Deliverable D 4.1

WP4 Report on case studies and analysis of transferability from other sectors

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Executive Summary

This deliverable reports on case studies and analysis of transferability to railways of approaches of artificial intelligence for railway traffic planning and management. The document addresses transferability of AI techniques used for traffic planning and management from related sectors to railways. It mainly considers applications in two fields: air and road transport. In particular, transferability from the following related sectors will be surveyed and analysed. This document presents:

- Proposed guidelines for carrying out transferability studies;
- Identified relevant AI-based approaches developed in sectors different than railways;
- Provided indications about transferability directions towards railway systems, focusing on time/flow predictions, planning and management.

Similar to Deliverable 3.1, we introduce a framework for transferability to perform a structured transferability analysis of AI applications from other sectors to railways by setting general dimensions, and their derived criteria. Transferability dimensions and related criteria have been defined by considering: a) the outcome of the DISCOVER phase, which provides guidelines from the relevant stakeholders and from the analysis of the railway problems related to traffic planning management; b) the transferability analyses conducted in other sectors such as aviation and road. The considered criteria are congruence, significance, similarity, maturity and implementability. In particular, the following AI applications have been addressed: traffic predictions, startegic and tactical traffic planning, and traffic management.

Further, several potential pilot case studies are proposed. There include applications in Train Delay Prediction, Railway Disruption Identification and Train Timetable Rescheduling. It is realised that as an important feature, the route of a train could be better represented. Approaches such as one-hot encoding have deficiencies. Efforts have been done including the use SDNE. Following that, a disaggregated modelling approach to predict frequencies and impacts of railway disruptions. Supervised machine learning would be an appropriate toll for such purposes. Moreover, a challenging issue is the design of a generic methodology to do the predictions. The expected outcome is to identify the location and time period accidents and disruptions are most likely to occur. Finally, it is noticed that reinforcement learning is gaining its importance in train timetabling and rescheduling, given its nature in producing optimised plans by repeatedly going through a series of episodes without the need of any historic data. There is already several work on this area. Reinforcement learning has the advantage of computational efficiency, compared to exact methods, and will often over-perform pure heuristics in solution quality. Often, a simulator is needed to provide the environment of train operations. States and actions need to be carefully designed to accurately reflect the operations and to make the right decisions.

Abbreviations and acronyms

Abbreviations / Acronyms	Description
ACO	Ant Colony Optimisation
ADS-B	Automatic Dependent Surveillance-Broadcast
AE-AD	Autoencoder-Autodecoder
AGTS	Air/Ground Trajectory Synchronisation
AI	Artificial Intelligence
ANN	Artificial Neural Network
ATC	Air Traffic Controller
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
BPNN	Back-propagation Neural Network
CANSO	Civil Air Navigation Services Organisation
CIoT	Cognitive Internet of Things
CNN	Convolutional Neural Network
CTMS	Cognitive road Traffic Management System
DBM	Deep Boltzmann Machine
DBN	Deep Belief Network
DCB	Demand-Capacity Balancing
DT	Decision Tree
EATCHIP	European Air Traffic Control Harmonisation and Integration Programme
eRCNN	error Recurrent CNN
FCM	Fuzzy C-Means
FIFO	First-In-First-Out
FNN	Fast Neural Network
FRBS	Fuzzy Rule-Based System
GA	Genetic Algorithms
GCN	Graph Convolutional Network
GPS	Global Positioning System
GPU	Graphics Processing Units
HMI	Human–Machine Interface
IoT	Internet of Things
IP	Infrastructure Provider
ITS	Intelligent Transport System
KF	Kalman Filtering
KNN	k-Nearest Neighbors algorithm
LIME	Local Interpretable Model-Agnostic Explanations
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-Layer Perception
PCA	Principal Components Analysis
PtMS	Parallel traffic Management Systems

RAI	Railway Accidents Identification
RF	Random Forest
RIoT	Rail Internet of Things
RL	Reinforcement Learning
RMSE	Root-Mean-Squared Error
RNN	Recurrent Neural Network
RTS	Railway Transport System
SAAM	System for traffic Assignment and Analysis at a Macro-scopic level
SDNE	Structural Deep Network Embedding
SHAP	SHapley Additive exPlanations
sMAPE	symmetric Mean Absolute Percentage Error
SoP	State-of-Practice
STANN	Spatio-Temporal Attentive Neural Network
STDN	Spatial-Temporal Dynamic Network
TBO	Trajectory-Based Operation
TDP	Train Delay Prediction
TMC	Traffic Management Coordinator
TOC	Train Operation Companie
TPM	Traffic Planning and Management
TTR	Train Timetable Rescheduling
UAV	Unmanned Air Vehicle
UTM	Unmanned aerial systems Traffic Management
WP	Work Package
XAI	eXplainable AI

1. Background

The present document constitutes the Deliverable D4.1 “WP4 Report on case studies and analysis of transferability from other sectors” of the S2R JU project “Roadmaps for AI integration in the Rail Sector” (RAILS). The project is in the framework of Shift2Rail’s Innovation Programme IPX. As such, RAILS does not focus on a specific domain, nor does it directly contribute to specific Technical Demonstrators but contributes to Disruptive Innovation and Exploratory Research in the field of Artificial Intelligence within the Shift2Rail Innovation Programme. The RAILS research is structured in three main phases:

- DISCOVER, covering all the preliminary survey and analysis activities.
- ASSESS, covering all the core development and experimentation activities.
- LEARN, covering all the follow-up and knowledge dissemination activities.

The work conducted in WP1 (State-of-the-art of artificial intelligence in railway transport) has achieved the preset objectives. Based on the findings and the application areas identified in WP1, the objective of the ASSESS phase is to define pilot case studies and to develop proof of concepts for a technology roadmapping of an effective pick-up of AI in the traffic planning and management field of the rail sector. Therefore, the ASSESS phase includes 3 technical workpackages that investigate different railway domains having the same task structure. Step 1 of the ASSESS phase is an analysis of AI applications from other sectors in order to enable transferability studies, and the identification of possible case studies. These case studies are not specifically meant for transferability but they provide the context of technical activities conducted in the workpackages.

Specifically, RAILS Project Work Package 4 addresses Artificial Intelligence (AI) techniques to support traffic planning and management in railways, and in particular:

- Railway traffic predictions, including predicting train delay time and locations of incidents;
- Rail traffic monitoring;
- Rail traffic planning and management, inclduing timetabling, rolling stock and crew scheduling;
- Rail traffic control.

2. Objective

This deliverable addresses transferability of AI techniques used for traffic planning and management from related sectors to railways. In particular, transferability from the following related sectors will be surveyed and analyzed, starting from the results achieved in Work Package 1 (State-of-the art):

- Aviation
- Automotive

Both of those two sectors have experienced a significant progress due to a huge amount of research efforts already been invested in the last few decades especially towards the AI aspect. In turn, the advancement on the AI-based applications would benefit humans with more reliable and trustworthy services. An excellent example is the conventional machine learning-based models that have been successfully implemented in the traffic prediction scenarios. Another sector where AI is experiencing a fast change is the explainable AI, where dynamic human-machine interactions are playing a more significant role to enhance the performance of algorithms. The main objective of this document is to identify and evaluate the most promising applications that we found in non-rail transport sectors, and to what extent the research findings of these applications would be effectively transferred towards the railway traffic planning and management domain. And then, the possibility of successfully implementing representative applications are evaluated by the predefined transferability criteria. This objective is achieved by elaborating the outcomes of the activities conducted in WP1, feedback from members of the RAILS advisory board and, and the survey carried out on challenges and state-of-practice of AI applications in railways. Specifically, this document will limit the scope within traffic planning and management tasks and the relevant evaluation definition will be coherent with the previous deliverables.

3. Introduction

Transferability studies aim at investigating the extent to which research findings or new technologies can be applied in other contexts. As such, this document reports the activities carried out in this direction by:

- Proposing guidelines for carrying out transferability studies;
- Identifying relevant AI-based approaches developed in sectors different than railways;
- Providing *indications* about transferability directions towards railway systems, focusing on railway safety and automation.

Determining whether research findings and/or technologies can actually be transferred from one context to another is a complex activity that cannot be performed within the time span of a limited analysis. Therefore, here we report the work performed to take a first step towards such an objective. This first step will help to design proper roadmaps to transferability scenarios. In particular, for the analysis, we focus on sectors that are close to railway transport and are expected to provide higher level of research developments and/or suitable for transferring to railways. These domains cover transport modes including Aviation and Road.

The remainder of the report is as follows. Chapters 4 and 5 report on research findings and technologies currently available in other transport modes including air and road transport, respectively. Chapter 6 introduces a framework for transferability analysis and establishes relationships between the Chapters 4 and 5 and the proposed directions. Notably, the results of this analysis are still *perceptions* of transferability/applicability, they provide indications but need to be verified through proper research. Chapter 7 identifies possible pilot case studies, taking into account both the potential that emerged by the activities carried out in task 4.1 and the needs expressed by the railway community according to the outcomes of WP1. The primary objective of the case studies is to provide the context in which some transferability activities can be developed. Lastly, Chapter 8 summarises the findings of these activities.

4. AI-based Emerging Technologies in Aviation

Current research in the field of air traffic management primarily focus on employing various methods to simulate potential aircraft trajectories, and then economic and ecological impacts of the optimal trajectory can be further evaluated. Examples are strategic conflict detection [1], time-based metering [2], fuel consumption estimation [3], arrival time prediction [4], and strategic traffic flow management [5]. In this chapter, we mainly investigate three essential application scenarios in the area of air traffic management: time prediction, strategic/tactical airspace management, and traffic flow management.

4.1. Traffic Prediction

For safety concerns, Air Traffic Controllers (ATCs) and Traffic Management Coordinators (TMCs) are obliged to keep aircrafts safely separated and move efficiently in the air or on the airport surface. Estimated times of arrival are of interest to many stakeholders. Firstly, airline operators are supposed to provide high-quality services to their passengers by arriving at the destination as scheduled, particularly if passengers or cabin crews need to transit/make connection to the subsequent flights. Secondly, airports and flight operators use arrival predictions to schedule support services for inbound flights (e.g. parking, fueling, loading). Typically a rearrangement of equipment and personnel resources is required for supporting these services and the limited nature of these resources makes timing critical for efficient operations at the airport. Flight delays have become a increasingly concerned subject for air transport because of the associated financial loses. Moreover, these potential delays not only cause inconveniences to the airlines themselves but also to the passengers.

