Using Information Engineering to Understand the Impact of Train Positioning Uncertainties on Railway Subsystems

by

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Abstract

Many studies propose new advanced railway subsystems, such as Driver Advisory System (DAS), Automatic Door Operation (ADO) and Traffic Management System (TMS), designed to improve the overall performance of current railway systems. Real time train positioning information is one of the key pieces of input data for most of these new subsystems. Many studies presenting and examining the effectiveness of such subsystems assume the availability of very accurate train positioning data in real time. However, providing and using high accuracy positioning data may not always be the most cost-effective solution, nor is it always available. The accuracy of train position information is varied, based on the technological complexity of the positioning systems and the methods that are used. In reality, different subsystems, henceforth referred to as 'applications', need different minimum resolutions of train positioning data to work effectively, and uncertainty or inaccuracy in this data may reduce the effectiveness of the new applications. However, the trade-off between the accuracy of the positioning data and the required effectiveness of the proposed applications is so far not clear.

A framework for assessing the impact of uncertainties in train positions against application performance has been developed. The required performance of the application is assessed based on the characteristics of the railway system, consisting of the infrastructure, rolling stock and operational data. The uncertainty in the train positioning data is considered based on the characteristics of the positioning system. The framework is applied to determine the impact of the positioning uncertainty on the application's outcome. So, in that way, the desired position resolution associated with acceptable application performance can be characterised.

In this thesis, the framework described above is implemented for DAS and TMS applications to understand the influence of positioning uncertainty on their fundamental functions compared to base case with high accuracy (actual position). A DAS system is modelled and implemented with uncertainty characteristic of a Global Navigation Satellite System (GNSS). The train energy consumption and journey time are used as performance measures to evaluate the impact of these uncertainties compared to a base case. A TMS is modelled and implemented with the uncertainties of an on-board low-cost low-accuracy positioning system.

The impact of positioning uncertainty on the modelled TMS is evaluated in terms of arrival punctuality for different levels of capacity consumption. The implementation of the framework for DAS and TMS applications determines the following:

- which of the application functions are influenced by positioning uncertainty;
- how positioning uncertainty influences the application output variables;
- how the impact of positioning uncertainties can be identified, through the application output variables, whilst considering the impact of other railway uncertainties;
- what is the impact of the underperforming application, due to positioning uncertainty, on the whole railway system in terms of energy, punctuality and capacity.

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List of Contents

List of Figures

List of Tables

List of Abbreviations

4Cs	Cost, Carbon, Capacity and Customer satisfaction
ACO	Ant Colony Optimisation
ADO	Automatic Door Operation
AG	Alternative Graph
ANN	Artificial Neural Network
AP	Access Point
API	Application Programming Interface
APOLO	Advanced Position Locator
ATC	Automatic Train Control
ATO	Automatic Train Operation
ATP	Automatic Train Protection
BeiDou	Chinese Navigation Satellite System
BF	Brute Force search
CBTC	Communications Based Train Control
C-DAS	Connected DAS
CIS	Customer Information System
DAS	Driver Advisory System
DMI	Driver-Machine Interface
Eco-driving	Energy-efficient driving
EGNOS	European Geostationary Navigation Overlay System
EIRENE	European Integrated Railway Radio Enhanced Network
ELR	Engineers Line Reference
EMU	Electric Multiple Unit
ERTMS	European Railway Traffic Management System
ETCS	European Train Control System
EVC	European Vital Computer
F/I	Mixed freight and intercity services
FCFS	First Come First Served
FRA	Federal Railroad Administration
GA	Genetic Algorithm
Galileo	European Global Navigation Satellite System
GEOGIS	Geography and Infrastructure System
GLONASS	Russian GLObal NAvigation Satellite System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GRAIL	GNSS introduction in the RAIL sector

GSM-R	Global System for Mobile Communications – Railway
H/I	Mixed high-speed and intercity services
HS1	High Speed 1
ICAO	International Civil Aviation Organisation
IMO	International Maritime Organisation
INM	Integrated Network Model
LOR	Line of Route
MILP	Mixed Integer Linear Programming
mph	miles per hour
MTS	Multi-Train Simulator
N-DAS	Networked DAS
NSL	Nottingham Scientific Limited
OSM	OpenStreetMap
PDA	Personal Digital Assistant
PPM	Public Performance Measure
PTC	Positive Train Control
PUR	Prediction Update Rate
RBC	Radio Block Centre
RDS	Reliable Data Systems
RNS	Railway Network Simulator
RSSB	Rail Safety and Standards Board
RTS2012	Rail Technical Strategy 2012
S-DAS	Stand-alone DAS
SL	Speed Limit
STS	Single Train Simulator
TCC	Traffic Control Centre
TMS	Traffic Management System
ToA	Time of Arrival
TPD	Train Positioning Deviation
tph	trains per hour
TSLG	Technical Strategy Leadership Group
U/I	Mixed urban and intercity services
UIC	International Union of Railways
WLAN	Wireless Local Area Network

1 Introduction

1.1 Overview

High demand is currently placed on the railway for both freight and passenger services. Rail infrastructure managers and operators have been put under pressure to make more of existing resources. This has motivated the railway industry to begin implementing automated and intelligent subsystems, such as Driver Advisory System (DAS), Automatic Door Operation (ADO) and Traffic Management System (TMS), in order to make more effective use of available capacity. These subsystems, henceforth referred to as 'applications', need a variety of input data, but real-time train position information is usually a vital factor. The accuracy of the reported train position influences the performance of proposed railway applications.

The railway industry has placed developing an accurate railway positioning system as one of its key targets for the future. In 1995, the US Federal Railroad Administration (FRA) stated that the target accuracy of railway positioning systems should be less than 11.5 feet (3.5 m) in order to support future railway systems [1]. In 2007, the UK Department for Transport presented the white paper entitled 'Delivering a Sustainable Railway' which detailed how new technologies and automated applications could contribute to future railway systems in terms of safety, punctuality and capacity. The paper implicitly encourages the rail industry to move towards more accurate positioning systems [2]. In response to what the paper presented about new technologies, in 2012, the Technical Strategy Leadership Group (TSLG), formed by key members of the UK rail industry, presented the Rail Technical Strategy (RTS2012), which provided a strategic plan and guidance on the utilisation and development of new technologies for the next thirty years. It claims that providing accurate train position and performance data in real time at Traffic Control Centre (TCC) is the enabler for using new technologies in traffic and control systems [3]. In 2017, the 'Capability Delivery Plan' was presented, which states twelve key capabilities needed to meet the targeted strategy [4]. One of them is 'services timed to the second', which aims to know the exact position and speed of all trains in real time, in order to increase operational flexibility, improve situational awareness and allow for faster recovery from disruption. In general, the railway industry is pushing for increasingly accurate positioning systems by using various types of sensor with elaborate algorithms and system fusions.

Train positions need to be known primarily for the issue of safety and to prevent train collisions. To keep a safe distance between successive trains, the railway line is conventionally divided into sections called blocks, and only one train should occupy each block section. When a train enters a new section, the sensor of that block section detects the train and the signalling system raises a danger signal (red signal), to indicate to following trains that the block section ahead is not free and that trains should not enter. The signalling system is the railway safety system that provides train movement authority for a train to proceed. The length of the block section determines the number of trains on the line at a time. This conventional signalling and control system has some disadvantages such as high maintenance costs and wasted capacity. Therefore, advanced control systems which are designed to overcome some of the conventional system shortcomings have been developed, such as the European Railway Traffic Management System/European Train Control System (ERTMS/ETCS) in Europe and Positive Train Control (PTC) in the US.

