergency schedules* proposed by the activity *Support rescheduling*.

If the quality of one of the available schedules is satisfactory, the action *Choose the best schedules, implement and update working schedules with them* is executed, the results are recorded in the outputs *disruption data* and *performance record*, and the activity is terminated. Otherwise, the *Support rescheduling* action is executed again and new *emergency schedules* are obtained and compared.

After the termination of the activity *Determine and implement a recovery plan*, first of all the *Inform stakeholders* action is repeated with the latest information on *disruption data*. Concurrently, if the timetable is fully recovered, the corresponding *Timetable fully recovered* signal is sent and the flow finishes. Otherwise, no action is performed and the process continues its execution. Remark that, as the *Mobilise resources* one, the *Determine and implement a recovery plan* activity will re-start as soon as it receives one of its accepted signals (*Infrastructure capability changed* and *Monitoring/Prediction*).

SUPPORT RESCHEDULING

The complex activity *Support Rescheduling* consists of an iterative loop executing five actions:

- Change timetable (Macroscopic);
- Change timetable (Microscopic);
- Change rolling-stock schedule;
- Change crew schedule;
- Collect results.

The initial action executed is *Change timetable (Macroscopic)*. Once it has finished, the new timetable is available through a token *timetable* placed on the output pin connected to a fork node. The token is replicated three times and each token is placed onto each output flow of the fork node.

The two actions *Change timetable (Microscopic)* and *Change rolling-stock schedule* immediately start their execution as all their input pins have a token available. If the action *Change rolling-stock schedule* changes the characteristics of the rolling-stock used, the action *Change timetable (Microscopic)* must be executed again with the new rolling-stock characteristics.

The execution of *Change crew schedule* can start only when the *Change rolling-stock schedule* has finished. The process of these actions will change the state of the *Trips* of the *Rolling-Stock Schedule* and the state of the *Trips* of the *Crew schedule*. In SysML, a state constraint can be specified on object tokens that flow from one action to another. This is equivalent to specifying pre-conditions and post-conditions on the flow of actions. A state constraint on an object node is shown by the name of the constraint in square brackets. Here, a state constraint on the *Trips* output of *Change* *rolling-stock schedule* specifies that it is a collection of trips with *[no resource]* state. This means that no rolling-stock composition has been appointed to each *Trip* of the collection. Similarly, the *[no resource]* state of the *Trips* output of the *Change crew schedule* means that no crew could be found for each *Trip*. Here, it is assumed that there is no partial resource assignment, i.e., there are only two possible states for each *Trip*: either all the required resources are assigned, or no resource is assigned. When one of these tokens is available, the Change timetable (Macroscopic) action is re-started to produce a new timetable compatible with the unavailability of part of the necessary resources. Thereafter, the *Timetable* must be adapted. To implement these pre- and post-conditions, the operation *HasResource()* has been defined in the block definition of *Trips*.

If *Collect results* indicates that the changes to *Timetable*, *Rolling-Stock* and *Crew Schedule* are feasible, then the variable *feasible solution* is set to true. This variable is tested on the guard of a decision node; if false, a new loop for changes is performed from *Change timetable (Macroscopic)*. If true, the activity terminates. The action *Collect results* also puts together all schedules and details of the timetable into a *Resource schedules* object. The contingency plans are added to this object in the *Add contingency plans to the resource schedules* action. This is done so that the people in charge of making a decision on the suitability of the implementation of the proposed schedule receive as a concurrent input the *contingency plan*. In fact, in the *Evaluate working schedule & emergency schedule quality* activity, based on the identified *KPI's*, on their expertise and on their knowledge of the system, they may decide to implement a known and possibly tested *contingency plan* rather than a new *resource schedule*. Even if the *Support rescheduling* activity returns a *Resource schedule* which appears to be satisfactory according to the criteria defined, the operator always has the last word on its implementation. The chosen *Resource schedules* is available as the output of the activity and therefore on the output pin of the action *Support Rescheduling*.

The actions involved in the *Support rescheduling* activity are not detailed here, but for a short report of their main features, as well as the inputs required and the outputs produced. These actions in principle necessitate the application of optimization algorithms, being them implicit in the form of human decisions based on experience or explicit in the form of automated optimization procedures.

CHANGE TIMETABLE (MACROSCOPIC)

As for the *Change Timetable (Macroscopic)*, the decisions that can be taken in the algorithm to change the timetable are the following:

- cancelling trains;
- reordering and retiming trains (i.e., determining a new schedule with different departure and arrival times at stations);
- re-routing trains (i.e., determining a new schedule with a different set of visited stations: this can be done for freight trains or for passenger trains between scheduled stops).

In particular, starting from the planned timetable and the information on the actual state, trains are rescheduled with the goal of applying as few changes as possible. Indeed, the objective function consists of minimizing the deviation from the original plan. The inputs considered are:

- The description of the railway *Infrastructure*,
- The *theoretical* and *working schedules*,
- The *Disruption data*.

The output of the action is the new computed timetable.

CHANGE ROLLING-STOCK SCHEDULE

After the macroscopic timetabling, the *Change rolling-stock schedule* action is executed: the rolling-stock has to be rescheduled to cope with the new timetable. The aim of rescheduling is to assign rolling-stock to as many planned trips as possible.

The input required for the rolling-stock rescheduling algorithm is as follows:

- the macroscopic timetable and
- the working rolling-stock schedule (rolling-stock schedule currently being operated).

The output of the action is an assignment of rolling-stock compositions to the trips, or a *[no resource]* indication for the trips to which it was not possible to find an assignment.

CHANGE CREW SCHEDULE

When the timetable is changed, the original crew schedule may become infeasible. The *Change crew schedule* action assesses this feasibility and reschedules the crews so that as many trains as possible have enough crew assigned to operate them. If, for a certain train service, not enough crew are available, the train cannot be operated and the *[no resource]* state will be assigned to the trip.

The input required for the crew rescheduling is the following:

- the working crew schedule,
- the macroscopic timetable and
- the changed rolling-stock schedule.

The output of this action consists of two items:

- a crew schedule (i.e., a list of feasible duties) and
- a list of trips for which no crew could be found.

CHANGE TIMETABLE (MICROSCOPIC)

The *Change Timetable (Microscopic)* considers the railway network at a high level of detail and it performs a microscopic check of the feasibility of the new timetable computed macroscopically.

The data required as input to the microscopic timetable action are as follows:

- *Macroscopic Timetable*: train services with arrival/departure times at stations; dwell times at stations; routes at the level of corridors between stations (global routes); non-commercial stops; train connections.
- *Infrastructure data:* track properties, signalling system data and ATP characteristics; interlocking system data.
- *Rolling*-stock data,
- unavailable tracks and
- a list of feasible train routes (local routes).

The output data returned by the microscopic timetable module is a conflict-free microscopic working timetable detailed at the local route level.

This system of requirements, blocks and activities formalises the disruption management process in use in different European countries. In (CAPACITY4RAIL, 2016) it has been validated by several IM's and its coherence has been assessed through model checking techniques.

Indeed, to include this process in a larger picture, the whole emergency management process needs to be considered, especially when focusing on extreme weather events.

1.2 Emergency Management

In the practice, extreme weather incidents are typically associated with emergency management, which is organized by authorities to reduce the effects of natural disasters (earthquake, extreme weather events), industrial accidents, terrorism, etc. In this organization, the management strategies implemented by the railway actors to deal with extreme weather events can be grouped in four emergency management phases: *prevention/mitigation, preparedness, response and recovery* (Figure 1-1).

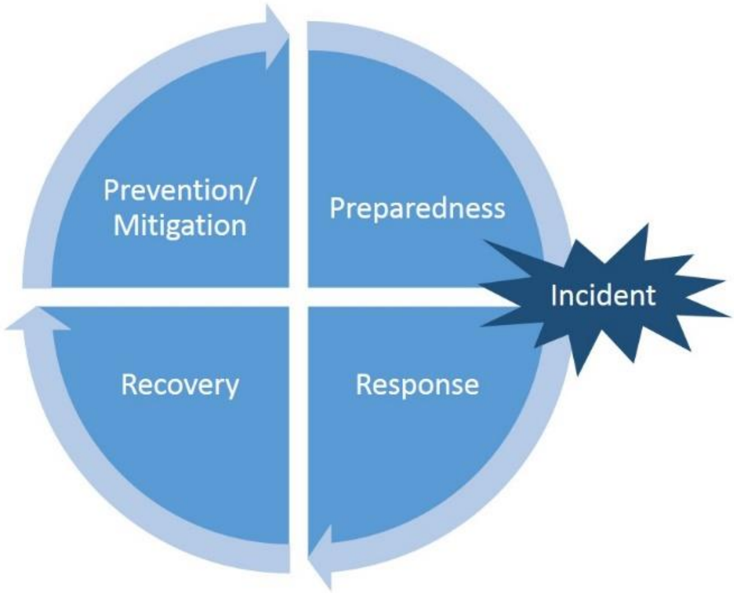

FIGURE 1-1 FOUR PHASES OF EMERGENCY MANAGEMENT

Applied to emergency management for railways, these phases can be described as follows (APTA RT-OP-S-007-04Rev1 2014), (Chu and Fornauf 2011).

Prevention / Mitigation

The mitigation phase of emergency management aims to minimize potential risks by eliminating, controlling or reducing hazards that may cause emergencies. Mitigation activities help prevent some emergencies and will help lessen the effects of emergencies that do occur. This includes, for example:

- infrastructural maintenance and renewal;
- application of warning devises;
- development of robust timetables;
- determination of appropriate mitigation strategies.

Preparedness

The preparedness phase of emergency management establishes the objectives, procedures and resources for future emergency response efforts. Preparedness includes, for example:

- development of documented emergency procedures, e.g., special timetables;
- assignment of responsibilities for all phases of emergency response and recovery;
- emergency response training.

Response

The response phase of an Emergency Management Plan implements planned emergency activities, responsibilities and agreements. The aim for railway operation is to sustain operation at least in a degraded operation mode. Thus, an effective coordination with the Operation Control Centre (OCC) is mandatory.

The OCC is responsible for, for example:

- minimization of delays;
- transfer synchronisation;
- Conflict resolution;
- Replanning of rostering and crew.

Recovery

The recovery phase of emergency management occurs after emergency response activities are completed and immediate danger has passed. The primary activities of emergency recovery are the restoration of normal operations and the documentation and assessment of emergency response.

DISRUPTION MANAGEMENT PROCESS AND CONTINGENCY PLANS

Although the response phase of Emergency Management is already connected with the OCC in the above mentioned response phase, the increase of weather-related incidents across Europe spots the focus on a stronger integration of the actions implemented to cope with extreme weather within the operational disruption management process. These actions should be planned in advance and specified in a contingency plan. Contingency plans help to deal with unexpected events and to respond effectively to possible disturbances. Preferably, contingency plans should be in compliance with the Emergency Management strategies that are agreed with external fire departments, authorities and other involved parties. In the presence of an extreme weather disruption, then, the contingency plan should be assessed and adapted to cope with the specific situation, possibly by following the same process used for other types of disruptions.

The existing EU legislation requires a degree of separation between IMs, which run the network, and RUs, which run the train services on it, to ensure fair and equal treatment of all RUs (EC 2013). In this framework, the contingency management of large disturbances shall be mainly coordinated by the IM of the affected railway line section.

1.3 GUIDELINES FOR DISRUPTION MANAGEMENT DUE TO EXTREME WEATHER FROM MOWE-IT

Weather-specific guidelines were already the topic of the “Management of Weather Events in the Transport System” (MOWE-IT) project. The MOWE-IT project performed extensive review of previous projects on the impact of weather on rail operations and identified relevant case studies. The focus were on heavy rain and flooding events, wind events and snow/winter conditions. The guidelines for the reduction of weather impacts on rail operations were synthesised from the experiences reported in the case studies. These were split into long-term planning and resilience building measures and actions which can be implemented before, during and after a given event. guidelines before the occurrence of the event are divided into long-term preparation and immediately before event. Despite the focus on infrastructural measures, MOWE-IT also highlighted operational guidelines (MOWE-IT 2014).

HEAVY RAIN AND FLOODING EVENTS

The analysis of four case studies concerning heavy rain reveals that the preparedness for those events has high influence on the outcome in terms of damages of infrastructure and disruption of traffic. A key determining factor in the level of preparedness appears to be the history of past experience of relevant conditions and hence the availability of strategies and management plans. A variety of measures can be implemented proactively or can be prepared in order to respond quickly on the course of the weather event. The operational guidelines concerning heavy rain and flooding events given by the MOWE-IT project are:

- Long-term preparation:
  - Have flood response plans in place - prioritise use of limited resources during flood events;
  - Use improved flood prediction models incorporating better weather forecasts and much more detailed information on topography, infrastructure, geology and hydrology;
  - Incorporate climate change projections into the design of drainage to cope with predicted future flooding frequency and magnitude.
- Immediately before the event:
  - Flood warnings should be given in plenty of time;
  - Interrupt operations before events occur.
- During heavy rain and flood events:
  - Quick responses are essential to limit further damage – having flood response plans in place helps to facilitate this;
  - Reduce speed limits or stop trains in flooded areas where appropriate;
  - Personnel – having extra personnel on standby to help with additional duties during a flood event or to replace crews displaced by delayed/cancelled trains.

WIND EVENTS

The guidelines of MOWE-IT were derived from four case studies. The implementation of a meteorological information and warning system is a reliable arrangement that enables IMs and RUs to act proactively in case of severe storm prediction, e.g., by restriction of train services. The intensity and impact of storms on the railway system can vary significantly depending on the region and topology of the landscape. Thus, the closure or opening of line corridors can be initiated individually. Any action shall be coordinated with respect of the overall system in order to get back to normal operation as soon as possible (e.g., clearance of track sections or prioritization of freight or long distance passenger trains). Replacement services and schedules shall be provided to enable necessary repair works. Passenger and customers of rail freight shall be kept informed.

- Long-term preparation:
  - Have wind response strategy in place - resources should be put in place before the events occur;
  - Use improved wind prediction models - wind warnings should be given as soon as possible;
  - Strategies for cutting departures and reducing passenger capacity should be put in place (special timetables, rerouting models);
  - Design a risk-based approach for speed restrictions and line closures.
- Immediately before event:
  - Interrupt operations before events occur and be prepared for this interruption.
- During:
  - Have additional personnel on standby to help with additional duties during a heavy wind event or to replace crews displaced by delayed/cancelled trains and to take care of passengers;
  - Reduce speed limits and cancel traffic where appropriate;
  - Use special timetables where traffic on lines needs to be reduced;
  - Keep trains inside the depot overnight.
- After:
  - Return to normal schedule as soon as possible;
  - Update plans and strategies in light of lessons learned.

SNOW/ WINTER CONDITIONS

Exceptionally hard winter conditions have huge operating and engineering impact on various key performance indicators such as:

- increased service train cancellations;
- decreased fleet availability;
- decreased performance.

These impacts directly influence the capacity of the rail network.

The focus of MOWE-IT concerning snow and winter conditions was on the North European countries and the incident of the Eurostar service in 2009 was examined.

Similar to wind and storm prediction, the level of preparedness for snow and winter conditions can be raised significantly by using meteorological information services. Furthermore, preventive maintenance seems to be a key factor. During hard winter conditions, the focus is on snow and ice removal in order to keep the infrastructure and rolling stock in operational conditions. Another issue is the improvement of the cooperation between different (operational) actors and the need for additional resources such as personnel, machines and equipment but also the availability of competent resources for the snow removal works.

As highlighted in the Eurostar case study, the guidelines for winter and snow conditions can be divided into three broad categories:

- increasing train reliability,
- establishment and regular updating of evacuation and response plans and
- improvement of communication and management of the situation.

1.4 Large disruptions in Sweden between 2000 and 2015

The aim of this analysis is to draw up a compilation of significant traffic interruptions on the Swedish railway and shed light on their causes, their extent and their consequences for traffic.

Significant traffic interruptions in this context are interruptions or disturbances in the traffic lasting one or more days and that affect several trains. A train that derails on a line, a passing line or a branch line and that does not affect other trains is not included but on the other hand a train that derails on the line or trees falling onto the tracks that result in a complete standstill.

METHOD

Several sources have been used, to begin with searches on the web and in the press. The primary source with the most complete information proved to be a magazine called TÅG (Trains). TÅG is a monthly magazine for train enthusiasts and contains relatively detailed information about all major events and accidents. In some cases, reports from the National Accident Investigation Authority, the Emergency Services and the Swedish Civil Contingencies Agency have been used.

The following details were included in the survey:

- Time, from (date) – until (date)
- Duration (number of days and number of hours)

- Location
- Type of event
- Cause
- Sections closed
- Diversion via
- Geographical effect
- Number of freight and passenger trains affected (estimate)
- Categorization of cause
- Possible measures to avoid interruption
- Possible measures to mitigate the consequences of the interruption

DELIMITATION

The analysis comprises interruptions in Sweden. Interruptions in other countries and in ferry traffic may also affect transportation for Swedish trade and industry. The period studied is from January 2000 until December 2015 inclusive.

FINDINGS

During the period in question, 56 major traffic interruptions were identified for freight traffic until December 2015, as shown in **Erreur ! Source du renvoi introuvable.**. These comprised a total of 343 days or 7,609 hours. At least 6,082 freight trains were affected (this figure is estimated). An average of 3.5 interruptions a year thus lasted 6 days and affected approximately 100 freight trains. About 60% of the operations were handled with diversions. Almost 40% of the interruptions lasted one or two days and 30% lasted one week or more. The figures are approximately the same for passenger trains but more trains were affected.

Derailments and weather conditions thus appear to be the greatest problems when it comes to long interruptions in railway traffic. Figure 1-3 shows the distribution of derailments, interruptions caused by weather conditions and other interruptions over the period counted in days of interruption. Examples of extreme weather conditions include torrential rain during 2000, hurricane Gudrun in 2005 and the snowy winters of 2010 and 2011. Derailments reached an exceptional peak in 2013-2014. The number of major traffic interruptions seems to have fallen dramatically during 2015, probably as a result of the measures taken by the Swedish Transport Administration. Most years, just as many major traffic interruptions occur in passenger traffic as in freight traffic, i.e., the same traffic interruptions affect passenger traffic and freight traffic but to varying degrees.

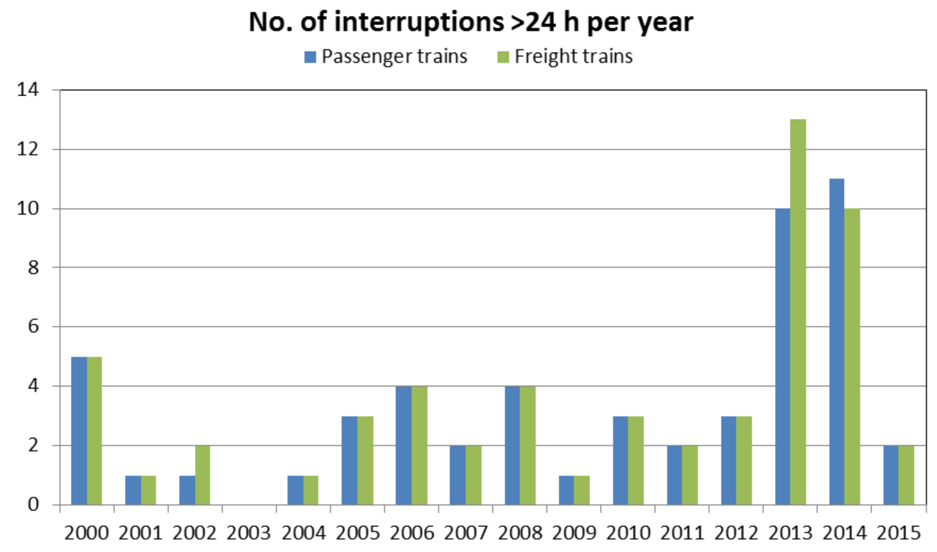

FIGURE 1-2 NUMBER OF TRAFFIC INTERRUPTIONS PER YEAR

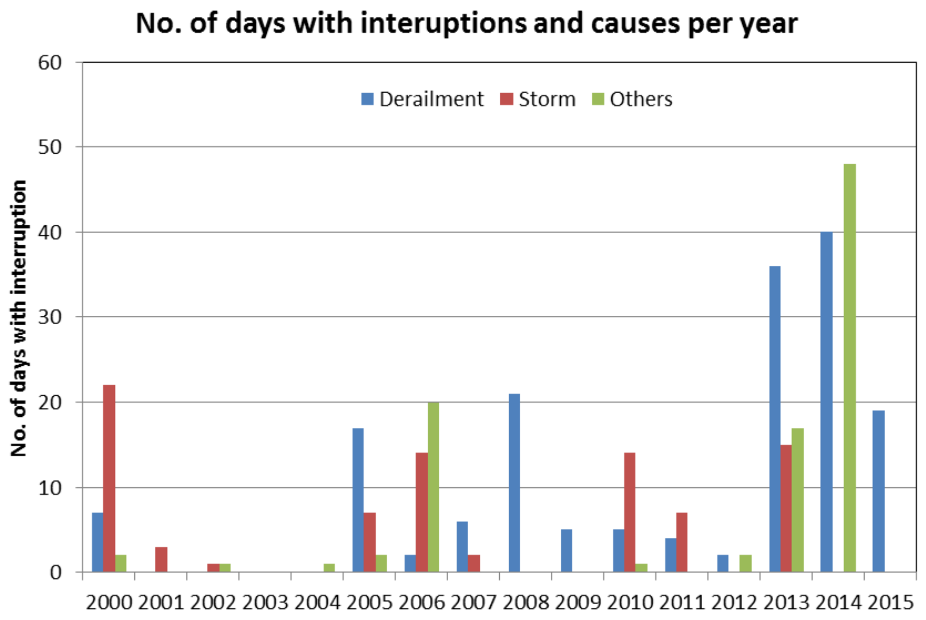

FIGURE 1-3 MOST IMPORTANT CAUSES OF INTERRUPTIONS AND DISTRIBUTION OVER TIME OF THE NUMBER OF DAYS OF INTERRUPTION

The causes of the interruptions are shown in Figure 1-4. As it emerges, approximately 51% of the interruptions were caused by derailments and 26% were due to weather conditions or natural disasters. Next come fires on trains or alongside the line with 7% and electrical and signaling faults with 6%. Collisions on the railway had 6% and at level crossings 4% of the cases but less share of the number of hours. Note that these only include accidents causing an interruption lasting a full day and that accidents at level crossings are the most common kind of accident on the railway but generally do not cause very long interruptions.

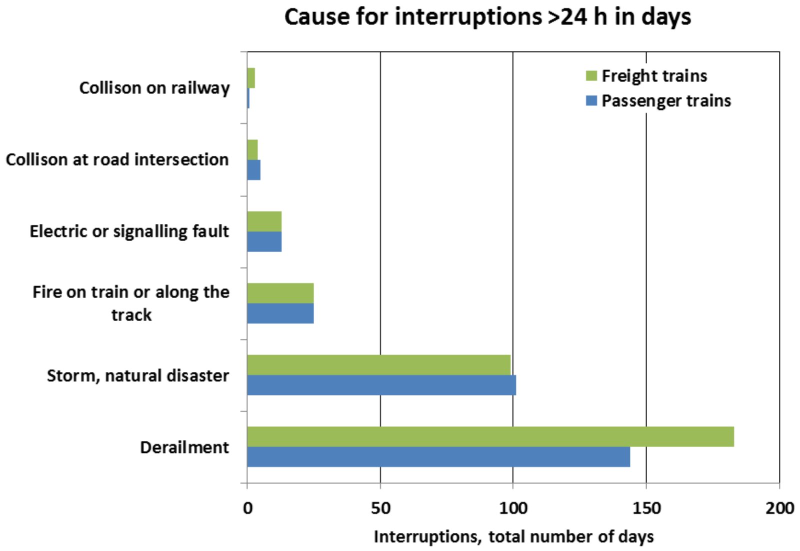

Figure 1-4 Days of traffic interruption due to different causes

The question is what conclusions we can draw from this survey. It is evident that derailments and weather conditions cause the greatest problems as regards long interruptions of traffic in Sweden. Our figures do not go further back but over the period in question the problems seem to have increased.

Derailments are problems that must be resolved within the railway system. It should to a certain degree be possible to predict such problems and take action to avoid them. The increase in the number of derailments might be due to both increased traffic and an accompanying increase in wear and maintenance backlog. This has also attracted great attention in Sweden among the railway's customers and players and among politicians, and measures to deal with the problem are an important feature in the Swedish Transport Administration's action plan.

The increase in extreme weather conditions is due to the climate crisis, which naturally does not only affect the railway. This is a problem that does not primarily have to do with the railway system but affects the whole of society to a greater or lesser extent. These problems are difficult to predict but it is possible to mitigate the consequences by taking action.

HOW CAN MAJOR TRAFFIC INTERRUPTIONS BE AVOIDED AND THEIR EFFECTS MITIGATED?

Several possible measures can be taken to avoid major traffic interruptions, and many of them can be obtained through automation increase.

In summary, 77% of interruptions had infrastructure-related causes and 23% operator-related causes, see Table 1-1. The question is how far it would have been possible to avoid these interruptions by means of maintenance, investments or some form of organizational measure.

TABLE 1-1 NUMBER OF TRAFFIC INTERRUPTIONS, RELATED TO INFRASTRUCTURE AND OPERATION, WITH AN INDICATION OF HOW THEY CAN BE AVOIDED

Alternative measures	Number of interruptions	Share %
Infrastructure-related		
Better track maintenance	18	32%
Better drainage	7	13%
Tree securement, rock removal	6	11%
Investment in road protection	4	7%
Operation, track works	4	7%
Investment in signalling system	2	4%
Better snow clearance preparedness	2	4%
Total, infrastructure	43	77%
Operator-related		
Better train maintenance	7	13%
Operation of train	5	9%
Total, trains	12	21%
Other	1	2%
Total	56	100%

As regards derailments, better maintenance is obviously crucial but better inspections of the line to detect faults and deficiencies in time may also be important. It is thus a matter of dealing with the whole chain with preventive maintenance, inspection of the line’s condition, and corrective maintenance before interruptions occur.

Roughly the same reasoning applies to derailments caused by vehicle deficiencies. With better detectors on the vehicles and on the tracks, faulty vehicles would be able to be detected in time in the same way as more preventive maintenance would reduce the risk of derailments caused by faulty vehicles. Investment in more track-friendly running gear would reduce wear to the track. Incentives for this may be needed, for example lower track access charges for vehicles with track-friendly running gear since these are often more expensive than vehicles with conventional running gear.

When it comes to interruptions caused by weather conditions it is obviously not possible to reduce the risk of adverse weather but on the other hand the risk of interruption can be reduced with preventive measures and measures to repair damage quickly. Regarding torrential rain, better drainage is one appropriate measure and fell trees to prevent storm damage another. At best the most serious deficiencies were rectified after the first extreme storms. As regards storm damage, Hurricane Gudrun in 2005 brought down as much forest as in a normal year of felling in Sweden. But forests still exist and the meteorologists are warning of more extreme conditions in the future.

It differs as concerns snow preparedness because snow cannot be cleared until it has fallen. Here it is not only a matter of money but also of organization. In this case, the deregulation of the railway has been of some importance since responsibility rests with several parties and the function was not given any high priority in procurement from the outset. The Swedish Transport Administration has now assumed overall responsibility for snow preparedness.

Other interruptions, for example interruptions due to collisions, are caused by incorrect operation, "the human factor", i.e., personnel have not followed rules or instructions. This may in turn be a result of insufficient training, inspection and preparedness. Examples include collisions caused by incorrectly set braking, derailments in marshaling yards and collisions with work vehicles carrying out work on the line. In some cases, the risk of accidents is minimized with the help of technical systems.

Regarding collisions within the railway system these have been minimized through the introduction of ATC (Automatic Train Control), which brakes the train automatically if it is not running at the right speed or risks missing a stop signal. The system has however not been installed everywhere, in particular not in marshaling yards where it would be both costly and impractical to have such a system. One example of a major interruption that could have been avoided with ATC is the derailment at Borlänge marshaling yard in 2000 where a freight train was running too fast and left the line. It was also a high-risk derailment since a number of wagons carrying LPG (Liquefied Petroleum Gas) had derailed and risked leaking their contents. Fortunately this did not happen, nor was anyone injured in the accident.