From the perspective of determinants, the reasons behind these delays vary a lot — ranging from air congestion (air traffic control) to bad weather conditions, mechanical issues, boarding difficulties (including passengers and cargo), and the inability to satisfy the demands with given capacities. Considering abundant and diverse reasons, initially physics-based and machine learning-based (ML-based) approaches are the two most popular practices for investigating the aircraft arrival time. For the former, existing applications were typically built upon a trajectory-based operation (TBO) paradigm, where the trajectory becomes one of the fundamental determinants that Air Traffic Management capabilities heavily rely on. Air/Ground Trajectory Synchronisation (AGTS) [6] is such an implementation that attempts to select the most accurate scheduled time of arrival at a meter fix. A novel estimated times of arrival prediction system for commercial flights was developed by Ayhan et al. [7], the system learns key features from historical trajectories and uses their pertinent 3D grid points to collect essential knowledge such as weather parameters, air traffic and airport data along the potential flight path. Simultaneously, a lot of well-known machine learning methods (i.e. Gradient Boosting classifier [8][9], Decision tree [10], Random forest [11], or a hybrid model of these algorithms[12]), have been largely implemented in the process of aircraft delay prediction.

Notably, two specific trends can be identified among the investigated literature. First, in the past, most of the prediction models have focused on weather-related delays, e.g. [13], and the propagation of these delays under severe meteorological conditions. Second, nowadays it can be seen that more and more applications estimate the future network-related delays on a certain airline. For example, using a systematic Bayesian network, Xu et al.[14] are able to capture interactions among airports. Another identified fact is that above introduced conventional machine learning-based methods typically perform less-optimal due to the complexity and volume of available data resources are ever growing, which requires more efficient ways to deal with the data. Deep learning techniques and Big data approaches are thus introduced in these cases, e.g. [15][16][17]. The motivation of introducing these learning technologies is taken from human neural network learning — a branch of machine learning and collection of algorithms that try to model high-level abstract contents through application learning in different layers and levels. Specifically, the combination of deep learning and big data techniques are able to process a bulky data volume in complicated data classification.

4.2. Strategic/Tactical Airspace Planning

In the field of civil air transport, the current Air Traffic Management (ATM) system worldwide is managing a high (and growing) amount of demand that sometimes leads to demand-capacity balancing (DCB) issues. Under this background, a novel AI-based solution has been proposed such as using unmanned air vehicles (UAVs) to perform three degree-of-freedom (3D) path planning, route algorithm and navigation. According to the findings of Amarat and Zong [18], the conventional and node-based algorithms are the most common choices for path planning. As for the tasks of route planning and hybrid routing protocols, graph-based algorithms are preferred for their better performance. Notably, they also found that critical link method for UAV path planning for large UAV networks is a promising area for the future research. In addition, recent interest in AI techniques focused research attention on their application in aviation systems including air traffic management (ATM), and unmanned aerial systems traffic management (UTM). By considering a novel cognitive human–machine interface (HMI), configured via machine learning, examined are the requirements for such techniques to be deployed operationally in an ATM system, exploring aspects of vendor verification, regulatory certification, and end-user acceptance. It is concluded that research into related fields such as explainable AI (XAI) and computer-aided verification needs to keep pace with applied AI research in order to close the research gaps that could hinder operational deployment. Furthermore, the increasing levels of automation and autonomy introduced by AI techniques will eventually subject ATM systems to certification requirements, and proposed are a means by which ground-based ATM systems can be accommodated into the existing certification framework for aviation systems.

4.3. Traffic Flow Management

Since demand for public air transport keeps growing more quickly than the development of system capacity, efficient and effective management of aerospace capacity is becoming significant for the operation of the future global air traffic system. The objective of this section is to review current research in the literature about the issue of ATFM. Generally speaking, although research in the past a few decades has made significant progress in relevant research fields such as ATFM and airport capacity modelling, research gaps in ATFM still exist and links between various sub-areas are required to enhance the system performance. Based on the literature, we categorise papers about air traffic management into two levels: system and airport. The system level of air transport research includes two main topics: air traffic flow management and airspace research (e.g. [19,20]), where the latter is highly relevant to the tactical aerospace management we mentioned before. On the airport level (e.g. [21–24]), research topics are: airport capacity, airport facility utilisation, aircraft operations in the airport terminal manoeuvring area as well as aircraft ground operations research. Potential research interests to focus on in the future may be the integration between airspace capacity and airport capacity, the establishment of airport information systems to use airport capacity better, and the improvement in flight schedule planning to improve the reliability of schedule implementation.

The challenge of airport capacity modelling/optimisation has been noticed by researchers since the early 1970s (e.g. [25]). They would benefit the understanding of the maximum airport capacity as well as a proper utilisation of these airport capacities. When the demand for air traffic reaches the ceiling of system capacity, the operation of a single airport starts influencing others, both visibly and invisibly, and the operational efficiency of the airport network due to the high interaction of air traffic operations between airports. The aviation flow management problem occurs when the airport capacity decreases due to different causes (e.g. severe weather conditions, military air traffic control), which would result in significant delays and shortage of aircraft rotation, i.e. delays to inbound and outbound flights. Unlike other public transport means, to prevent aircraft delays caused by the shortage of airport capacity, an effective solution is to assign flights with ground-holding delays at the origin airports (e.g. [26]). Therefore, the procedure of assigning ground holds to aircraft is a part of ATFM. The purpose of this method is to allocate limited capacities optimally to all users during the shortage of airport capacity, and hence to minimise potential severe flight cancellation and flight delays. From this point of view, although the effects of networked-airport operations have become more significant, research which requires links between multiple operators (airport operators, airlines and airport ground handling agents) and multiple operational levels (en-route air traffic control and regional air traffic control) have not yet been well conducted. The representative solutions to this area include: deterministic models (e.g. [27]), stochastic and dynamic assignment models for ground-holding (e.g. [28]). More recently still, the research focus has shifted to optimising the air traffic control in a multiple airport network by using AI-based heuristic methods and dynamic simulation methods (e.g. [29]), with the task of analysing aircraft trajectory.

Another challenge in implementing ATFM strategies is user equality. Basically, the assignment of ground delay and airborne delay to an aircraft is determined by unit delay costs, expected delay probability, and flight priorities. It was found in the literature that the First-In-First-Out (FIFO) principle remains the fairest control strategy to all airspace users but obviously not the optimal choice for solving this issue. In addition, the proper inclusion of models of aircraft en-route flight time will help improve the performance of management. Since the en-route flight time of an aircraft in the airspace is influenced by many factors such as airspace congestion and air traffic controls, the modelling of the arrival time of an aircraft at the destination airport is usually done by adopting simple assumptions, e.g. constant en-route flight time models ([30], [31]). However, aircraft departure delay might be compensated by scheduling buffer time in flight schedules or simply by flying faster. Therefore, how to assign ground-holding delays equally to balance ground and airborne delays among all users is still a future research topic ([26]).

The programme named "European Air Traffic Control Harmonisation and Integration Programme (EATCHIP)" was a project led by Eurocontrol, aiming to model the structure of the

European airspace as well as to simulate/optimise general air traffic flows in the European region ([32]). The Airspace Modelling Service Unit of Eurocontrol has successfully developed a systematic model called "System for Traffic Assignment and Analysis at a Macroscopic Level (SAAM)", to provide an integrated simulation platform for macroscopic design, evaluation, and presentation of airspace as well a simulations of airport terminal manoeuvring areas operations. The commonly seen objective function used in networked-aerospace studies is to minimise the overall airspace congestion costs (e.g. [33]). However, by the dynamic and stochastic features of aircraft operations, it is difficult to perform exact quantitative analysis on the aircraft delay costs in the air. Additionally, minimising the fuel consumption of an aircraft among different jet routes was also investigated by some researchers (e.g. [34]).

Very recently, the emerging demands for unmanned aerial vehicles (UAVs) and general aviation aircraft aggravate the huge burden on air traffic flow management. It is possible to establish a more intelligent ATFM architecture thanks to the development of automatic dependent surveillance-broadcast (ADS-B) technology such that the aerial vehicles can be tracked and monitored in a real-time and accurate manner. All these advances must be constructed on the basis of Big Data technology and powerful machine learning algorithms – an aviation Big Data platform comprises a set of distributed ADS-B ground stations ([35, 36]). By exploiting the extracted information obtained from constructed datasets, and mapping them along the routes (i.e. where the flights pass by and depart/terminate), the air traffic flow between different cities can be effectively captured and predicted. The experimental results based on real-world data demonstrate that this novel traffic flow prediction model would achieve better performance while implementing Long Short-Term Memory (LSTM) as the core predictor.

In this context, there seems to be little doubt that artificial intelligence (AI) and machine learning (ML) will be key enablers for advanced functionality and increased automation in the ATM system of tomorrow. Already we see the widespread adoption of AI and ML techniques in other industries driven by recent technological advances (graphics processing units (GPUs), cloud computing, big data, and deep learning algorithms) that are leading a resurgence in the field. AI is finally on the brink of realising its long-promised potential after several false starts and many governments and companies launched concerted AI initiatives. AI and ML are important technologies for the digitisation of ATM—a very relevant topic today. The theme for the Civil Air Navigation Services Organisation's (CANSO) 2018 Global ATM Summit, one of the most important ATM events globally, was "Air Traffic Management in the Age of Digitisation and Data". The conference considered the likely impact of big data technologies on the industry, exploring aspects ranging from operational, such as the migration of ATM systems to the cloud, the storage of voluminous space-based Automatic Dependent Surveillance–Broadcast (ADS–B) surveillance data, and cybersecurity, to commercial, such as econometric analysis and forecasting, digital partnerships, and supplier relationships.

5. AI-based Emerging Technologies in Road transport

To better understand what can be reused and transferred from the automotive sector to the railway scope, in terms of both data and approaches, in this chapter we separately analyse the evolution and the current usage of AI-based solutions in some popular application domains such as Traffic congestion prediction (Section 6.1), Recommended route planning (Section 5.2.1), Mass surveillance (Section 5.3.2), and Traffic flow estimation (Section 5.3.1) by summarising and making comparisons between some of the most recent surveys. As such, we aim to properly provide theoretical support for transferability analysis.

5.1. Dynamic Traffic Prediction

5.1.1. Congestion hot-spots identification/traffic congestion prediction

Depending on the data characteristics and quality, different classes of AI are applied in various studies including clustering, probabilistic reasoning, and shallow and deep learning algorithms. We evaluated the relevant papers in the context of road bottleneck identification and automotive traffic congestion estimation.

Clustering Algorithms Some existing studies clustered the acquired data before applying specific machine learning models to predict road traffic congestion. This process concerns several different traffic engineering strategies: Fuzzy C-Means (FCM) or original C-means clustering methods are the most commonly used techniques and they play a significant role in traffic pattern recognition (e.g. [37],[38]), while K-means clustering [39] is considered an effective and flexible algorithm for large datasets. According to [40], a lot of the investigated studies have applied clustering before the main prediction model except for those using deep learning algorithms as the functional prediction model since it can process input data on different layers of the model. From this perspective, clustering and data pre-processing are typically conducted simultaneously, at least initially, with datasets that are largely unstructured and unclassified.