Over time, more automated railway systems and applications have been developed for the purpose of efficient energy use, better use of line capacity, increased safety, improved passenger comfort and reduced maintenance costs. In general, not all of the proposed new automated and intelligent applications need the same positioning system or levels of accuracy. Some automated applications, such as ADO – which opens the train doors automatically once a train stops in the right position on the station platform – cannot work without very accurate positioning data. However, other automated applications such as Customer Information System (CIS) that informs passengers about the train journey progress and following stops, may require less accurate positioning data. Therefore, depending on the type of application, different levels of accuracy of real-time positioning data are needed for it to work effectively.

Moreover, some applications need different positioning accuracy when used on different railways. For example, the train headway in peak hours on the Thameslink line in London is about 2 minutes while the train headway in peak hours at Dundee Central station in Scotland is about 30 minutes [5]. Due to this huge difference in the system demand, the performance required from some applications varies depending on where they are used, and so their requirement for positioning accuracy will be different. However, this difference in required accuracy still needs to be quantified.

On some railway lines, only one type of service or rolling stock utilises a line, for instance, on metros. Other railway lines can be used by one service with different rolling stock or by mixed traffic; for instance, freight trains travel on parts of intercity and high-speed lines [6]. As a result, some applications' requirements for positioning accuracy on a line with only one type of rolling stock or service could be different from that on a line that runs mixed traffic services, due to the differences in train length, speed, braking distance, etc.

RTS2012 points towards the future railway challenges and specifies the UK railway strategies that aim to lower costs, reduce carbon consumption, increase capacity and improve customer satisfaction (often referred to as the 4Cs). Furthermore, one of the capabilities mentioned in the Capability Delivery Plan to meet the targeted strategy is 'low-cost railway solutions' which aim to reduce the cost of lines with low traffic density. Moreover, focus is given to the ERTMS Regional standard, a newer concept for lines with low traffic density, in order to reduce ERTMS installation and maintenance expenses. ERTMS Regional has a simplified control system for interlocking and issuing movement authorities for lower density lines [7]. Similar to the ERTMS Regional system, the 'PTC-equipped dark territory' system has appeared in the US and is based on PTC [8]. From the above, it can be concluded that the railway industry around the world seeks to reduce railway expenses in the future.

The railway industry intends to upgrade some railways with sophisticated positioning systems in order to prepare an appropriate environment for using automated and intelligent railway applications. This is because accurate positioning is a key requirement for some applications. However, not all applications need a high-accuracy positioning system and not all railways need applications based on high-accuracy positioning data. Moreover, there is no general railway standard, so far, specifying the application requirements for positioning accuracy. In addition, there is no railway standard or rules to analyse the performance of railway applications with respect to positioning accuracy. There is scope to investigate the implementation of a number of applications on a wide range of railway lines with low-cost low-accuracy positioning systems.

The motivating idea for this study is that a number of applications can achieve the required performance for specific lines with low-accuracy positioning data, thereby mitigating the need for high accuracy sensors and thus reducing costs. Research has been carried out to obtain a preliminary understanding of the trade-off between railway application effectiveness and positioning accuracy. As a result, a framework has been developed to find the trade-off between positioning accuracy and application performance with respect to its requirements. First, the railway network attributes are analysed. Next, the attributes of the proposed positioning systems are considered. The range of positioning uncertainties is defined. Then, the application capability is analysed. On applying the framework, the performance of a particular application on a railway network with a preselected positioning system can be assessed, and so the required positioning accuracy to get the desired performance can be proposed.

1.2 Railway Strategies

To contribute to the delivery of the 4Cs railway strategies, energy consumption, punctuality of train arrival times and capacity consumption are used to indicate railway performance in the framework presented in this thesis. The following is an introduction to railway energy consumption, punctuality and capacity and how they can be improved.

1.2.1 Energy

Energy efficiency in railway systems has become a global concern and it is a subject being explored with the purpose of reducing energy consumption, as a result of rising energy prices as well as environmental concerns [9][10][11]. One method for reducing energy consumption in railway systems is to drive at an optimal speed which can be realised using a driver advisory application DAS. A DAS is an on-board application that enables the train driver to drive efficiently by following an optimised speed profile. A DAS is expected to be able to significantly improve energy consumption; therefore, it has been chosen as one of the applications to verify the proposed framework.

1.2.2 Punctuality

Railway punctuality is a general expression that concerns the deviation from scheduled departure or arrival times of train services [12]. Disturbances to traffic are inevitable during railway operations due to, for instance, a track blockage, a serious accident or bad weather conditions [13]. The conventional way to handle traffic disturbances is to rearrange train movements either based on signallers' experience with the help of some rules or based on ready-made alternative plans for each type of disturbance [14]. A TMS is a railway application that provides an optimised traffic plan to solve disruption problems by predicting a potential conflict before it happens and finding the best way to avoid it or reduce its impact. It is expected that a TMS can significantly improve railway punctuality; therefore, it has been chosen to be investigated within the proposed framework.

1.2.3 Capacity

How to improve the use of railway capacity is among the most serious concerns of many railways around the world. Railway capacity can generally be described as the traffic volume capability regulated by 'line headway time', i.e. the time interval between successive trains [15][16]. Train headway includes margin times considering the requirements of conventional signalling and control systems [17]. One way to improve railway capacity is to reduce the headway time. However, this solution may increase railway traffic sensitivity and the potential for conflicts. It is expected that a TMS can help cope with the consequences of increasing capacity consumption; therefore, different levels of capacity consumption under different positioning capabilities are investigated in this study.

1.3 Research Motivation

This thesis focuses on the research problem of how to understand the positioning system requirements for individual applications, specifically considering DAS and TMS. The main issues that motivate this study are as follows:

- The majority of previous studies assume that very accurate positioning data are already available in real time in the TCC and ready to use by the proposed new automated and intelligent application. This may not be the case, and the impact of less accurate positioning data needs to be investigated.
- The UK Capability Delivery Plan 2017 aims for services timed to the second whilst also aiming to develop new low-cost railway solutions. So far, the trade-off between high accuracy positioning and system cost is not clear.
- There are no standards or general rules that can define the trade-off between the positioning accuracy and system performance for railway applications.

- There is a significant capability gap between modern fully automated railways based on the current technologies and conventional railways, which are based on older technologies. This gap could be filled by using new subsystems that consider a trade-off between system cost and performance.
- A lot of energy is wasted every day because trains do not follow an optimised speed profile [18].
- A lot of passengers suffer from delays every day because conventional, localised approaches are used to detect and handle traffic disturbances [19].
- A lot of capacity is wasted by adding high margin times to train headways [20].

1.4 Research Hypotheses and Objectives

The research hypothesis is that the required positioning accuracy for an application can be determined so that it meets the desired performance quality based on the type of railway service. The following are sub-hypotheses related to the railway strategies and applications considered in this research.

- Energy consumption in the railway sector can be reduced by using a DAS application with a low-cost low-accuracy positioning system.
- Railway punctuality can be improved by using a TMS application with a low-cost low-accuracy positioning system.
- The capacity consumption of railway lines can be increased without negatively affecting the railway punctuality by using a TMS application with low-cost low-accuracy positioning system.

In order to test the above hypothesis, this research aims to design a framework that can characterise railway applications (especially new automated and intelligent subsystems) in terms of their positioning requirements. It takes into account the context in which they operate, i.e. the type of railway system, as well as cost and performance targets.

The objectives of the research presented in this thesis are as follows:

- Review the railway positioning systems that are currently used and the alternative positioning systems that could be used to improve current railway performance. The review should cover detection techniques, integration methods and connection techniques. Review the railway applications that rely on train positioning data and their positioning accuracy requirements.

- Develop a framework that can characterise railway applications based on the minimum positioning system requirements needed to maintain robust operational performance.
- Verify the framework by implementing it for DAS and TMS applications and evaluating the outcomes in terms of energy, punctuality and capacity, as recommended in RTS2012. In order to apply the framework:
  - Implement a simulated DAS application that can find an optimised train trajectory which minimises train energy consumption.
  - Implement a simulated TMS application that can find an optimised traffic plan which improves railway punctuality and capacity.