The root cause of the train running too fast, however, was that the driver was drunk. The question then is whether installing ATC in all marshaling yards, a multi-billion investment, is the best measure. An alternative is to install alcohol safety interlock devices in all locomotives, which would be cheaper than installing ATC in all marshaling yards but on the other hand would not prevent other kinds of accident. Yet another measure is better control and driver training, but this measure cannot eliminate all risks either.

Regarding collisions between cars and trains, a program exists to reduce the risk of accidents through better protection for road users and grade-separated crossings. All new lines are constructed without level crossings so, technically speaking, it is possible to eliminate accidents by redesigning the crossings but this is not possible for practical and financial reasons.

When it comes to mitigating the consequences of interruptions, regardless of their cause, the possibility to divert traffic onto other lines is of strategic importance. Many interruptions have occurred on the Northern Main Line north of Vännäs where there is no parallel railway. South of Vännäs there is now the Bothnia Line which can fulfill this function.

Another measure to facilitate diversions is to ensure that good connections exist between different lines, e.g., in the form of triangle tracks between strategic links. A triangle track means that freight trains can run directly between two lines without the locomotive having to change ends. In order to facilitate diversions, the administrative routines for diverting trains can be simplified. The establishment of a National Traffic Management Centre, which is being planned by the Transport Administration, is also a measure that will facilitate control and diversion of train traffic. Indeed, the diversion of traffic will have to be effectively planned.

DELAYS LONGER THAN ONE HOUR IN SWEDEN IN 2014

An investigation has also been done of delays more than one hour in passenger and freight traffic in Sweden in 2014 by KTH. While delays in passenger traffic are normally measured in minutes, requirements as regards freight traffic vary from one hour to some days. In the case of a delay longer than an hour, travellers risk being so delayed that their journey is rendered pointless or that the benefit from the journey is severely limited. A delay longer than an hour may disturb the train circuits so that other trains are also delayed, causing additional costs for operators and customers.

Individual distribution by cause for freight trains, passenger trains can be seen in Figure 1-5 and aggregated data of grouped by possibility to impact the delay in Figure 1-6. Infrastructure is the major cause in the case of passenger traffic, electrical installations being the predominant cause with 21%. Accidents and natural events are very significant as regards passenger traffic, with 29% of the delay hours, while this category accounts for 10% in the case of freight traffic.

Railway companies are the biggest cause in freight traffic with 37% of the delay time, Late from depot being the predominant cause with 16%. Infrastructure faults are also very significant with 22%, the most common cause being electrical installations.

Passenger traffic thus has a relatively high share of infrastructure-related causes, in particular as regards electrical installations and signal installations. The fact that the passenger trains produce a greater number of train-kilometres is important, since risk increases the longer the distance driven. Almost three times as many train-kilometres were driven in passenger traffic as in freight traffic in 2014.

Putting the number of train-kilometres in relation to the number of delays lasting longer than an hour, a freight train can travel approximately 3,000 kilometres before it is subject to an extra delay of more than an hour. A passenger train can travel an average of 42,000 kilometres before being subject to a delay of more than an hour. The risk of being delayed by more than an hour is thus 14 times higher for freight trains.

One conclusion that can be drawn is that long delays in the case of passenger traffic are due to external factors in the form of overhead wire faults, people on the tracks, storms and being disturbed by other trains to a greater extent than in freight traffic. Such causes are difficult for the railway companies to influence directly and can only be influenced to a degree by the Infrastructure Manager.

Regarding freight traffic, Late from depot or to/from abroad and also disturbed by other train are very significant and can in some cases be considered internal factors over which the railway companies themselves can exert some degree of control. The fact that late from depot has such great impact is on the other hand an indication of the need for more flexible timetable planning and operative management of freight traffic.

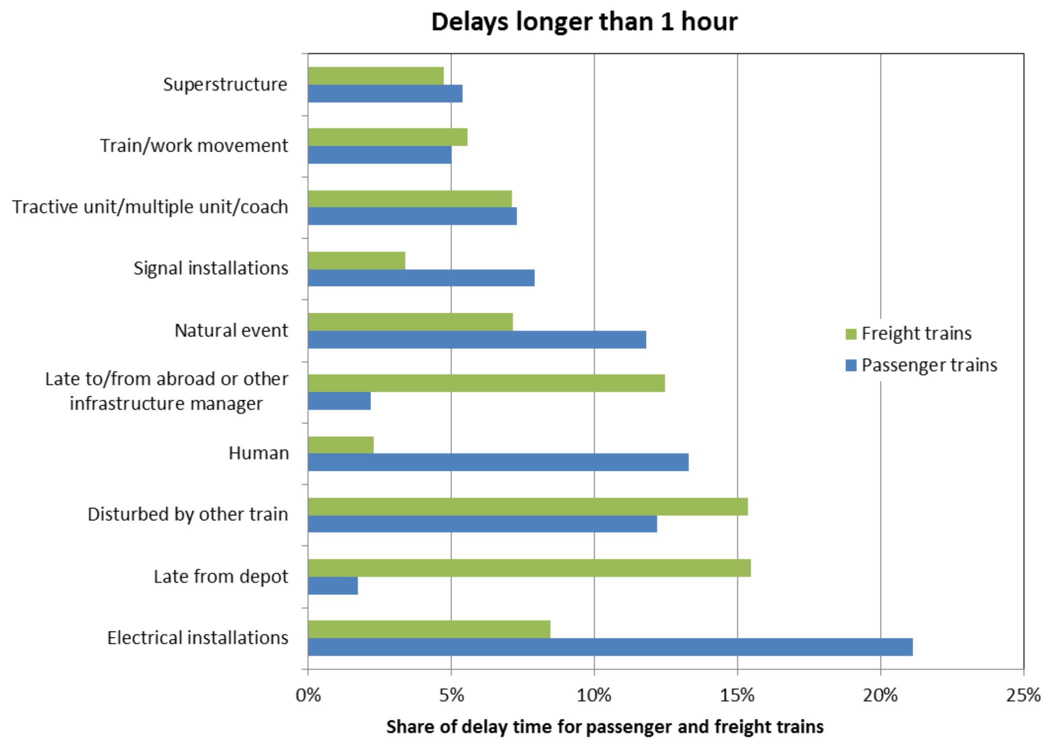

FIGURE 1-5 COMPARISON BETWEEN FREIGHT AND PASSENGER TRAINS: DELAYS OF MORE THAN 60 MINUTES, BY CAUSE ON LEVEL 2, RANKED BY SHARE OF DELAY TIME FOR FREIGHT AND PASSENGER TRAINS.

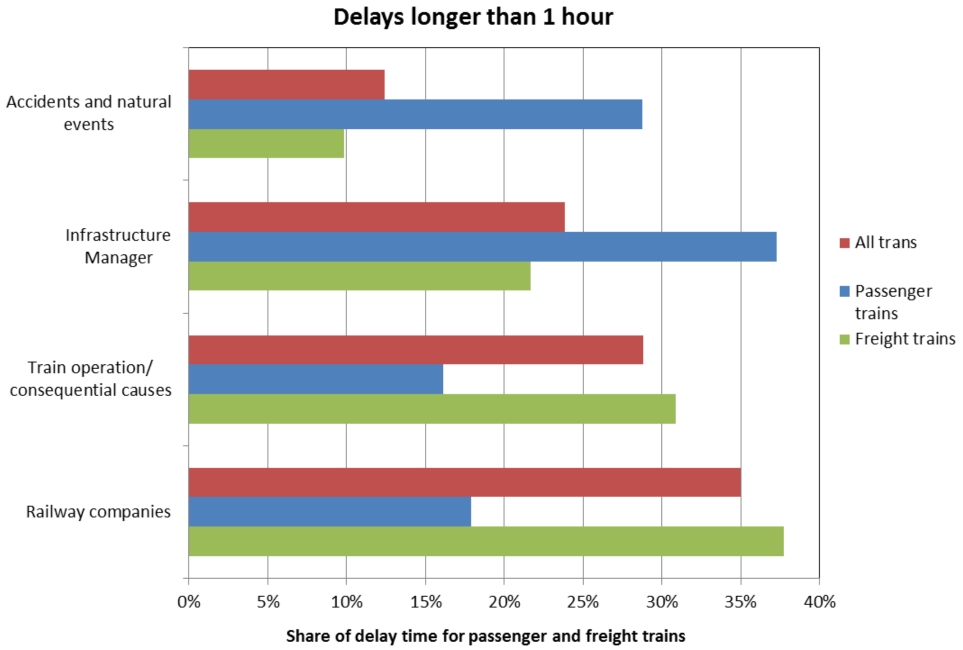

Figure 1-6 Comparison between freight and passenger trains: delays of more than 60 minutes, grouped by impact possibility; share of total delay longer than one hour.

2. Case studies of disruption management process implemented for dealing with extreme weather

In this chapter, we analyse the disruption management process currently in place in Spain and in the UK. Specifically, we consider the procedures implemented to cope with extreme weather disruptions. After a general analysis for the two countries, we focus on four case studies of actual floodings happened in the UK, paying particular attention to the respect of the process formalized in (CAPACITY4RAIL, 2016) and summarized in Section 1.1. Finally, we conclude with a discussion on the lessons learned from this analysis, with a particular focus on the level of automation in use. Some recommendations are given on where automation may be increased.

2.1 Disruption management by ADIF

The Spanish railway infrastructure owned by the state is managed by the 'Administrador De Infraestructuras Ferroviarias' (ADIF). In 2016, ADIF published a totally reworked "Network Statement" in accordance with updated national and European regulations, directives and laws. The document describes primarily the features of the infrastructure available to Railway Companies, and provides information on the conditions of access to the same. Furthermore, it details general rules, deadlines, procedures and criteria concerning charges and capacity allocation, together with the information required to process an infrastructure capacity request (ADIF 2016).

Within this network statement, chapter 4.8 "Disturbances and Traffic Control" states that the traffic control shall take appropriate measures to restore normality in case of disruptions or disturbances of the rail traffic due to a technical failure, accident or any other incident. Therefore, ADIF has prepared a contingency plan, that includes a set of alternative procedures to normal operations, which purpose is to allow the operation, even in case of failures or facilities due to an incident either internally or outside the organization; and with the mission to create a comprehensive action plan to manage and resolve any contingency that disrupts the normal development of rail traffic on a preventive, predictive and corrective level (ADIF 2016).

The contingency activities are managed by the "H24 Network Management Center" ADIF's division, which has as main duty the coordination of rail traffic management and the provision to RUs with alternative solutions to traffic scheduling changes and any other solutions that help to maintain traffic regularity and normality. If required by the operating conditions, this division will also establish alternative transport plans for the various contingencies and incidents that may occur in the Network (ADIF 2016).

Nevertheless, ADIF has no specific disruption management approach dedicated to extreme weather, which is thus handled according to the general contingency plan. The contingency plan goes beyond operational aspects and deals also with emergency management and environmental aspects.

The existing contingency plan is also considered in case of extreme weather and faces four types of actions in the evolution of an incident:

- organisation and resolution of problems affecting the RUs (passengers and freight);
- organisation and implementation of activities aimed at the normalisation of traffic;
- organisation of information on injury accidents: dissemination of personal data, status of possible injured, hospital locations, etc.;
- minimization of the impact on the surroundings and the environment.

The second action, *organisation and implementation of activities,* aims at the normalisation of traffic and corresponds to the response phase of the Emergency Management concept and, of course, on the disruption management process. For this action, a general contingency plan is prepared (Table 2-1). It is characterised by ten phases. These phases can be classified into *scheduled procedures and coordinated effort*s and cover the overall incident management approach:

TABLE 2-1 TEN PHASES OF INCIDENT MANAGEMENT BY ADIF

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 to achieve the recovery.
	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 Railway Companies 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: designation of the person in charge at the incident place for coordination and communication purposes, flow of information and recovery forecasts.
	Phase 10	Alternative Transportation Plan.

Within the *scheduled procedures*, measures involving the operational disruption management can be identified:

- urgent security measures and protection of traffic for incident prevention or minimisation (Phase 1): this includes the involvement of OCC, e.g., operation in degraded mode, line closure, etc.;

- identification of the type of incident and gathering of information to achieve the recovery (Phase 2); the intensity of involvement of the OCC depends on the type of incident and its restrictions on the infrastructure and operation. Of course, information exchange between the Emergency Management and the OCC is bidirectional;
- mobilising the intervention resources (Phase 4); this includes the use of rescue trains as well as the re-routing of trains;
- information to the railway companies and bodies of the railway infrastructure administration (Phase 5); besides the official information flow to involved railway companies, the OCC communicates to the affected RUs within their responsibility zone at least by signalling.

For the *coordinated efforts*, the person in charge is designated, and she is responsible for the communication and coordination between the incident point and the central level (Phase 9), which is the OCC for any operational aspects.

Concerning the operational aspects, they are in compliance with the disruption management process presented in (CAPACITY4RAIL, 2016).

2.2 Case studies on Floodings by Network Rail

For major incidents, Network Rail complies with the Significant Incident Performance Review (SPIR) process. A SPIR is held if the threshold of 1,000 minute delay is not breached but all parties agree that there are obvious lessons to be learnt from a particular incident. This applies particularly to extreme weather events. SPIRs are conducted face to face where possible, with teleconferencing facilities available in order to maximise the level of participation and ensure the right people attend. Technical root cause, incident response and service recovery are all discussed in detail, with actions being captured and tracked. The results are recorded in form sheets.

The forms include a header to give information about date, kind of incident, location, impact, etc., followed by a body to describe relevant facts about technical root cause, incident response and service recovery (see **Erreur ! Source du renvoi introuvable.**), and a conclusion with actions being c aptured and tracked.

Table 2-2 Body of the Significant Performance Incident Review form sheet (Network Rail)

Line	Description
Cause	What was the underlying or root cause of the incident? – e.g., ask “Why” five times. Consider both why the incident occurred in its entirety and, if significant, why it occurred at such a costly place or time of day. Is the incident a one off or the continuation of a trend?
Prevention	In relation to the cause, how could the incident (of such magnitude) have been prevented? What preventative measures are already in place; what further measures can be considered to control the risk of recurrence?
Incident response	How good was the response? Are the response resources well organised and located? How could the operations and/or technical response be improved? Were there any problems

	with contractors or external parties? Were resources deployed effectively?
Detection, diagnosis & repair	How good are the response resources once on site? Do they hold appropriate competences, leadership skills, etc.? How could we improve the speed/quality of fault detection and diagnosis? How could we reduce the time required for repair and testing? Were effective temporary repairs made to get trains running again quickly – without jeopardising efficient full repair?
Train service management & recovery	Did we have a plan for altered train running and how did it work? How could we improve any temporary operational arrangements applied during the incident and recovery after return to normal working? Did we get a sensible balance of delays vs cancellations and between PPM and CaSL? How well were reactionary delays, lost connections and other knock impacts managed? How well did we manage Service Recovery for the TOC's? Engage the TOC's in this section
Service to Passengers	How well was the interface with passengers managed and how well did the industry maintain a service to customers? Were there any significant issues with overcrowding (including overcrowding sufficient to cause safety concerns), provision of alternative transport, etc.? How well did we manage information flows to passengers? Engage the TOC's in this section where appropriate and use their immediate feedback to guide how much focus should be placed on this section
What went well?	
Transferable lessons	Identify actions that either reduced the impact of the incident or made it worse which are likely to be of value to learn about in other areas. For specific actions – e.g., by professional heads or corporate champions - identify the owner
Urgent performance advice	Identify any specific and obvious transferable lessons comprising good practice or bad practice that is urgent and / or otherwise worth other areas and routes knowing about. Identify the issue, reasoning and local owner of the action.

NR provided several SPIRs about flooding incidents on the London North Eastern (LNE) route from 2009 to 2011. The current cause for floodings is the amount of rain over a short period and the limited capacity of drainage systems.

According to the reports, the drainage systems along the line were not only fed by rain fall over the railways, but came also from external drains of surrounding land. Additionally, the siphon system under the railway can be impeded by backlogs downstream beyond the responsibility of NR. This calls a close coordination with local authorities as it is known from the Emergency Management and as it is performed successfully at sites with flooding history. All case studies reveal that a good preparation of the infrastructure and a reliable knowledge on the drainage system are good conditions to deal with floodings.

Furthermore, the interests of the different parties must be assessed: The operational interests are on sustaining the train operation at least with restricted speed in order to minimize the delay minutes. Furthermore, operations of different RUs (passenger & freight) must be coordinated. Concurrently, the infrastructure must be restored as soon as possible, e.g., by installing pumps and cleaning the drains. Hence, the earthwork and drainage engineers play a key role as they finally give the release for the termination of line closure or local speed restrictions.

Ideally, all persons in charge are already on the alert before the weather event occurs. The cooperation with weather forecast institutes and internal systems to detect severe weather activity is worthwhile. The benefit is documented in a case study, wherein at least the area of heavy rain and an approximate time frame was predicted although the exact location was unknown. Nevertheless, all staff was prepared, extra staff and vehicles were on standby, the location of drains, their inlet and outlet were identified, and the duty to care of the local Council were checked to prevent the amount of water moving from the highway onto the railway.

Of course, during the rainfall, there is little that the staff can do. Nevertheless, the knowledge about critical sites and the short travelling distance guarantee best reaction times.

In the following, we analyse four specific flooding incidents, as reported in official documents from NR. The documents report in detail processes and actions taken to tackle four flooding incidents which occurred in different parts of the UK railway network between June 2009 and December 2010. Processes and actions reported for each of the incident are compared with the disruption management process outlined in (CAPACITY4RAIL, 2016) in the form of SysML to spot similarities, differences and levels of automation employed. Description of the case studies and results of the comparison are given in detail in this document.

Incident: Morley flash flooding on Monday 15th June 2009

The incident consisted in intense rain over a two hour period starting at 1:43 pm at Morley station causing flash flooding. Figure 2-1 shows the part of the London North Eastern route H which was touched by the disruption and Morley station is circled in red. Two railway undertakings provide services on the disrupted line: TPE (TransPennine Express) and NRL (Northern Rail Ltd).

A MOM (Mobile Operations Manager) was on site before the beginning of the disruption, thanks to weather forecasts.

To reallocate the resources due to the disruption, the existing contingency plans were immediately applied, since the heavy rain had been forecasted. The application was prior agreed by the RUs in a conference call organized by the Extreme Weather Action Team (EWAT) after the weather forecast arrived.

A part of the traffic was rerouted through Normanton (pink arrow). The result of the disruption and of its management through the contingency plans implied 748 minutes of delay, 12 pines (train service that is short-turned so just part of its journey is cancelled) and 9 capes (cancelled train services) and 2 failed stops for TPE. NRL suffered 231 minutes, 1 cancellation and 18 PPM (Public Performance Measure) failures, that is, situations in which a passenger train does not arrive at its final destination within 5 minutes of its scheduled arrival time (within 10 minutes for Long Distance services).

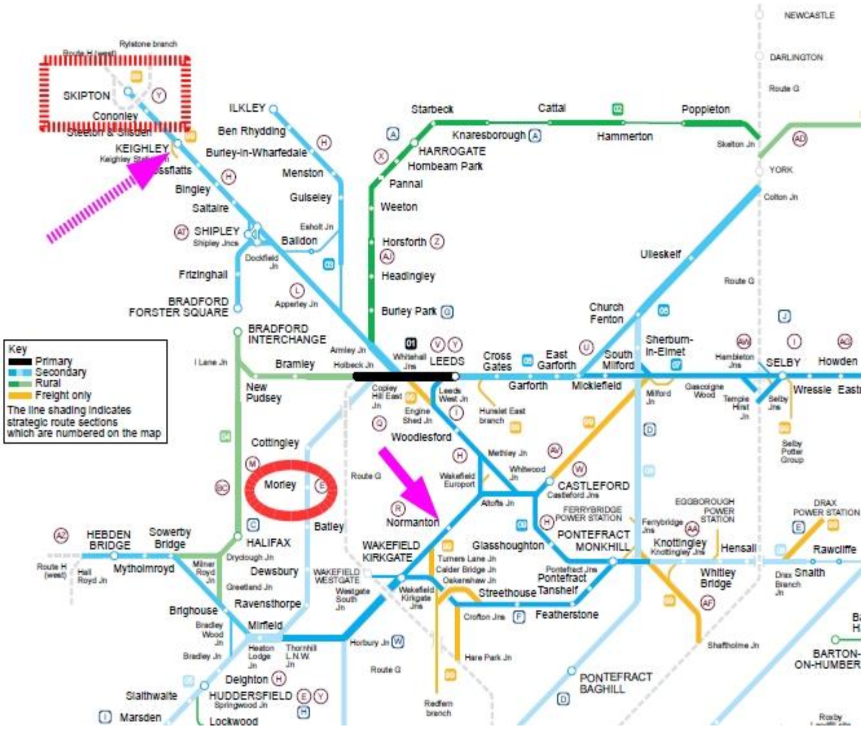

FIGURE 2-1 FROM MOVING AHEAD. PLANNING TOMORROW'S RAILWAYS: ROUTE PLANS 2010. ROUTE PLAN H CROSS-PENNINE, YORKS & HUMBER AND NORTH WEST (HTTP://WWW.NETWORKRAIL.CO.UK/ASPX/4451.ASPX)

For TPE, the normal operations were resumed at 4:18pm; for NRL no specific information is available: the normal operations were resumed as soon as possible.

During the disruption, staff on site monitored the situation at the station and along the line in both directions. For the whole time, the screens dedicated to the customer and operational information systems at the stations were updated for passenger information.

The management of this disruption followed quite closely the process formalized in the SysML diagrams of (CAPACITY4RAIL, 2016). Nonetheless, some parts of the process were performed differently. Specifically, the trigger of the process was the weather forecast rather than the incident itself. The weather forecast was very accurate. Hence, the sequence of activities related to the location of the incident, the mobilisation of resources, the disruption diagnosis and the organisation of the disruption management could be done a priori. Similarly, the determination of the recovery plan was done a priori with the agreement of the RUs. No optimisation tools were used to determine this plan, since existing contingency plans were implemented. Passengers were informed through screens at stations.

As it emerges from the report, the process was not really automated. In particular, the communications took place in the form of a conference call, no specific resource reallocation choices were made, and the monitoring of the situation was personally performed by staff members.

INCIDENT: FLOODING AT HARPERS BRIDGE AND CONONLEY ON WEDNESDAY 18TH NOVEMBER 2009

The incident consisted in intense rain falling for several hours in an area close to Skipton, along the London North Eastern route H. In Figure 2-1, Skipton station is highlighted with a red dashed rectangle. The trains of only one operator (NRL) were touched by the disruption. Weather forecasts were available, but the drainage system could simply not handle the volume of water over a short period at the site.

No MOM was available at the time of the incident, but two NR representatives arrived quickly on site when the incident occurred. The line was blocked between 7:30 to 8:45 am. At the same time the area was dealing with cable theft at Ardsley Tunnel, situated to the south of Leeds, and a serious derailment at Neville Hill depot, situated to the east of Leeds railway station.

To cope with the disruption, NRL stopped some services at Keighley (dashed pink arrow in Figure 2-1). The incident implied cancelling twenty services which for the Leeds North West service is extremely good especially considering that the incident was in the middle of the morning peak time. No rerouting was implemented.

As for the previous case study, neither optimisation nor automation was employed to manage the disruption occurred.

INCIDENT: RIDING MILL FLOODING ON WEDNESDAY 31ST MARCH 2010

The incident consisted in heavy rain falling for several hours in an area close to Riding Mill, along the London North Eastern route G. Figure 2-2 shows the part of the network touched by the disruption. This is a known flooding site which has not been correctly rectified as the track still floods due to no outfall connection. The area is susceptible to flooding which causes track circuit failures and until the flooding subsides, the track circuits cannot be relied upon. It must be noted that there were further floodings occurring simultaneously at Stocksfield and Dunston on the same line. Also, a bank slipped at Farnley Haugh. The thick red arrows show all these specific locations in Figure 2-2.

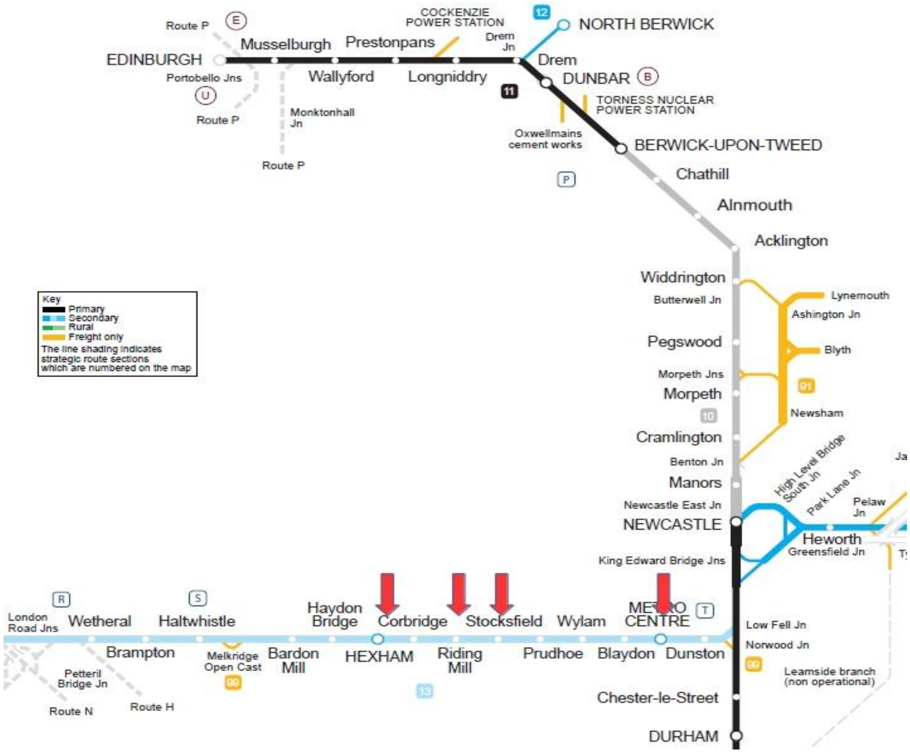

Figure 2-2 From Moving ahead. Planning tomorrow's railways: Route plans 2010. Route Plan G East Coast and North East (http://www.networkrail.co.uk/aspx/4451.aspx) Location of the disruptions in Riding Mill and its neighborhood (thick red arrows)

To deal with the disruption, single line working was introduced at the Farnley Haugh bank slip site plus a block to freight traffic was imposed. In the end, 20 services were cancelled, 37 suffered PPM failures, and 7 further trains were delayed. The total number of minutes of delay was 1020. The first delayed train was recorded at 4:50 am, and the last at 10:34 pm, while the actual disruption lasted from 3:47am to 9pm. The site was inspected at 6 a.m. to confirm the flooding after the first advice given by a signaller at Prudhoe. A team was then moved on site to use pumps to lower the water levels. The monitoring of the situation was done by staff members.

No information is present on the availability of weather forecasts, but it can be conjectured that they could not play a major role since it is mentioned that the incident was exceptional in that it occurred due to very heavy rainfall. However until the renewal of the outfall it is highly likely to occur again. To prevent similar incidents the drainage of the track needs improving and particularly the creation of new better outfall. Until this is completed the only mitigation that can be done is to try to pump the water away when it floods. This was done during the incident under analysis and it lowered the water levels enough to allow trains to pass the site all be it at a reduced speed. However the track circuits did not pick up until all the water had drained away.

As in the previous case studies, the management of this disruption follows quite closely the process formalized in the SysML diagrams. In particular, in this case details are given on the fact that a team was mobilised to locate the incident, first, and to restore the infrastructure (pumping the water away), afterwards. Once the disruption was diagnosed, the recovery plan was defined, by setting a temporary speed limit on some areas and imposing a single track circulation. However, no optimisation or automatic procedure was applied to decide on how to circulate trains over the temporary single track until the disruption was solved. Similarly no automatic sensors were applied to detect the end of the disruption. The communication was phone-based.

INCIDENT: SPITTAL (TWEEDMOUTH) FLOODING ON FRIDAY 10TH DECEMBER 2010

The incident consisted in a large amount of water collected in the field adjacent to the running line on the down side of the ECML. Specifically, the incident was noticed at 5:52pm of December the 10th, 2010, at Spittal, along the London North Eastern route G (shown in Figure 3 and indicated with a thick red arrow). The same area had been touched by a similar incident a few months earlier. On that occasion floodwater overtopped the embankment and caused significant erosion of the up side of the embankment.