However, to generalise traffic congestion forecasting studies using different models is not straight forward. The common factors of the relevant articles include the study area, data collection horizon, predicted parameter, prediction intervals, and validation procedure. Many articles took transport corridors/segments as the study scenarios (e.g. [41][42][43]). Other study scenarios include the traffic network ([44][45]), ring road ([46]), and arterial road ([47]). The data collection horizon varied from years ([48]) to less than a day ([49]). The validation methods that compare their results with the ground truth value or other models include mean absolute error (MAE), symmetric mean absolute percentage error (sMAPE) and root-mean-squared error (RMSE).

Probabilistic Reasoning is semantically a significant components of the traditional definition of AI. It has been largely applied in the field of traffic congestion understanding and identification for dealing with uncertain knowledge and reasoning. With the vastness timeline and spatial dependency, traffic data are becoming more complex and nonlinear. In the field of dynamic traffic congestion prediction, fuzzy logic has become one of the popular solutions due to its excellent ability to deal with uncertainty and vagueness instead of binary outcomes [50]. The fuzzy rule-based system (FRBS) is the most common fuzzy logic implementation in traffic engineering research. It can effectively deal with the complexity resulting from real-world traffic situations by representing them in operational IF-THEN rules. In practical, these rules are optimised by applying various genetic algorithms (GA), for instance, an Ant Colony Optimisation (ACO) algorithm was incorporated in the fuzzy logic system by Daissaoui et al.[51] to predict traffic congestion one minute ahead from the moment that information is provided by past cars. The GPS data from each vehicle was taken as a pheromone, highly consistent with the concept of ACO.

Shallow Machine Learning With the increment of available data, data fusion methods are becoming popular. The fusion of historical and real-time traffic data can achieve a higher level of traffic congestion prediction accuracy. The shallow machine learning algorithms include these traditional and simple ML algorithms that usually consist of one or a few hidden layers. One of the facts of these methods is that they are not able to extract essential features from the input, but the expected feature need to be defined beforehand, that is, the model training procedure can only be conducted after feature extraction.

Other studies conduct traffic congestion prediction based on various traffic flow parameters. Drivers' behaviours data has been analysed and used in predicting congestion in the study of Ito and Kaneyasu[52]. They observed that vehicle operators would act differently on different phases of the journey or different conditions. Based on this, one layered Backpropagation neural network (BPNN) has been successfully implemented to learn the behaviours of female drivers and extract travel phase according to that.

One of the advantages of shallow machine learning model is its a flexible structure and neurons of the layer can be adapted according to the input data. A general ANN model can be easily developed and applied for different road types by using its nonlinearity capturing ability.

Deep Machine Learning Various deep learning techniques have been greatly proposed/applied/validated in existing studies, while the most common one is the long short-term memory (LSTM) technique. From the investigation conducted by Diamanta et al.[53], although it has been mentioned the most, LSTM itself is not necessarily the optimal option that can be used for every congestion prediction scenarios. Interestingly, this model can perform better if it is integrated with other techniques. For example, He et al.[54] proposed a novel framework "STANN" (Spatio-Temporal Attentive Neural Network) based on LSTM concepts, which combined Recurrent Neural Network (RNN) with LSTM. This attempt allows them to capture spatio-temporal dependencies from historical traffic time series and especially benefits the network-wide links and long-term traffic prediction.

On the other hand, Yao et al.[55] used Convolutional Neural Network (CNN) and LSTM to handle spatial and temporal information. Flowgated local CNN is used to capture spatial dependency based on traffic flow information, and LSTM to extract sequential dependency. The proposed Spatial-Temporal Dynamic Network (STDN) is able to preserve long-term periodic information as well as temporal shifting in traffic sequence. Based on this framework, Mena-Oreja et al.[56] evaluated its outcomes with the eRCNN (error recurrent CNN) model, where the latter can effectively learn from prediction errors from abrupt traffic event changes. It is shown that eRCNN has been proven to outperform CNN+LSTM in predicting traffic speed and flow while they have the same performance in predicting traffic congestion.

The above described methods are prone to be good candidates in terms of deep learning-based techniques that can be used to predict traffic congestion condition. However, it is not necessarily to compare the fore-mentioned methods and come to a conclusion regarding which one proves to be a better one than others, since each result was concluded from different datasets and were done under different experimental settings.

5.2. Tactical Road Capacity Planning

5.2.1. Alternative routes service/recommended route planning

IoT-based methods Recently, the usage of cognitive computing in the Internet of Things (IoT) has gained wide popularity as such self-learning strategy is easily to be injected into smart objects or things in order to simulate human's learning procedure. Normally known as Cognitive Internet of Things (CIoT). In the past, drivers take ful responsibility to control the vehicle in different unexpected situations, such as acceleration/deceleration, change of lanes etc. However, human drivers may behave drowsy or distracted, which would potentially lead to irrational consequences such as road accident, wrong path selection and speeding. From the public transport perspective, it will help the intelligent transport system to move passengers in the most safe and efficient way. Achieving this level of efficiency requires real-time access to the data as and when they are produced. At the same time, the connectivity possibilities of vehicles with traffic control centres will make transport safer because of the improvements in the proper estimation of traffic flow. For example, the trajectory/volume data collected by sensors, cameras and IoT equipment that are distributed on buses, trains and subway systems would be analysed to provide a dynamic map of the flows of travellers. This allows intelligent route planners to analyse people's movements at an individual level and hence perform a more accurate and professional recommendation. [57] developed an application which aims to provide route recommendations and incident notifications for those citizens who want to travel by bus. This implementation was achieved by processing the real-time bus arrival-departure data streams and incidents reported by citizens. In this system, each passenger acts as a real-time traffic contributor and IoT information feeder while they would benefit from the network in return.

MLP-based methods The successful experiments on determining the possible travelling routes definitely extended the scope of traditional road traffic planning and management. For example, in order to fulfil the ever-growing e-commerce business demand especially the delivery service at the end of this commercial chain, [58] utilises the open data resources of Google Maps and its "multiple destination" function to search for possible routes between storage and destination. These routes were fed into a multi-layer perceptron model for traffic condition simulation. The optimal route choice would be produced by Dijkstra's algorithm. Where all the possible routes from original to destination have been calculated, the ANN part only contributes to the process of predicting the traffic congestion situation for all the possible routes above. Notably, this innovative method included the information of the transportation records (i.e. the average speed, travelling distance, and time spent in idle driving for any given vehicle) and the climate condition for each trip helps to improve the forecast accuracy precisely. Experimental results show that the Multi-Layer Perception (MLP) model would reach a stable prediction accuracy when it was trained more than 170 epochs, with the accuracy of 95% or more.

5.3. Traffic Flow Management

5.3.1. Traffic flow estimation/road infrastructure management

As we identified in section 5.2.1, autonomous driving is trending nowadays as an effective solution to avoid severe road accidents from the perspective of traffic management as it potentially decreases the occurrence of irrational human behaviour and thus lower the risk of unpleasant consequences. In order to allow autonomous vehicles to act efficiently, traffic congestion patterns should be largely eliminated from the transportation system. One solution to handle this problem is the timely prediction of traffic flow, and therefore traffic flow estimation has drawn so much attention in the automotive field. Similar with congestion hot-spot identification, traffic flow prediction is an important component of the autonomous driving system and it concerns both spatial and temporal processes. The simulated traffic flow information can be communicated to a traffic control centre/local decision making hub for further actions. In addition, with traffic flow estimation, an optimal routing plan along with traffic management can be done. Vehicle path planning, timing of traffic signal optimisation, and real-time congestion control are several significant applications for traffic flow prediction. In other words, traffic flow prediction can be seen as the fundamental application of other downstream activities.

Notably, road traffic flow is a complex amalgamation or combination of heterogeneous traffic. Thus, before the actual traffic flow has been estimated, traffic pattern prediction modelling could be a necessary and important stage to be performed. During this process, it is important to effectively acquire and analyse historical and real-time vehicle data from the variety of data sources such as radio detection and ranging, surveillance camera, light detection and ranging, inductive proximity, floating cellular data or digital positional records (GPS). A classical paradigm is to feed collected real-time traffic flow data from the past into the prediction model, based upon which the future traffic flow is generated as an output from the model. In the last few decades, most of those studies were designed to improve self-learning algorithm for capturing complex and dynamic relationships of the transport system. The self-learning algorithms here can be broadly divided into two parts, i.e., parametric and non-parametric [59].

Parametric methods The commonly used techniques in parametric methods include time series models [60] and Kalman Filtering (KF) [61]. The parametric methods have a higher accuracy with less errors during the prediction compared with non-parametric ones except when there is noise and disturbance in the network. Traffic flow prediction can vary a lot even in a given environment since it is affected by various factors such as forecasting horizon, format of dataset, type of area and sampling frequency. Existing literature present mostly short-term prediction approaches rather than expanding their horizon into days due to the uncertainty and complexity of traffic flow patterns. Normally, the larger the value of forecasting horizon, the lesser is the accuracy of the expected output, and similarly, the smaller the forecasting horizon gets, the more complicated is the prediction.

Non-parametric methods Non-parametric methods seem to be far preferable by researchers due to its capabilities of dealing with stochastic, non-deterministic and non-linear characteristics of traffic flow data. From the relevant papers, we discovered that commonly used methods in predicting local/global traffic flow are deep learning based methods due to their prominent ability of dealing with a lot of complex spatio-temporal data[62]. Among the many methods that have been investigated, we found three techniques that are used the most for road traffic flow estimation: Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) or a combination of them[63]. Besides them, Deep Belief Network (DBN), Autoencoder-Autodecoder (AE-AD) and Deep Boltzmann Machine (DBM) are discussed or explored along with their applicability in traffic flow prediction.

5.3.2. Traffic surveillance/vehicle detection

In recent years, automatic video analysis from traffic surveillance cameras is an emerging area with the support of computer vision techniques. It already became one of the fast-growing core technologies to intelligent transport system (ITS) and efficient traffic management paradigms. Video detection is one of the essential methods to collect traffic states in Parallel traffic Management Systems (PtMS) [64]. That is to say, tracking and detection is not a significant task considering the non-deterministic feature of the moving subjects, but how we can reliably detect and track these objects in surveillance video matters, which forms a basis for the higher level intelligence applications. Therefore, we want to discuss traffic surveillance under the context of road traffic management. Conventional techniques for traffic measurements, such as inductive loops, sensors, and microwave detectors, have the drawbacks of expensive installations, traffic disruption during maintenance, and fails to detect slow or temporary stops vehicles. On the contrary, video supervision systems are easy to install, or available directly using the existing mass surveillance. These systems can be easily upgraded and they offer the flexibility to redesign functionality by simply changing the system algorithms. However, individual vehicles may not be recognised (well) by other vehicles or by background obstacles such as road signals, trees and weather conditions. The performance of the digital video surveillance system would highly depend on the traffic environment and the applied approaches to detect, track and classify vehicles.