1.5 Thesis Structure

Chapter 1 provides a general introduction to the background, research motivation, research hypotheses and research objectives, followed by the thesis structure.

Chapter 2 provides a general review of current and future positioning systems in terms of their capabilities, features, limitations and challenges, and also reviews the communication systems that are used to transfer positioning data from sensors to the TCC, taking into consideration the transmission time uncertainty. This is followed by a review of the railway applications that use positioning data in real time or off-line. The information presented in this chapter helps to identify the gaps in knowledge between state-of-the-art railway positioning systems and railway application requirements, taking into consideration the variety of railway networks and services.

Chapter 3 describes a framework to evaluate the impact of positioning data accuracy on railway performance that also considers impact on the 4Cs. The framework requirements are discussed from three points of view: the application, the positioning system and the railway simulator. The framework implementation is discussed, and the railway simulators that are used in this thesis to implement the framework are described. The knowledge presented in this chapter will be used throughout Chapters 4, 5 and 6.

Chapter 4 presents first an introduction to how a DAS system can save energy by calculating an optimised train trajectory. Then, a discussion of how a DAS can be implemented considering the framework requirements and how the accuracy of the positioning system influences the DAS performance is presented. Following this, an explanation of how the system is simulated and how the experiment is set up is presented, followed by a discussion of the experimental results.

Chapter 5 presents a general description of a TMS and how the traffic rescheduling process is considered. Then, a discussion of how a TMS can be implemented is presented considering the framework requirements and how the accuracy of positioning system can influence the TMS performance. An investigation of the impact of positioning uncertainty within a TMS system is demonstrated on the Stenson and North Stafford junctions with a variety of services and mixed traffic. Then, a general discussion of the experimental results is presented.

Chapter 6 introduces railway capacity consumption and its evaluation methods. Then, a discussion of how a TMS can improve railway capacity use is considered, including the impact of positioning uncertainty. An experiment on timetables with different levels of capacity consumption at Dundee Central Junction is presented. Finally, a general discussion of the experimental results is given.

Chapter 7 gives a conclusion of the applications implemented. This is followed by a general description of how the framework can be used in future work to investigate the impact of other railway parameters of uncertain value, in addition to positioning uncertainty, on the performance of applications and railways in general.

2 Railway Positioning Systems and Applications

2.1 Introduction

Many railway applications, including new automated and intelligent subsystems being considered in this study, need a variety of input data and real-time train position information is a vital factor. This chapter provides a general review of positioning-related terminology, train positioning systems and applications that interact with them. First, current train positioning systems are reviewed in terms of historical development, capability, limitations and challenges. After that, state-of-the-art and proposed alternative positioning systems for future railways are reviewed. In order to be able to understand railway positioning requirements, the diversity of railways that exist nowadays is then reviewed, in terms of different infrastructures, control systems and services. The railway applications that rely on train position are reviewed, and their requirements are discussed. The chapter is concluded by pointing out the knowledge gaps in the literature on railway application studies and railway positioning studies. It is important to indicate that this chapter will not review the positioning requirements of each application described in the literature. This will be covered for the relevant applications in Chapters 4 and 5.

2.2 Railway Train Positioning Systems

To understand the positioning methods used in the railway industry, this section begins with defining the necessary terminology. Then the train detection and positioning systems that are currently used and alternative systems that are proposed to overcome the current system limitations are reviewed. The technologies for transmitting the train positioning data from on-board sensors to the TCC are also reviewed, in order to understand how the accuracy of real-time train positioning data can be affected by transmission technologies.

2.2.1 Positioning Terminology

First and foremost, there are some terms related to the positioning methods are used in this thesis that need to be discussed and shown how they are used. The terms ‘position determination’ and ‘location determination’ usually used to answer a question, for example ‘where am I?’, but in different ways. A position is given by a set of coordinates related to a well-defined coordinate reference frame [21]. Every reference frame requires, besides others, a convention on its origin and on the orientation of its coordinate axes. The process of obtaining a position is called position determination. Alternatively, the shorter term ‘positioning’ is applied in the same sense. There are two modes of positioning systems: point positioning and relative positioning [21]. Location describes a position in terms of topological relations. The process of obtaining a location is called location determination. Besides, the shorter term ‘localization’ is used in the same sense [21]. Topology in this context describes properties of an object with respect to others, e.g., being connected or being adjacent to each other, contacting or intersecting each other, containing other objects, etc. [21].

A position can be determined with respect to a coordinate system, usually geocentric, with respect to another point, or within the context of several points [22]. The type of observations collected and the kind of coordinates desired dictate whether the mathematical model of position is formulated in a one-dimensional, two-dimensional, or three-dimensional space [23]. Dimension defines whether a system provides one-, two-, or three-dimensional positioning. Some positioning systems have the ability to derive also the fourth dimension, i.e., time [21].

Point positioning is the determination of the coordinates of a point on land, at sea, or in space with respect to an implied coordinate system [23]. The problem of point positioning may be stated as follows: given the coordinates of observed extra-terrestrial objects, such as stars or satellites, along with the measurements of quantities linking a terrestrial point to these objects, compute the coordinates of the point [23].

Relative positioning is the determination of the position of one point with respect to another, either by measuring directly between the two points or by measuring indirectly from the two points to extra-terrestrial objects [23]. The problem inverse to relative positioning may be stated as follows: given the coordinates of two points, compute the direction from one to the other, and the distance between the two points [23]. To summarise, the following example shows the difference in the use of the above terms according to this thesis. The answer to the question ‘where is train A?’ is:

Location: in the station yard.
Point position: at latitude: 52.477711, longitude: -1.900527.
Relative position: 20km from station B in the direction of station C.

If the object to be positioned is stationary, the relevant technique can be called ‘static positioning’. When the object is moving, it can be called ‘kinematic positioning’ [22]. To describe the motion of an object, it needs to be able to describe the position of the object and how that position changes as the object moves [24]. For one-dimensional motion, the x axis is often chosen as the line along which the motion takes place. For example, a train is on a track at position x_i at time t_i. At a later time, t_f, the train is at position x_f. The change in the train’s position is called a displacement. Displacement is the difference between the final position x_f and the starting point x_i. The Greek letter Δ (uppercase delta) is often used to indicate the change in a quantity; thus, the change in x can be written as ($\Delta x = x_f - x_i$). The displacement represents the distance travelled, but it is a vector, so it also gives the direction. It is important to recognize the difference between displacement and distance travelled. The distance travelled by an object is the length of the path an object takes from its initial position to its final position [24]. Distance is a scalar quantity and is always indicated by a positive number. Displacement is the change in position of the object. It is positive if the change in position is in the direction of increasing x (the + x direction), and negative if it is in the − x direction [24].

In railway systems, there is static positon information for infrastructure such as stations, bridges and junctions. The interest of this thesis is the kinematic positioning of the train, which is the tracking of train movements in real time, usually called train positioning. It is concerned with the distance travelled not the displacement. Train position is the linear distance that has been travelled along the tracks of a specific route from a reference point [25]. It is given as a specific track (track number/identity) and position on this track [26], see Section 2.2.2.1 for more details.

Metrology-related terminology (accuracy, uncertainty, error, etc.) is defined in detail in the appendix section of the thesis. For this study it is particularly important to understand the difference between error and uncertainty. The term ‘positioning error’ (or ‘positioning deviation’) indicates the difference between the measured position and the ‘actual position’ of a train, for example, the error (or the deviation) in the train position was ‘+35 m’ or ‘−25 m’. Actual position (or ‘true value’) is the value that would be obtained by a perfect measurement [27]; in the context of this thesis, it can be obtained directly from the train simulator. The term ‘positioning uncertainty’ is used in this thesis as a quantification of the doubt about the measurement of the train position, which is expressed as '± uncertainty' [27]. That is to say, error is a known value and it is possible to try to correct it; but any error whose value is unknown is a source of uncertainty [27].