As a result of the report on the flooded field, the Morpeth Track Section Manager ordered an emergency speed restriction. At 6:28pm both roads were stopped to all traffic since the amount of water running down from the surrounding land had totally overwhelmed the drainage and was starting to seep through the embankment. The Route Geotechnical Engineer was contacted and requested to attend the flooded site. Following a discussion between the Route Geotechnical Engineer and the Track Section Manager, at 6:55pm authorisation was given to run bi-directional traffic over the down line at 5mph. The railway undertakings providing services on the line) were updated immediately, and then throughout the whole disruption period (East Coast - now Virgin Trains East Coast -, DB Schenker and Cross Country). Passengers were kept informed through the screens available at stations.

At the first light on December the 11th, two Network Rail Geotechnical Engineers attended the site to review the situation. The speed limit was increased to 20mph at 10:15am and the up line was opened to traffic at 11am, after the installation of pipes under the running rails for pumps to clear water. After a further increase of the speed limit to 50 mph at 2:55pm, the speed was resumed at 9am of December the 12th.

To define the resource rescheduling plan, two conferences were held between the railway undertakings, the NR remote condition monitoring (RCM) in Glasgow and the National Rail Communication Centre (NRCC), one at 2:30 and one at 3:15 am of December the 11th. The stakeholders negotiated to reach an agreement on which trains to circulate.

The total number of minutes of delay due to the flooding was 2425, with nine trains being cancelled and 13 suffering a PPM failure.

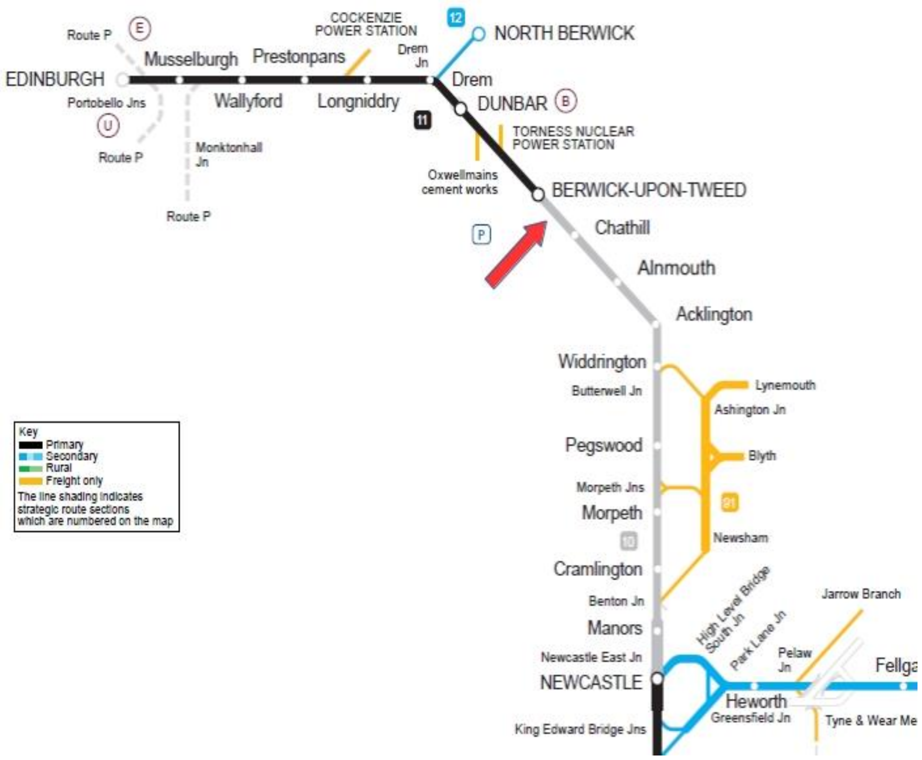

Figure 2-3 From Moving ahead. Planning tomorrow's railways: Route plans 2010. Route Plan G East Coast and North East (http://www.networkrail.co.uk/aspx/4451.aspx). Location of the disruptions in Spittal (thick red arrow)

Again, the management of this disruption follows the process formalized in the SysML diagrams. As in the previous case study, details are given on which were the teams to be mobilised 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. Again no automatic sensors were used to detect the start, the duration or the end of the disruption. The communication was mostly phone-based.

SUMMARY

In conclusion, the analysis of these four case studies of disruption management in the UK allows us stating that the process formalised in (CAPACITY4RAIL, 2016) through the SysML activity diagrams well represents the one normally implemented in practice.

Despite the case studies reported here refer to the period between June 2009 and December 2010, results of the comparison are fully valid since no update to disruption management processes have been introduced in Network Rail since then. This means that management processes used to tackle railway disruptions in the UK is today still the same as the one described in the various case studies in this document.

After carefully studying the reports of the incidents and disruption management, it emerges that almost no automation is in place to detect and monitor incidents on the railway line. Moreover, the disruption diagnosis is mostly based on experience of the expert on site. No automatic or optimised tool exists to define an ad hoc recovery plan.

Finally, communications between members of the staff and between the different stakeholders are mostly based on phone calls or conferences, but no common data base is available to automatically share the information.

Discussions with the other IMs involved in the project bring us to state that the same type of conclusions can be drawn for the other European countries.

2.3 LESSONS LEARNED

The analysis of the case studies reveals several aspects that should be considered to improve the disruption management to cope with extreme weather events.

PREPARATION OF CONTINGENCY PLANS

The application of universal emergency management strategies on disruption management processes to cope with extreme weather is not sufficient, as the complexity of railway operations requires resilient processes that consider the specificities of weather phenomena as well as interdependencies within the system.

So far, there is no common guideline, but the recommendations from the MOWE-IT project could serve as a reference standard that shall be implemented in contingency plans that are coordinated with the available management process for system inherent disruptions. The consideration of prediction models enables an early adaption of the railway operations in order to minimise adverse effects on the network. Furthermore, contingency plans related to extreme weather events shall consider the characteristics of the event as well as geologic and geographic peculiarities of the affected region.

COORDINATION OF DISRUPTION MANAGEMENT AND EMERGENCY MANAGEMENT

The case studies analysed reveal strong interactions with railway system internal and external responsibilities. Disruptions due to external reasons, e.g., extreme weather events, do not only affect the railway system itself, but also the environment and often other transport modes. Thus, disruption management and emergency management shall work hand-in-hand and benefit from each other:

- interfaces of disruption management and emergency management shall be defined, i.e., internal and external responsibilities;
- disruption management process shall not impede emergency management actions and vice versa;
- parallel processes shall be coordinated.

RESPONSIBILITY FOR EXTREME WEATHER MANAGEMENT

The implementation of disruption management strategies is a sovereign task of the IMs and is thus decoupled from the emergency management that coordinates the measures of local authorities and civil protection. The IMs are responsible for the conflict-free operation of their railway network, not only considering the operational circumstances and adverse weather conditions, but also the handover of trains from or to neighbour IMs. Moreover, extreme weather events can directly affect the territories of several IMs, even spanning national borders, and this complicates the disruption management. Furthermore, the IMs have to ensure the communication with the RUs in case of disruptions.

HIGH IMPORTANCE OF ORAL COORDINATION AND COMMUNICATION

In case of weather incidents, the coordination of all affected parties and the gathering of information are mainly done face-to-face by phone calls or meetings. On-site visits facilitate the coordination process and shorten the decision-making path.

In absence of technical devices, the use of, e.g., sensor data to support the decision making is not common practice. Since the availability of sensor data (e.g., humidity saturation sensors of the substructure) will increase, decisions during extreme weather events shall rely on both experience and technical data.

It is mandatory, that all involved parties get consistent information as soon as possible in order to rearrange operation.

2.4 Analysis of the level of automation observed

The case studies analysed reveal the importance of close coordination between IMs, RUs and local authorities in order to minimise the disruptions due to extreme weather events. Currently, the direct communication on-site or by phone prevails whereas automated procedures are subordinated.

While automation in metro systems is quite advanced, the constraints for automation in operation on main-lines are more challenging because of the diversity of trains, the complexity of the network and the interoperability needs due to multiple RUs operating on interconnected infrastructures (Bienfait, Zoetardt und Barnard 2012):

- the track layout is extensive and complex;
- the roll-out of new systems across the network takes many years, resulting in most journeys spanning lines with significantly different levels of fitment of infrastructure;
- a lot of different train types coexist (with different performance and door layout);
- the trains are not all dedicated to a particular line; they may go anywhere on their national network, and in certain cases anywhere in Europe;
- many journeys have to take place during periods when substantial on-track engineering work is in progress;
- infrastructure owners, train owners and operators are independent – and sometimes, other parties are also involved – such as train leasers.

Nevertheless, Automatic Train Operation (ATO) will find its way to main line operations, driven forwards by ETCS and ERTMS systems. However, the field for automated applications for the disruption management is quite limited.

Scales of automation for guided systems

Disruption management procedures are adjusted according to the information that is received. Thus, the level of automation in disruption management is highly linked to the level of automation in communication.

In order to determine the level of automation in the case studies analysed, the decomposition of the process into four stages according to Sharples et al. (Sharples, et al. 2011) is applied:

- Information Acquisition (IAc);
- Information Analysis (Ian);
- Decision and Action Selection (AS);

- Action Implementation (AI).

This approach is presented in (CAPACITY4RAIL 2016) and defines for each stage of human-automation interaction five level of automation (Table 2-3):

Table 2-3 Four-stage model of human-automation interaction with distinction of automation levels (Sharples, et al. 2011), (CAPACITY4RAIL 2016)

		stages of human-automation interaction			
		Information Acquisition (IAc)	**Information Analysis (Ian)**	**Decision and Action Selection (AS)**	**Action Implemen-tation (AI)**
Level of Automation	**None**	human gathers all information without assistance from com-puter or technology, using senses for dynamic information and paper-based sources for static information	human analyses all information	human makes all decisions, without any support	human implements all actions and communications
	Low	human gathers all information but with assistance from IT (telephone/fax/email /CCF/TRUST)	computer analyses information as it is received and detects conflicts only as they occur	computer provides decision support to the human to help ensure decision is not unsafe	computer augments human's physical labour (e.g., hydraulic assistance on lever)
	Medium	information acquisition is shared between the automation and the human	computer gives a future prediction based on basic information for the short term (e.g., current trains on the workstation)	computer performs basic decision making (e.g., first come first serve and run trains to timetable) and leaves perturbed modes to the human	computer implements physical actions, but human is required to perform communications (possibly with assistance from information and communication technologies)
	High	computer and technology provide the majority of the information to the human	computer gives a future prediction based on fuller information (e.g., trains arriving in future, infrastructure state, and current situation on other workstations), and highlights potential problems/conflicts over a longer period of time	computer performs mid-level decision making (e.g., apply set rules to delayed trains) and has basic plans for implementation during perturbed operations	computer implements physical actions and basic communications but human is required to perform complex or unusual communications

	Full	computer gathers all information without any assistance from human	computer gives a long-term future prediction using all relevant data (e.g., up-to-date information on train speeds, infrastructure state, etc.)	computer makes all decisions under all circumstances using complex algorithms to determine the optimal decision (e.g., based on a high-level prediction of the future state and optimal conflict resolution) and provides flexible plans for disrupted operations	computer implements all actions and communications

The following section examines the level of automation of the disruption management procedures presented in the case studies above. As the kind of measures varies considerably, and due to the fact that the case studies are on different focus and granularity, a uniform assessment can hardly be performed.

2.4.1 MOWE-IT: Scales of automation

The MOWE-IT project summarises guidelines from case studies and describes them in a mostly generic manner, adaptable for any railway. Nevertheless, some of the recommendations can only be put into practice since the technology and hence the automation of processes is advancing.

For instance the involvement of weather forecast institutes for information acquisition and prediction models for their analysis presume a high level of human-automation interaction. The use of these resources results in a significant improvement of the preparedness in case of extreme weather events.

Beyond this, actual reports from on-site during severe weathers owning none or low level of human-automation interaction supports individual operational decisions.

The level of automation of the decision and action selection, as well as of the implementation of actions, depends highly on the general level of automation of the OCC. The level of automation for the main lines is assumed to be high. In case of perturbed operations, the level will be downgraded at least one step in order to increase the responsibility and freedom of choice of the human operator.

The level of automation can then again be increased, provided that contingency plans are available. The development of those contingency plans mostly relies on human experience, i.e., with medium level of automation, whereas their implementation can again be on a higher level, depending on how their application is prepared.

2.4.2 ADIF: Scales of automation

ADIF provides no information concerning disruption management explicitly dedicated to extreme weather but considers disruptions in general.

The ADIF H24 Network Management Center coordinates the measures to minimise the negative effects of extreme weather events for the railway operation. So far, input from weather forecast institutes are not instantly available and is not considered with priority. Prediction models for regions at particular risks are not established. Thus, precautionary measures rely on human experience.

The H24 Network Management Center is also responsible for Emergency Management and manages the communication with local authorities as well as with RUs. Naturally, the coordination with external parties is between designated staff, face-to-face or by phone calls. In this case, the level of human-automation interaction is low.

The internal procedures to react on disruptions due to extreme weather events follows the settled operational procedures supported by the availability of contingency plan for extreme weather events.

2.4.3 NR: Scales of automation

Network Rail succeeded in the integration of weather forecast information as an early warning system in the operational control. The benefit is to expand the time slot for preparation and to localise the area that will probably be affected before an extreme weather event occurs. The human-automation interaction level of this procedure is assessed as medium/high: in case of need, the weather information arrives automatically in the OCC.

The decision and implementation of appropriate measures is then in the responsibility of the local OCC, i.e., decisions are taken on-site, even if their consequences may affect larger areas and neighbour OCC's, e.g., temporary speed reductions or line closure.

Preferably, contingency plans and response plans for extreme weather are available. Their preparation relies on experience and, if possible, the plans are reworked according to the NR SPIR form sheets described in Section 2.2.

As the incident reviews of NR are very detailed, the reports reveal the vulnerabilities of the response plans: Extreme weather events disturb the railway operation by damaging parts of the infrastructure. In case of floods, obstructions of the siphons are often the sticking point, which impede the water to drain off. Currently, the maintenance work on the siphons is not supported by automation; each siphon needs to be inspected manually. The deployment of sensors to replace this kind of inspection would reduce the current workload and improve the operational conditions.

Furthermore, the NR case study illustrates that the communication between affected parties is of high importance and is effectively done face-to-face, i.e., with low level of human-automation interaction.

2.5 Recommendations on possible specific automation improvements

The level of human-automation interaction is generally quite low in case of disruption, aiming to increase the independence of decision-making, but also the responsibility of the human operator. The higher influence of human operators in case of exceptional incidents allows a response fitted to the circumstances in those cases where experience is missing. Nevertheless, if specific extreme weather events occur more frequently, the application of automation becomes reasonable, and also the way of communicating may become more formalized in order to implement procedures with higher level of automation.

Integration of meteorological services

The automatic integration of weather forecast models in the preparation for extreme weather events in the railway operation is not yet common, although severe weather alerts influence of course the precautions. For instance, Germany's National Meteorological Service, the Deutscher Wetterdienst (DWD), is legally obliged to provide meteorological services and to safeguard aviation and shipping transport. Furthermore, there is a tight cooperation with rescue services, through the provision of a meteorological warning system tailored for civil protection. So far, there is no dedicated cooperation with the railway transports (DWD 2015).

The success of the cooperation of Network Rail and the National weather forecast institutes will drive the development of a cooperation with the meteorological services as it is already state of the art, e.g., in aviation. This requires a profound knowledge of topologic and geologic characteristics, a dense network of sensors along the lines, a tailored prediction models and in a final step, an automated integration in the disruption management process.

Beside the extreme weather events with direct impact on the region where they occur, the consequence of volcanic eruptions in distant countries is also a case of application for the integration of meteorological services. The consideration of the propagation paths of ash clouds may enable to adapt the freight service and the long-distance train service in areas where air-traffic is or will be limited. Thus, IMs and RUs may benefit from enlarged time frames to adjust the train operation according to the restriction in air traffic.

COMMUNICATION ACROSS ORGANISATIONS

The communication in railway operation between IMs, RUs and other involved parties is regulated by Technical Specifications for Interoperability (TSIs). Therefore, the European Commission have specified a common Information Exchange Architecture that favours mostly a Peer-to-Peer interaction model (European Commission 2014).

This document regulates the exchange of data (process & protocol) between RUs and IMs, e.g., concerning a Path Request, a Train running forecast, but also Service Disruption Information, etc. It is intended to replace the manual work and support the incident management in general (ERA Telematics Team 2016).

Although the management of disruptions due to extreme weather events is not mentioned explicitly, the final objective of the common Information Exchange Architecture is to transmit any kind of communication.

So far, the communication procedures are not formally organized. In most cases, the parties involved make an arrangement instantaneously, without considering previous events in a systematic way. Often after a bi-directional communication other affected parties need to be informed, and this brings the emergence of time lags in the information chain. Thus, more organization, formalization and finally automation would improve the quality of information in the sense of same information for anyone at any time. In particular, the available information may be immediately shared with all the involved IMs and RUs, but also with passengers and other organizations managing other transportation modes. This may ease the multi-modal coordination, and hence speed up the definition and deployment of effective contingency plans.

DECISION SUPPORT TOOLS

Most of the decisions in the definition of recovery plans are made by humans based on their sole experience. The automation of the processes involved in the resource reallocations is to be sought. Such automation shall take the form of decision support tools capable of allowing a faster response to disruptions and of providing optimized reallocations. Several optimization algorithms exist in the academic literature to be the basis of such tools. However, a topic that has not been sufficiently studied yet is how negotiation between stakeholders can be integrated. Indeed, this is a very important topic, especially in the current railway system, in which the IMs need to deal with several RUs and sensible compromises need to be reached.

MONITORING

During disruptions, the operational teams on site typically monitor the state of traffic and infrastructure. Concurrently, the charged dispatchers manually monitor the evolution of the implementation of the contingency plans. Automatic monitoring devices can be used instead. With such devices, the measurements may be more frequent and precise, allowing a more prompt response and a quicker recovery of normal operations.

3. Roadmap for automation increase

3.1 Automation on the Railway

As detailed in (CAPACITY4RAIL, 2016), automation can be defined as any automatic response to a situation that is initiated by either a machine or a human. The human automatic response is the culmination of years of experience in handling of tasks and routine execution of actions. This experience is particularly relevant when dealing with large disruptions. "Automatic response that is mechanised is what we usually term as automation" (Sheridan, 2001). This response of a machine could be the culmination of: sensing activity, through a sensor array; problem detection, through signal processing and stimuli identification; a decision making entity, such as a computer; finally a reaction is solicited from the system in a mechanised manner. The impact of the response must be found in the efficiency of the system management also thanks to the narrowing of the interaction between the environment and the system itself, which has proven to be very important in the automation of rail metro lines. For example, automatic doors on platforms may prevent obstacles from getting on the track and reduce the interactions between passengers and trains; automatically monitored level crossing may avoid collisions between road vehicles and trains; automatically monitored track neighbourhoods may allow the prevention of accidents due to external obstacles as for example trees growing around the rail and causing traffic interruptions.

Mainline railways, unlike metro systems, are complex socio-cognitive systems. That is, they involve the use of both humans (drivers, controllers, station managers and designers) and machines (point machines, signalling centres, solid state devices and trains) so as to produce a single output, which is a journey on such a system or a reaction to a disruption. Automation of such a complex system requires an understanding of how such systems interact with their various interfaces, and in particular how the human interface with this system. Therefore it is necessary to delineate the primary activities. A railway system can be defined as a wheel on rail system that provides transportation of a person, or a commodity, from source to destination with a predefined level of repetition, punctuality and security."

Using this definition it would be prudent to infer that the goals of a railway system are to:

1. Provide the capacity to carry persons or goods,
2. Provide safe passage of its occupants across the system,
3. Adhere to a predefined schedule for running more than one service.

These three goals can be further elaborated into the following subsystems, as shown in Figure 3-1:

1. Rolling stock (trains), to provide seats and carry freight,
2. Command and control systems that can detect and route trains to the right destination,
3. Stations, so that passengers can alight or depart on a journey,
4. Infrastructure so as to establish and maintain track, signalling and power systems for the rolling stock.

Automation of a mainline railway would involve the introduction of mechanisation or computerisation into the various activities that influence or govern the operation or performance of the above subsystems. Each subsystem could be said to comprise various sub activities. In the following, we discuss the automation of the four subsystems separately.

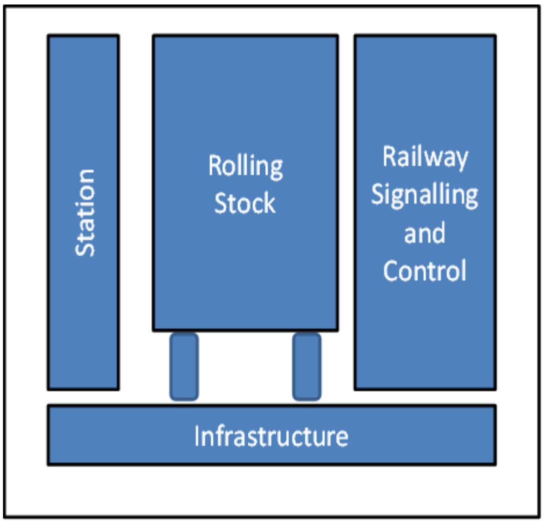

FIGURE 3-1 DECOMPOSITION OF THE RAILWAY SYSTEM INTO SUBSYSTEMS

3.1.1 ROLLING STOCK

Rolling stock is a critical component of a railway system as it carries within it the passengers and goods on a journey. The chief activities on this subsystem are:

1. Driving: to engage the motors and move in a safe and efficient manner;
2. Dwelling: to stop at required stations or freight yards so as to allow the exchange of passengers and goods.

All of these activities can be automated at various levels. EN62290 provides a standard in order to automate driving (BSI, 2006) and control. An Automatic Train Operation (ATO) system is used centrally to control train movements from a driving perspective. Table 3-1 lists the features of an urban railway system with reference to the equivalents of a mainline railway system. The objective of running a mainline railway is different to that of an urban railway system. The mainline operator is chiefly concerned with:

a. Achieving uniform journey times so as to reduce the variability of arrival and departure times. This also reduces the need for allowing a large margin in the timetable for recovery from delays.
b. Achieving lower carbon targets as energy consumption is a critical issue for mainline operators (electric or diesel traction). Reducing energy consumption is not only beneficial to the environment but also to reduce operating cost.

TABLE 3-1COMPARISON OF FEATURES OF URBAN AND MAINLINE RAILWAY SYSTEMS

Urban Railway Systems	**Mainline Railway Systems**
Little or no mixed traffic	Mixed traffic (freight & passengers)
Short end to end journey times, not exceeding an hour in most cases	Long end to end journey times
Intensive passenger operations	Demand based operations (high density near urban centres)
Highly monitored infrastructure	Fenced but unmonitored infrastructure
Simple track alignments	Complex layouts with remote but highly sensitive junctions
Homogeneous rolling stock	Heterogeneous rolling stock

Ideally, mainline operators would like to reach a satisfactory target which is a blend of the above mentioned objectives. This can be achieved by controlling the driving style. Driving on a mainline can be categorised into the following levels (

Table 3-2):

i. Manual Train Operation (MTO) Systems – The driver is completely in control, with the addition on track magnets (balises) (The UK employs an Automatic Warning System (AWS) and Train Protection Warning Systems (TPWS)) to transmit movement authority and also to protect against exceeding movement authority around signals.

ii. Semi-Automatic Train Operation (STO) Systems – Introduction of Automatic Train Operation (ATO) systems with European Train Control System levels 1 and above. The trains are equipped with an interventionist computer that enforces movement authority instructions (LOA) from the Automatic Train Protection (ATP) system (actively braking the train when it over speeds or is exceeding the advised speed).

iii. Driverless Train Operation (DTO) Systems - ATO equivalent systems where the driver is considered as a supervisor and only intervenes when the system is in a faulty condition. In such an arrangement the driver could be situated in the cab or driving from a remote location. The on-board system provides speed demand for the train control systems and uses the ATP equivalent system to provide safety.

iv. Unattended Train Operation (UTO) Systems – An ATO equivalent system is integrated into ETCS system and drives the train without any need for supervision.

TABLE 3-2: METHODS FOR AUTOMATION WITH DIFFERENT LEVELS OF DRIVING SYSTEMS ON TRAINS

Driving
Manual
Semi-Automatic
Driverless

Unattended

The impact of automation increase in rolling stock driving will be critical mostly in terms of the quick implementation of contingency plans. For example, with manual driving the contingency plan must be communicated to the driver, who will have to understand it first and implement it afterwards. The specific implementation will depend on the driver, and this may imply a rather high noise in the plan deployment. With increasing automation up to the unattended driving, instead, the contingency plan will simply be uploaded in the ETCS system and it will be immediately and precisely followed by the whole fleet of trains involved.

3.1.2 Command, Control and Communication (CCC) Systems

Command and Control systems (CCSs) provide for the safe operation of trains on a railway. CCS subsystems have the following chief tasks:

1. Detecting trains on the infrastructure,
2. Analysing conflict of resources between trains,
3. Allocating resources at the right time to each train,
4. Ensuring there is a safety margin between consecutive trains,
5. Communicating information on the railway to each type of train.

The aforementioned railway control functionalities have evolved due to various additions and adaptations made to the CCC system over the last century. Various systems can be employed to achieve the tasks mentioned above. These systems are:

1. Train protection systems (TPS): - These are systems that protect the movement authority of trains so that the safety of the system can be maintained. The TPS consist of a detection system followed by a data transmission system.
    a. Train stops: - These are mechanical stops set along the track sides that activate the train's brake if it exceeds movement authority (signal). Although it is an efficient system, it suffers from the need to be maintained regularly so as to ensure reliability.
    b. Induction based protection: - Use of magnets for AWS and TPWS so as to transmit to the driver the aspect ahead. If the information is not acknowledged the train's braking system is triggered. This provides for more efficient data transmission to the train.
    c. Radio based protection: - Using radio transmission it is possible to track distances between trains and enforce moving block restrictions so that more trains can be accommodated onto the network. The ETCS relies on GSM-R transmission for train reporting and transmits movement authority.
    d. Autonomous Protection: - These are ATO systems that calculate the train position and speed and transmit it back to the control centre. They receive information continuously from other trains on the route and vary the driving accordingly.
2. Train Detection systems: - Detection systems are crucial to identifying the position of the train on the infrastructure. Based on this the control of a railway system is feasible. Types of train detection system are:

a. Manual reporting: Early railways had a visual confirmation of a train passing a particular junction box: the location was telegraphed or telephoned to the box ahead. With an increase in traffic, such a system becomes unsafe and inefficient.

b. Track circuits: These are large electric circuits that are closed with the passage of a wheelset over them leading to detection. With the introduction of electric traction, frequency based track circuits have become necessary.

c. Axle counters: These machines count the number of axles that enter and exit a particular track section. The advantage offered over the track circuit is that sometimes track circuits depend on the axle resistance. If this changes due to environmental factors, a track circuit might overlook the train and fail to detect it. Also axle counters require minimal maintenance and installation is relatively simple.

d. GPS based location: Previous systems relied on detecting a train but the introduction of faster ETCS based system requires active position reporting. A transponder installed on the train transmits the current position and speed to a central Radio Block System (RBS). This system provides the greatest accuracy with respect to location.

3. Traffic management system: - Traffic management systems on the railway function to resolve resource conflicts and route trains efficiently through the network. In order to maximise resource availability, it is important to assign a route to a train as late as possible and release it as early as possible. This is done to maximise the availability of the system. The types of route setting systems are:

a. Manual set and release systems with the junction signaller setting a point and then a signal. The disadvantage is that the signaller has to confirm visually or orally the position of a train near the route entry point.

b. Manual Traffic management (centralized traffic control - CTC): - Once relay based interlocking has been introduced, it is possible to “mimic” a local track layout and specific routes can be set by pushing buttons on the mimic board. The route can be cleared by a simple reset button. Such a system allows for the development of central traffic boxes that covers large areas on the network.

c. Rule Based Traffic Management: - The introduction of Solid State Interlocking (SSI) with computers allows for programming default routes. This is much faster than previous systems and the controller needs to only intervene when there are significant conflicts due to delays.

d. Autonomous Traffic Management: - Rule based systems can be further refined to set routes based on a timetable. Such a system records the strategies for conflict resolution from a human and employs these techniques to resolve conflicts autonomously.