Vehicle detection and classification In intelligent transportation systems, research on vehicle detection and classification has high theoretical significance and application value. Mahammad et al. [65] proposed an innovative vehicle classification framework that is able to process traffic monitoring images automatically. In this framework the fast neural network (FNN) as a primary classifier and the convolutional neural network as the second-layer classifier. Where the FNN construct potential correlations between the input and the weighted neurons using a multi-layer perceptron to provide detection with a high level of accuracy. In order to reduce the effect of variations in illumination, a lighting normalisation method is employed in the CNN layer. By contrast, a new vehicle detection method was proposed by Khalid et al. [66], in which the processed images were acquired by embedded cameras that installed on each of the moving vehicle. Based on their research, Psyllos et al.[67] developed an advanced model recognition scheme that can effectively identify the vehicle type and manufacturer. Such scheme was enhanced by multi-colour recognition for achieving a more reliable output.

Traffic surveillance Besides the vehicle appearance images acquired from various sources, public traffic surveillance such as highway surveillance video analysis is also an important part of traffic pattern recognition. Sensing vehicles ahead and identifying traffic situation identification are significant aspects not only for driving safety, but also automatic driving and cruise control would benefit greatly from these techniques. For instance, [68] presented an algorithm for automatically detecting the frequency domain features that is produced by the vehicles passing through road areas in videos, to realise automatic segmentation and recognition of the road areas.

6. Transferability Analysis

6.1. Transferability Pillars from the AI-persective

In order to preserve the consistency regarding to the assessments criteria when identify the potential of AI techniques in this specific subdomain — railway traffic planning and management (TPM), and also make this core chapter contains coherent argument on structured transferability analysis, we hence leverage the knowledge acquired from the research activities conducted in the context of WP1 (specifically, D1.2[69] and D1.3[70]). Based on these documents, we aim to delineate some promising transferability directions within the background of traffic planning and management. Therefore, we firstly make a summary of the relevant TPM problems emerged from WP1 and other transport sectors we investigated in chapter 4 and 5Section 6.2); And then, we establish transferability criteria according to the relevant statements in deliverables [71] and [72] of the RAILS project (Section 6.3). It is notable that these criteria would be highly consistent with the previous assessment framework but some details could be adjusted accordingly; Next, we would summarise the main AI-based applications we found in Aviation and Automotive sectors (Section 6.4); Finally, we perform an analysis to provide possible transferability directions by crossing the information coming from the WP1 and the above chapters (4 and 5), on the basis of the defined transferability criteria (Section 6.5).

6.2. Relevant Railway Problems

In deliverable D2.1 [71] and D3.1 [72], separate transferability investigation has been conducted, which is on the subject of **Unmanned aviation vehicles and Autonomous driving – rail automation** and **Vehicle health monitoring and General safety examination – predictive maintenance and defect detection for railway**, respectively. Specifically, D2.1 is a transferability analysis that starts from other sectors, mainly automotive, but also considering what has been implemented in unmanned aerial and ground vehicles, and it was created to understand to what extent AI-based solutions developed in these sectors can be transferred to move towards train autonomous driving and control or increase the operational safety. While D3.1 more focuses on maintenance aspect under the background of aviation, automotive, manufacturing, cybersecurity, physical security. In this deliverable, to recognise the major relevant railway problems for which AI-based solutions have been or could be provided to improve the performance of traffic planning and management activities. These problems were identified by merging information coming from the literature we reviewed in previous deliverables, the analysis of Shift2Rail projects, as well as the advisory board, etc. Figure 6.1 shows the subset of the railway problems falling in the context of traffic planning and management, which is largely derived from the relevant ontology definition of D1.2[69]. It is worth noting that ”stop planning and track design” is related to both infrastructure design and traffic planning.

According to the Survey on Challenges and State-of-Practice (SoP) of Artificial Intelligence in railways conducted involving the railway stakeholders, addressing these problems using AI-based approaches the following major obstacles are to be expected:

- The challenges of an increasing travel demand, CO2 emissions, safety concerns, and

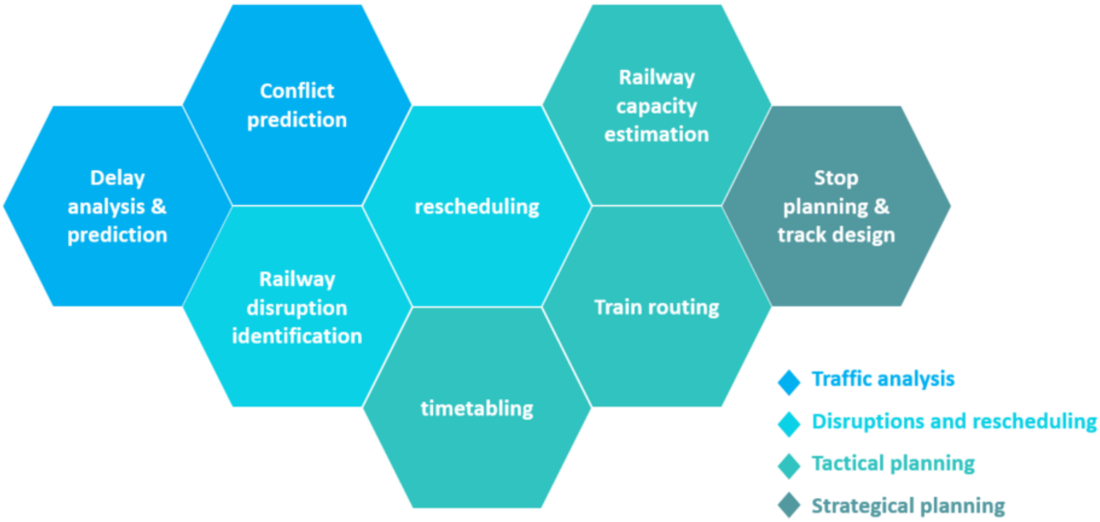

Fig. 6.1. Railway problems for AI application in WP4 (excerpt from D3.1 [72])

environmental degradation;

- Lack a good understanding of the relationships between AI techniques and available datasets;
- Properly determine transportation system characteristics and variables that suitable for training the AI models.

Several application areas have been proposed based on the results of the activities conducted in WP1, where D1.2 mainly aims to identify the potential of AI techniques within each railway subdomain and it shows that a great advancement has occurred in light of the subdomains of **railway maintenance and inspection** and **railway traffic planning and management**.

6.3. Transferability criteria Statement

Transferability in this deliverable refers to the possibility of transferring the results or findings of research from one *source* domain (e.g., automotive), to another *target* domain (e.g., railway). According to [73], transferability primarily involves the perception of who is interested in assessing the applicability of the research findings or technology that can be of potential use. Specifically, it requires people pay more attention to the implementability of the intervention in the new setting, than to whether it would be as effective there. The factors affecting this perception are based both on general considerations, i.e. *dimensions*, that may be universal in terms of all the railway subdomains, and domain-based concerns, i.e., *criteria*, which may vary according to the specific subdomain. Therefore, in this section, we introduce a **framework for transferability** to perform a structured transferability analysis of AI applications[1] from other sectors to railways by setting general *dimensions*, as in

[1] Similar with D3.1, in this deliverable, we summarise the qualified methodologies, approaches, methods, techniques, and technologies that concerning AI components as *AI applications*

Deliverable D2.1 [71] and D3.1 [72], and their derived *criteria*.

We internally define the transferability dimensions and related criteria with several supportive references: a) the outcome of the DISCOVER[2], these three phrases provide guidelines from the relevant stakeholders and from the analysis of the railway problems related to traffic planning and management; b) the transferability analyses conducted in other transport-related sectors (i.e. chapter 4, chapter 5). Although these investigated studies are tailored to other scientific areas and other objectives, they provide some general indications. Also, social, political, and legal dimensions are not included in the scope at this analysis, rather we would only focus on scientific and technical aspects of the relevant AI applications. The order used to list transferability dimensions and criteria is not random. Instead, they are sorted in descending order according to their importance for the realisability and purpose of transferability. Note that the order may change for different domains/contexts.

Table 6.1 gives the information about the descriptions of the transferability dimensions we have adopted in previous deliverables (i.e. D2.1 [71] and D3.1 [72]), these dimensions roughly can be summarised as five, including **congruence, significance, similarity, maturity** and **implementability**. Below each dimension we have defined the detailed criteria for providing subsequent descriptions about how we assess the AI-based applications. The definition of corresponding transferability criteria are given in Table 6.2. It's worth to note that all the criteria mentioned here are coherent with the related definitions in D2.1 [71] and D3.1 [72].

Table 6.1: Transferability Dimensions

Dimension	***Description***
Congruence	the adherence between the AI application intended to be transferred in the source domain and its counterpart in the target domain.
Significance	the benefits that the AI application may bring in the target domain if successfully transferred, regardless of its maturity.
Similarity	the similarities between the specific goal of the AI application in the source and target domains and between the characteristics of the two domains.
Maturity	the advancement of the AI application in the target domain.
Implementability	the effort and costs needed to implement the AI application in the target domain considering the required technologies, skills and the possibility to maintain the application over time.