The term 'positioning accuracy' is used in this thesis to indicate the closeness of the agreement between the measurement of the train position and the actual position (positioning accuracy is a qualitative term only), for example, the measurement of the train position was 'accurate' or 'not accurate' [27]. It is important to understand the difference between accuracy and precision. Precision is a measure of how close independent results are to one another when the same measurement is made repeatedly and does not require knowing the actual position. The term precision is, however, not used in this thesis to describe the train position.

In the practice of railway positioning, the true value of train position cannot be absolutely determined in real time [28]. Therefore, the railway systems usually considers the train position in safety-critical functions at the most forward of the uncertainty interval [29][30], as shown in Fig. 2.1. The following sections present the general limitations in determining train positions in current railway systems in UK.

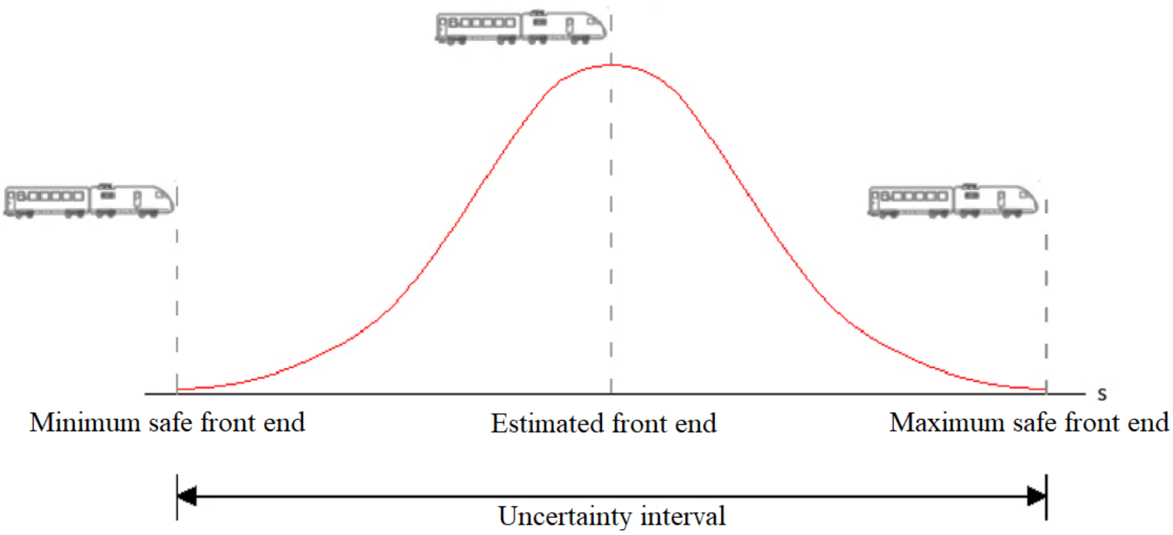


Fig. 2.1 The front end of the train position in relation to the positioning uncertainty [29]

2.2.2 Current Positioning Systems: Limitations and Challenges

This section outlines how the railway industry in the UK determines the position of static railway infrastructure and equipment; it also outlines the current systems used for reporting on train positions in real-time. The limitations of available information about the train position in the UK railway industry are then reviewed.

2.2.2.1 Identifying positions in the railway system

When early railways in the UK were designed, the position of features such as bridges and stations were indicated by a cumulative longitudinal ‘mileage’, using miles and chains, from a datum point at the origin or headquarters of the railway, or the originating junction of a new branch line. A railway route is the path along the tracks of a train, usually for a regular passenger service, which includes the stations/stops/platforms served by the train along with the specific line on which the train travels. Since railway routes are linear in topology, the ‘mileage’ or ‘chainage’ is sufficient to identify a place uniquely on any given route [31]. Thus, a certain bridge position may be shown as 100 miles and 60 chains from a route’s origin. All railway routes are measured from some datum point, often a convenient major place, for example, a London terminus. This leads to numerous instances of the same mileage, giving possible cause for confusion if the route is not also identified. To identify which route any given mileage is on, a three letter (sometimes also with a numeral) code is allocated to each line, called Engineers Line Reference (ELR) [32]. The ELR was originally used for the purpose of identifying a unique position for bridges. Any static position on a route can be referred to by using a combination of the ELR and the mileage of the place, for instance, (BAG1 44 73) refers to ‘University Station’ on the Birmingham and Gloucester line ‘BAG’. The station is 44 miles and 73 chains from the datum point of the line, at Derby station. There are approximately 1200 ELRs in the UK railway network [32]. The UK railway also uses a Line of Route (LOR), which refers to a strategic rail route, and can be made up of several ELRs. ELRs differ from LORs, in their use, format and in what they demarcate. Moreover, the UK routes are supported with mileposts to indicate the mileage from the datum point. Mileposts are installed at a distance of one quarter of a mile from each other, with numbers or marks inscribed thereon denoting the distances [33]. Mileposts mainly act as reference points that can be used to specify a position on the infrastructure, for example, to guide engineering work.

2.2.2.2 Static infrastructure data

There are many approaches used by railway industry to represent railway infrastructure data. The positions of railway infrastructure are usually presented in tables and maps. Network Rail (the main infrastructure manager in the UK) designed sectional appendices for the UK railway infrastructure. A sectional appendix contains information, which is updated every 12 weeks, about each railway route including speed limit, loading gauge and vehicle restrictions [34]. It contains a sequence of diagrams for the routes; the route details, such as LOR and ELR, located in the heading of each diagrams. The sectional appendix represents the mileage of the route pointing out the position of stations, bridges, tunnels, junctions and the positions of speed limit changes. The positions are given in miles and chains and the speed limits are in miles per hour (mph).

The UK railway industry also uses other maps that represent the railway infrastructure such as 'Railway Track Diagrams' and '5-mile diagrams'. These maps are extracted, by private companies, from existing Network Rail documents. Railway Track Diagrams are a series of books (Quail volumes 1 to 6) presenting the railway tracks and stations of the UK and Ireland, published by TrackMaps [35]. The maps contain detailed track level information as it exists showing all tracks, junctions, level crossings, tunnels, signal-boxes, sidings and depots complete with their ELRs and railway mileages. Position is also given in miles chains.

The 5-mile diagrams are digital (softcopy) maps presenting the infrastructure data of each 5 miles of the routes in one diagram, developed by WatermanGroup [36]. All the 5-mile diagrams are linked to each other, so that it is possible to scroll along a route. Each diagram is linked to a geographical map. By selecting the required position on the geographical map, the related 5-mile diagram will be opened. There is a search facility by ELR, station and junction name. The scale diagrams include track, switches and crossovers, signals, gradient profile, curves, line speeds, access points, station platforms, bridges, viaducts, culverts, level crossings etc. There is a mileage bar in the top of each diagram and kilometre bar in the bottom of the diagram. Each mile on the mileage bar is divided into 16 parts (approximately 100 metres each).

Network Rail has collected its infrastructure data in a single database source called the Geography and Infrastructure System (GEOGIS). GEOGIS is the Network Rail infrastructure asset register database which contains information on the physical position and type of track using four digit track ID's to identify each individual position by track direction, track use, and track number [37]. This database is private for the use of Network Rail only and it is updated periodically. In July 2017, Network Rail replaced GEOGIS with the Integrated Network Model (INM). INM replaces the GEOGIS database with a modern web-interface and geospatial representation of the network. It combines the network data models and plain line track information into one consistent system. Network Rail stated that the track sections are more accurately measured in the new system than the GEOGIS system and therefore there are small variances in the data indicating track mileage and layout. However, the majority of the variations are of less than ten yards [38].