The route management systems automatically progress from a manual system to a completely automated system. This enables the introduction of complementary systems that can enhance the efficiency of this system. Table 3-3 shows the CCC systems of a railway.

TABLE 3-3: PROGRESSION OF SYSTEMS IN THE CCC OF A RAILWAY

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 TM

The CCC automation increase will improve the large disruption management under different perspectives. First of all, the automated train protection systems will allow the precise implementation of the contingency plans, in parallel to what discussed in the context of rolling stock automation. Second, an automated and optimized traffic management system will be crucial in the implementation of the contingency plan by organizing the disrupted traffic a smoothly as possible. This may also shorten the time needed to re-establish nominal traffic after the end of a disruption. Finally, the automated and punctual train detection systems will be helpful for the containment of all trains which are close to the disruption and for the diagnosis and prognosis of the disruption itself. These are all relevant activities identified in the formalised process of (CAPACITY4RAIL, 2016).

3.1.3 PLATFORMS

Platforms are critical areas for automation as they involve the transfer of passengers. Delays accrued on the platform are a major contributor to the performance of the railway. Platforms are required in:

1. Passenger guidance systems: - Passengers need to be able to enter and exit trains at platforms. The key to maintaining an operation time is to enable passengers enter and exit the trains as quickly as possible so that the trains can depart on time. This can be enabled by:
    a. Manual door operation: the doors are controlled by the driver or train staffs, whose responsibility it is to ensure that passengers are offloaded and the doors are clear for the train to leave. The responsibility for the safety is completely shouldered by the train staff.
    b. Automatic door operation: the doors are released automatically on arrival in the station and close at a predetermined time interval. Interlocking with the train traction is implemented so that trains cannot leave with a door open. The system assumes complete responsibility for the safety of the passengers. The information about door open and close is released by the driver upon arrival at the station.
2. Train Dispatch: - Once the train's doors are closed for departure the dispatcher needs to be notified so as to clear the route in front. This can be done manually or automatically.
    a. Manual dispatch: - On a platform, staff verifies that the train is ready to depart and indicate to the driver and dispatcher. The on-platform staff ensures that the trains leave on time and that there is no visible obstruction to the trains' movement.
    b. Automatic dispatch: - Once the train is ready to depart, the driver can request to leave and transmit the information to the dispatcher who will release the route to the driver. Platform screen doors (like on metros) can be used to ensure that the train is clear and dispatch information directly transmitted to the train.
3. Passenger management systems: - With overcrowding on the platform there is an added risk of a passenger ending up in a dangerous situation (like stuck in the door, fallen into the gap between platform and train or other serious emergencies on the platform).
    a. Platform staff will be required to monitor crowding situations and thereby closing off platform access so as to ensure safety.

b. An active monitoring system that senses the crowding level in platform and changes the state of systems to control the crowd. This could be from changing directions on escalators to activating full evacuation systems to control a fire and also alerting a station staff for assistance if there is a passenger related issue.

Freight trains also require management at yards for loading and unloading of goods at terminals and for quick turnarounds. Similar to platform systems the offloading and loading can be automated.

TABLE 3-4: AUTOMATION INCREASE ON THE PLATFORM INTERFACE

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

Platform automation will be critical in disruption management mostly due to the elimination of the need for manual interventions, which may perturb the implementation of the contingency plans as discussed with respect to the rolling stock automation. Moreover, automated passenger management systems may be particularly helpful during disruptions since typically main station platforms end up being extremely crowded. The precise crowd monitoring and the application of specialised control systems may also allow a better organization of multi-modal responses to large disruptions.

3.1.4 INFRASTRUCTURE

Infrastructure is the cornerstone for the wellbeing of railway operations. A well maintained and monitored infrastructure can provide the reliability required to run high density operations. Infrastructure maintenance cannot be done at any time; there is the need of advanced planning to create a slot of time (possession) in the timetable so as to minimise the impact on the running railway. In order to fulfil completely autonomous operations, it is required for the infrastructure condition to be continuously monitored and for any future drops in reliability to be predicted. The operators are required to use a blend of predictive, proactive and preventive maintenance so as to make the railway available around the clock. Infrastructure on the mainline can be broadly categorised into three major sectors:

a. Rail, switches and crossings: - Rails are constantly under pressure with increase in usage. Crack propagation, deformations and wear are major issues which can stop the railway system from running to optimum capacity. Switches and Crossings are a critical part of the rail infrastructure, switches and crossings failure can lead to serious delays on the railway and in rare cases lead to a major accident.

b. Sub-Structures: - Sub-structure is a grouping of the sub grade, ballast and track bed quality. These factors influence the ride stiffness by affecting the track stiffness. Also checking the movement of the ballast and sub ballast structure is vital in order to prevent degradation of service.

c. Structures: - These include catenary, bridges, tunnels, culverts and retaining walls that are found on a mainline railway. All of these structures are critical to ensure availability of the railway.

Infrastructure management is related to the measurement, monitoring and maintenance the above sectors. Railway infrastructure maintainers are required to first identify potential areas of failure on the railway, create a maintenance plan and execute the planned activity with little or no disturbance to the running railway. Infrastructure maintainers have an option of selecting low, medium or highly detailed resolution analysis, with

- Low resolution analysis containing an experience-based identification of critical factors and very preliminary analyses using trend curves.
- Medium resolution analysis can provide specifications for track friendly trains, which will only impact the infrastructure in a manageable manner.
- Highly detailed analysis looks at impact factors due to various upgrades to the infrastructure and also allows for methods and techniques for automated fault identification and resolution recommendations.

Maintenance of a railway is a socio-cognitive output, i.e., humans and machines combine to produce a single output. As such we can create levels for automation that vary from being completely manual to the system being autonomous, similar to previous subsystems. It is important to understand that each of these levels contain a combination of humans and machines, with the roles of both changing in each level. Table 3-5 defines each level.

The impact of infrastructure automation on large disruption management will be threefold. First, an automated effective monitoring may allow the decrease of the occurrence of disruptions thanks to the possible preventive maintenance. Then, the monitoring will be crucial for observing the evolution of the disruption, and so the current status of the infrastructure, and of the implementation of the contingency plan: a constant and precise traffic monitoring in large areas of the railway network may allow detecting deviations from the defined plan which need to be urgently tackled, as well as supplying information necessary for the diagnosis and the prognosis of the disruptions, as mentioned in the discussion on CCC systems. Moreover, the use of automated robots for performing maintenance activities may shorten the response and the infrastructure restoration time in case of disruption.

TABLE 3-5: LEVELS OF AUTOMATION FOR 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.	

3.2 ROADMAP

Individual subsystems can have an automation progression as detailed in the previous section. A roadmap helps to visualise all of the above changes into a single table to show the progression of the railway system from a simple manual system to a fully autonomous and automated one.

Using a Grade of Automation framework it is possible to define each level of a railway and also show the role the automation with each subsystem. Table 3-6 gives general railway grade of automation level definitions.

Based on these grades Table 3-7 reports a roadmap for automation in mainline railways, distinguishing for the different subsystems detailed in the previous section. This roadmap is graphically represented in Figure 3-2 and Figure 3-3. In the figures, circles represent state enablers, that is, technological evolutions which will allow the attainment of certain levels of automations, shown in rectangles. Arrows link state enablers within individual subsystems and across different ones. This is to show the interdependencies of the subsystems and the strict connections existing between them. The existence of these connections explicates the need for a coherent evolution of the different subsystems, since some of the technological evolutions, and then of the possible automation levels, depend from the development of the others. The different GOA identified in Table 3-7 are graphically shown in Figure 3-4 to Figure 3-9.

TABLE 3-6 RAILWAY GRADES OF AUTOMATION

Automation Level	**Description**
GoA 0	The preliminary level where most systems are predominantly handled by humans and the machines participate in executing commands
GoA 1	Humans are augmented with processors that provide partially digested information for humans to make decisions. The machines still require human supervision.
GoA 2	Humans have given over control of specific subsystems to machines but still retain the right to reject decisions made by the machine and in cases completely switch the system to manual.
GoA 3	Machines make decisions automatically and request approval from a human only if the situation is safety critical. The human can intervene in the system.
GoA 4	Machines are autonomous for most of the subsystems, with the human only acting as providers and maintainers with operations being fully automated.
GoA 5	Machines are completely autonomous with little or no input required from humans during operation. Such a level describes an operationally intelligent network that constantly routes trains according to demand for additional capacity.

TABLE 3-7: GRADE OF AUTOMATION (GOA) FOR MAINLINE RAILWAYS

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

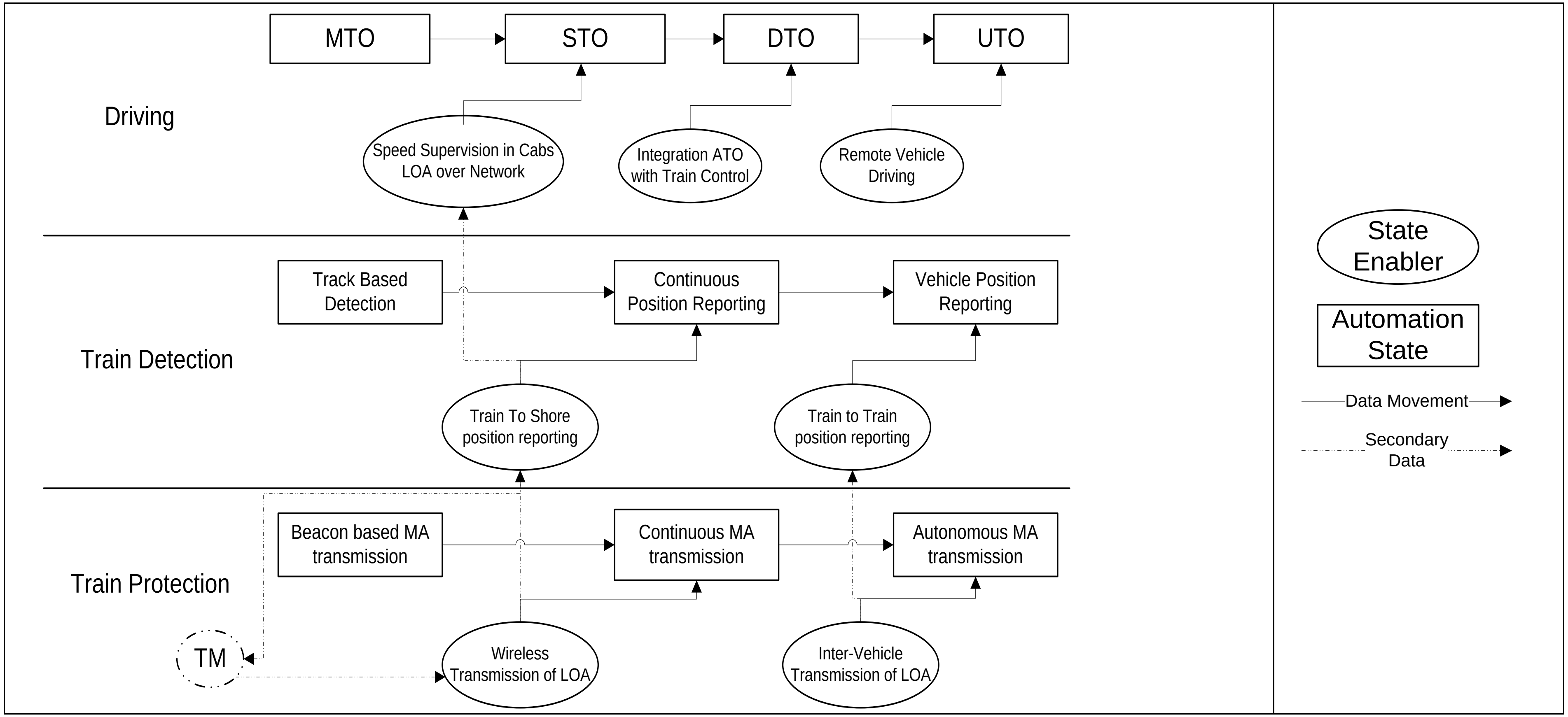

FIGURE 3-2 GRAPHICAL REPRESENTATION OF THE ROADMAP FOR AUTOMATION (A)

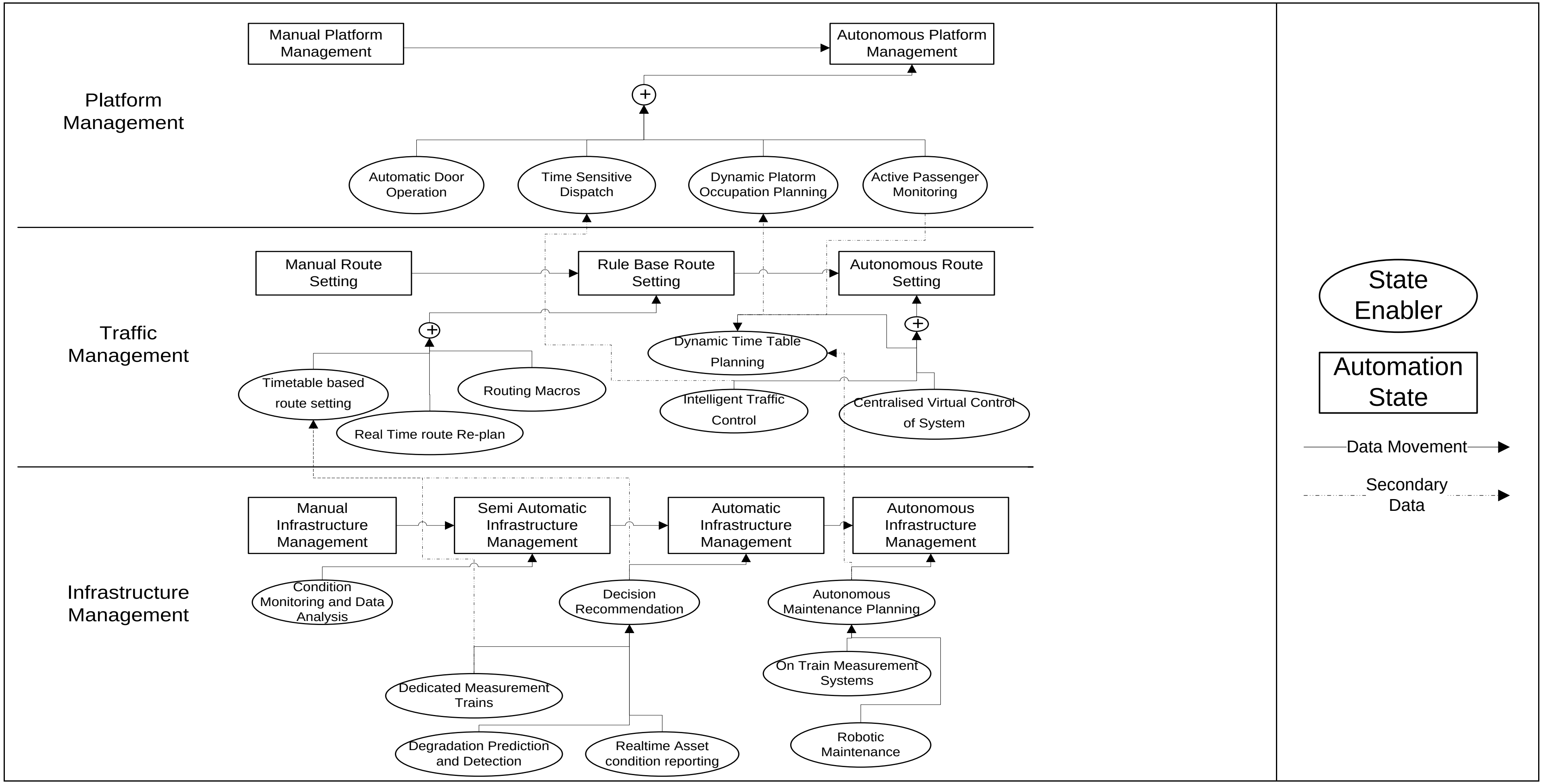

FIGURE 3-3 GRAPHICAL REPRESENTATION OF THE ROADMAP FOR AUTOMATION (B)