Table 6.3 shows a Transferability Table (TTable) combining dimensions and criteria for a *transferability analysis*. The five levels (Very High, High, Medium, Low, and Very Low) specify *to what extent the transferability criteria are met* by a particular AI application, i.e. they indicate the perceived status of the AI application that is intended to be transferred. According to the specific dimension, levels may have different specific meanings; However, in general, the level "Very High" indicates that the application is easily transferable from a given point of view (i.e. criterion); differently, the level "Very Low" indicates that there is still a huge effort required in order to successfully transfer from source area to target domain in terms of this dimension/criterion. For example, a "Very High" mission/aim/scope indicates that the application intended to be transferred is highly suitable for our purposes; By contrast, if it

[2]The RAILS project includes three phases: DISCOVER phase (including WP1), ASSESS phase (including WP2, WP3, and WP4), and LEARN phase (including WP5)

Table 6.2: Transferability Criteria

Dimension	Criterion	Description	Example
Congruence	*mission/aim/scope*	the adherence of the AI application that is intended to be transferred to the mission, aims, and scope in the target domain.	Two surface defect detection applications have the same mission/aim/scope in both the source and target domain, even though their specific implementation may vary depending on the domain characteristics.
	previous experience	the previous experience, i.e. the research/developing status of an AI application in the source domain.	?
	failure severity	the gap that exists in terms of unpleasant consequences between a valuation error in the source domain and a valuation error in the target domain.	A valuation error in the quality assessment phase of a consumer product (e.g. a textile product) leads to slighter consequences than an incorrect quality assessment of a component that will be used in transport systems, where human lives may depend on it.
Significance	*potential effectiveness*	how much effective could be the AI application if successfully transferred.	?
	impact	the positive impacts that the AI application would have in the target domain in successfully transferred.	?
Similarity	*goal*	the similarities between the specific goal of the AI application in the source and target domain as, even though they may have the same mission/aim/scope in both the domains, their specific implementation may vary depending on the specific goal.	Considering two AI applications, one aiming at detecting defects in textile products and the other aiming at detecting defects in train bogies. The mission/aim/sope is mostly the same, i.e. defect detection, but the two specific goals are quite different. For instance, the former may be oriented to detect only scratches, the latter to detect also missing components.
	domain characteristics	how different are the target and source domains in terms of their peculiarities.	If an AI application performs properly in the source domain, it may not work as well in the target one, given the conformation of the domain itself. There may also be inconsistencies in terms of safety requirements and regulations.
Maturity	*AI application*	the grade of maturity that the AI application has achieved in the target domain in terms of its research/developing status.	?
	automation	the grade of automation that can be associated to an AI application in the source domain.	?
Implementability	*technology*	whether the technology in the target domain is mature enough to accommodate the AI application or further improvement are needed.	?
	sustainability (costs and effort)	the costs and effort needed to maintain the transferred AI application in the target domain over time.	?

Table 6.3: Transferability Table (TTable)

Dimension	Criterion	Evaluation: *Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope* *previous experience* *failure severity*					
Significance	*potential effectiveness* *impact*					
Similarity	*goal* *domain characteristics*					
Maturity	*AI application* *automation*					
Implementability	*technology* *sustainability* *(costs and effort)*					

Source Domain(s): [domain_1], [domain_2]

is assessed as ”Very Low”, it means that the development of the evaluated application still on its early stage or the corresponding requirements have not been fulfilled in the target domain. That is to say, we can only use that application as a starting point regarding to this specific criterion, and significant adjustments would be needed for its effective integration to our purposes. Therefore, cells contain checkmarks (✓) indicating the perceived level of the corresponding criterion (there would be a single checkmark within each row). The colours have been introduced to visually support the TTable: the more checkmarks falling into the ”green area”, the more the AI application is suitable for transferring. Note that the tables do not assess the level of progress of the considered source sectors, but its suitability to railways. Moreover, the assessment of these levels is subjective (as in many other qualitative analysis) and a way to establish the thresholds for their evaluation must be provided case by

case.
To summarise, the goal of the TTable is to provide guidelines for the transferability of a given AI application to the railway sector for a specific objective[3]: it says whether it makes sense, and to what extent, to take further steps in that direction. Notably, for a given AI application identified within a specific sector, there may be similar counterparts in other domains. Therefore, in Section 6.4, we summarised the possible applications that may be of interest to transfer. Then, in Section 6.5, we adopted the following methodology to select the most suitable AI application to transfer to the railway: i) we considered similar solutions coming from other sectors (if multiple); ii) in case of multiple hints from multiple source domains, we selected the most suitable one to be transferred; and lastly, iii) we provided a TTable and related explanation for the AI application identified in the previous point (if necessary). We adopted this reasoning for each different AI-based solution we found promising to transfer in Section 6.4.

6.4. Synthesis of AI applications in Aviation and Automotive sectors

In this section, the most promising applications we identified in Chapters 4 and 5 would be presented. The parts concerning that how and to what extent the AI-based solutions have been adopted in both Aviation transport and Automotive transport sectors would be highlighted in this section. To present the evaluated AI approaches in logical manner, such approaches have been clustered according to the categories identified in Section 6.2. The aim is to point out the more relevant topics discussed in the previous part of the document.

Cognitive Internet of Things for boosting alternative routes services As we mentioned in section 5.2.1, travellers or traffic contributors generate real-time state information including traffic condition data, travel speed, vehicle location, action updates even the operational records. Incorporating these data into the existing traffic management system consequently provides a comprehensive view of the current state of the transport environment and forms the core database which intelligent transport management system would draw upon during its decision making process. In return, the AI-aid management system typically would supply travellers with information on the occurrence of potential traffic congestion for a certain area, provide travellers more available mode of transportation options, the best route to take, the existence and availability of services/parking, even in-vehicle hazard warning and road signing optimisation.

Artificial Neural Networks for driver behaviour identification ANNs, including hopfield network, feed-forward network, and back-propagation network show a great potential in diverse parameter analysis tasks. especially under the circumstance that researchers have known the experimental settings in advance. Notably, ANN is the only model that has recently been applied for driver/passenger behaviour identification for traffic congestion. In fact, ANN is popular in every section of road transport — congestion estimation[], traffic flow prediction[], vehicle noise control[], and recommended route planning[].

[3]This represents a first step towards the definition of a transferability methodology that needs to: i) be further developed in the next project tasks, perhaps supported by discussions with the Advisory Board and future workshops; ii) be integrated with additional studies or tools (e.g. proper checklists)

Challenges of Traffic surveillance and vehicle detection Technical speaking, tracking video objects properly can be a particularly challenging task since vehicle tracking essentially entails estimating the location of a particular region for successive frames in a video sequence. Moreover, the shape and size of vehicle vary a lot according to its type, and these vehicles may change their locations and orientation over subsequent video frames. No matter how advanced object tracking algorithms have been introduced in this area, there would be errors between the detection image and the ground truth, which will eventually cause a drift from where the vehicles actually are. In this chapter, we are trying to find such an appealing algorithm that can minimise the drift such that the tracking process would be more accurate over the frames, and to discuss if such an algorithm is eligible to be transferred into the railway sector.

Hybrid vehicle delay predictors by introducing considerations of Explainable AI In the literature, there are a plenty of studies aiming at analysing/predicting Train arrival/departure delays at stations/along the route either by exploiting AI-based approaches or by adopting a specific mathematical algorithm. From this academic point view, we can generally conclude that the corresponding development in rail sector has achieved an advanced grade so far; Hence, a transferability analysis for solely introducing **AI-based vehicle delay or arrival time prediction applications** from other transport areas may be superfluous and unnecessary. Differently, the **hybrid train delay predictors integrated principles of Explainable AI** is rather worth to be explored. The reason behind it is that, at the dawn of artificial intelligence it was discovered that problems which could be formally described by a list of mathematical rules could be easily converted to a set of machine instructions, this enables computers to solve logical problems that were difficult for humans. The mathematical-based solvers certainly are able to deal with most of the difficult decision-making problems due to the people's travel demand and public transport utilisation were still in a relatively under-developed stage in the early stage of traffic planning and management. However, with the growing of complexity of proposed model and travelling activities using public transport ways, simply applying traditional methods is not the best option for meeting the needs of actual situations. On the other hand, a man-made agent would instead struggle with less formulated problems, such as the procedure of identifying objects in photos/videos and recognising spoken words – these are the problems require human intuition and automatic feelings greatly. Even more abstract concepts has been proposed on the technical aspects but at the end we have to put things under the background of traffic planning and management for public transport and translate the requirements for machines, these are significant challenges that hinder the performance of predictors reach a better level (e.g. section 6.1). Actually, for example, attempts have already been performed within the rail sector towards integrated arrival delay prediction that combining machine learning and exact mathematical even heuristic methods (e.g. []) but, to the best of our knowledge, it is still at an early stage.

6.5. Potential directions for Transferability

The traffic planning and management subdomain is one of the most investigated area within the railway sector, a lot of mature and well-developed applications has been presented for solving the potential challenges in this area. Therefore, finding brand new applications to transferring their concepts from other transport-related domains to this domain is not that straightforward. In the remaining part of this section, we would perform the transferability analysis and provide TTables for some of the most promising applications, taking also into account those that could be helpful to cope with some of the scenarios we would like to investigate in the near future.

6.5.1. Integrating heuristic searching strategies with deep neural networks for vehicle routing

As we discussed in chapter 4, referring to the tasks of path planning, route algorithm and navigation for aircraft, graph-based methods especially critical link method and queuing theory are more popular on Unmanned aerial vehicle's path planning compared with the traditional node-based methods. The potential application values on the railway sectors derived from this observation can be basically summarised as following: currently the research findings in the aviation sector are specifically regarding the path planning/routing tasks of Unmanned Aerial Vehicles (UAVs) other than the general public avionics transport. Unlike the aircraft, railway vehicles must running on the constructed tracks and follow the instructions of dispatchers to move/halt. Path planning on public transportation system from the macro scope level, although conceptually similar, is a significantly harder problem not only due to its inherent time-dependent and multi-criteria nature, but also considering that most of the railway networks with the characteristics of heterogeneity. A review of the literature indicates that previous studies on this topic mainly focused on choices offered by a single railway network path without much consideration of the other types of railway network (e.g. freight network and high-speed network and the normal-speed network). Thanks to the hints obtained from aviation sector, a method based on the generalised cost can be proposed to discover the valid routes from the original station to the destination station for the trains in the integrated network of the normal-speed and high-speed railways, especially in the circumstances that high-speed railway network is expanding rapidly among the areas of European and China, etc. The potential influential factors including: total travelling time, total energy consumption, amount of on-board passenger, capacity of chosen tracks, and other possible factors on the generalised costs of trains. Theoretically, the valid routes can be generated by considering the defined train schedule, and an effective route search algorithm could be designed using the deep traversal method in a new valid route searching network.

Several attempts has been made based on this proposal, for example, [74] verifies the practicability of the generalised cost calculation method, as well as that of the valid routes search method in the Lanzhou-Beijing train travel routes. A method of path selection of trains for against the random delays has been proposed [75] based on reliability of travel choice, which considering heterogeneous passengers from different railway networks. As we can see, traditional path planning algorithms can efficiently find the optimal paths in graphs using simple heuristics. However, formulating a simple heuristic is challenging under the road network setting since there are multiple factors to consider, such as road segment length, edge centrality, and speed limit. Recently a novel study investigates how a neural network can learn to take these factors as inputs and yield a path given a pair of origin and destination in the road network, may give us some inspirations about how the DNN can contribute to the railway path planning tasks. A staggered approach is applied in progressing this investigation [76]. Firstly some random graphs are generated, which monitoring the size and properties of the training graph without caring too many details in the network. And then whether a neural network can learn to traverse simple graphs with multiple strategies would be determined. Finally, including factors that might affect the path finding in real road networks would be scaled up. Overall, the training data is optimal paths in a graph generated by a shortest path algorithm. The model is then applied to new graphs to generate a path given a pair of origin and destination. The arrival rate and time efficiency are calculated and compared with that of the corresponding optimal path. Such method investigated and innovatively combined the deep traversal strategies and deep neural networks to perform route planning for vehicles.