In other transport sectors, the navigation systems of aviation and maritime usually use a map-matching technique to identify vehicle position. Map-matching is the concept of matching position information onto a digital map database. Map-matching techniques use positioning information given by positioning sensors and adjust this to a position on the digital map database [39]. The navigation systems of aviation measure the vertical profile of the terrain below the vehicle with respect to sea level and match it to a stored profile. Maritime navigation systems determine the shape of the seafloor with sonar and compare the measured profile to stored maps [40]. In 2014, the Rail Safety and Standards Board (RSSB) published report T952, which focuses on providing a digital map that shows an accurate tracking for the movement of trains in real time. The report reviews several studies. One study, carried out by Reliable Data Systems (RDS), aims to create track-precise maps using image analysis of video from a forward facing camera mounted in a small number of service trains. The proposed maps will provide a global source of map data for position-based rail applications [41]. The study assumed that there is no existing map data and it started from scratch with free open source map OpenStreetMap (OSM). Another study, carried out by Nottingham Scientific Limited (NSL), proposed two types of maps: the first type is a map in the TCC, which is intermittently updated from train sensors; the second type is an on-board train map, which is also updated from the train sensors [42]. The report has proved the concept of the proposed techniques, based on data that has been provided by Network Rail.

2.2.2.3 Train Detection systems

Railway control systems are used to maintain a safe distance between trains on the same track. The train separation is maintained through a signalling mechanism that issues the authorisation for a train to proceed on its journey on the track. The conventional signalling mechanism on the railways is known as a block signalling system [43]. The track is divided into blocks, and one block can hold only one train. The block section (also called track section or fixed block) is a portion of railway track having fixed boundaries and for which train detection system provides information on its state of occupancy [44]. The train detection system is equipment and systems forming part of or providing input to the signalling systems. Currently, there are two types of train detection systems used in the UK, which are usually deployed along the tracks [45]. Each type is designed for a different application and therefore uses different detection sensors. The first type detects the presence or absence of trains within the limits of a block section. This type of sensor is commonly used along the route to indicate the section occupation status. The second type detects that a train has reached, is passing, or has passed a specific position on the tracks. This type of sensor is commonly used at critical positions on the line, such as switch points and level crossings, to provide train approach information [43][45]. Both types of detectors consider trains moving anonymously on the network since they do not know any ID number of the occupying trains. For this reason, they are able to return only track occupation related data for a specific section [29]. In the following, a description of the most common sensors used to detect trains in practice is provided.

1. Track Circuits

In the early days, train presence was detected by a human called a signaller who informed others by raising the danger signal (red signal) [46][47]. The use of rails to act as electrical conductors for signal purposes was first suggested in mid-19th century UK patents [47], but it was not until 1872 that William Robinson designed a track circuit system which is a fail-safe system that can detect the presence of the train and set the necessary signals [47][48]. Track circuits are still commonly used nowadays in most railways around the world. In its simplest form, the system passes a current through the tracks in order to energise a relay. When the block section is free, the circuit is open and the relay is energised so the signal is green, as shown in Fig. 2.2 (a), while once the block section is occupied by a train the circuit is closed (short-circuited) and the relay is de-energised so the signal is red, as shown in Fig. 2.2 (b).

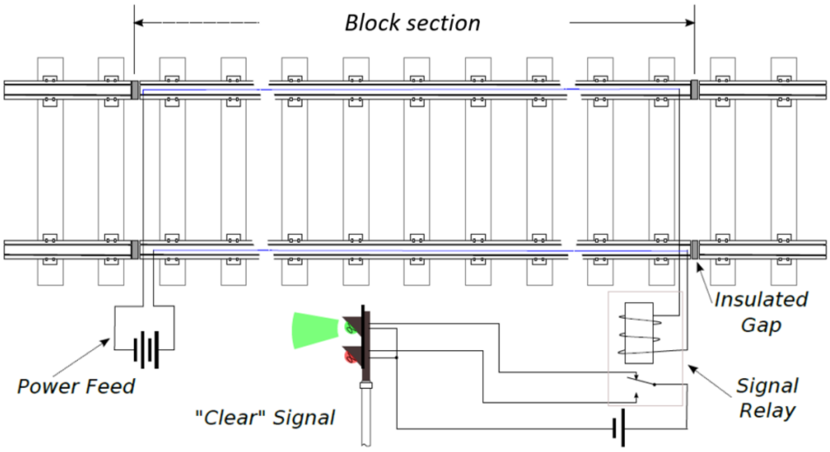


Fig. 2.2 (a) Unoccupied track circuit [43]

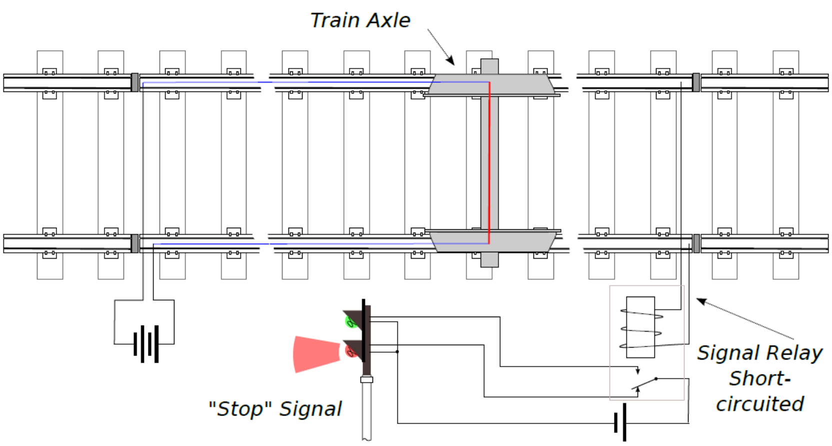


Fig. 2.2 (b) Occupied track circuit [43]

The presence of closed track circuits are considered as fail-safe since if a power breakdown occurs, track circuits indicate the corresponding block section as occupied [29]. Even though the track circuit is fail-safe (in the case of loss of power supply or broken wires), the track circuit can fail to detect a train and so an occupied section would not be reported. This type of track circuit failure mostly occurs for short periods of time. Most of these cases are due to the lack of good electrical contact between the rails and the train axles such as caused by leaves during leaf-fall season. However, the other potential case for track circuit failure is caused by traction return current on electrified railways. As a railway design requirement, only AC track circuits tend to be used on DC electrified railways, and vice versa, in order to prevent the signal relay been accidentally energised by the massive current drawn by trains on the line.

Although nowadays track circuits come with different operating frequencies, modern traction units packaged with various electrical devices such as variable frequency drives, chopper circuits and inverters can simply generate interference right across the frequency spectrum. An example for this case is the interference between the monitoring unit and Class 375 Eurostar (high-speed train) on London and Kent lines, see [49] for more details. Lastly, track circuits have many disadvantages such as the high initial investment required and maintenance costs and susceptibility to poor environmental and weather conditions. Therefore, some railways have started replacing track circuits with axle counter systems [50].

2. Axle Counters

An axle counter is introduced into the railway as an alternative to a track circuit. It can provide similar information to the track circuit about the occupation status of a specific track section. Compared with track circuits, no bonding and less cabling is required in an axle counter units which implies less expensive installation and maintenance [50]. An axle counter system is composed of two electromagnetic sensors called counting points installed at the two opposite boundaries of a block section. The counting points detect trains in and out by counting the number of train axles at both ends of a block [51]. A block section is considered cleared only if the number of axles counted at the entrance of that block section is equal to the one counted at the exit; otherwise the track section is considered occupied [29]. The track section is considered as occupied as soon as the first axle of a train enters that track.