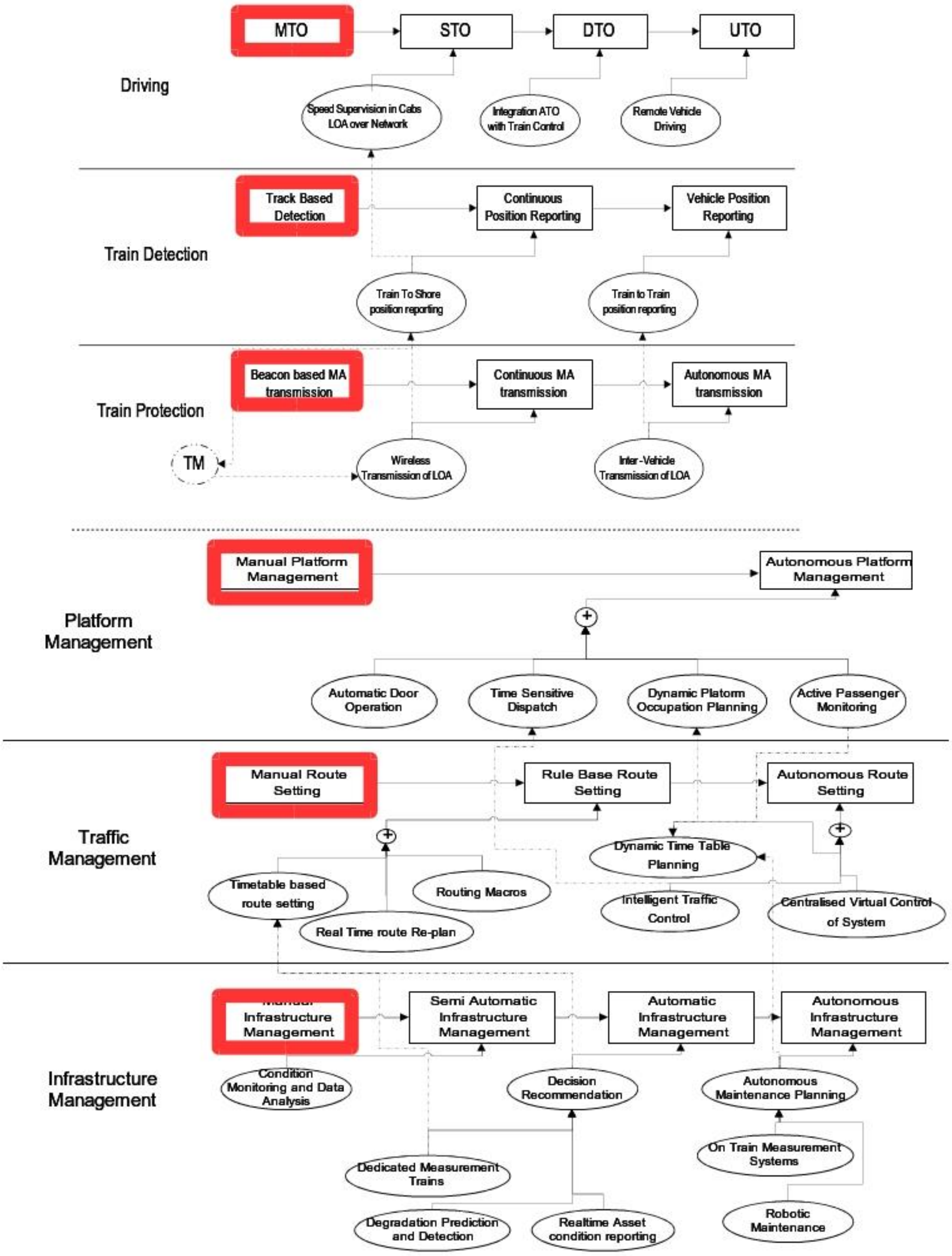

FIGURE 3-4 GRAPHICAL REPRESENTATION OF GOA0

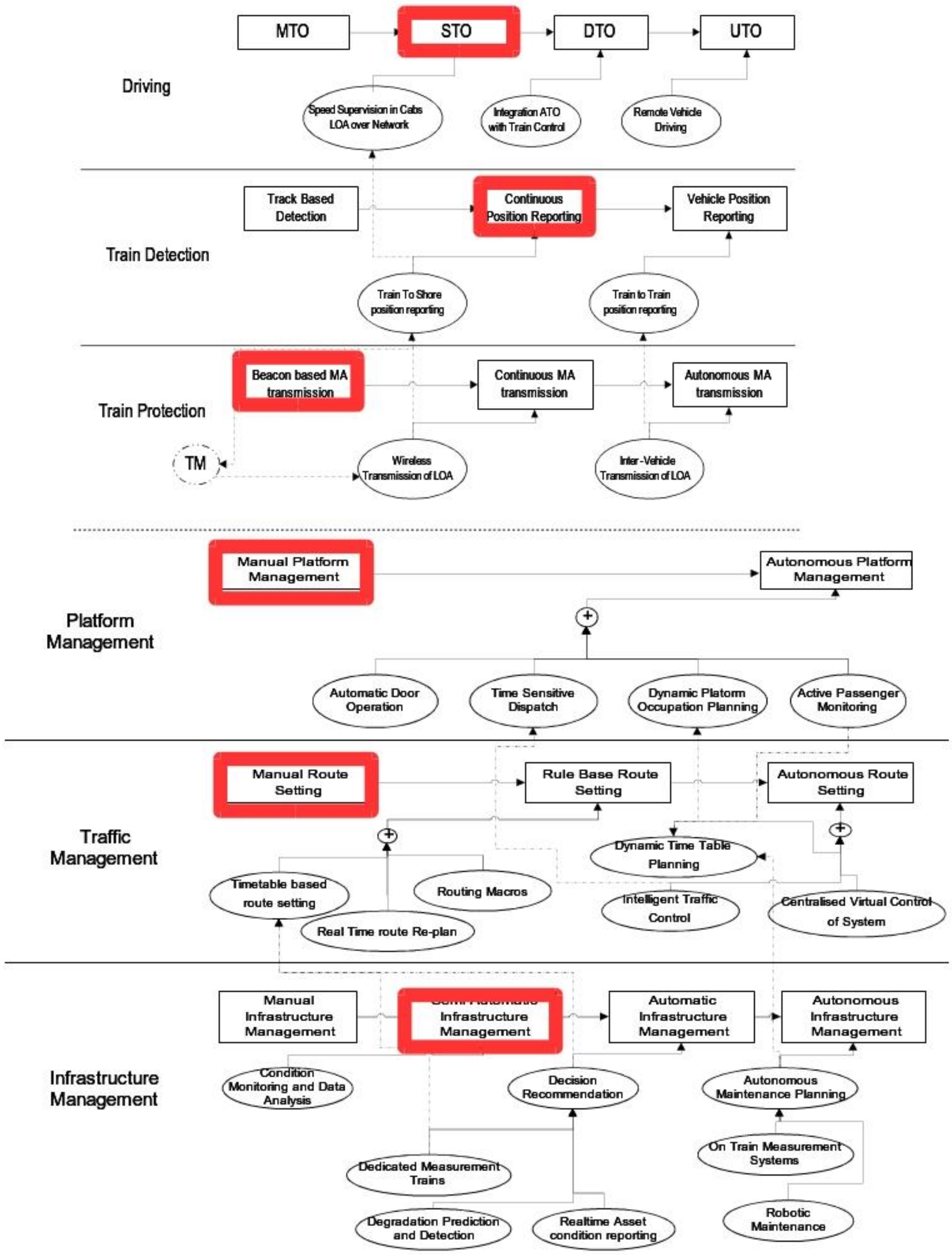

FIGURE 3-5 GRAPHICAL REPRESENTATION OF GOA1

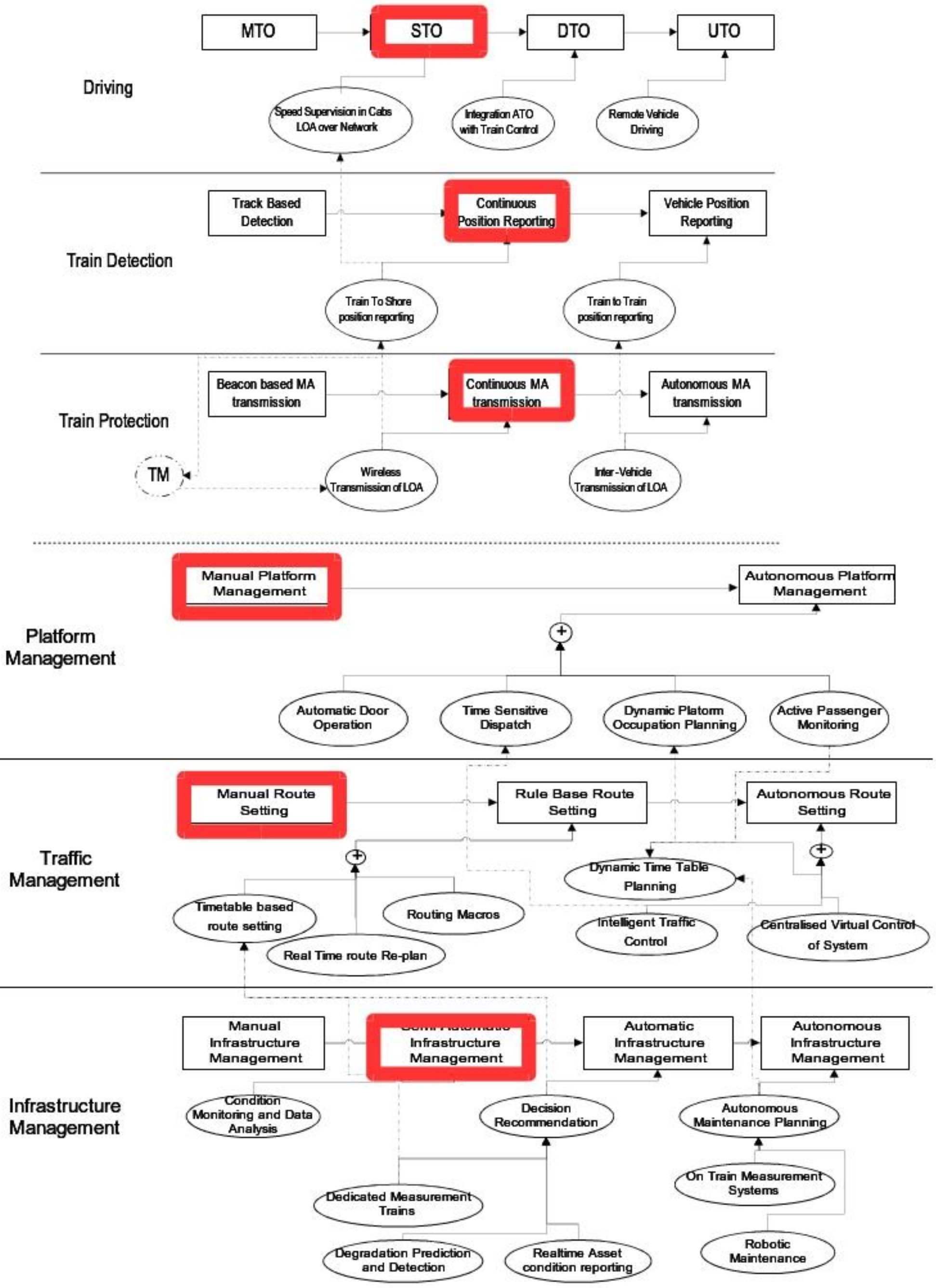

FIGURE 3-6 GRAPHICAL REPRESENTATION OF GOA2

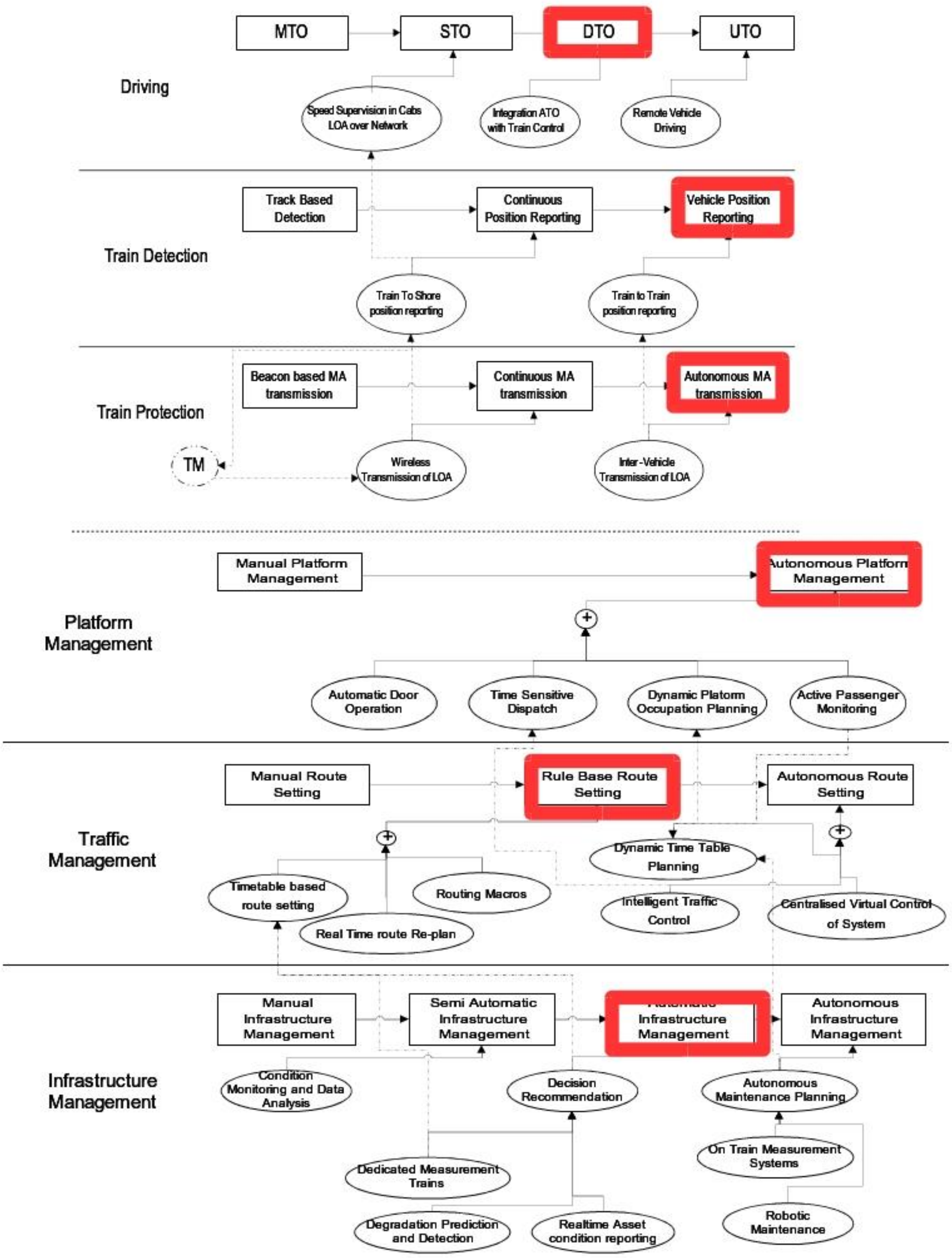

FIGURE 3-7 GRAPHICAL REPRESENTATION OF GOA3

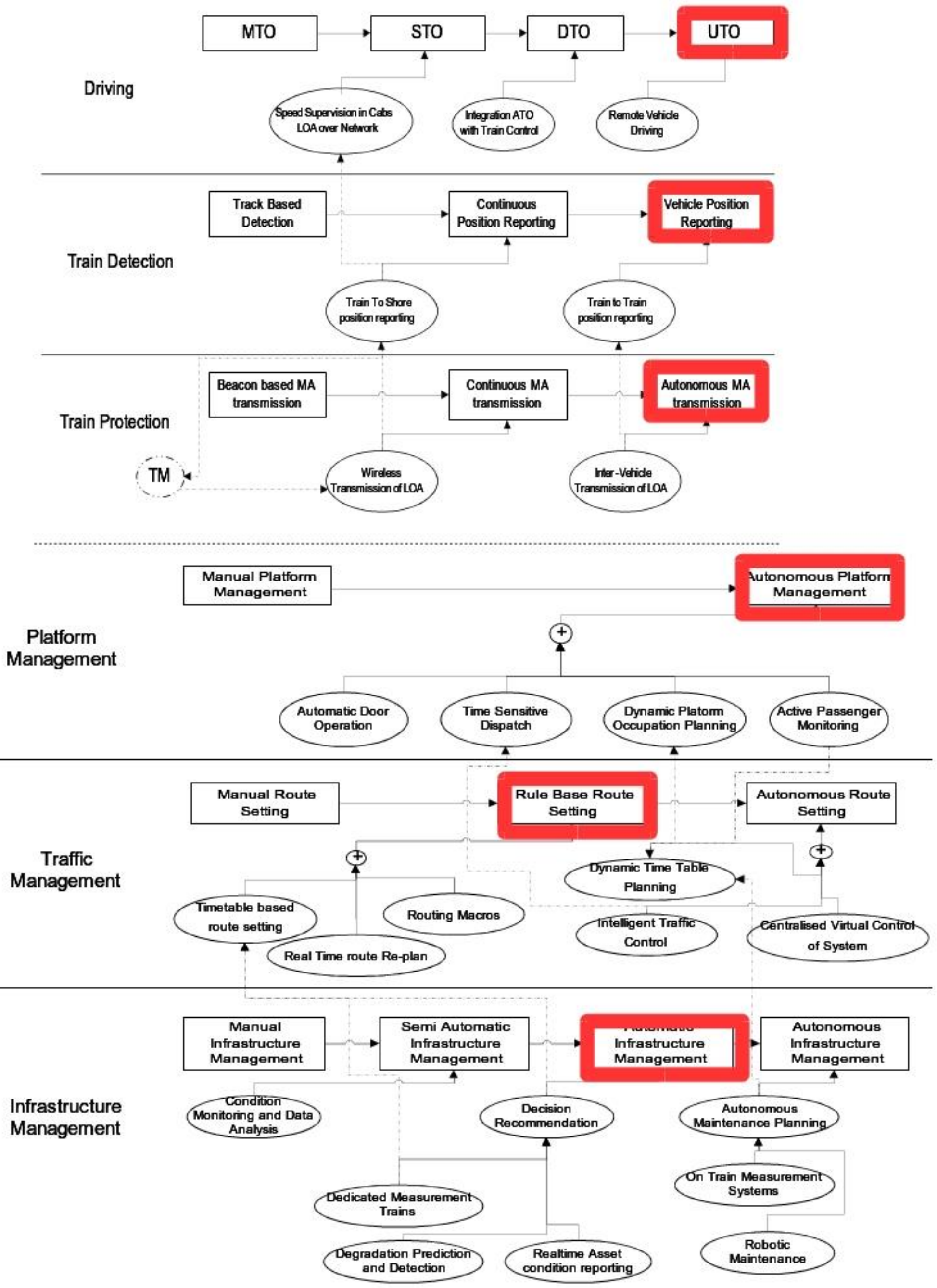

FIGURE 3-8 GRAPHICAL REPRESENTATION OF GOA4

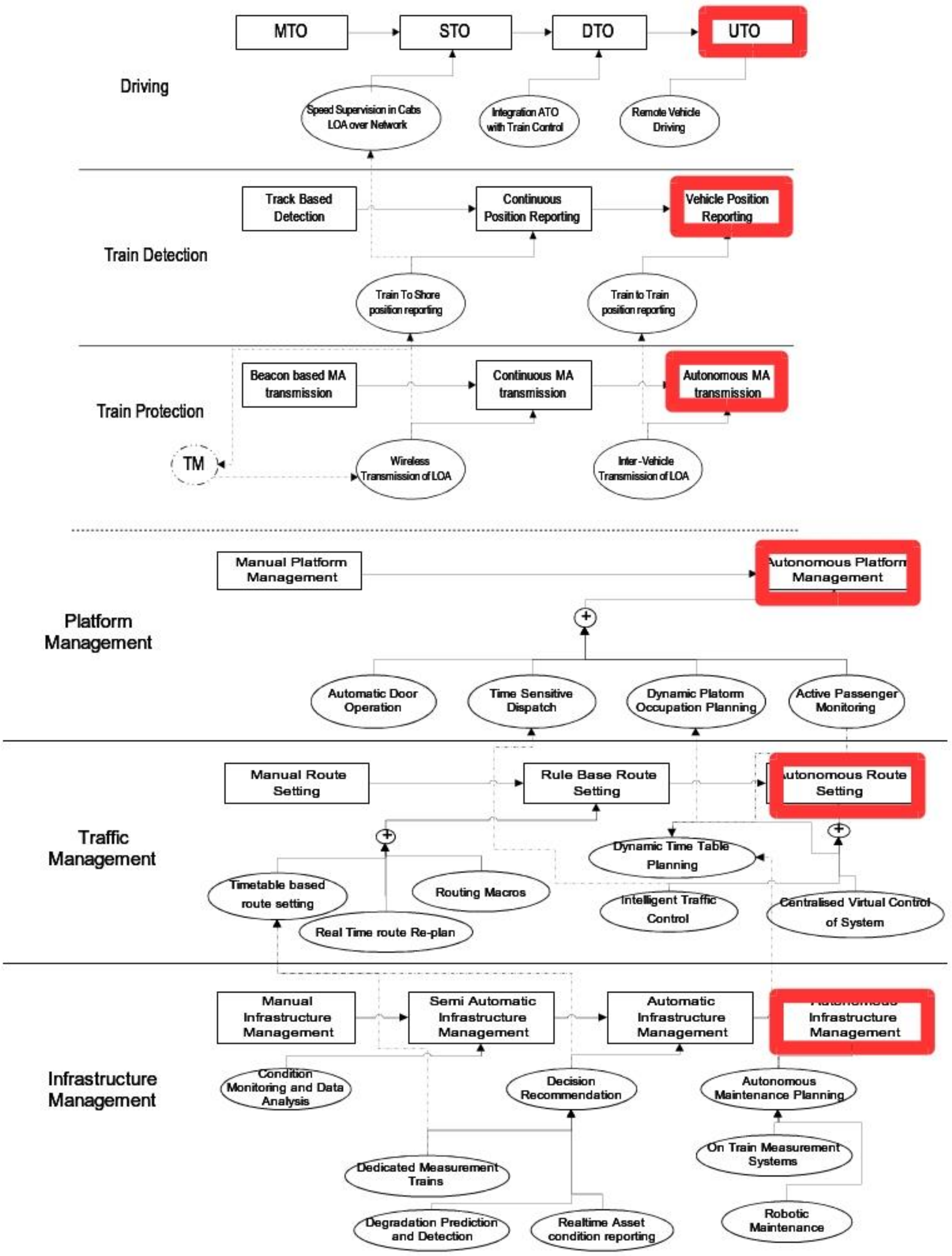

FIGURE 3-9 GRAPHICAL REPRESENTATION OF GOA5

This roadmap shows a progression from a low automation level to that which is highly automated. The progression from one level to another is featured with multiple activities of change coherently to the railway system. Although it must be stressed that incremental changes will not in themselves lend to delivery of capacity and reliability changes. The overall improvements will be derived once the system has reached a maturity level.

3.2.1 Data Requirements

Table 3-8 shows for the data necessary to enable a particular automation state/level at high level of abstraction.

Table 3-8 Data needed for automation

Enabling Technologies	Data
Speed supervision in Cabs LOA over Network	Block length messages to trains
Integration of ATO with Train Control	Transmit speed profiles
Remote Vehicle Driving	Relative distance locations/ GPS co-ordinates
Train to Shore position reporting	Location, Telemetry
Train to Train position reporting	Speed, Position and Train length
Wireless Transmission of LOA	Movement authority
Inter Vehicle Transmission of LOA	Movement authority
Automatic Door Operation	Traffic Information
Time Sensitive Dispatch	
Dynamic Platform Occupation Planning	Timetable , passenger counter
Active Passenger Monitoring	
Timetable based route setting	Position, telemetry, infrastructure condition
Real time route Re-plan	
Routing Macros	
Dynamic Timetable Planning	
Intelligent Traffic Control	
Centralised Virtual Control of System	
Condition Monitoring and Data analysis	Track geometry ,rail condition, axle condition, routine inspection, point machine
Dedicated Measurement trains	
Degradation Prediction and Detection	
Real Time Asset Condition	

Reporting	
Autonomous Maintenance and planning	
On train Measurement Systems	
Robotic Maintenance	

The infrastructure section is much better defined in this respect, as ongoing work through various projects (Table 3-9) has already specified the required data architecture (BSI, 2015), (BV, 2014).

TABLE 3-9 PROJECTS WORKING ON INFRASTRUCTURE AUTOMATION DATA

Condition Monitoring and Data analysis	ISO 13374 document , with MIMOSA specified sensorML
Dedicated Measurement trains	
Degradation Prediction and Detection	
Real Time Asset Condition Reporting	AUTOMAIN project
On train Measurement Systems	
Robotic Maintenance	Building a Business Logic architecture
Autonomous Maintenance and planning	

3.2.2 VALIDATING THE ROADMAP THROUGH SIMULATION

In order to demonstrate the above mentioned statement according to which the overall improvement of capacity and reliability will be achieved only when the whole system will have reached a maturity level, it can be useful to adopt a simple line as shown in the Figure 3-10 below. The line has 10 stations on the mainline and a further 2 stations on the branch line. So as to avoid complex interactions between various levels it would be adequate to use a simple automation progression as shown in Table 3-10 below. In particular, for each type of signalling (4 Aspect, ETCS 1, ETCS 2 and ETCS 3) we consider five levels of 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). The automation progression is increasing from level1 to level5. By considering different types of signalling, we assess how different groups of technologies behave under different conditions. This is aimed at supporting the claim of the beginning of this Section 3.2 according to which real improvements thanks to automation will be possible only identifying suitable complimentary technology groups which define specific levels of automation.

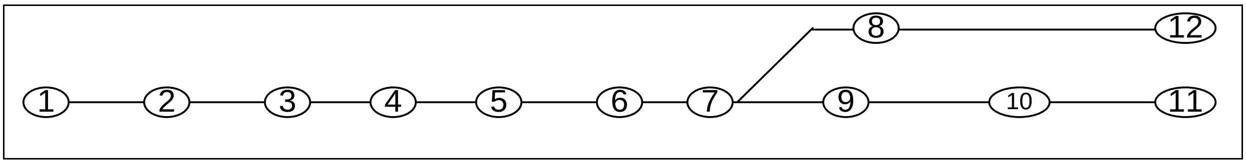

FIGURE 3-10 SINGLE LINE FOR THE PURPOSE OF SIMULATION

TABLE 3-10: EXPERIMENTAL SETUP FOR SIMULATION

Automation Level	Signalling	Driving	Platform Departures
1	4 Aspect	Manual	Train Staff Supervised
			Station Staff Supervised
		Automatic	Automatic
2	ETCS 1	Manual	Train Staff Supervised
			Station Staff Supervised
		Automatic	Automatic
3	ETCS 2	Manual	Train Staff Supervised
			Station Staff Supervised
		Automatic	Automatic
4	ETCS 3	Manual	Train Staff Supervised

			Station Staff Supervised
		Automatic	Automatic

For the simulations, we use a microscopic simulator (BRaVE) to find the changes that the system undergoes on applying improved levels of automation. Figure 3-11 below shows the simulation flow and outputs. Figure 3-12 shows the simulation architecture used to run and analyse each scenario.

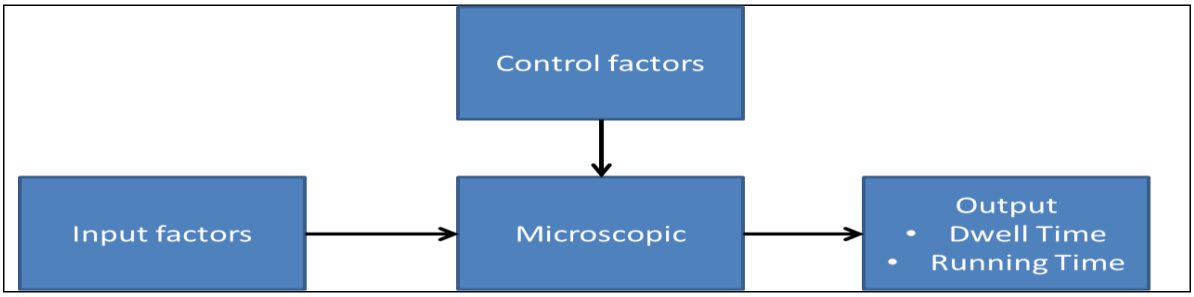

FIGURE 3-11 MONTE CARLO SIMULATION FRAMEWORK

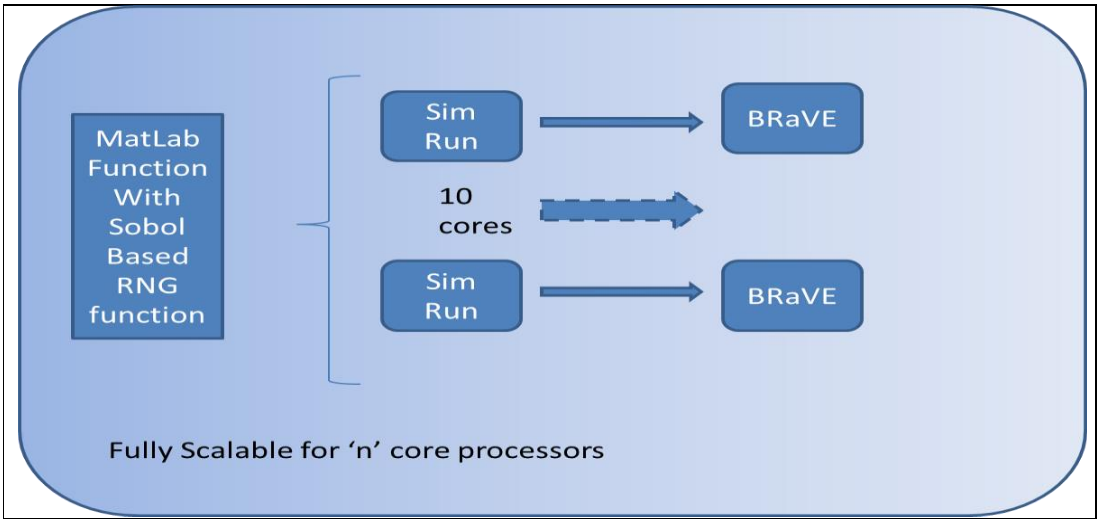

FIGURE 3-12 SIMULATION ARCHITECTURE

TABLE 3-11 PARAMETERS SET IN THE SIMULATION ANAYSIS

Test case	Speed	Traffic Density	Description

1	Same	Same	All trains are limited to a speed of 125 km/h and traffic density of 18tph.
2	Different	Same	All trains have varying speed limits (between 125- 250km/h) and same traffic density of 18tph.
3	Different	Different	All trains have varying speed limits (between 125- 250km/h) and varying traffic density.

We selected three central test cases to specifically test the change in system performance with improvements made to the system by introduction of automation. The chief determinants, from an operations standpoint, would be traffic density and speed. The description of each is as detailed in Table 3-11.

The output of the simulation is measured in journey time (seconds) overall to check the system under different traffic densities and speed with respect to their signalling capabilities. In this analysis we consider journey times as a proxy for capacity: the longer the journey times, the lower the capacity. In total, each experiment was simulated for 2000 times for each test case in order to achieve a stable result and also to be able to observe a distribution of the results. The output from the simulations is tabulated into independent scatter plots and a boxplot of these outcomes are shown below. It is important to note that each scenario was set with an acceptable traffic limit based on signalling and the infrastructure constraints.

Figure 3-13, Figure 3-14 and Figure 3-15 show the results of the simulations for the three test cases, respectively. As a general conclusion, it is evident that as we move from a low automation system (on the left) to a highly automated system (on the right) each step provides for improvement in journey time.

FIGURE 3-13 RESULTS OF THE SIMULATIONS FOR TEST CASE 1

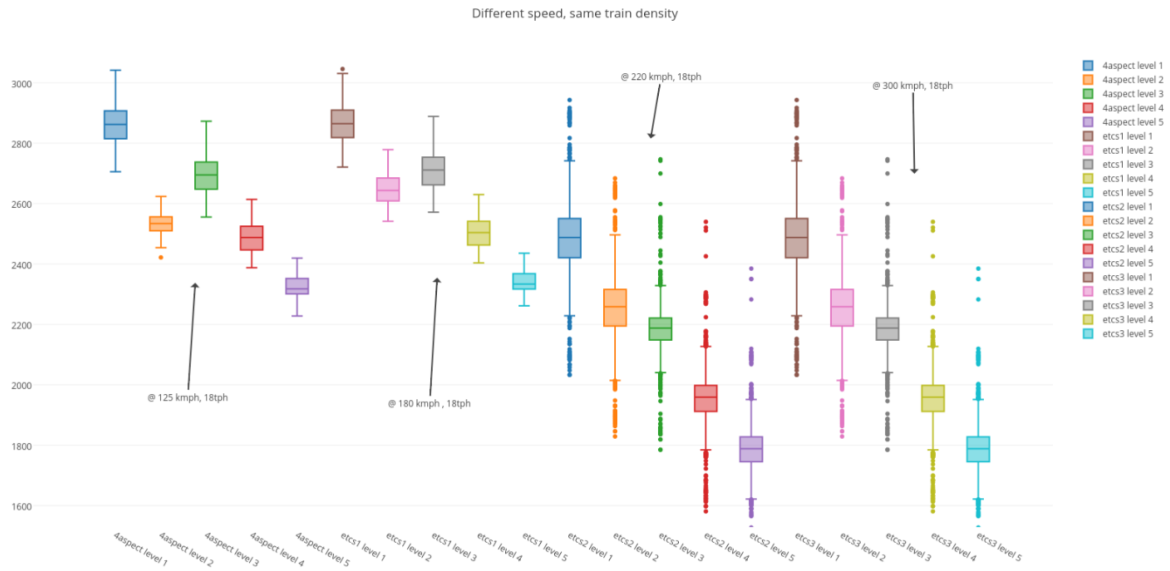

FIGURE 3-14 RESULTS OF THE SIMULATIONS FOR TEST CASE 2

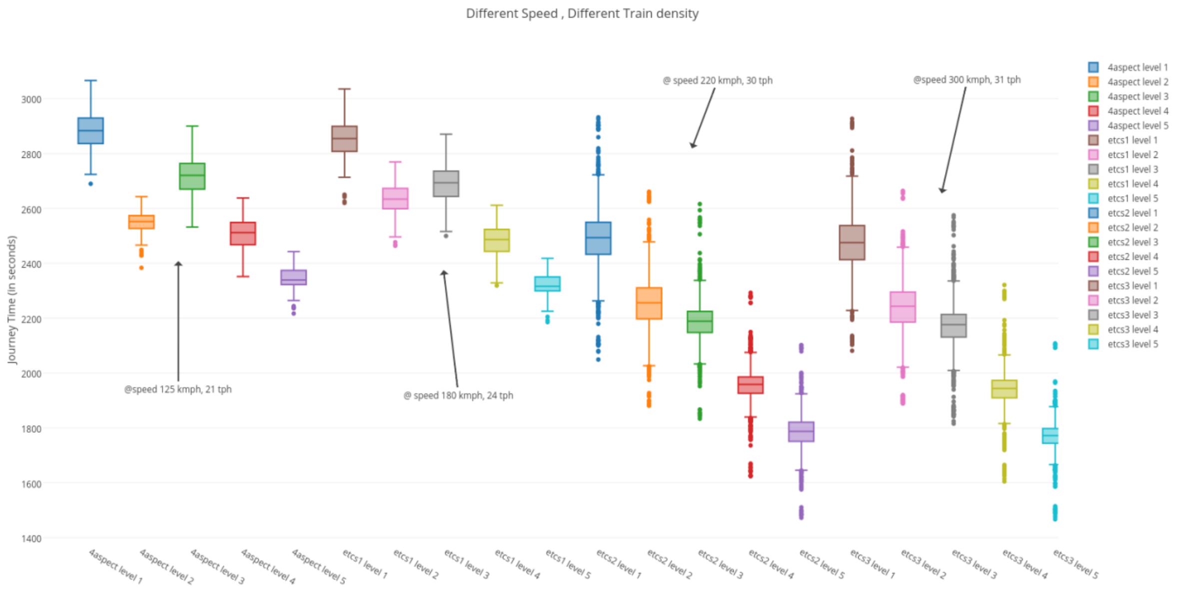

FIGURE 3-15 RESULTS OF THE SIMULATIONS FOR TEST CASE 3

For all of the test cases, we observe that instead of a smooth reduction of journey time from level to level, the second level is almost always lower than the third level when a fixed block system is applied (4 aspect and ETCS 1).

Recall that level 2 specifically is a case where the rolling stock doors are operated manually but the platform is supervised by staff. Level 3 on the other hand is a train with automatic opening and closing of doors without any supervision on the platform. The significance is that in a fixed block system the sensitivity of the overall journey time to the dwell time is higher than in the case of moving block systems. This is because there is no flexibility involved when a train is occupying a platform, dispatch time becomes important and any anomalies to timely dispatch would mount a stochastic delay on the trains behind. Specifically a supervised platform ensures that trains depart without any need for the driver/train manager to perform multiple duties of ensuring the platform is clear and/or also manage a train.

In a moving block system (ETCS 2 and ETCS 3), trains can be stacked flexibly behind each other and if there is any time being lost on the platform this time can be recovered in the section. Also when the speed is allowed to vary in test case 2, fixed block systems perform much better. This is directly because of the section time becoming more important for improving journey times over dwell time.

By observing the results of Figure 3-13 where same speed and same traffic density are considered for all automation levels, we can see that the signaling type seems to be a minor contributor to the decrease of journey times (and hence to the increase of capacity). A more noticeable role is played by the automation of driving and platform management. However, it is possible to envisage that different types of signalling are coupled with different technologies which bring the increase of the allowed speed. Hence, Figure 3-14 shows how journey time changes if the speed allowed increases from 125 to 180, 220 and 300 km per hour when passing from 4 Aspect to ETCS1, ETCS2 and ETCS3. Here, the complimentary technology groups show a clear decrease of journey times, especially when passing to ETCS2 or ETCS3. Finally, Figure 3-15 allows the verification of the fact that such complimentary technology groups allow maintaining a somehow constant journey time even in case of increase of traffic density, from 21 to 24, 30 and 31 trains per hour when passing from 4 Aspect to ETCS1, ETCS2 and ETCS3.

In conclusion, the results show that incremental improvements do not necessarily show capacity improvements but rather that automation when applied in groups, such as the one proposed in the roadmap above, yields better results. However it is important to note that the understanding of what factors affect automation quantitatively is still being studied. Any tool capable to do so would lends towards framing a complete picture for the impact of automation on railway system development.

4. Analysis of an instance of automation increase: delay prediction

The objective of this section is to present the work done on the data-driven train delay prediction, as an instance of automation increase. Although this work is treated in the most general way possible, the case study is focused on the Italian railway network and on the data provided by the related Infrastructure Manager (RFI- Rete Ferroviaria Italiana) without loss of generality.

Improving the quality of delay prediction thanks to automation will bring, first of all, improved passenger information system, by increasing the perception of the reliability of train passenger services and, in case of service disruptions, providing valid alternatives to passengers looking for the best train connections. Moreover, a better freight tracking will be possible, thanks to the precise estimation of good’s time to arrival so to improve customers’ decision-making processes. Also timetable planning will profit from such an automation increase, which provides the possibility of updating the train trip scheduling to cope with recurrent delays. Finally, of course, correct and automated delay predictions will ease traffic management, allowing dispatchers to reroute trains so to utilise the railway network in a better way.

The following sections are organized as follows. Section 4.1 introduces the problem of train delay prediction from a data analytics perspective, and describes in details which types of delays can be analysed. Section 4.2 introduces the framework of time-series forecasting in which the prediction of train delays fits perfectly, and briefly describes a set of methodologies and techniques for the treatment of these kinds of problems. Section 4.3 describes in detail the data needed to tackle the problem of train delay prediction, focusing on the data related to train movements usually collected by TMS (Traffic Management Systems). Section 4.4 clearly identifies the data format that must be supplied to data-driven algorithms. Additionally, it describes the different KPI’s defined to evaluate the quality of the predictive models. Section 4.5 describes the data analysis algorithms selected as final proposals for solving the problem of train delay prediction, and shows how the proposed modelling approach works. Section 4.6 describes, on the one hand, the simulation methodology and setup, and, on the other hand, the results obtained on a real-world dataset. Finally, Section 4.7 discusses how these methods can be used in the large disruption management problem.