Table 6.4 gives a straightforward illustration about how the pre-defined criteria apply for the transferability dimensions in terms of **Integrating heuristic searching strategies with deep neural networks for vehicle/passenger routing and path planning**. Generally speaking, most of the checkmarks fall into the categories from ”Very High” to ”Medium”. Except for those measures for ”AI application” and ”sustainability”, with the rating of ”Low”. We describe each dimension with the following measures.

Table 6.4: TTable: Integrating heuristic searching strategies with deep neural networks for vehicle routing

		Evaluation				
Dimension	**Criterion**	*Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*			✓		
	previous experience		✓			
	failure severity	✓				
Significance	*potential effectiveness*		✓			
	impact			✓		
Similarity	*goal*			✓		
	domain characteristics			✓		
Maturity	*AI application*				✓	
	automation	✓				
Implementability	*technology*	✓				
	sustainability (costs and effort)				✓	

Source Domain: Road Transport

Congruence. The *mission/aim/scope* in the source domain is to find the optimal path for a pair of given origin and destination by training a set of optimal paths of known graphs that generated by a shortest path algorithm. Until now this this mission (or similar aim with this one) has not been fully discussed both in the source domain of automotive and railway domains. The routing/path planning is typically performed with the task of rescheduling in rail sectors. Due to the movements of vehicles in road transport are more random and unscheduled while the schedules for trains are highly time-dependent, which should be determined before travelling (except for rescheduling/emergency cases), This measure we marked as ”medium”. The criterion *previous experience* is ”high” here because the current research stage in the source domain is relevant advanced and most of the progress for supporting the problem of self-driving car navigation/cruise. As for *failure severity*, it is assigned with ”very high” — same as the consequences of valuation error in road transport, once there is a mistake made during routing/path planning procedure, severe public accident even conflicts caused it will be tremendous.

Significance. Obviously, the successful implementation of integrated heuristic searching/deep neural networks may bring to us several benefits. One of the them is to provide the possibility of maximum using the existing railway capacities without constructing extra infrastructures (i.e. platforms, tracks). Additionally, the successful transferred application is able to perform a supportive advisory model when dispatchers assign the original timetables. This is why we evaluate the *potential effectiveness* and *impact* as "high" and "medium" respectively in this table.

Similarity. The dimension of *goal* in the source domain is quite different with that of in target transferred domain. That is, the hybrid vehicle routing application in automotive area was designed totally for improving the performance of autonomous driving cars on the road and the safety and non-collision are the essential requirements. But in the case of rail car we aim to apply it as a tool of rescheduling, for meeting specific requirements such as minimum energy consumption, prevention of congestion areas, and maximum usage of infrastructure capacities. Not surprisingly, we have great differences regarding the *domain characteristics* as well.

Maturity. In general, hybrid path planning application based on heuristic searching strategies with deep neural networks in railway domain have not been investigated before, even the concept of Integrated routing platform for vehicles has not been proposed for a long time in the source transport sector. There is still a huge gap regarding the systematic train vehicle routing framework to improve the degree of maturity for the applied *AI application*. As for the measure of *automation*, the application was originally designed for the the navigation of autonomous cars therefore we can see the degree of its automation is quite high.

Implementability. Either ANN technique or the heuristic searching method is mature enough to be implemented according to the previous experiences, however, there is no evidence shows that attempt has been made to combine them together for addressing the systematic path planning for all the trains in the network. We already have a lot of studies about how to implement ANNs to enhance the process of optimisation for strategical planning. It is said this potential application would be a perfect practice to explore the optimal performance and speed up the calculation time, and surely massive efforts are needed to successfully transfer.

In conclusion, the hybrid framework integrating deep searching strategy and ANNs not only enables data resources from heterogeneous railway networks to be incorporated for an universal usage, but also addresses the inherent challenges of traditional routing models. This is a revolutionary innovation that could perform a systematic rescheduling framework based on it.

6.5.2. Alternative routes services/navigation for passengers based on Cognitive Internet of Things

In this subsection, we would describe the transferability background from the perspective of passenger (micro-scope), the travel route selection for individual passenger is also important. Due to passengers on the same train typically have different destinations — there are a set of intermediate stations between original and terminal stations and each passenger may leave the train at any of the intermediate station as they need, even transfer to another train afterwards. The behaviours/travelling patterns of the individual passenger are more difficult to be captured and simulated just simply adopting either the mathematical methods or heuristic search algorithms. There are more complex influencing factors effect on passenger's travel choice. The considered quantitative parameters including: total travelling fare, travel time, transfer difficulties, travel convenience, comfort, and other possible factors on the generalised expenses of passengers. Relevant studies regarding this consideration has been found but they are limited: [77] used the Beijing Metro as an example, investigated the travel time reliability and estimation of passenger route choice behaviour. Specifically, a rail journey was decomposed and each component was studied with regard to the uncertainties involved. By leveraging the inferred platform elapsed time and transfer time from the smart card transaction data, the journey time distribution of any possible path can be generated, and methods were proposed for estimating route choice proportions.

Current research on Internet of Things (IoT) majorly focuses on the general perception of visual object, voice messages, and sensible signals, and make these captured information connected to share the observations hence make decisions. However, it is not enough that only connections are established, but the general objects should have the capability to learn from external inputs, think independently, and understand both physical and social environment by themselves. Therefore, a new paradigm, named Cognitive Internet of Things (CIoT), has received attentions to empower the current IoT with the "intelligent brain" for a higher-level automation. Typically, an operational CIoT framework mainly characterises the interactions among five fundamental cognitive tasks [78]: perception-action cycle, massive data analytics, semantic derivation and knowledge discovery, intelligent decision-making, and on-demand service provisioning. All in all, compared to the traditional passenger route design services even the IoT-based framework, CIoT has the capability to bridge the physical world (with physical objects, facility resources, etc.) and the social world (with human demand of travelling, social behaviour, etc.), and enhance smart resource allocation, automatic network operation, and intelligent service provisioning.

From the literature we have found several promising studies relate to this topic, some of them specifically improve the performance of services for railway users (e.g. Rail Internet of Things (RIoT) by [79]), but others may enlarge their scope under the public transport systems (e.g. cognitive road traffic management system (CTMS) by [80]). Table 6.5 shows the evaluation of the transferability criteria by considering the research outputs that have been achieved within the road transport sector. Regarding the application of **Alternative routes services/navigation for passengers based on Cognitive Internet of Things**. solutions found in the automotive sector shows a medium level of advancement, and it is promising to be properly transferred to rail sector. We would measure each dimension with the following Table.

Congruence. The *mission/aim/scope* is highly consistent (we evaluate this measure as "very high") within the domain of source and target due to these applications are both interested in generating a feasible even optimal path for public transport users between origin and destination. The give the mark as "high" regarding *previous experience* because the specific studies in the domain of automotive is emerging recent years and some relevant progress can be seen but not particularly for passenger navigation. And

Table 6.5: TTable: Alternative routes services/navigation for passengers based on Cognitive Internet of Things

		Evaluation				
Dimension	**Criterion**	*Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*	✓				
	previous experience		✓			
	failure severity			✓		
Significance	*potential effectiveness*	✓				
	impact	✓				
Similarity	*goal*		✓			
	domain characteristics		✓			
Maturity	*AI application*				✓	
	automation		✓			
Implementability	*technology*				✓	
	sustainability (costs and effort)		✓			

Source Domain: Road Transport

then we assign *failure severity* as ”medium” — a less optimal result during navigation procedure is not a fatal error in real life for most of the users, some unpleasant consequences (e.g. missing the next train want to transfer) can be compensated by finance.

Significance. The existing development of the AI-based personal navigation system is not mature enough for effectively implementing in the industrial products. However, as passenger experience becomes an important measure of public transport quality, train operators and station owners have to improve the effectiveness and convenience of passenger travel through novel artificial intelligence techniques, to meet ever-growing practical needs. To the best of the author's knowledge, similar applications have not been proposed in the railway industry so this practice would be meaningful if successfully transferred. This is why we evaluate the *potential effectiveness* and *impact* as ”very high”.

Similarity. The *goal* of passenger route navigation in road transport network or open areas is rather well-implemented so far. By contrast, the proposed application in railway sector put emphasis on how to efficiently move in a closed environment (e.g. a large integrated transport hub with dozens of platforms). The latter application concerns more about the interactions between users and infrastructures, while the former one do not understand the physical and social environment comprehensively. So we set *domain characteristics* as ”high”.

Maturity. In the past, routes services/navigation for passengers based on Internet of Things techniques have not been investigated, even the concept of CIoT for navigation has not been found in the rail transport sector. A great research gap should be fulfilled if we want to improve the degree of maturity for the applied *AI application*. As the proposed application capture information from environment, objects and other passengers, it is a significant advance of *automation* compared with the human self-motivated routing.

Implementability. For achieving the desired application, the successful transferability may require a huge amount of effort regarding the fundamental cognitive tasks we mentioned before: the perception-action cycles require intelligent agent (e.g. wearable devices, mobile sensors) to learn, think, and understand the social relationships behind the real world. Additionally, the results of data analysis knowledge discovery need to be combined with the feedback from passengers, and then make further decisions. Such process requires efficient and high-performance computing resources, and the innovative semantic frameworks.

To sum up, the Cognitive Internet of Things routes services/navigation tend to present an innovative and intelligent paradigm for the passenger's routes services/navigation problem. However, the current station equipment and rail infrastructures are not already equipped with appropriate sensors, it may be challenging to incorporate all the available information and extract the hidden patterns from them in a real-time manner. Once properly transferred, the performance of rail passenger service would be enhanced to a higher level.

6.5.3. Attributing Primary and Secondary delays in Railway networks using Explainable AI

Potential motivations of proposing this application include two aspects: the first one is the research direction of explainable AI (XAI) needs to be synchronised with the investigated railway research areas, for narrowing the research gaps that could hinder operational deployment. Secondly, the procedure of understanding/labelling/learning the knowledge from massive data seems not that easy and it has not been fully understood at this stage, so we need a powerful framework to explain the mechanism of AI models to those who are expert at traffic planning and modelling but have little working experiences on the AI side. explainable AI is becoming ever important as many AI systems result to be too complex to be properly understood by humans; therefore, XAI approaches and methods are necessary to make the reasoning process and the outputs understandable by human operators.

On the one hand, the problem of discerning different reasons for which train delays occur is tough and complex. train dispatchers want to know which train builds up how much delay at which station, as well as why this delay build-up occurs. On the other, XAI has not received practical attentions in the rail sector. The only contribution can be found in [81], where the authors tackled the problem of discerning different reasons for the occurrence of train delays. Hence, there is much interest in the causes of delays, as different causes imply different ways to prevent these delays from occurring and propagation. Given the total amount of delay a specific train builds up at a specific station, we discern the primary delays that would have occurred if there was no other train in the network, such as vehicle problems, from secondary delays which are knock-on delays. The proposed approach is to train an ML model that predicts the additional delay of a train, given a set of primary features (e.g. weather conditions) and secondary features (e.g. the delays of nearby other trains). Methods from explainable AI help to classify to which amount the primary features and to which amount the secondary features contribute to a specific prediction of the model.