The whole axle counter unit is divided into two parts: detector and an evaluator. Detectors are used on both ends of the track section. Each detector usually includes a pair of sensors across the rail. These detectors are used to detect passing axles and decide whether an axle is moving in or moving out the section. The count for the number of axles in the section is stored in the evaluator. Each axle entering the section detected increases the count while each leaving axle detected decreases the count [43]. A zero count indicates a clear section. The overall process is shown in Fig. 2.3.

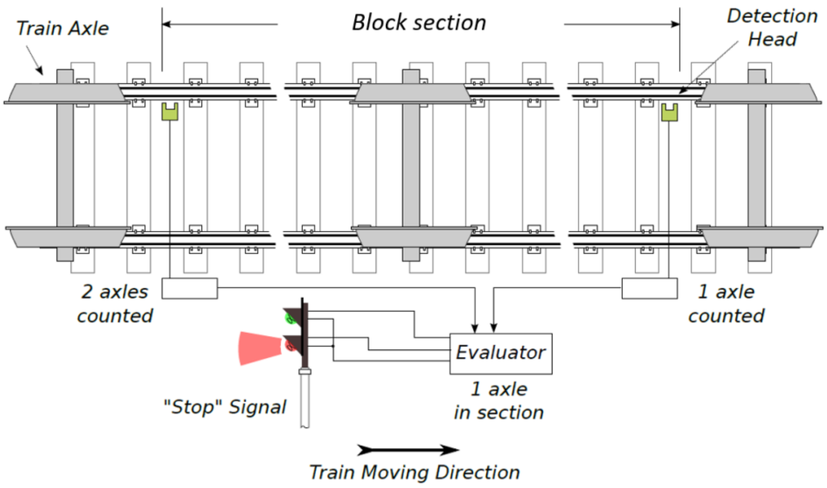


Fig. 2.3 Occupied axle counter [43]

The main disadvantage of an axle counter over track circuits is its lack of a fundamental fail-safe mode [48]. Moreover, the majority of the failure cases of axle counters are related to the fact that the evaluator is unable to detect the presence of a train in the section directly. A counter would have a problem maintaining a correct count when a train can switch rails at switch point between pairs of axle counters or the train wheels stop directly on the detector [50]. The axle counter requires lower initial and maintenance costs than for a track circuit. However, it requires a processor in the evaluator unit to count, save and then compare the number of train axles in and out. Unlike track circuits it does not provide broken rail protection and requires a manual reset if for any reason there is a failure in the counting process [50].

3. Treadles

A treadle is a mechanical or electrical device that is used on the railways to detect the movement of a train passing a particular point. There are different types of treadles used on the UK railways. The most common type of treadle is an electro-mechanical device with a small arm that lies across the inner side of a rail [48]. When the arm is pressed down, an electrical unit connected with the arm changes the unit output. Fig. 2.4 shows an example of an electro-mechanical treadle.

Fig. 2.4 An electro-mechanical treadle [48]

Treadles are not as widely used as track circuits and axle counters. They provide additional information about the train position when needed throughout railway systems. The use of treadles in combination with track circuits is to ensure reliable detection of approaching trains in critical positions on the line such as at the strike-in points of automatic level crossings or switch points where the train changes track and different rails intercept with each other [43][45].

4. Inductive Loop

Some urban train signalling systems and trams use inductive loop technology in combined positioning and communication systems. It is a semi-continuous communication system based on a leaky feeder cable mounted at the foot of the rail that is used to transfer information to trains passing over it [52]. The system consists of two cables along the track which are twisted every 25 m to create a transmitting and receiving medium [47]. The train antenna detects the twisted points and counts them. The inductive loop is used as a bi-directional communication between the trains and the trackside in addition to a positioning system [52].

Inductive loop is laid alongside the full length of the track that makes it vulnerable to slip and trip, sagging, prone to being cut, and prone to damage during rail grinding etc. Loops are relatively sensitive to a number of disturbing influences, such as neighbouring loops or current-carrying cable laid in the vicinity [53]. Besides, a complex design is necessary in switching and crossing areas to avoid any communication loss or null points. Moreover, cable theft and vandalism are a great concern for the loop system.

5. Communications Based Train Control

A new positioning and communication system which has been used in some urban railways is based on Communications Based Train Control (CBTC). The CBTC standard can accept a variety of communication systems [54], such as inductive loop cable [52] or Wireless Local Area Network (WLAN) [55]. CBTC uses a WLAN to continuously communicate with all trains via trackside equipment called Access Points (APs) [55][56]. The train calculates its position, independently of the track circuits, by considering the train speed data and uses an assistance positioning system, such as balises, to fine-tune the calculation [57]. The train continuously sends its position to the TCC through an AP. The TCC sends back a distance-to-go message to the train which is based on the position of the train in front and the train braking curve.

6. European Rail Traffic Management System

ERTMS is a European signalling system specification that has emerged to replace conventional systems. ERTMS includes new control and communication systems, ETCS and Global System for Mobile Communications – Railway (GSM-R). The ERTMS positioning system, unlike a conventional system, is based on an on-board odometry sensor. The odometer is a train-side sensor that measures position of the train by directly recording wheel revolutions. Since this is an on-board device, position measurements are given in terms of local coordinates, i.e. they are relative to a local reference system integral with the train. The European Vital Computer (EVC) is an on-board computer employed to collect and record the train positions measured by the odometers [29].

Positions measured by odometers are affected by several errors due to shape irregularities in the wheel geometry (out-of-roundness, wear, and diameter) or in the roadbed condition (e.g. unevenness). In this case measurement errors increase progressively with the distance, that is to say that the confidence interval of such measures increases linearly [29]. Therefore, ERTMS uses also trackside balises to fine-tune the odometer measurements. A balise contains information regarding its exact position and communicates it to the trains to fine-tune the position measurements given by the odometer. Balises are placed along the rail, at suitable intervals and around critical positions such as junctions and stations. The balise information is always affected by a systematic error (therefore not eliminable) made by transponders while reading the exact reference position of the track. The confidence interval of this measurement has a constant size and is called ‘offset’ [29], see Fig. 2.5.

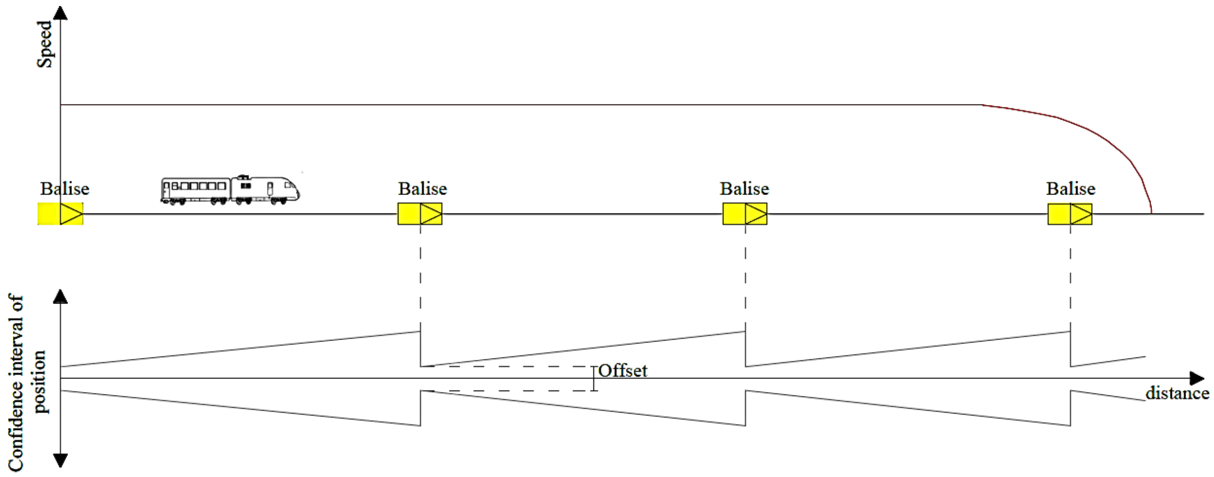


Fig. 2.5 Confidence interval of positioning in relation to odometer measurements [29]

The implementation of ERTMS is divided into three levels. Levels 1 and 2 are based on the fixed block principle while level 3 is based on a moving block principle [58]. A moving block signalling system allows trains to run closer to each other by continuously calculating the required safe separation distance (braking distance with sufficient margin) for each pair of trains, taking into consideration the trains’ position and speed in real time. The positioning data, collected by the EVC, are used for the calculation and the dynamic supervision of the braking curve on the basis of the movement authority that can be given to the train via balises (when the ERTMS level 1 is installed), or via GSM-R from the Radio Block Centre (for ERTMS levels 2 and 3) [29].