4.1 Introduction to Train Delay Predictions

The automation increase in train delay prediction is expected to address current train delay prediction systems, which are based on basic, albeit robust, methodologies. For example, some current solutions, even if not very accurate, focus on robustness because they aim at computing delays by considering time supplements and buffer times (Hansen, Goverde, & Van Der Meer, 2010).

The automation increase in train delay prediction is expected to be achieved by exploiting recent advances in general prediction methodologies (Box, Jenkins, & Reinsel, 2011) and through the exploitation of specific recent results on predicting train delays and running time (Hansen, Goverde, & Van Der Meer, 2010) (Higgins & Kozan, 1998) (Yuan, 2006) (Van Lint, 2008), with particular reference to its causes (Dingler, Koenig, Sogin, & Barkan, 2010) (Ruihua & Anzhou, 1995) (Espinosa-Aranda & Garcıa-Rodenas, 20013) (Siji, Quanxin, Jinyun, & Zhaoxia, 1994), with the purpose of optimizing the dispatching of the trains (Kraft, 1987) (Sauder & Westerman, 1983), in finite capacity infrastructures (Mattsson, 2007), and from the point of view of avoiding negative economic impacts (Schlake, Barkan, & Edwards, 2011).

In this context, to derive meaningful results from the delay prediction, at least four different delay categories should be addressed:

1. Structural (systemic) delay: a delay that occurs systematically and it is due to small errors in the calibration of the nominal train timetable;
2. Meaningful statistical recurrent delay: a delay that occurs a meaningful number of times on the same train and is due to a recurrent event on the line;
3. Delay caused by known, recurrent exogenous events: a delay connected to recurrent exogenous events (e.g., rainy days, celebrations, strikes 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).

It is worth noting that the nominal train timetable should not be considered as a static object by the delay prediction system, as this could be changed (and is regularly) by railway operators, for example for coping with structural problems identified in the past or taking into account modifications in the level of service.

The problem could be addressed as a time series forecast (Chatfield, 2013) (Lutkepohl, 2005) (Montgomery, Johnson, & Gardiner, 1990) (Box, Jenkins, & Reinsel, 2011) (Bloomfield, 2004) (Hamilton, 1994), with the objective of predicting the delay of each train in all the subsequent "checkpoints" of interest with the highest possible accuracy, with an estimate of the forecasting accuracy itself and the estimate of the causes of the delay (i.e., the sensitivity of the delay to the different variables).

As the analysis and forecasting of time series occurs in a large variety of applicative fields, ranging from economics to engineering, and methods for the analysis of time series constitute an important area of statistics, it is expected that, by exploiting the approaches developed in these fields and the specific developments in the railway transportation area, it will be possible to identify with a reasonably high level of confidence: (1) structural delays, and (2) meaningful statistical recurrent delays, just by considering the current and historical data related to all the trains on the target railway infrastructure.

In order to predict delays caused by recurrent exogenous events (3), related exogenous data shall be collected. For this purpose, it could be necessary to consider different sources of information like, for example:

- Data about weather conditions and forecasts (rain, snow, ice, temperature, humidity, solar radiation, etc.)
- Data about people flows (tourists, commuters, etc.)
- Data about local or global events (religious festivities, strikes, festivals, etc.)

Obviously, the above described methods, which are based on statistical methodologies, cannot cope with unpredictable delays (4) where no recurrences exist. A pure speculative effort could be devoted to analyse if at least part of these delays could become predictable through the collection and analysis of indirect exogenous information (e.g., information on media channels).

A positive by-product of the train prediction itself could be the use of the delay forecasting model, once this has been inferred from the data, to gain insights not related to the delays themselves, but to other factors that might be useful for the automation increase or for decision support like, for example, the analysis of the effects of each variable or set of variables (pattern) on the delays. This analysis could open the possibility to correlate the delay of one of more trains with others, and eventually to exogenous variables. This process may allow understanding structural weaknesses either in the train timetable or in the infrastructure that may be not trivial to detect. In particular, it should be possible to search for the information that mostly affects the delays.

4.2 Time series forecasting for the prediction of delay

As summarized in the previous section, the problem underlying the delay prediction can be casted as a stochastic, discrete time series forecasting problem. The stochastic behaviour is due to the fact that the prediction is considered as a non-deterministic function of current and past values (eventually including exogenous variables) and the discrete assumption is intrinsic on the application, because observations are taken only at specific times, as well as desired forecasts. The main assumption is that future values of interest follow a probability distribution, which is conditioned by the knowledge of the current and past information.

The specific literature abounds with algorithms for time series analysis and forecasting, which can be applied at different levels. Visual approaches are often useful for looking for trends, seasonal fluctuations, etc., but automatic approaches must resort to probabilistic models, which infer the optimal one that, according to some metric, best fits the time series under analysis. The inference can be performed in the time domain, the frequency domain, or by building state-space models. Often the algorithms assume that the underline phenomena generating the data are univariate and linear, but recent advances in the field propose advanced approaches, which are able to deal with both multivariate and non-linear cases.

Due to the vast number of algorithms on the subject, only some brief sketches are provided in following parts of the document. A selection of the best approaches is performed after a deep analysis of the requirements and an Exploratory Data Analysis of the variables involved in the forecast problem.

TIME SERIES TERMINOLOGY AND FORMALISM

The time series are composed by observations of a quantity $y_{i,t}$ representing delays of a train i sampled at measurement points $t \in \{1, \dots, T\}$. Additional information (e.g., other measurements of delays of other trains and other, eventually exogenous, variables) is indicated with $x_{j,t}$ that represents source of information $j \in \{1, \dots, N\}$ with $j \neq i$ sampled at time $t \in \{1, \dots, T\}$. The main task is to predict $y_{i,t+1}$ given $y_{i,t}$ with $t \in \{1, \dots, T\}$ and $x_{j,t}$ with $j \in \{1, \dots, N\}$ with $j \neq i$ and $t \in \{1, \dots, T\}$.

The accuracy of the predictive model can be evaluated with reference to different measures (Ghelardoni, Ghio, & Anguita, 2013). Based on the outputs of the model $\hat{y}_t$ and the actual value y_t at different $t \in \{1, \dots, T\}$ it is possible to compute several performance indicators:

- mean absolute error
- mean absolute percentage error
- mean square error
- normalized mean square error
- relative error percentage
- Pearson Product-Moment Correlation Coefficient, which allows the computation of the correlation the prediction and the actual values.

4.2.1 AUTOREGRESSIVE MODELS

In the discrete-time case, the major diagnostic tool is the sample autocorrelation function (Chatfield, 2013). Inference based on this function corresponds to the analysis in the time domain.

BASIC AUTOREGRESSIVE MODEL

The most basic algorithm for time series forecasting is the following zero-order autoregressive model:

$$\hat{y}_{t+1} = y_t$$

which assumes that future values will be equal to the current one. Obviously, this model is not useful for predictions, but it can be used as a reference baseline. In fact, it must be noted that complex models are at risk of overfitting the data and can perform worse than a zero-order model in some situations.

AUTOREGRESSIVE MOVING AVERAGE MODELS (ARMA)

These models perform an average of the past values. The dependency of the prediction from past values is linear, so they are not able to grasp possible nonlinearities of the underlying phenomena, but they are, in practice, quite robust.

In the basic formulation, the only parameter that must be tuned is the model order (*k*), and this tuning can be performed through model selection approaches widely available in the literature.

More advanced ARMA models exploit a weighted sum of the past values:

$$\hat{y}_{t+1} = \sum_{i=0}^{k-1} \alpha_i y_{t-k}$$

In this case, both the model order and model parameters $\alpha_0, \dots, \alpha_{k-1}$ must be identified with model selection and best fitting algorithms.

4.2.2 DATA MINING MODELS

Contrary to the previous approach, which assumes that there is a fixed law which connects past events to the future ones, data mining models make deeper use of historical data (Bishop, 1995) (Dietterich, 2000) (Shawe-Taylor & Cristianini, 2004) (Vapnik, 1998). The Data Mining (or Data Analytics) approach performs a computational process for discovering patterns in data sets, involving methods at the intersection of artificial intelligence, machine learning, and statistics. The goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. In particular, the focus will be on predictive analytics models.

In this case, the purpose is to find for each series i at time T in the historical data all the configurations of $y_{i,t}^H$ with $t \in \{1, \dots, T\}$ and $x_{j,t}^H$ with $j \in \{1, \dots, N\}$ with $j \neq i$ and $t \in \{1, \dots, T\}$, and then to apply this information, along with $y_{i,T+1}^{H}$, in order to predict $\mathrm{y_{i,T+1}}$ based on the actual value at time T, $y_{i,t}$, with $t \in \{1, \ldots, T\}$ and $x_{j,t}$ with $j \in \{1, \ldots, N\}$ with $j \neq i$ and $t \in \{1, \ldots, T\}$.

PATTERN MATCHING METHODS

One of the basic and most successful approaches is the group of the Pattern Matching methods, like the K-Nearest Neighbours (k-NN) algorithm, which is simple but statistically non-parametric method. The algorithm computes the prediction based on the K most similar patterns and averaging the prediction value. k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computations are deferred until the prediction is requested.

Several variants exist in which, for example, weights are assigned to the contributions of each pattern, so that more similar "neighbours" contribute more to the average than the more dissimilar ones. For example, a common weighting scheme consists in giving each neighbour a weight of $1/d$, where d is the distance to the neighbour.

KERNEL METHODS

Kernel methods are a class of algorithms for pattern analysis, whose best-known member is the Support Vector Machine (SVM), which is considered one of the state of the art algorithms for pattern recognition. One of the advantages of Kernel methods is their capability of dealing directly with raw data, without the need of complex pre-processing phases. In fact, for many patter recognition algorithms there is the need to explicitly transform raw data into feature vectors via a user-specified feature mapping (e.g., autoregressive model); in contrast, kernel methods require only a user-specified kernel, i.e., a similarity function over pairs of data points in raw representation. For this reason, they are also well suited to deal with high-dimensional data and, in general, where the number of samples is scarce respect to the size of the problem. It is forecasted that this case could easily arise in the case of delay prediction and, therefore, they seem an ideal tool for this purpose.

ARTIFICIAL NEURAL NETWORKS

Thanks to the recent advances in computational resources, Artificial Neural Networks (ANNs) (Bishop, 1995) have become prominent in the field of pattern recognition and have shown to be both versatile and effective in solving problems usually approachable only by human experts. One of the reasons of their effectiveness in this particular field is that, in addition of being a family of statistical learning models able to approximate high-dimensional functions, they are inspired by biological networks (the central nervous systems of animals and, in particular, the brain). The new generation of ANNs (Deep networks) is currently considered the state of the art method for high-dimensional problems, and able to outperform humans in some pattern recognition tasks.

ENSEMBLE METHODS

In several applicative fields, it has been shown that seldom a single algorithm always outperforms all the others. In data analytics, ensemble methods use multiple models (e.g., pattern matching, kernel methods, neural networks) in order to obtain better predictive performance than the ones that could be obtained from any of the constituent models. The main difference between data analytics ensemble methods and statistical ensemble methods is that in statistical ensemble the combined models are infinite, while in data analytics the concept of ensemble refers only to a concrete finite set of alternative models, but typically provides a more flexible structure. Evaluating the prediction of an ensemble typically requires more computation than evaluating the prediction of a single model, so ensembles may be thought of also as a way to compensate for poor performing algorithms at the expenses of additional computation. Fast algorithms such as Decision Trees are commonly used with ensembles (for example Random Forest), although other slower algorithms can benefit from ensemble techniques as well.

4.3 DATA SOURCES IDENTIFICATION AND DATA NEEDED BY ALGORITHMS

This section is devoted to the identification of available data sources and of their own data format, as well as a preliminary analysis of the content by exploiting statistical methodologies. The integration of external variables that could be measured and integrated into the actual data collection systems will be assessed.

4.3.1 AVAILABLE DATA SOURCES IDENTIFICATION

This section aims to define which data is available in railway information systems that could be used in order to tackle the problem of predicting train delays. Indeed, railway information systems store large amounts of data internally, which could be used to build predictive models for train delays based on what happened in the past. Moreover, other exogenous data sources could be useful in order to improve the performance of the predictive models, such as weather conditions data.

Combining the knowledge on the design and development of railway information systems, and the results of a literature review on these topics (see for example (Hansen, Goverde, & Van Der Meer, 2010) and (Berger, Gebhardt, Müller-Hannemann, & Ostrowski, 2011)), the most valuable data needed to analyse train delays is:

- Data about train movements, with precise time and position references (e.g., timestamps at checkpoint arrivals and checkpoint unique IDs), so to be able to reconstruct the entire history for a particular train and for the rest of the trains travelling on the network.
- Theoretical timetables, including planning of exceptional train movements, since they have to be compared with the actual movement data.

This data can be retrieved from Traffic Management Systems (TMS) and related information systems, which include historical data both about the movements of the trains and about the plans for theoretical timetables. Furthermore, although these kinds of systems are usually proprietary and each IMs implemented its own software solutions, the data that can be exported is quite homogeneous. In fact, TMS and related information systems store and provide almost the same raw information in different formats, meaning that information can be easily made compatible. For instance, some systems provide the theoretical time and the delay of a train, while others provide the theoretical time and the actual time, making the two information sets exchangeable without loss of information.

For these reasons, the rest of the chapter considers the particular case of the Italian railway network and its IM Rete Ferroviaria Italiana (RFI). Please note that all the references to the real data are presented in aggregated form and anonymized in order to avoid privacy and security issues. Please also note that exogenous variables that could be theoretically used will be presented in the following sections, and their possible inclusion in the creation of data-driven models will be formalized.

4.3.1.1 Theoretical Background

Firstly, it is important to give some definitions in order to create a common knowledge for understanding this analysis. In the following, a railway network is considered as a graph where nodes represent a series of checkpoints connected one to each other (e.g., Figure 4-1). Any train that runs over the network follows an itinerary characterized by a station of origin, a station of destination, some stops and some transits (see Figure 4-2). For any checkpoint$C$, the train should arrive at time t_A^C e and should depart at time t_D^C, defined in the timetable. Usually time references included in the nominal timetable are approximated with a precision of 30 seconds. The actual arrival and departure time of the train are defined as $\widehat{t_A^C}$ and $\widehat{t_D^C}$. The difference between the time references included in the nominal timetable and the actual time – either of arrival $(\widehat{t_A^C} - t_A^C)$ or of departure $(\widehat{t_D^C} - t_D^C)$ – is defined as delay. Moreover, if the delay is greater than 30 seconds or 1 minute, then the train is considered as "delayed train". Note that, for the origin station, there is no arrival time, and analogously, for the destination station, there is no departure time.

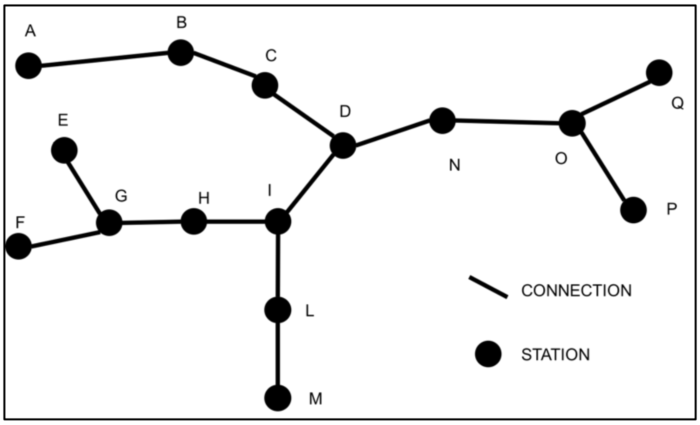

FIGURE 4-1: A RAILWAY NETWORK

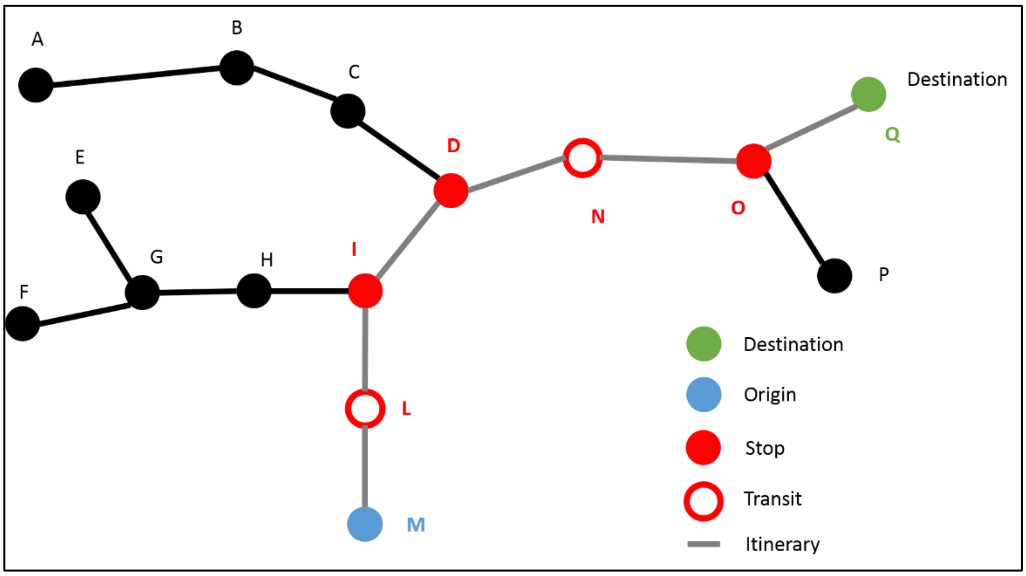

FIGURE 4-2: AN ITINERARY OF A TRAIN ON THE RAILWAY NETWORK

4.3.1.2 DATA AVAILABLE FROM TMS

Databases devoted to the storage of the TMS data contain information for each train that travels along the railway network. In particular, taking the RFI databases as an example, every time a train passes through a station or a checkpoint, the following data fields are recorded:

- TRAIN DATE: the date expressed in day, month and year (formatted as "dd/mm/yy") of the passage

- TRANSPORT NUM: the unique identifier of the train
- PIC PLACE CODE: the unique identifier of the checkpoint
- PLACE DSC: the name of the checkpoint
- ARRIVAL DATE: the date of arrival of the train in the checkpoint (formatted as “dd/mm/yy”)
- ARRIVAL TIME: $\widehat{t_A^C}$ expressed in hours, minutes and seconds (formatted as “hh:mm:ss”)
- ARRIVAL DIFF: the delay of arrival $(\widehat{t_A^C} - t_A^C)$ expressed in minutes
- DEPARTURE DATE: the date of arrival of the train in the checkpoint (formatted as “dd/mm/yy”)
- DEPARTURE TIME: $\widehat{t_L^C}$ expressed in hours, minutes and seconds (formatted as “hh:mm:ss”)
- DEPARTURE DIFF: the delay of departure $(\widehat{t_D^C} - t_D^C)$ expressed in minutes
- PASSAGE TYPE: the type of checkpoint from the train point of view. There are four possible values:
    - O (Origin)
    - D (Destination)
    - T (Transit)
    - F (Stop)

Any train, together with its itinerary (defined by TRANSPORT NUM), has its own particular frequency (daily, workdays only, holidays only, monthly, etc.). Moreover, RFI stores in its databases other useful information:

- The nominal timetable with the t_A^C and t_D^C time references for each train that runs over the network
- The so-called “allungamento”, a sort of buffer time that represents the amount of time (expressed in minutes) that can be regained from the delay by going from two connected checkpoints C_1 and C_2. However, it is important to note that there exists an “allungamento” for the section going from checkpoint A and B, but not for going from A to C. In this last case, one needs to sum the “allungamento” for going from A to B and the one for going from B to C.

4.3.1.3 External Data

Other useful exogenous information to be correlated with train delays could be retrieved from external databases, like for example:

- Information about the tourists’ presence in an area. Unfortunately, these data are often not available because of privacy/confidentiality issues.
- Information about the number of passengers on each train. This information is often available only for trains with seat reservations and not for commuter trains.
- Information about weather conditions that could influence the delay of the train. For instance, for a particular area, it is possible to access to a big number of weather stations. For any

weather station, it is possible to retrieve the measured values and the forecasted values (for different time horizons) of many variables:

- atmospheric pressure (at sea level and the level of the weather stations)
- solar radiation (hours of sun and average radiation)
- temperature (average, minimum, and maximum)
- humidity (relative humidity)
- wind (direction and average, minimum, and maximum intensity)
- rainfall (millimetres of water fallen every square meter)

Since the granularity of these weather stations is quite fine, it could be possible retrieve also the actual and forecasted weather conditions for all the stations, sections and checkpoints by searching for the closest one (as depicted in Figure 4-3).

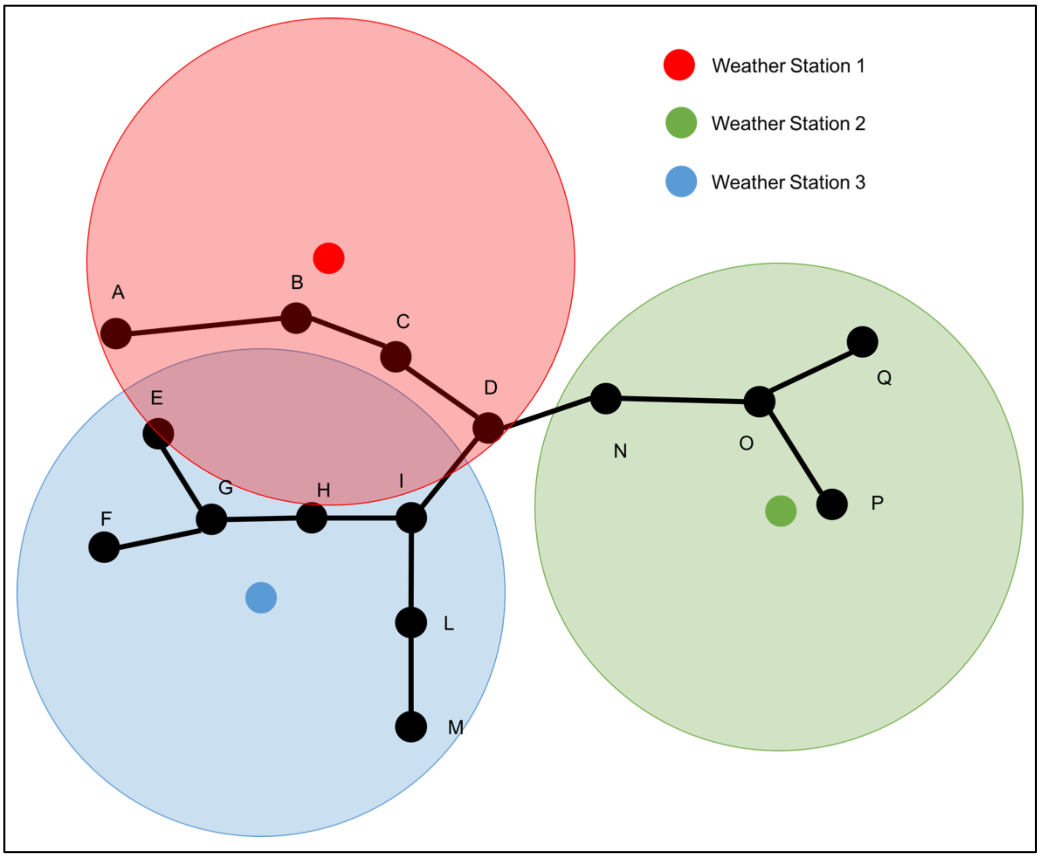

FIGURE 4-3: WEATHER STATIONS AND RAILWAY NETWORK

These exogenous variables are only theoretically introduced in this document and their possible usage in the creation of data-driven model is conceived, although not implemented.

4.3.2 Preliminary analysis

This section reports a preliminary statistical analysis of the data described in the previous sections. In particular, the following four characteristics of train movements have been analysed with classical statistical tools:

- Train Delay distributions for each train, either per checkpoint and per itinerary
- Travel times for each train over the different sections of its itinerary
- Dwell times for each train at each checkpoint of its itinerary
- Linear Train Delay correlations for each couple of trains

For instance, Figure 4-4 shows the distribution of the delay of a particular train at different stations, while Figure 4-5 presents the average delay distribution over the whole itinerary of the train. This is quite important in order to detect, among other things, some errors in the definitions of the timetable. Indeed, if the mode of the distribution is not zero, it is highly probable that there is a structural problem in the timetable definition. In Figure 4-4, the timetable plan for Station 2 seems to present this particular problem. Instead, if the mode is zero (for example see Station 9 in Figure 4-4), it confirms that the timetable is well planned.

Figure 4-6 shows the distribution of travel times for a particular train over the different sections that characterize the itinerary of the train. This information is quite useful in order to understand which sections show major problems. For example, in Figure 4-6 it is possible to note that there is a frequent cause of change in the travel time for Section 7 that is not understandable by just looking at the data. Anyway, providing this information to the infrastructure managers could be useful to understand some issues related to the railway network.