Many factors may interfere in the occurrence or propagation of delays. As we summarised in section 6.4, researchers have employed well-functional machine learning and AI-based techniques in the area of train delay management for data analysis and prescriptive modelling. In this section, we aim to explore the possibility of transferring XAI concepts to get better understanding of the delay transmission and propagation. The approach of analysing correlations in order to understand the process of delay propagation is a widely studied subject however little progress has been made with respect to the explainable AI side according to the literature. Relevant work including the SHAP values introduced by [82] for explaining the deviation of the expected value to the prediction.

Table 6.6 gives the information about how the transferability criteria being marked based on the aforementioned applications for explainable AI investigated within the aviation sector oriented to XAI-based attribution for train delay causes and types. Considering the checkmarks, both the criteria belonging to the significance dimensions are “Very high”, which means that such kind of application, if successfully developed, will bring huge benefits to the railways. The AI application, sustainability, and failure severity criteria are set to “Low”. Dimensions and criteria are described below.

Table 6.6: TTable: Attributing Primary and Secondary delays in Railway networks using Explainable AI

		Evaluation				
Dimension	**Criterion**	*Very High*	*High*	*Medium*	*Low*	*Very Low*
Congruence	*mission/aim/scope*		✓			
	previous experience		✓			
	failure severity				✓	
Significance	*potential effectiveness*	✓				
	impact	✓				
Similarity	*goal*			✓		
	domain characteristics		✓			
Maturity	*AI application*				✓	
	automation		✓			
Implementability	*technology*			✓		
	sustainability (costs and effort)				✓	

Source Domain: Aviation

Congruence. The *mission/aim/scope* of the application in the source domain is real-time situation analysis and operational risk monitoring, a little different from that of railway domain, which is discerning primary and secondary delays with their potential causes. We assign the result of ”high” for this measure. And the *previous experience* regarding the post-hoc explanation methods such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) [83], already been investigated for interpreting the black-box prediction model and its results. As for the dimension of *failure severity*, there is no critical adverse impact can be foreseen if the relationship between individual feature is not completely transparent and comprehensive — we hence set it as ”low”.

Significance. We investigated the effectiveness if the proposed interpretable AI framework being properly transferred. The original study presented previously is restricted to conventional air-traffic management area due to limited available data; However, it is believed that the framework can be applied directly to general railway network and urban metro system as long as mature datasets become available. And the AI-based decision-support systems are foreseen to integrate eXplainable AI (XAI) in order to increase interpretability and transparency of the reasoning procedure, and consequently, build up the human operator's trust towards these systems. So we evaluate the two dimensions in *Significance* as ”very high”.

Similarity. Specifically, the *goal* of train delay prediction is to train a ML model that is able to predict the additional delay of a train, given a set of features/factors relate to primary delays and secondary delays. In the air transport sector the original application exploits aviation occurrences and meteorological databases to train a ML-based risk-prediction model. From this point view, the application scenarios in both domain are required to access the operational data and the environment parameters, that is why we give the measure of *domain characteristics* with ”high”.

Maturity. While progress has been made with respect to train delay prediction, little work exists which tries to decompose physical delays into its primary and secondary causes. We can say, currently the *AI application* in the target domain is not mature enough for a further development. Compare to the previous practices (i.e. implication rules, stochastic method), this XAI-based framework can better understand the prediction process and explain the model's mechanics effectively.

Implementability. The major obstacle that hinder this application to be transferred is the sole availability of mall samples to learn from and a rather rudimentary procedure of the feature selection and feature engineering. In order to demonstrate the real predictive power of the application, informative value and proper feature engineering strategies should be chosen.

Taking into account what has been done in the railway sectors on this specific topic, we could develop a more reliable attributing system for the general delay cases by borrowing the proposal from aviation sector. And surely have more insights with the delay causes such that some potential delays can be avoid by the learning process. A more trustworthy and transparent railway system can be expected.

7. Case Studies

One of the main recommendations provided in D1.3, when closing the DISCOVER phase of the project, was to define pilot case studies/demonstrators to investigate the effects of AI solutions on safety-related applications. In this chapter, several potential pilot case studies are proposed. They are indicators for future research and are not intended to be all addressed within this project. In the following deliverables, we will select a few of them to lead to proofs of concept and benchmarks within the RAILS project. The selection will be made taking into account that a pilot case study has to meet at least two among the following requirements, in order to guarantee its adherence to the objectives of the project:

- it falls into one or more application areas identified in D1.3;
- it allows to perform a transferability study along with at least one of the directions identified in Chapter 6;
- it has been suggested and/or supported by the project Advisory Board.

In the following, some possible case studies are introduced; some of them can be already detailed, others need to be further discussed with the railway stakeholders and the Advisory Board. Therefore, the final choice will be made as part of Task T4.2.

7.1. Case Studies Identification

In chapter 6, we have analysed and discussed which promising applications from the neighbour domains (i.e. aviation and automotive) show the potential to be properly transferred to the railway industry, and to what extent these transfers can be realised regarding the current situation. Based on the previous investigation and discovery, three possible case studies that are among the most promising to be selected: Train Delay Prediction for each train service, Disruptions Attribution among a network, and Rescheduling after delays, respectively. These case studies are going to be investigated from a novel perspective – considering interactions between network elements and the hidden correlations behind them, where suitable AI-based technologies, such as graph embedding, graph convolutional network, and reinforcement learning are proposed to be transferred and exploited to cope with the conventional traffic planning and management problems above.

Disruptions and abnormal events in Rail Transport Systems (RTS) would not only have major implications both for the decision making of Train Operating Companies (TOCs) and Infrastructure Providers (IP), but also lead to additional waiting time or in-vehicle time of passengers, which consequently increases their total travel time. These passengers are obliged to receive possible fare reimbursement for their revenue lost when they are affected by delays derived from the occurrence of incidents. In some cases, a delay would propagate to the rest of the network if no fast and proper measures are applied [84], especially when the services of a TOC were affected by another company.

From the point view of a tactical decision making process, identifying adverse events from massive amount of operational logs/incident reports and learning knowledge from the causes of these incidents may avoid the re-occurrence of potential accidents and similar dangerous events ([85]). To promote the reliability and quality of railway passenger services, and at the same time reduce costs of passengers and service providers, a considerable amount of studies have been investigated under the context of Train Delay Prediction (TDP), Railway Accidents Identification (RAI) and Train Timetable Rescheduling (TTR) problems. From a strategic perspective, accurate train delay prediction and accident estimation information can provide railway dispatchers with a powerful basis for train rescheduling in the follow-up steps, and they can also allow passengers to choose a desired time and route to re-plan their journey with fewer predicted overall delays and potential abnormal events, thereby avoiding or alleviating traffic congestion situations. However, there are multiple considerations when exploiting incident information and learning lessons from past extreme events. They can be summarized as below:

- The learning process could be affected by subjective judgements from traffic controllers. These judgements largely rely on their previous experiences or overall perception towards a specific scenario.
- Quantity of available data is another crucial aspect to be considered. It is not that easy to acquire a plenty of accident cases, especially extreme events, from real-world operational data. The percentage of severe disruptions/critical delays instances is phenomenally less than those without abnormal conditions. The process of obtaining a qualified dataset may be time-consuming.
- Unplanned incidents occur randomly in terms of their types and frequency, typically with no general pattern to follow [86]. Some commonly seen disruptions, such as malfunctioning of vehicle doors or mis-operations from train drivers, would occur frequently however have limited impact on the network. By contrast, rare RTS disruptions, for example, vehicle derailment, or signal failure, are relatively less frequent seen but more destructive.
- The format of typical accident reports is quite different compared with other statistics of railway systems (i.e. timetables, traffic flows, passenger demands). Not only because the hybrid data structure – including incident time, incident date, incident location, but the cause of incidents are typically unstructured text representations. Certainly, we can extract informative knowledge from them if we use it wisely but it is difficult to conduct this process manually.

7.1.1. Train Delay Prediction

There are two obvious limitations that can be derived from the literature of delay propagation analysis. That is, most of current studies mainly based on stochastic-based models and statistical distribution models, but a handful of projects utilised ML-based methods to understand the mechanism of delay propagation and predict delays. Furthermore, abundant studies have investigated the distribution pattern of knock-on delay solely or combined with primary delay for predicting. Yet not many of them have taken the disruptions occurrence (e.g. failures, breakdowns, accidents) into account – which is the significant reason why the delay happened at the first place. Such disadvantage may weaken the interpretability of the proposed models, especially for the stochastic-based models. In other words, researchers focus a lot on the impacts the primary delays have but fail to capture why/where these delays derive from. Although a few of these researchers have considered spatial dependence and temporal correlations, it seems that none of these researchers has studied the relationships from the perspective of graph embedding or graph neural network-based algorithms. A variety of applications of deep learning and machine learning methods (e.g. recurrent neural network, supervised-learning models) have been utilised in train delay prediction problems and delay propagation investigations. However, it is difficult to find an attempt to combine machine learning methods with graph embedding set together for implementation. To fill this gap, we propose a graph embedding/graph convolutional neural network-based train delay prediction framework in this case study. An open challenge for this area is how to find a method that is able to effectively capture the highly non-linear network structure without losing any global and local characteristics.

7.1.2. Railway Disruption Identification

Successfully incorporating empirical data into the statistical analysis has counted for the most significant highlight in the tasks of predicting abnormal events/disruptions. Such data may contain information about the frequency/location/time of different disruptions. However, through the literature we found that it is insufficient to only use empirical data to study disruption frequencies and impacts of multiple disruption types for individual rail elements. For example, if we consider a medium-sized rail network consisting of 200 stations, where our aim is to predict disruption frequencies and impacts for 30 different disruption types, within five different time periods of the day, and separately for each season. Then 200×30×5×4=120,000 instances are at least required empirically. In other words, this requires sufficient empirical observations for each of these 120,000 instances to fit a probability density function. In practice, this means it is impossible to assemble such a huge amount of available empirical data from past disruption records. It is promising and necessary to introduce a supervised learning prediction model to predict disruption frequency and impact for each individual rail network element as this allows for the predictions of disruptions be conducted at any particular station for specific time period, without needing sufficient empirical disruption observations for each location and time period. Furthermore, this approach can boost the efficiency of the prediction process of disruption impacts, especially there are massive amount of disruption instances. Therefore, supervised learning methods have the advantage of addressing the computational challenges of the typical traffic simulation models being used for real-world RTS networks.