2.2.2.4 Addressing the current limitations

Current railway systems have two limitations related to accuracy of the train position data in real time. The first limitation is related to the accuracy of the recorded / measured infrastructure data, railway maps and converting the measurement forms. The second limitation is related the accuracy of the train detection sensors and the accuracy of the positioning data at the TCC in real time.

1. Infrastructure data

In the Network Rail sectional appendix, the 5-mile diagrams and TrackMaps, the positions of stations, bridges, tunnels and junctions, are given in miles and chains. However, the length of bridges, tunnels and platforms is given in miles and yards. The positions of speed limits are also given in miles and chains in the sectional appendix and 5-mile diagrams; TrackMaps does not provide information about line speed limit. The 5-mile diagrams shows the positions of the signals along the track, however, the positions of signals are not directly numerically given, but can be determined from the mileage and kilometre bars. ETCS level 2 is implemented on UK's Cambrian Line. The sectional appendix of the line shows the distance in miles and chains (1 mile = 1.6 km and 1 chain = 20.11 metres) [34]; however, the speed limit is shown in km/h. The UK's High Speed 1 (HS1) uses a metric system showing the distance in kilometres and metres from the datum at London St Pancras station. On the whole, the majority of the recorded / measured infrastructure data in the UK railways are given in format of ELR or track ID plus miles and chains [31]. These measurements give considerable uncertainty for some advanced applications since 1 chain is equal to 22 yards and 1 yard is equal to 0.9144 metres. In other words, the accuracy of most of the recorded railway infrastructure is ± 22 yards (20.1168 metres). Moreover, the majority of advanced applications use the metric system for distance measurements [42]. Therefore, these measurements suffer from discrepancies from true distance due to rounding in the process of changing the imperial units to metric units [37]. For example, some systems use 1 mile = 1.609 km [59], other systems use 1 mile = 1.6 km [34].

Moreover, there are other factors the affect the accuracy of the infrastructure data. When the track was designed, there would have been a good idea of the length of rails needed, but the actual installation results in a distance that is not known accurately [31]. An N-parallel track line has different lengths for each track due to curvature. The track on inside of a curve is shorter than the track on the outside the curve. Mileposts are not exactly one mile apart, due to the changes to the track layout and the inside and outside of curves [31]. The milepost cannot give an accurate measurement along the track; in some cases the position of the milepost could be off by up to 200 m due to changes in track layouts during the maintenance work [60]. Temperature changes affect the distance of a rail between two places at the decimetre level. Therefore, the distance along the track between two places can never be truly known [31]. On the other hand, to get accurate information about the track occupied by a train, accurate information about the train length is required. The train length is used to know when the back of a train will have exited a block section (i.e. to release the block section) where the detected point position is considered to be the front end of the train, as shown in Fig. 2.1. The train length information is also required for several other railway functions such as knowing whether trains fit on platforms and in planning timetables. In the UK railway industry, the registered train length includes the vehicle body length over body ends and the body length over buffers and/or couplers [61]. However, at the decimetre level, the length of train vehicles may not exactly be equal. Moreover, the length of a train at station could be slightly different from a moving train due to the allowance in couplers.

The accuracy of the overall positioning system is only as good as the accuracy of the weakest component, which could be the map, if the map-matching technique is used [62]. Furthermore, in the RSSB T952 report, RDS decided to start work with the assumption that there is no existing map data due to the discrepancies between the available map data [41]. Moreover, many studies and software systems, carried out by Network Rail, were made based on GEOGIS [37]. The discrepancy between GEOGIS and INM data [38] can reduce the value of systems and processes that use GEOGIS-provided information.

2. Train detection systems

The train detection system is used to detect either the presence or absence of trains within a block section; or that a train has reached, is passing or has passed a specific position such as treadles, balises or inductive loop. The accuracy of train positioning is based on the track circuit length [53]. The block section can contain more than one track circuit. The length of track circuit varies, greatly relying on track circuit type, rail sleeper type and the ballast resistance; it could be more than 1200 m long [63]. Track circuits are usually of short length in junction and station areas, and long on open tracks. The accuracy of an axle counter positioning system is similar to that of a track circuit. However, an axle counter, unlike a track circuit, can be used with an unlimited block section length.

Treadles provide position information for specific places. The accuracy of the treadle system is based on the accuracy of its recorded position in the infrastructure database. The accuracy of the inductive loop system is based on the distance between the twisted points e.g. ±25 m; however, the inductive loop has disadvantages such as being expensive and requiring frequent maintenance because of slipping, sagging, cutting etc. In principle, the accuracy of a balise is the same as the accuracy of treadle, since the balise is uploaded with its position information. However, position information of balises suffers from the uncertainty in the conversion process from one measurement scale to another along with rounding, for example, from the miles and chains to metric to balise telegram form. This is in addition to the systematic error in reading balise data; see Section 2.2.2.3 for more details.

The accuracy of an ETCS positioning system is based on the odometry sensor accuracy and the distance between consecutive balises. The ERTMS standard for train position accuracy is ±(5 m + 5%) of the distance travelled since the last balise; therefore, the distance between balises should be arranged to keep the uncertainty less than the European standard [30][42].

To sum up, even if the positioning sensor measurement was exact, there are other more fundamental problems in that the distance along the track between two positions on the ground along the track is not known exactly. As has been seen in Section 1.1, the railway industry has decided to move forward with investing in positioning systems which are more accurate than the current systems. Therefore, the following sections review the positioning requirements and the positioning systems investigated in recent academic and industry studies.

2.2.3 Positioning Requirements

Railway system requirements for positioning systems are different based on the type of the railway service and the employed applications. It has been found that there are no single, stand-alone technologies that deliver all of the UK railway's future positioning requirements [64]. Nevertheless, the general train positioning system requirements [65] are as follows:

1. The system must be able to be installed on all trains operating on a railway network, due to the need to know position of all trains for the system to work.
2. The system must be completely self-reliant and stand-alone.
3. The system must continue to function where trackside positional infrastructure is not available. For example, if a sign is moved overnight, the system should still work.
4. The system must be independent of Global Navigation Satellite System (GNSS) but could use it as supplementary.

5. The system must be resilient to single component failure within the railway network - if a single positioning system fails, trains can continue with a backup system.
6. The system must be resilient to theft/tampering which is not the case for trackside infrastructure.
7. The system must work in all operable lighting and weather conditions: day, night, wind, snow, rain, fog, very bright direct sunlight.
8. The system must be resilient to change in rail track appearance.
9. The system must be resilient to power fluctuations and work on standard train operating voltages.
10. The system must not produce electromagnetic interference which adversely affects other on-board or trackside electronics.

2.2.4 Alternative Positioning Systems

Numerous studies have been carried out to propose, design and test new train positioning systems which could be used by intelligent railway applications. This section reviews the positioning systems that are proposed to replace or assist the current systems. The review points out train detection techniques, data integration methods and railway industry collaborative projects.