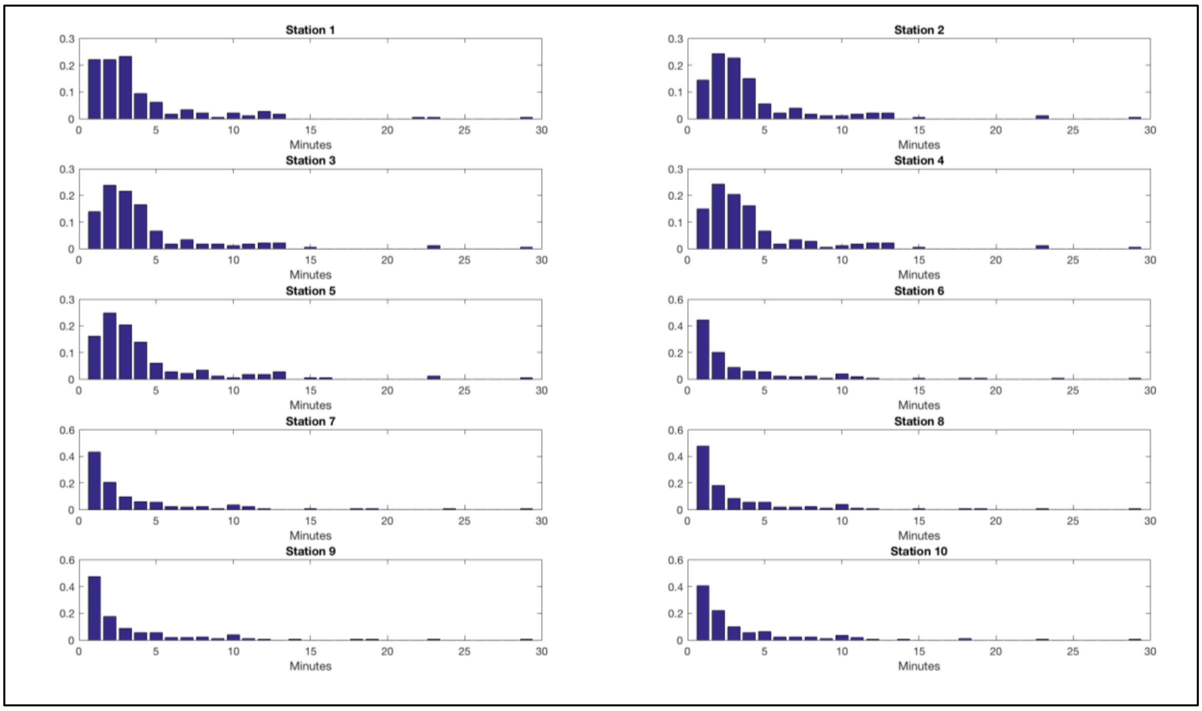

FIGURE 4-4: DISTRIBUTIONS OF DELAYS FOR A PARTICULAR TRAIN AT DIFFERENT CHECKPOINTS

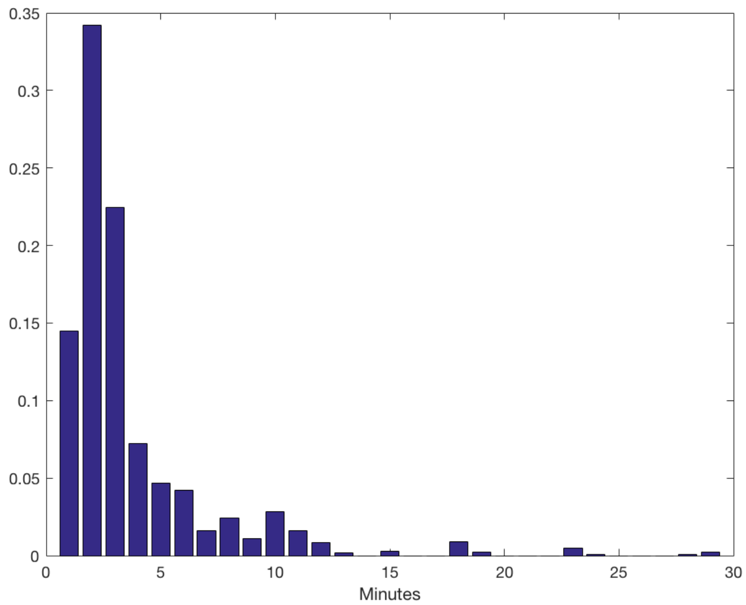

FIGURE 4-5: DISTRIBUTION OF THE DELAY OF A PARTICULAR TRAIN IN THE WHOLE TRIP

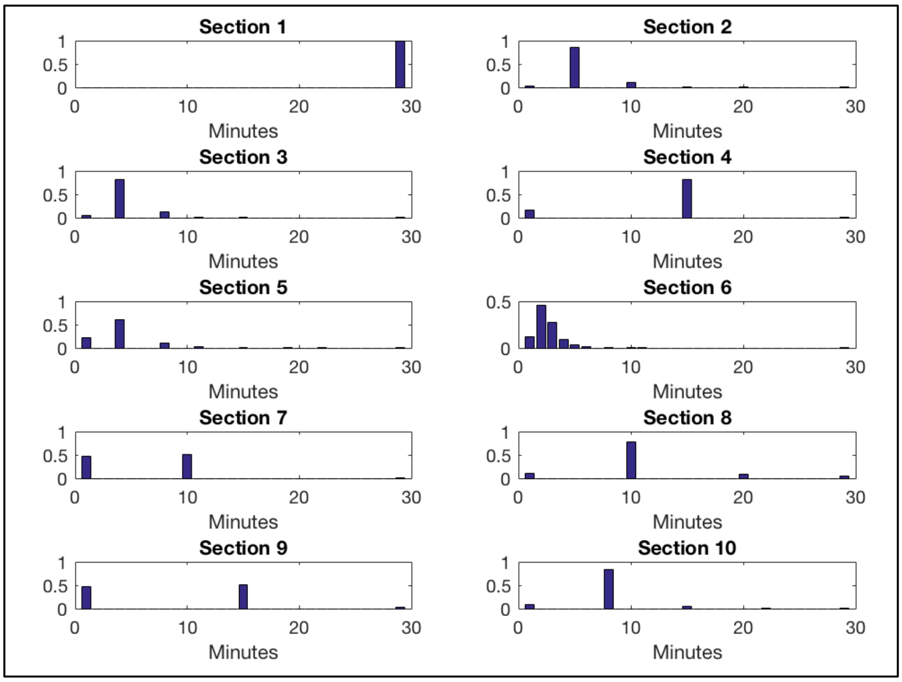

FIGURE 4-6: DISTRIBUTIONS OF TRAVEL TIMES FOR A PARTICULAR TRAIN BETWEEN DIFFERENT CHECKPOINTS

Figure 4-7 reports the distributions for another important parameter that characterizes the behaviour of a train, i.e., the dwell time at different checkpoints. This parameter is defined as the difference between the departure time and the arrival time for a fixed checkpoint ($\widehat{t_D^C} - \widehat{t_A^C}$); in other words, it represents the amount of time the train stops at a particular station. Dwell times are important because they can give indirect information about how much the train is crowded.

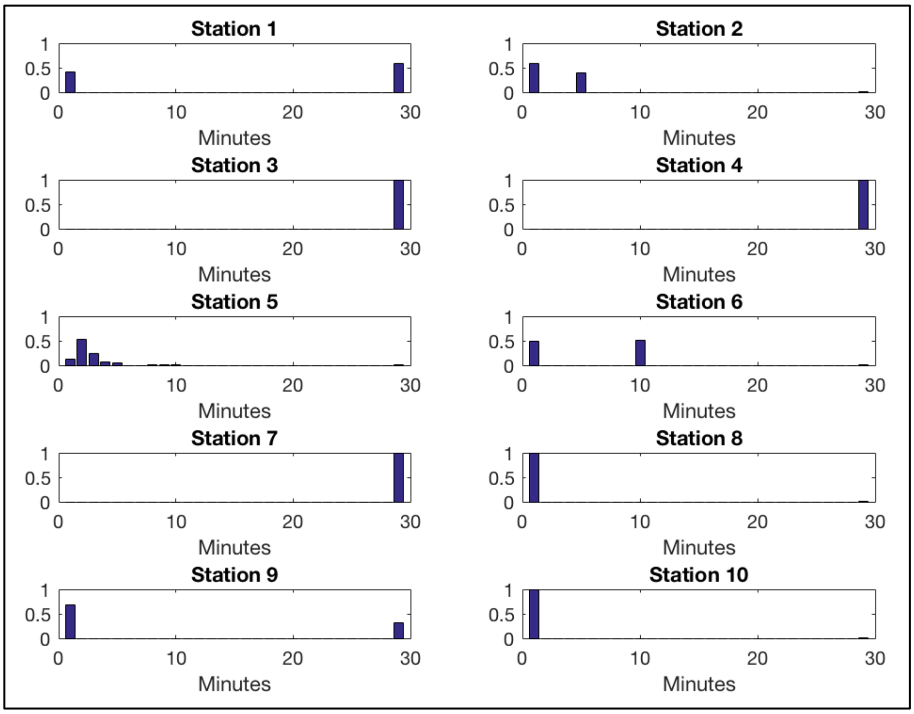

FIGURE 4-7: DISTRIBUTION OF DWELL TIME OF A PARTICULAR TRAIN AT DIFFERENT STATIONS

Finally, Figure 4-8 reports a more refined analysis, i.e., the scatter plot of the delay of a train at a particular station compared with the delay of another train at another station. This graph shows how the delays of two trains can be correlated, and it gives the possibility to predict one delay using the other.

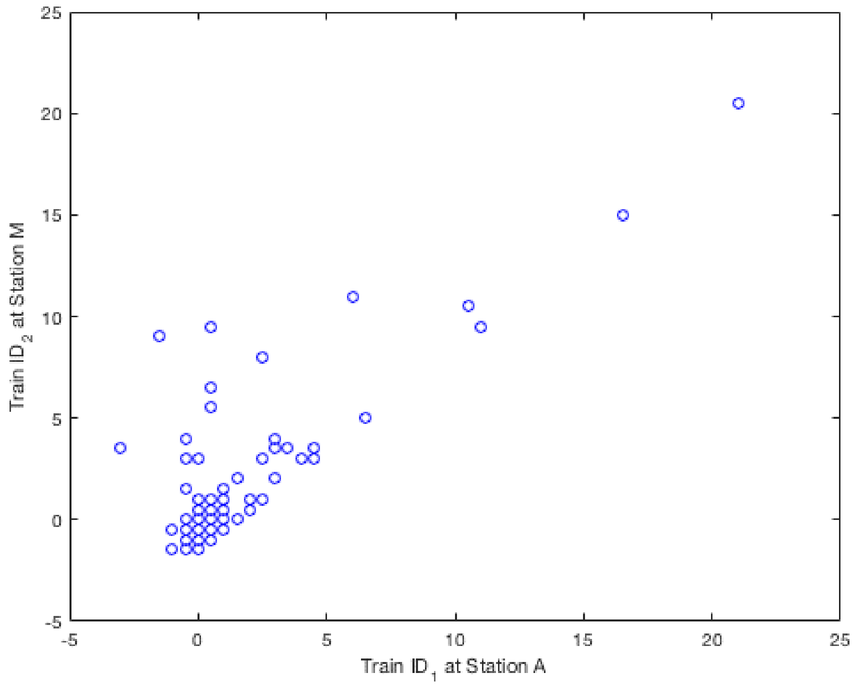

FIGURE 4-8: SCATTER PLOT OF THE DELAY OF TWO DIFFERENT TRAINS AT TWO DIFFERENT STATIONS

4.4 FORMAL DEFINITION OF DATA CHARACTERISTICS

In this section, the data characteristics are defined in terms of data format and representation, contemporarily recalling the associated data sources from which data are extracted. Moreover, this section describes how to normalize the data in order to obtain a homogeneous set, which will be used to perform the test and validation phases. Finally, the Key Performance Indicators (KPIs) are identified.

4.4.1 FORMAL DEFINITION

Based on the available data sources and on the goals to be achieved, it is possible to identify a formal definition of the data needed to build data-driven models to predict the delays of all the trains on the network. In particular, it is important to retrieve a number of tables including the following information:

- TABLE 1: the first table is the list of checkpoints with
  - ID of the checkpoint (expressed with a unique alphanumerical value)
  - Name of the checkpoint (alphanumerical value)
- TABLE 2: the second table is the list of trains with

- ID of the train (expressed with a unique alphanumerical value)
- Itinerary of the train (list of checkpoint IDs, taken from TABLE 1, sorted from origin to destination)
- List of days in which this train is scheduled (expressed in "dd/mm/yy")
- Train frequency (daily, workdays only, holidays only, monthly, etc.)
- Timetable of the itinerary (list of arrival and departure nominal times at each checkpoint included in the itinerary, expressed as "hh:mm:ss")

- TABLE 3: the third table includes the minutes that can be regained in each section of the network with:
  - ID of the origin station (the ones of TABLE 1)
  - ID of the destination station (the ones of TABLE 1)
  - Time (expressed in minutes) that can be regained in this section
- TABLE 4: the fourth table, instead, contains a set of information that characterizes each train movement on the railway network
  - Date (expressed as "dd/mm/yy")
  - ID of the train (the ones of TABLE 2)
  - ID of the checkpoint (the ones of TABLE 1)
  - Type of passage at the checkpoint
    - O: Origin
    - D: Destination
    - T: Transit
    - F: Stop
  - Scheduled time of arrival (expressed as "hh:mm:ss")
  - Actual time of arrival (expressed as "hh:mm:ss")
  - Scheduled time of departure (expressed as "hh:mm:ss")
  - Actual time of departure (expressed as "hh:mm:ss")
  - Delay at arrival (expressed in minutes)
  - Delay at departure (expressed in minutes)
  - Dwell time in the checkpoint (expressed in minutes)
  - Travel time for travelling from the previous checkpoint to the current one (expressed in minutes)

Note that, there should be no missing information in the table, and in case some information is missing, one possibility is to discard all the data related to that situation.

4.4.2 Data normalization and KPIs identification

In order to be able to feed the data-driven algorithms and to build the predictive models, a set of homogeneous and normalized data to work with is needed.

In particular, for each train that has run over the railway network at time t, it should be possible to retrieve at each previous moment $t_\delta = (t - \delta)$ the situation of the entire network. This historical data could be used to build a model, which could be applied to the current state of the railway network and finally validated in terms of performance based on what really happens in a future instant. Obviously, this procedure can be simulated by splitting the available data (e.g., 6 months of records) in two different parts. The first part (e.g., 1 or 2 months of data) can be used to build the model, while the remaining one (e.g., 4 months) can be employed for testing the model. Furthermore, it would be interesting to adopt online approaches that consider the possibility to update predictive models every day, so to take advantage of new information as soon as it becomes available. In this case, all the data related to the first 4 months could be used to predict the delay from the 5th month onwards.

Consequently, given a railway network, a historical set of data is needed, including the following information:

- The list of trains that have been scheduled to run over the network
- The list of trains that have actually run over the network (note that it may be different from the one above because of some train cancellations)
- For each train:
  - Its position over the network for each significant instant over time.
    In case it stopped at a station:
    - Its delay of arrival
    - Its travel time from the previous station

    Otherwise, in case it was travelling:
    - Its delay of departure
    - Its dwell time in the last station

Consequently, it is possible to build a model that, at time t, uses all the available information described above at different past times, such as $t, (t-30s), (t-60s), \dots, (t- \ \delta)$, supposing that data granularity is in the order of half a minute. The model can be used to predict the delay of each train on the network at time $(t + \Delta)$, where delta (Δ) is a desired time horizon. In order to build the model, the algorithms have to use all the examples of the configuration of the railway network at time t of the previous days included in the historical dataset, since for the previous days both the information about $t, (t-30s), (t-60s), \dots, (t- \ \delta)$ and about $(t + \Delta)$ are available. Note that it is important to only consider the days included in the historical data where the train that should have run over the network. Moreover, it is important to select only the same type of days (e.g., workdays, holidays) like the one for which the model is used to make the prediction, because, for example, trains travelling during workdays might be different from the ones travelling during holidays.

Figure 4-9 shows an example of the data needed to build a forecasting model based on the railway network depicted in Figure 4-1.

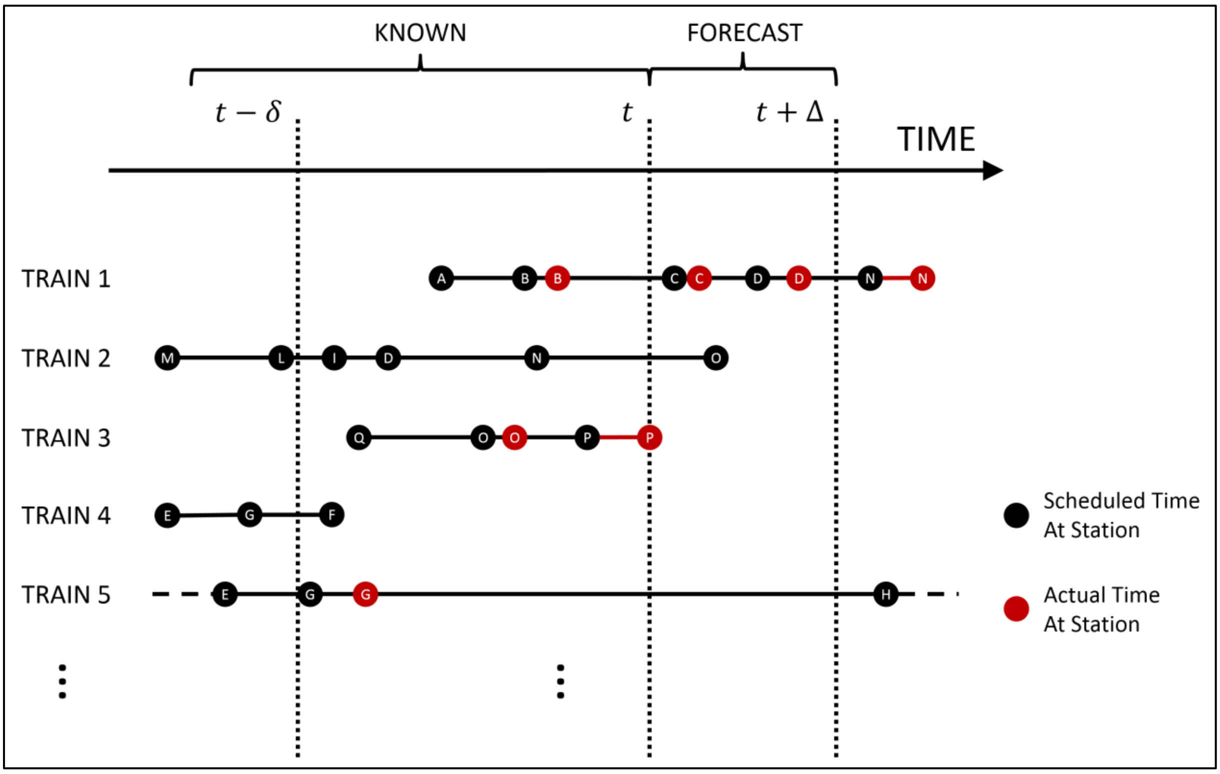

FIGURE 4-9: DATA NORMALIZATION FOR TRAIN DELAY FORECASTING MODEL

4.4.2.1 KPIs IDENTIFICATION

Since the purpose of this work is to build predictive models able to forecast the train delays, different indicators of the quality of these predictive models will be used as KPIs. Note that the predictive models should be able to predict, for each train and at each checkpoint of its itinerary, the delay that the train will have in any of the successive checkpoints. Based on this consideration, three different indicators of the quality of predictive models will be used, which are also proposed in Figure 4-10 in a graphical fashion:

- Average Accuracy at Checkpoint i for train j (AACij): for a particular train j, the average of the absolute value of the difference between the predicted delay and its actual delay, at the i-th station, is computed.
- AACi: is the average over the different trains j of AACij

- Average Accuracy at the i-th following Checkpoint for train j (AAiCj): for a particular train j, we average the absolute value of the difference between the predicted delay and its actual delay, at the i-th following checkpoints with respect to the actual one.
- AAiC: is the average over the different trains j of AAiCj
- Total Average Accuracy for train j (TAAj): is the average over the different checkpoint i-th of AACij (or equivalently the average over the index i of AAiCj).
- TAA: is the average over the different trains j of TAAj

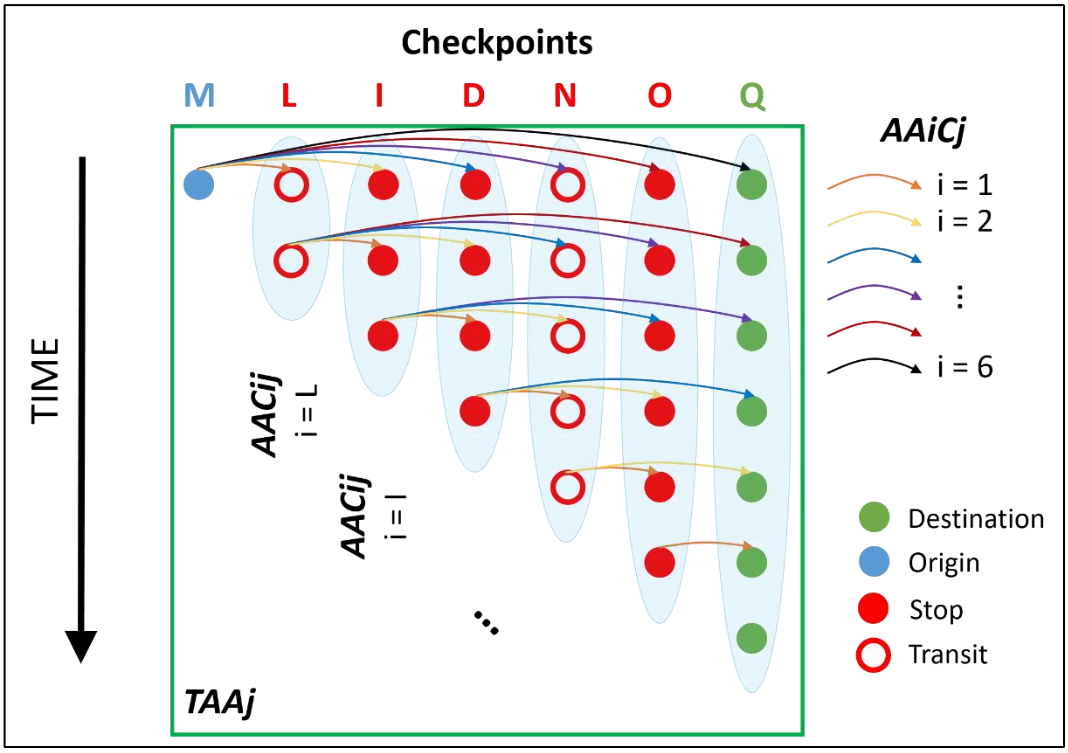

FIGURE 4-10: KPIS FOR THE TRAIN AND THE ITINERARY DEPICTED IN FIGURE 4-2

4.5 DATA ANALYSIS ALGORITHMS IDENTIFICATION AND SELECTION

As discussed in the previous sections, the train delay prediction problem can be seen as a time series forecasting problem (Bloomfield, 2004) (Box, Jenkins, & Reinsel, 2011) (Chatfield, 2013) (Hamilton, 1994) (Lutkepohl, 2005) (Montgomery, Johnson, & Gardiner, 1990), where train delays are studied according to historical data about train movements collected by TMSs. In order to solve the time series forecasting problem using a data-driven approach, it can be mapped into a multivariate regression problem, and consequently tackled using state-of-the-art data mining algorithms (e.g., kernel methods, artificial neural networks, etc.).

This section introduces the mapping between the train delay prediction problem and the multivariate regression problem and describes the general modelling approach that is proposed, lists some state-of-the-art algorithms that could be successfully exploited in this context, and finally briefly shows why and how to tune specific parameters (called hyperparameters) of these algorithms.

4.5.1 Train Delay Prediction as a Multivariate Regression Problem

Firstly, it is worth to recall the general idea guiding data-driven methodologies, which relates to using historical data (in this specific case, data about train movements) to see what happened in the past and extract knowledge in order to predict what will happen in the future. Given an historical database, data is analysed by data mining algorithms in order to build data-driven models (usually black-box) that are able to respond to new, previously unseen input data. Indeed, these data-driven models can be effectively used to perform predictions of the future by exploiting the extracted knowledge of the modelled phenomena in combination with the data describing the current situation.

As already stated, the train delay prediction problem can be mapped to a multivariate regression problem. In particular, focusing on the prediction of the delay profile of a single train, the problem includes a variable of interest (i.e., the delay profile of a train along its itinerary) and other possible correlated variables (e.g., information about other trains traveling on the network, day of the week, etc.). The goal is to find a solution able to model the link between the variable of interest, its past values (i.e., its history), and the other correlated variables. In other words, the resulting model(s) should predict (with the highest possible accuracy) the delay that will affect a specific train for each subsequent checkpoint (included in its trip) with respect to the last one in which the train has transited. Given the previous observations, it is easy to map the train delay prediction problem into a classical multivariate regression problem (Shawe-Taylor & Cristianini, 2004) (Vapnik, 1998) (Takens, 1981) (Packard, Crutchfield, Farmer, & Shaw, 1980)**Erreur ! Source du renvoi introuvable.**. M oreover, due to the dynamic nature of the problem, the regression problem is also time varying, consequently only the most recent part of the historical data has to be used, which represent the distribution under exam.

In this context, the proposed modelling approach is based on a set of data-driven models that, working together, make it possible to perform a regression analysis on the past delay profiles and consequently to predict the future ones. In particular, for each train and for each checkpoint composing its trip, a set of data-driven multivariate regression models is built connecting one checkpoint to its successive ones. An example is shown in Figure 4-11, where a train has just started its trip from its origin station *A* and the prediction system has to provide predictions of arrivals at (departures from) the checkpoints *B, C, …, G* composing the train trip. In this picture, each arrow represents a data-driven model that outputs a delay prediction for the arrival at (departure from) the pointed checkpoint. It is worth to note that, as soon as the train arrives at checkpoint *B*, this approach exploits a different set of data-driven models for providing predictions of arrivals at (departures from) the checkpoints *C, D, …, G*. Consequently, the number of models to build and manage increases exponentially with the number of trains and checkpoints to be considered.

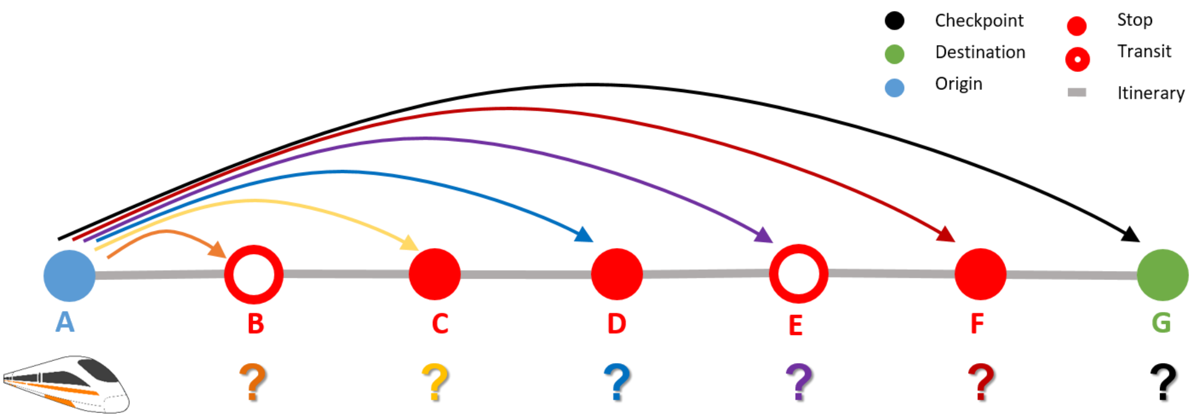

Figure 4-11 Proposed data-driven modelling approach

Taking a closer look to the models, for a single train arriving at (departing from) a specific checkpoint included in its trip, the data-driven multivariate regression models take as inputs:

- The current day of the week (Monday, Tuesday, ...)
- A Boolean value indicating whether the current day is a holiday or a working day
- The sequence of arrival (departure) delays affecting that specific train in the current day at its passage/stop in the previous checkpoints (i.e., from origin to the last visited checkpoint)
- The collection of train delays affecting other trains travelling on the railway network in the current day
- The sequence of running times and dwell times for both the considered train and the others travelling on the railway network in the current day.

The models give as output:

- the sequence of arrival (departure) delays that will affect the considered train for each subsequent checkpoint with respect to the last one in which the train has transited.

Finally, Figure 4-12 shows a graphical representation of the mapping of the train delay prediction problem into a multivariate regression problem. For instance, in this representation, the variable of interest is represented by the delay profile of a train T_k . The other correlated variables are represented by dwell times and running times for train T_k, and by the information regarding all the other trains traveling along the network simultaneously to train T_k. An example of the inputs taken into account by the set of models used when train T_k has already passed by or departed from checkpoint B is highlighted in red. Analogously, all the aforementioned elements of the regression problem are depicted in the figure under examination.

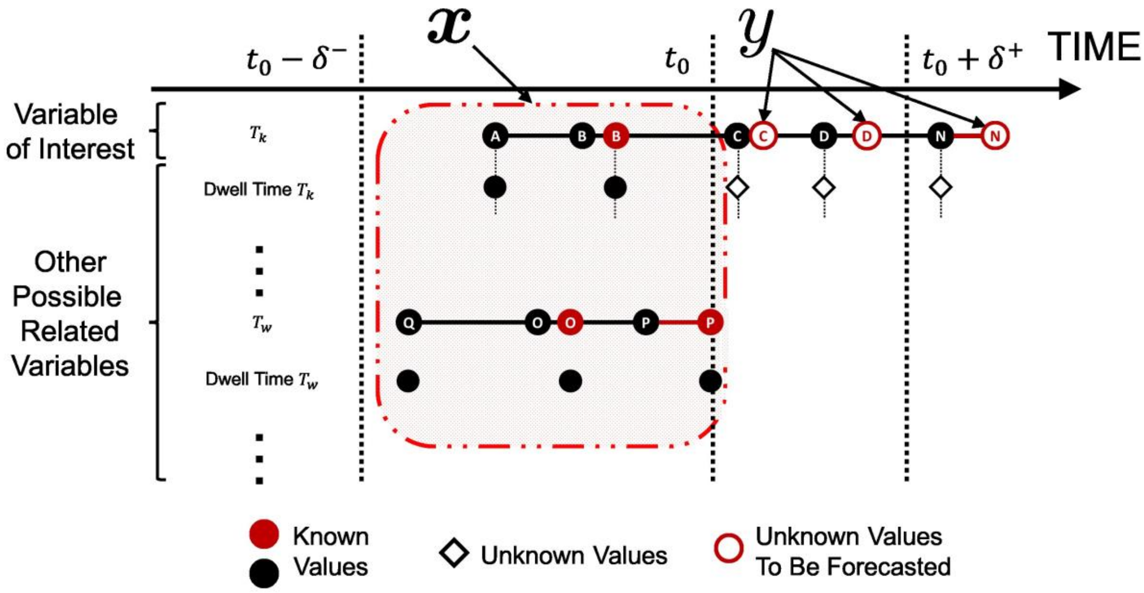

FIGURE 4-12 - MAPPING OF THE TRAIN DELAY PREDICTION PROBLEM INTO A MULTIVARIATE REGRESSION PROBLEM

4.5.2 STATE-OF-THE-ART ALGORITHMS FOR MULTIVARIATE REGRESSION

As described in the previous sections, many data mining algorithms able to cope with multivariate regression problems exist. In order to perform tests and simulations on real world data, a particular type of Artificial Neural Network models have been selected, i.e., Extreme Learning Machines (ELM). Figure 4-13 shows a graphical representation of the ELM neural network structure.