There has been a few works towards predicting incident frequencies from the background of railway traffic safety. One of the limitations in this subject is that most of these traffic researches primarily used descriptive and aggregate models to predict accident probabilities [87]. The proposed disaggregated models remain limited. A reason behind this is often a lack of good quality disruption log data, since this kind of models require relatively infrequent occurrences of disruptions. Nevertheless, currently no adequate disaggregate models have been developed to predict frequencies of disruptions for individual RTS stops or links. Another gap we identified is that some of the reviewed papers put their attentions on predicting disruption impacts but fail to recognize the importance of disruption distribution pattern [88], [89]. However, focusing on disruption impacts without considering disruption frequencies can incorrectly put the emphasis on incidents that are very severe yet very rare. From this angle, predicting how often different locations in a RTS network are exposed to various disruptions is a relatively less-discussed topic.

7.1.3. Train Timetable Rescheduling

We already investigated in D1.2 recent implemented rescheduling methods in railway systems such as exact optimization algorithms, discrete event-based methods, and expert-knowledge supported methods. Each of them has its own advantages and shortcomings when applied in train timetable rescheduling tasks. In this section we would summarize the potential drawbacks derived from previous practices and identify our research interests accordingly:

- Normally the mathematical optimization process and most of heuristic search approaches can find an optimal solution in the vast solution space, however this requires massive computational resources and time expenses.
- In reality, due to the complexity of train rescheduling models, it is difficult to find the optimal solution rapidly, efficiency-first methods such as siscrete-event methods, simulation techniques and expert systems were created as the compromise of re-generating high-quality timetables within an acceptable computational time.
- Although a trade-off for reinforcement learning techniques between training efficiency and rescheduling quality has been verified by several recent studies, the train rescheduling strategies by using RL-based methods still have not attracted high attention from the researchers in the literature. In terms of quantity, we have found around 6 relevant studies, and in terms of timeline, all this literature was published no more than in the past five years, which provides us a promising but under developed research direction.

With these concerns, aiming to efficiently reschedule trains, we are particularly interested in developing a RL-based train rescheduling strategy for a bi-directional-track railway network within the framework of discrete event models.

7.2. Case Studies Description

The goal of delay prediction in these three case studies is to predict the average delay level of a specific period in the future based on the delay data of multiple periods in the railway operating history, the static features of each railway station in the network, as well as the structural network characteristics (i.e. connectivity between these stations, weight for a given route, and the network density for different areas). Typically the delay status in each railway station is affected by other stations and is ever changing. Therefore, the impact of other stations needs to be considered—the closer the geographical distance between railway stations, the more significant the impact. Moreover, this research will firstly attempt to integrate a graph embedding module into the framework of a spatial-temporal network of railway. To the authors' knowledge, this is the first time to investigate the problem of train delay prediction/rescheduling by considering the occurrence frequencies and impacts of railway disruptions simultaneously, and incorporating deep graph embedding techniques as well as reinforcement learning methods, in which the spatial-temporal dependence of delay between stations would be effectively preserved and the knowledge of the graph is essentially useful for the downstream prediction/rescheduling tasks. On the one hand, the inherently complex nonlinear spatial-temporal relationships or interactions between traffic participants broadly determine the propagation pattern of disruptions and then the occurrence of primary delays. They are difficult to be accurately predicted in practical scenarios if we fail to preserve these relations. On the other hand, directly feeding all the observed relations/deterministic factors and graph objects into the conventional statistical analysis function or descriptive model would result in a vast computation space that would undermine computations efficiency. In order to compress the essential information of the target railway network more significantly and thus reduce the dimensions of available features, we propose to integrate the obtained highly-related node embedding vectors (i.e. nodes/stations distributed consecutively on a specific route) into a route embedding vector that contains more structural information compared to single node embedding vectors. The expected route embedding representations have to satisfy the following considerations:

- Regardless of the length of a specific route, the obtained route embedding vectors must have a uniform size to be conveniently used as input features for the subsequent prediction tasks.
- Such route representations are able to explicitly reflect the characteristics of the entire route, including the density of en-route stations, the sequence of these stations, and the congestion degree of this route.
- Route embedding vectors can effectively preserve local characteristics and global characteristics.

7.2.1. Train Delay Prediction

Some preliminary work has shown the potential of predicting primary delay by employing multiple ML-based models (Decision Tree, Random Forest Neural Networks) are feasible on the current UK railway network. Is there any possibility to the improve existing primary prediction models by introducing node embedding methods rather than one-hot encoding to process the station vectors? Is it a more efficient way to further incorporate a series of node embedding representations into a route embedding vector? Based on the statements at the beginning of this section, a further question is – how to capture the essential railway network information as much as possible by introducing Structural Deep Network Embedding (SDNE) [90]? Great progress has been made with respect to delay prediction solely while little work exists which tries to decompose delays into its primary and secondary causes. And these approaches only try to explain the propagation of delay from one train to another but fail to determine to which specific amount of delay is caused by secondary or primary effects. A Graph Convolutional Network (GCN) is typically powerful to data represented by graphs: we have node features (the data of nodes) and the structure of the graph (how nodes are connected). For the former, we can easily get the data from each node, but when it comes to the structure, it is not trivial to extract useful information from it. But GCNs avoid consuming a lot of time and efforts on feature engineering (i.e. to distill the structure into available features). It would be advantageous to preserve both the node features and the structure as the input, and let the machine to figure out what information is useful by itself instead of humans. Hence, we need graph convolutional networks. In fact, the effectiveness of the graph convolutional network has been demonstrated in processing graph-like data on the tasks of graph node classification, link prediction, and clustering [91]. We must input original real-world information on primary delay and graph characteristics. What are the potential correlations between primary delay and secondary delay by implementing Graph Convolutional Network (GCN), and what are the most relevant prerequisites and influencing factors that determine the occurrence of secondary delays (by considering station features and network structure simultaneously)? The challenge we are addressing in this problem is how we can infer from historical delay data the amount of primary and secondary causes, by training a graph based convolutional network for accurate delay prediction.

A fundamental prerequisite for the whole research and the successful delivery of this task would provide an effective template and paradigm for the following works. One of the main goals is to generate a deep structural embedding representation by introducing SDNE method for the entire network. The SDNE model can only generate node embedding vectors for each station and we also have interests to capture network structural information from the route perspective. When route embedding representations are incorporated in the existing primary delay prediction model, the input dimension of available features would be reduced significantly. This helps to improve computational efficiency and acquire better prediction accuracy. The output of this module is the predicted overall train delay level for each train in a railway operating log, and its performance would be evaluated and compared with the existing preliminary primary delay prediction model.

Currently we already yield the best performance with 84.8% accuracy on a 3-layer neural network in this model, and this accuracy significantly exceeds that of its two counterpart algorithms (DT and RF). The applied strategies including PCA, time-domain feature engineering, z-score normalization and re-sampling techniques. The preliminary implementation was conducted on the dataset from TransPennine Express, which consists of 1348 train instances that operating in a medium-sized network with 177 stops/stations and 192 edges/links between these nodes in total. The result of SDNE model can be optimized according to the feedback of the evaluation result and it can be used in next module.

7.2.2. Railway Disruption Identification

Next, we will develop a disaggregated modelling approach to predict disruption frequencies and to predict the corresponding impacts of each disruption. A supervised learning approach is proposed to perform these predictions, which allows the predictor to estimate disruptions at individual stations for each time period. Considering there are no sufficient empirical disruption observations available for each location and time slot, this approach would enable a fast and accurate prediction of disruption impacts for more unknown disruption instances without requiring a lot of historical disruption observations. How to develop a generic methodology to predict disruptions and their impacts on primary/secondary delays, for different disruption types, individual stations, and multiple time period, by incorporating the specific characteristics of the different stations? Scientifically, the aim of this module is to employ multiple supervised machine learning model (i.e. Logistic regression, MLP, KNN and Random Forest) to predict the frequency of occurrence for different kinds of accidents and their passenger delay impacts for individual railway stations, by incorporating the specific characteristics of each station. Practically, we aim to provide a dispatch agent with predicted disruption impacts for each individual station in the network, for each distinguished time period and disruption type, supporting the agent to prioritise locations where to put mitigation measures (rescheduling) in place. The expected output of this module is to identify the location and time period where and when accidents/disruptions are most likely to occur, which will be quantified by its corresponding occurrence probability.

7.2.3. Train Timetable Rescheduling

Many factors have to be considered when addressing the train timetable rescheduling problem due to its complexity on its determinants. And thus it is difficult but extremely important to find a relatively suitable method to address TTR problems properly. According to the review output, the numerous environment factors having a significant influence on the optimal solution. The supervised learning approach, where an agent learns from examples of good solutions of rescheduling problem, is not feasible. From another perspective, reinforcement learning combines the advantages of dynamic programming and supervised learning, which is particularly suitable in solving problems of train rescheduling. The major task of this module is to develop a reinforcement learning model that is able to reschedule an existing timetable affected by special disruptions, with the aim of minimising the overall delay for each train service. Unlike many black-box algorithms such as deep learning and CNN, the update procedure and decision-making mechanism of reinforcement learning is easily to be interpreted and explainable. Secondly, the reinforcement block we obtained by training on one specific problem instance is capable to be transferable to other unseen instances without extensive retraining. The predictions on delay time and accident/disruption events can be effectively integrated into a more powerful rescheduling system, in which an intelligent agent learns how to reschedule a timetable and then can be applied to make an alternative dispatching decision by sensing the current state of the railway environment, especially when the occurrence probabilities of disruptions at different stations and periods are already available. The aim of this part is to propose a reinforcement learning-based model that is effective to conduct train timetable rescheduling when special disruptions occur. It can be divided into several supportive objectives:

- Developing a discrete event simulator, it defines the event list and assigns local resources to each train during every training episode. This functionally drives the downstream algorithm block.
- Defining the fundamental components for the reinforcement learning model, including: agents, state-action pairs, objective function, reward function, and Q-values function.
- Performing an example study based on real-world instances.

8. Conclusions

The overall goal of this document, representing the results of Task T4.1 in WP4, is to investigate which AI methods has already been used in other transport and non-transport sectors (here aviation and road) could be exploited and borrowed into the rail sector in order to enhance railway traffic planning and management. The analysis has been conducted starting from the findings and application areas identified in WP1.

An overview of the main current and emerging AI-based technologies in other transport (air and road) sectors has been addressed. Based on the work performed in D2.1, a similar transferability framework has been defined through the identification of some transferability criteria, helpful to make a qualitative evaluation of the AI-based applications' degree of transferability to railway.

Particular emphasis has been put on technologies including supervised/unsupervised machine learning, deep artificial neural network and bio-inspired evolutionary methods.

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