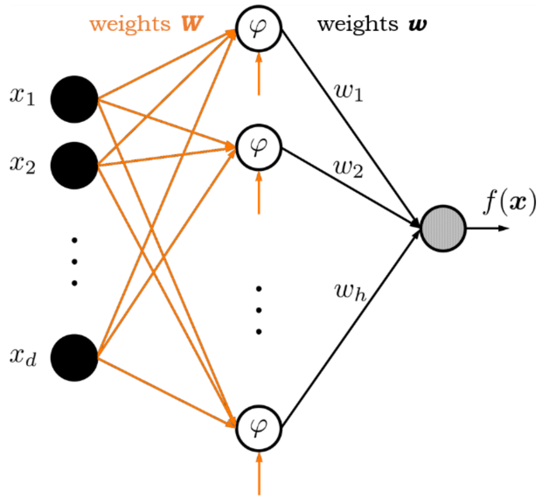

FIGURE 4-13 - ELM STRUCTURE

ELM (Bisio, Gastaldo, Zunino, & Cambria, 2015) (Huang, Chen, & Siew, 2006) (Huang, Zhou, & Siew, Extreme learning machine: a new learning scheme of feedforward neural networks, 2004) (Huang G. , Zhou, Ding, & Zhang, 2012) were originally developed for the single-hidden-layer feedforward neural networks, i.e., a neural network including an input layer composed of d neurons, connected to the hidden layer (composed of h neurons) through a set of weights W and a nonlinear activation function. The peculiarity of ELM is that weights W are chosen randomly, and that the neural network is trained by exploiting a simple, efficient procedure that involves few simple steps and that allows determining the set of weights w connecting hidden neurons to the output one. Despite the apparent simplicity of the ELM approach, they represent a crucial milestone because they demonstrate that even random weights in the hidden layer endow a network with notable representation ability. The ELM approach was introduced to overcome problems posed by back-propagation training algorithm: potentially slow convergence rates, critical tuning of optimization parameters and presence of local minima that call for multi-start and re-training strategies.

4.5.3 MODEL SELECTION

Model Selection (MS) deals with the optimization of the performance of a learning procedure by tuning its hyperparameters (Anguita, Ghio, Oneto, & Ridella S., 2012) (Bartlett, Boucheron, & Lugosi, 2002). Performance assessment of data-driven models 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.

This section gives a brief and concise overview of the state-of-art methodologies for Model Selection. Resampling techniques like hold out, cross validation and bootstrap (Bartlett, Boucheron, & Lugosi, 2002) are well known and often used by practitioners because they work well in many situations.

Nevertheless, other methods exist in literature: for example, (Vapnik, 1998) is the seminal work on Vapnik-Chervonenkis Dimension, later improved by the Rademacher Complexity (Bartlett & Mendelson, Rademacher and gaussian complexities: Risk bounds and structural results, 2002), together with its localized counterpart (Bartlett, Bousquet, & Mendelson, Local rademacher complexities, 2005). The theory of (Floyd & Warmuth, 1995), later extended by (Langford & McAllester, 2004), was another step forward that tightly connects the concept of “compression” to learning. A breakthrough was made with the Algorithmic Stability (Bousquet & Elisseeff, 2002) (Poggio, Rifkin, Mukherjee, & Niyogi, 2004) (Oneto, Ghio, Ridella, & Anguita, 2015). The PAC-Bayes theory represents another fundamental brick (Lever, Laviolette, & Shawe-Taylor, 2013) (Tolstikhin & Seldin, 2013) (Germain, Lacasse, Laviolette, & Marchand, 2015) (Bégin, Germain, Laviolette, & Roy, 2016) for MS, especially in the context of ensemble methods (Nitzan & Paroush, 1982) (Catoni, 2007). Finally, Differential Privacy (DP) allowed reaching a milestone result (Dwork, et al., 2015), for which a major result is a novel procedure called Thresholdout (Dwork, et al., Generalization in adaptive data analysis and holdout reuse, 2015) (Dwork, et al., The reusable holdout: Preserving validity in adaptive data analysis, 2015).

In this project, we propose to use the Cross Validation, which is one of the most powerful tool in the context, and consequently, we further describe its principles. Cross-validation is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. In a prediction problem, a model is usually given a dataset of known data on which training is run (training dataset), and a dataset of unknown data (or first seen data) against which the model is tested (testing dataset). The goal of cross validation is to define a dataset to “test” the model in the training phase (i.e., the validation dataset), in order to limit problems like overfitting, give an insight on how the model will generalize to an independent dataset (i.e., an unknown dataset, for instance from a real problem), etc. One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set). To reduce variability, multiple rounds of cross-validation are performed using different partitions, and the validation results are averaged over the rounds. One of the main reasons for using cross-validation instead of using the conventional validation (e.g., partitioning the data set into two sets of 70% for training and 30% for test) is that there is not enough data available to partition it into separate training and test sets without losing significant modelling or testing capability. In these cases, a fair way to estimate properly model prediction performance is to use cross validation as a powerful general technique. In summary, cross validation combines (averages) measures of fit (prediction error) to derive a more accurate estimate of the model prediction performance.

4.6 Tests and simulations

This section describes the tests and simulations performed on real data in order to retrieve the final results on the data-driven modelling of the problem of train delay prediction. Firstly, the simulation methodology and setup are described, and then the complete results are reported.

4.6.1 Simulations Methodology and Setup

The general idea behind simulations for assessing the performance of the data-driven models follows the one at the basis of the model selection procedures. Again, part of the available data is used to build the models, while the rest is exploited for performance evaluations. The former set of data is called "training set", while the latter is called "test set". It is important to underline that this section presents the simulation methodology exploited for this project (i.e., specifically tailored to the case of train delay prediction) in a general way, so that the principles could be directly followed in a large-scale test environment exploiting the entire available dataset.

In this project, real data about train movements are exploited. They provided by the Italian Infrastructure Manager, RFI. The data refer to 6 months of train movements in the area of Milan, and 1 year in the area of Genoa, and are formatted as described in the related sections.

The simulation procedure includes several steps, which are repeated for each day of data included in the test set. Moreover, an online-approach is adopted, which updates predictive models every day in order to take advantage of new information as soon as it becomes available. The list of simulation steps is reported below:

- build the needed set of ELM models for each train in the dataset based on current training set
- tune the models' hyperparameters through Cross Validation (model selection phase)
- consider the next test day
- consider each train and the corresponding trip made of several 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 has really happened
- 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.

The results of the simulations have been compared with the results of the current train delay prediction system used by RFI. The RFI system is quite similar to the one described in (Kecman & Goverde, 2015), although the latter includes process mining refinements which potentially increases its performance. In short, the current technique used by RFI for train delay prediction is based on line characteristics, on trains characteristics and on simple statistics, aiming at computing the amount of time needed to complete a particular section of the train trip and exploiting it for predictions.

In order to fairly assess the performance of the proposed prediction system, a set of novel KPIs agreed with RFI has been designed and used, which have been already presented in Section 994.4.2.1. These KPIs represent different indicators of the quality of these predictive models.

4.6.2 Results

In summary, the proposed methods improve the stat- of-the-art ones, which rely on static rules built by experts of the railway infrastructure based on classical univariate statistic. Results on real world train movement data show that advanced analytics approaches can perform up to twice as well as current state-of-the-art methodologies. In particular, exploiting historical data about train movement gives robust ELM models with high performance with respect to the actual train delay prediction system of RFI.

The performance of the two different methods has been compared:

- **RFI:** the RFI system has been implemented.
- **ELM:** the Extreme Learning Machine has been exploited.

In Table 4-1, Table 4-2 and Table 4-3 the KPIs of the two different methods have been reported. Please note that the tables are not complete due to space constraints and that the train and checkpoint IDs have been anonymized.

Here below the results are discussed on a per-table basis:

- Table 4-1 reports the AAiCj and AAiC. From Table 4-1 it is possible to observe that the ELM method improves up to a factor 2 the current RFI system. In general, ELM improves over the RFI system by a large amount. Finally, note that the accuracy decreases as i increases since the forecast refers to an event which is further into the future, and note that some trains have fewer checkpoints than the others (this is the reason of the symbol "-" for train j = 14, which only passes through two checkpoints).
- Table 4-2 reports the AACij and the AACi. From Table 4-2 it is possible to derive the same observations derived from Table 4-1. In this case it is important to underline that not all the trains run over all the checkpoints, and this is the reason why for some combinations of train j and checkpoint i there is a symbol "-".

- Table 4-3 reports the TAAj and the TAA. This table is the most concise and underlines best the advantage, from a final performance perspective, of the ELM method with respect to the RFI prediction system.

TABLE 4-1 - ELM AND RFI PREDICTION SYSTEMS AAICJ AND AAIC (IN MINUTES)

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	1.7	**1.1**	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**	
. . .									
AACi	3.0	**1.6**	2.9	1.7	3.2	2.0	3.4	2.2	

TABLE 4-2 - ELM AND RFI PREDICTION SYSTEMS AACIJ AND AACI (IN MINUTES)

AACij	RFI	ELM	RFI	ELM	RFI	ELM	RFI	ELM	
j \ i	1		2		3		4		
1	2.9	**2.3**	-	-	-	-	2.2	2.2	
2	**0.0**	0.1	-	-	-	-	2.5	**1.7**	
3	0.2	**0.0**	-	-	-	-	2.2	**1.6**	
4	1.7	1.5	2.3	1.8	2.9	1.8	-	-	
5	-	-	**1.1**	**1.1**	1.1	**0.9**	-	-	
6	-	-	**1.2**	1.4	1.8	1.8	-	-	
7	-	-	1.8	1.3	1.7	**1.5**	-	-	
8	-	-	1.5	1.4	3.0	2.5	-	-	
9	-	-	1.1	1.0	1.2	1.1	-	-	
10	-	-	1.9	**1.2**	1.8	1.4	-	-	
11	-	-	-	-	-	-	-	-	
12	-	-	-	-	-	-	-	-	
13	-	-	-	-	-	-	-	-	
14	-	-	-	-	-	-	-	-	
15	1.3	**1.1**	1.8	1.1	1.2	1.1	-	-	. . .
16	-	-	-	-	-	-	3.9	1.0	
17	-	-	-	-	-	-	5.8	**2.7**	
18	-	-	-	-	-	-	6.7	4.3	
19	-	-	-	-	-	-	3.8	1.0	
20	-	-	-	-	-	-	3.7	**1.0**	
21	-	-	-	-	-	-	5.9	2.4	
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	
				. . .					
AAiC	3.3	**1.5**	3.1	1.5	3.3	1.4	4.2	**2.2**	

TABLE 4-3 - ELM AND RFI PREDICTION SYSTEMS TAAJ AND TAA (IN MINUTES)

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	1.2	1.0
16	3.9	1.0
17	5.8	2.7
18	6.7	4.3
19	3.8	**1.0**
20	3.7	1.0
21	5.9	2.4
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
		. .
TAA	3.3	2.0

4.7 Possible contribution of these methods to large disruption management

The proposed method is particularly suitable to predict train delays when traffic is being operated in “normal” conditions. This means that minor perturbations are taken into account if recurrent: if the trains often suffer a delay when leaving a certain station, for example, then the method will predict so also for the future.

However, in case of large disruptions, as the ones considered in this deliverable caused by extreme weather events, the train delays cannot be anticipated by looking at what has happened in the past. This is because most big disruptions occur very seldom, unless they are indeed unique. Then, no sufficient historical information is available to know what to expect in the future.

Nonetheless, a slightly modified variant of the ELM method may be extremely useful during the traffic state monitoring following the decision of implementing a recovery plan, which is a fundamental activity in the disruption management process formalized and validated in (CAPACITY4RAIL, 2016). For example, if it is necessary to monitor traffic after the infrastructure has been restored or in an area where the infrastructure is fully available, the historical data can regain their original usefulness. Indeed, in these cases, a possibly strong delay affects the trains already at their arrival in the area under study. However, independently of this initial delay, the trains are likely to suffer within the area from the same problems which affect normal traffic, and which may then be predicted using a method as ELM. The modifications necessary to take into account the initial delays can be easily envisaged without changing the nature of the method, which would constitute an important increase of automation in large disruption management.

5. Automation improvement and capacity planning

In Work Package 3.2 of the Capacity4Rail project, we have developed a framework for modelling and simulation of enhanced capacity (CAPACITY4RAIL, 2017). In this chapter, we propose a brief analysis on large disruption based the same principle there used. In particular, we have considered the capacity utilization planning process as a step by step process including three levels: we distinguish between strategic level (planning of infrastructure) tactical level (timetabling) and operational level (dispatching). Moreover, we have observed that closely related to the operational planning are Driver Advisory Systems (DAS), which in the future may be extended towards fully automatized driving. Figure 5-1 shows how demand for and supply of capacity influence the capacity utilization planning at all levels, in the nominal case without disturbances. As the main vertical arrow indicates, the capacity utilization planning is a step-wise, sequential process, where later steps are heavily dependent on earlier ones. In (CAPACITY4RAIL, 2017), we have focused on the tactical and on the operational level, including the DAS.

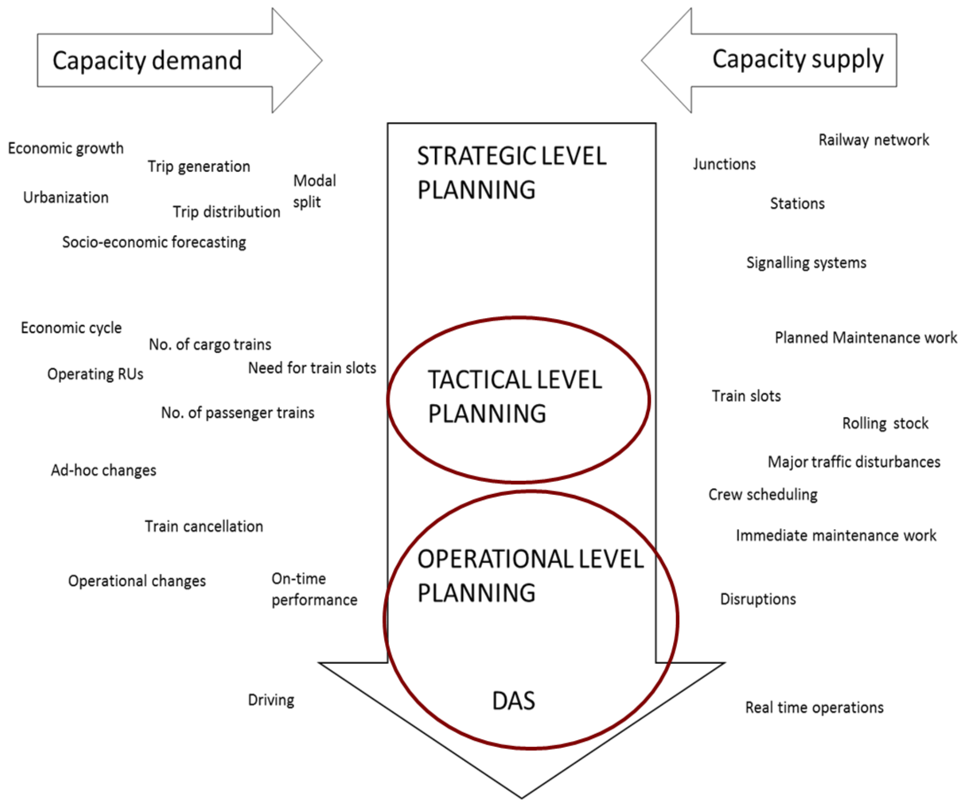

FIGURE 5-1 CAPACITY DEMAND AND SUPPLY: THE TWO CIRCLES INDICATE THE FOCUS IN (CAPACITY4RAIL, 2017)

5.1 Framework for support in capacity planning

Based on the capacity utilization planning process sketched above, we can identify the need for decision support tools on various levels. In Figure 5-2 we have summarized the needs in a schematic way. Unlike the one-directed planning progression depicted in Figure 5-1, the modelling framework also include backward arcs representing a feedback of information to an earlier planning stage. These connections are of special interest when handling major disruptions. However, that is not always uncomplicated.

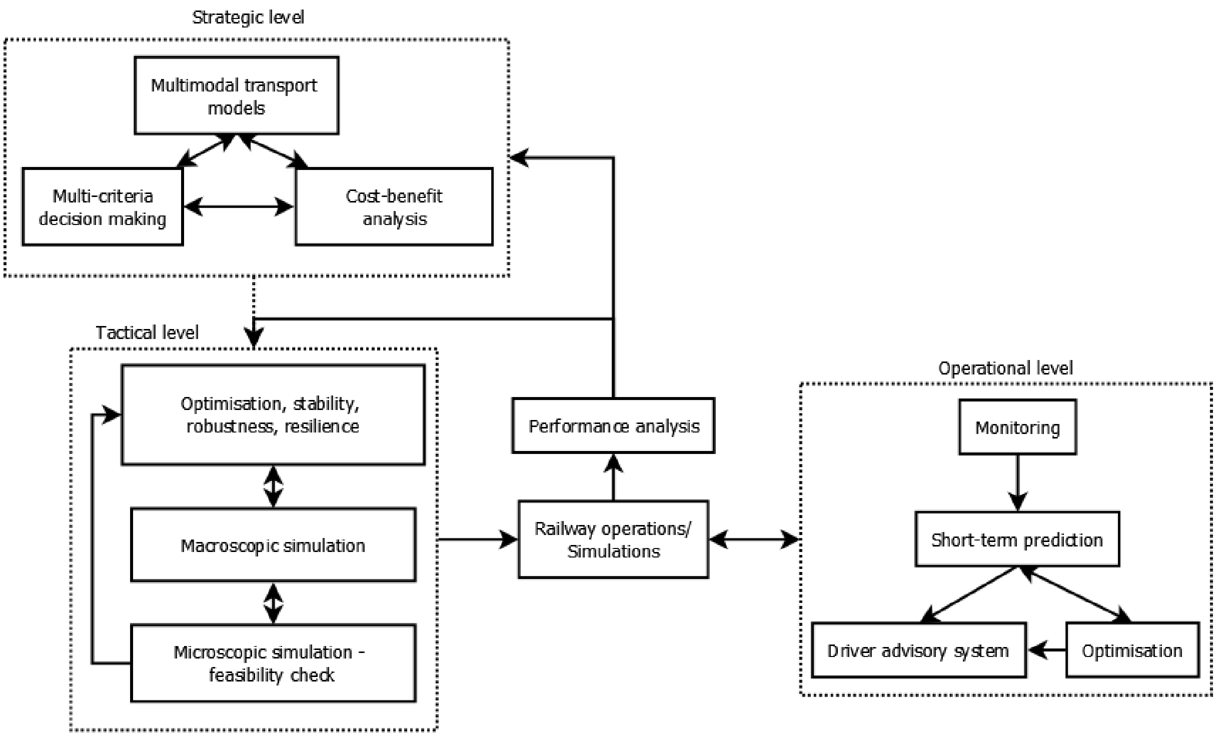

FIGURE 5-2 FRAMEWORK FOR SUPPORT IN PLANNING PROCESSES RELATED TO RAILWAY CAPACITY

Disruptions normally occur very late in the capacity utilization planning process but have effects also on all levels. For example, modal split is normally considered in strategic planning to estimate the demand which the infrastructure will need to satisfy, considering 5 to 10 years ahead. However, it happens sometimes that disruptions in road or air traffic cause an immediate increase on the demand for rail transportation. The air traffic interruption due to the eruptions of the volcano Eyjafjallajökull in Iceland, with the consequent ash cloud, in 2010 is a good example of such a modal transfer toward the rail due to a disruption. If suitable, these modal transfers may be considered in the strategic level to design a robust infrastructure.

In the following we go through possibilities and challenges on all levels.

5.2 Disruptions on a strategic level

Demand modelling on strategic level typically relies on normal conditions. Important assumptions are, for example, the rationality principle, basically saying that a passenger chooses a certain departure because it maximizes his own utility. In road traffic planning, link capacity and induced travel times are based on the Wardropian equilibrium principle, telling that no single vehicle could get a shorter travel time by changing route. Normally also complete knowledge of travel time on all alternative routes is assumed. For a deep analysis on models for demand modelling, we refer the reader to, e.g., (Ortúzar & Willumsen, 2011). In a disturbed situation, this type of assumptions is barely valid.

However, there are some types of major disruptions, which are long lasting and known well in advance, for which strategic level models can be useful. Some Swedish examples are the complete construction and upgrading of the Svealand line (Fröidh, 2003) and the electrification of the Blekinge Coast line, where a complete railway line has been closed for traffic several years. This can be modelled considering the need for bus replacement and increased car traffic. Another example is Kiruna, in northern Sweden, where the extension of the mining field has given rise to a complete movement of the inner city (Kiruna, 2017). For some years, the railway station has been temporarily moved to a new place, outside of both the former and the future city. This disturbance certainly has impact on the demand for railway journeys.

5.3 Disruptions on a tactical level

Capacity modelling on tactical level typically also relies on normal conditions. The outcome of the planning process is a timetable, which meets the wishes from rail undertakings as well as possible, while still respecting the given capacity. Planning assumptions on this level concern the number of rail undertakings and their rolling stock. The plan is decisive for the rail undertakings' business: What products should be offered to the customers, and how should the prices be set in a yield management perspective depend on the timetable.

Disruptions that can be counted for in the tactical process are, for example, major maintenance works: rails must be changed, or electrical powerline renewed, meaning that parts of the railway network must be temporarily closed. We can then reduce the available capacity, for example during night time, or by closing one of the tracks on a double track line. Some models taking into account such disruptions are available, but more research is needed for scheduling of maintenance work, see, e.g., (Lidén, 2016).

With existing models, we can also relatively easy make reduction plans, to activate at, for example, hard weather conditions. They are typically called contingency plans. An important input to do so is the available capacity. Typically several plans must be made, for various scenarios.

Problems arising when using this type of models with a short time horizon are the effects of plan changes on crew scheduling, vehicle circulation, etc. Normally the planning process iterates between infrastructure manager and rail undertaking, which makes it complicated. It is important not to systematically change the market situation between different rail undertakings and different rail products (freight train, passenger train, local train, etc.). Rail undertakings normally have contracts with their end customers, making it hard to accept large changes.

5.4 Disruptions on an operational level and Driving Advisory Systems (DAS)

On an operational level, planning is handled by the train dispatchers who set the switches and signals and decide the train order. The models developed here are intended for monitoring and short term planning. They normally rely on standard conditions, for example average values for acceleration, deceleration, speed, and dwell-time. With a major disruption, these values are probably not valid, and an automated decision tool will not give the best suggestions.

A clear example of this is the LiU-CAIN model, which is described in (CAPACITY4RAIL, 2017). Here a new train path can be inserted into an existing timetable, such that the expected delay impact is minimized. The method relies on the assumption that everything, but the new train path, propagates as usual. In a heavily disturbed situation this is unlikely the case. For example, when there is much more passengers than normal due to disturbances in other travel modes and/or another part of the rail network, the model will be biased, and dwelling times will be systematically underestimated. Further, if more than one train is inserted, or insertions are combined with cancellations, the progression process will change significantly from the normal state, and the statistics collected during the last couple of months will not be a meaningful base for short-term forecasts.

Indeed, the need for better models and higher degree of automation in case of major disruptions is of course large. A good starting point may be the IS KADR tool from Oltis Group. KADR and KANGO are the systems for planning, construction and evaluation of the real-time timetable implemented at both infrastructure managers in the Czech Republic and Slovakia. A special function is dedicated to the request of train path by the railway undertaking. Depending on time distance from the day of requested operation, it is divided as:

- In proper time: received by IM before the validity of a new timetable – system KANGO.
- Ad-hoc paths: all requests received after the starting the new timetable – system IS KADR.

The system KANGO serves as a tool for yearly timetable construction and contains a rail infrastructure description. This system utilizes the following systems for retrieving inputs: Rolling stock reference database (REVOZ), requests and determination of the route of exceptional transports (MIMOZA/SYMOZA), database of companies operating as RUs, IMs, vehicle keepers, etc. (KAFR), infrastructure restriction notification database (DOMIN).

The system KADR features include: request for path and capacity during the validity of the timetable (ad-hoc request): manual input or import of data from a system of operators, transmission of “data timetable” in form of TSI TAF messages, evaluation of requests and proposal of “data timetables”, input and processing changes into existing timetable (incl. cancellation), input or acceptance of train paths activation / deactivation, handing over all necessary information to assemble systems of the infrastructure manager, support of communication in TSI TAF/TAP (ver. 2.1), path request, path details, path cancelled, receipt confirmation and changes in the timetable.

The IS KADR tool is also the basis of the LiU-CAIN software, where the Oltis tool suggests a new train path which is evaluated with the LiU tool based on statistical analyses. Also this software can be improved and adjusted to be a useful support too in case of major disruption. The current version of the tool relies entirely on post-ex information (here: statistics), to estimate an expected delay impact.

Considering a different perspective, we would also like to use goodness measures based on ex-ante information, that is, information calculated solely from the timetable, to deal with disruption. Such information can rely on capacity utilisation and various measures for robustness and heterogeneity. For an overview of interesting ex-ante measures we refer to, e.g., (Anderson, 2014). Also other key performance indicators may be used as proposed in, e.g., (Nicholson, Kirkwood, Roberts, & Schmid, 2015) and (Solinen, Nicholson, & Peterson, 2017).

6. Conclusions

In this deliverable we have focused on the increase of automation in the railway system with particular attention to the management of large disruptions, especially due to extreme weather.

The first objective of this work was the development of recommendations for this management. After the analysis of the process and with the aid of the reports on actually occurred disruptions, we proposed four major recommendations for increasing the automation in sensible contexts. First of all, the integration of weather forecast models in the preparation for extreme weather events in the railway operation would definitely bring important benefits. Even in the current practice where this is not frequently done, the higher efficiency of the process is remarkable when it is the case. The second recommendation concerns the improvement of the communication sharing across organizations and within individual ones. The potential benefits of having the instantaneous and automated sharing of information are intuitive, but this is not yet achievable in the current practice. Third, automated decision support tools for optimizing the resource reallocation necessary in case of large disruption still lack, and may strongly help to improve the efficiency of the process. Finally, also the monitoring of traffic evolution following the implementation of a contingency plan for resource reallocation today is almost completely manual. By increasing the level of automation, it may be possible to obtain more precise and timely updates on the traffic state.

The second objective was of the definition of a roadmap for automation strategies. To do so, we first analyzed the envisaged levels of automation of different subsystems: Rolling stock (trains), to provide seats and carry freight; Command and control systems that can detect and route trains to the right destination; Stations, so that passengers can alight or depart on a journey; Infrastructure, so as to establish and maintain track, signalling and power systems for the rolling stock. Then we studied how the different levels of automation of these subsystems may evolve to bring an increase of capacity of the whole railway system. This study explained and validated through simulations that only a coherent development of all subsystems can actually have a noticeable impact on capacity. In particular, we identified six grades of automation which would be coherent at the system level and hence definitely useful. In the first grade, all processes and elements are manual, e.g., driving, traffic and platform management. In the intermediate level 3, for example, driverless trains intervene, together with rule based traffic management and automatic platform management. Finally, in the highest grade, driving become unattended and traffic management joins platform management becoming automatic as well.

Finally, the third objective was the assessment through simulation of the impact of an increase of automation. To do so, we proposed a model for delay prediction as an instance of automation increase. It is based on state-of-the-art tools and techniques able to grasp the knowledge hidden in historical data about train movements. The proposed solution improves the state-of-the-art methodologies actually exploited by the IMs. Indeed, the results on the real world data about train movements provided by RFI show that the model performs up to twice as well as the current state-of- the-art methodologies. Future works will take into account also exogenous information available from external sources, such as weather information, information about passenger flows (e.g., by using touristic databases), about railway assets conditions, or any other source of data which may affect railway dispatching operations. In particular, the In2Rail[1] H2020 project is currently studying and developing a novel solution that will be able to integrate relevant exogenous information into a system for predicting train delays.

[1] Innovative Intelligent Rail - In2Rail (European Union's Horizon 2020 research and innovation programme under grant agreement 635900) http://www.in2rail.eu/

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