Many researchers have concentrated on innovative ways to achieve more accurate positioning. Positioning studies have proposed several sensors and techniques that can be used to determine the train position in near real-time. However, the majority of these studies do not specify the intelligent applications that could use the proposed systems. Moreover, since the application requirements and constraints have not been deeply studied and identified, most of these studies focus on achieving highly accurate positioning data to avoid the consequences of providing positioning data of lower than the practical required accuracy.

Some of the sensors studied do not really sense the position but the speed, and then estimate the position relative to the time record. Some of these sensors can be installed on-board trains, some can be installed on trackside and other systems need equipment installed on both sides (train and track). In this thesis, the sensors are classified based on where data is collected. The data is collected from either on-train equipment or off-train (trackside) equipment. The sensors are reviewed based on the techniques that are used to detect the train position in real time. Examples of sensors with associated references are given for more detail. Table 2.1 provides a summary of the reviewed techniques and their attributes.

It appears that none of the sensors reviewed in Table 2.1 can meet the UK railway industry ambition which is an accurate train position known to the second [4]. Therefore, some sensors need to be used in combination to give better performance. However, integrating diverse sensors raises the expense of the system significantly. Data integration is the process of collecting the positioning data from multiple positioning sensors and providing a single positioning solution with high accuracy. Integration of the positioning data can be performed by considering dynamic weighting for each sensor, so that the same sensor can have different weights based on the current data integrity (accuracy guarantee). The integration algorithm estimates the position of the train in real time by continuously evaluating the truthfulness of the data collected from sensors. The integration methods and algorithms are varied [66]. For example, a Bayesian filter is used by [67][68], a Kalman filter is used by [69][70], and a Particle filter is used by [71][72].

In the last quarter of the 20th century, a new method of positioning based on satellite constellations was devised, later referred to as Global Navigation Satellite System GNSS. It started with GPS (US Global Positioning System) in 1978 and afterwards GLONASS (Russian GLObal NAvigation Satellite System), BeiDou (Chinese Navigation Satellite System) and EGNOS (European Geostationary Navigation Overlay System). EGNOS was officially declared available for safety operations in aviation. In the 1990s, Galileo (European Global Navigation Satellite System) was introduced, to be completed by 2020 [73]. This promotes the idea of using satellite technology to detect a train’s position in real time. GNSS is now very widely used in other sectors, such as aviation and maritime transport, for positioning and other uses [74]. However, one should highlight that, contrary to the case in the aviation or maritime sectors, railways do not have common GNSS rules and therefore, common requirements [73]. The ICAO (International Civil Aviation Organisation) or IMO (International Maritime Organisation) have defined precise technical requirements for most of their GNSS functions. In the railway industry, there is no GNSS specifications table shared by the entire industry [73].

Table 2.1 Summary of positioning systems used in railway studies

On-train/ off-train positioning	**System**	**Train/ track equipment**	**Position/ speed**	**Cost**	**Accuracy**	**Notes**	**Example**
On-train	Inertial sensors	Train	Position + speed	High	Errors accumulated with time	Measures the position and speed by assessing the train acceleration and orientation in different axes	IMU [75]
	GNSS (Global Navigation Satellite System)	Train	Position + speed	Low	Accuracy varies based on satellite constellations and environments	Employs a satellite constellation to specify the position of the client receiver	GPS, D-GPS, Galileo [76]
	Signals of opportunity	Track	Position + speed	Low	Errors accumulate with distance; affected by weather and signal noise	Measurements can be taken based on Time of Arrival (ToA)	Radio, TV broadcasts, Wi-Fi [71]
	Radar	Train	Speed	High	Errors accumulate with distance; affected by weather and environment	Detects changes in the phase angle of signals indicating the train speed	Doppler Radar [77]
	Tachometer	Train	Speed	Low	Errors accumulate with distance; affected by slip-slide and weather	Wheel sensor indicates speed of rotation	Odometry [78]
	Transponder	Train + Track	Position	Mid	Errors accumulate with distance; affected by weather and environment	Transponders transmit their position to the train-based receiver	Balise [79]
	Cameras	Train	Position	Low	Affected by weather conditions; lens cleaning is frequently required	Compares stream images with a database in order to determine the camera's position	Camera [80]
Off-train	Block occupation detection	Track	Position	High	Same as block length	Detects the presence or absence of trains within a specific block	Track circuit [47]
	Ground-based detection	Track	Position	Low	Errors accumulate with distance	Tracks trains as they pass specific points	Eddy current, mass detector [81]
	Digital maps	Track	Position	Low	Difficult to identify the right track of parallel tracks	Compares the acquired position with a rail tracks database	Map-matching [40]

There are many projects being carried out in Europe and around the world to introduce the use of GNSS in the railway sector; some are more concerned with Galileo. Results of using GNSS coming from the other sectors (aviation and maritime) have been reviewed in the context of railway requirements [82]. Unfortunately, the results coming from these sectors, especially in terms of accuracy and availability of the positioning information, have a low level of applicability in the railway environment, because of the peculiarities of this environment itself. In fact, the typical obstacles that are present in railway environments, such as buildings, hills, canyons and tunnels, emphasise sources of errors that were not relevant for other application sectors and so not taken into account there. These typical obstacles can have a huge impact on the availability and on the accuracy of the positioning information in railway environments [82]. The first project that introduced the use of GNSS in the railway sectors started in 1999, and more than 20 projects have since been issued to serve different stages in this direction. Table 2.2 refers to some of these projects; for more detail see [83][84][85].

Table 2.2 Projects using GNSS in railway positioning studies

Project name	**Period**	**System**	**Notes**
APOLO	1999–2001	GPS	Testing the base element of GPS for train localisation
LOCOPROL	2001–2004	GPS	For low-density lines, extending ERTMS train protection systems
ECORAIL	2001–2005	GNSS	Integration of GNSS into safety-critical railway applications
RUNE	2001–2006	GNSS	GNSS as a virtual balise, safety application with EGNOS
GEORAIL	2004–2008	None	Guidelines for the application of CNTD for train localisation
GRAIL-1	2005–2008	GNSS	A common specification for the GNSS subsystem at different levels of ERTMS/ETCS architecture
GRAIL-2	2010–2012	GNSS	To define, develop and validate a GNSS-based enhanced odometry (ETCS) application in high-speed railway lines
GaLoROI	2012–2013	Galileo	Developing a certifiable safety-relevant satellite-based localisation unit for low-density railway lines
EATS	2012–2016	Galileo	A model of the complete on-board ERTMS system behaviour to eliminate interpretation differences
STARS	2016–2018	GNSS	Developing a universal approach to predict the achievable GNSS performance in railway environments
ERSAT GGC	2017–2019	EGNSS	Integrating satellite technology into ERTMS and certifying EGNSS resources according to the ERTMS standard

2.2.5 Time Uncertainty

The accuracy of real-time train positioning data can be affected by transmission technologies. In this context time uncertainty is the doubt about the true value of the required time to transmit the positioning data from the positioning system to the TCC. This section discusses the impact of time uncertainty on the accuracy of train positioning data at the TCC. Train positioning data are collected in the TCC in different ways according to the type of positioning sensor. The positioning data are collected either from on-train equipment or off-train equipment. Data that are collected from off-train (trackside) systems are usually sent to the TCC by cables, while there are many transmission techniques used to transmit the positioning data from on-train sensors.

Different railway control systems use different communication or transmission techniques to communicate with trains. Some railways use cable along the track for communication and positioning systems which communicate based on an inductive loop technique. For example, cable is used in the London Underground and in some high-speed lines in Germany which is called LZB umbilical cable [86]. Some railways use coded track circuits as a means for communication instead of using cables along the track [47][87]. Moreover, some urban railways use a WLAN technique for communication and positioning purposes, usually used with a CBTC system [88]. However, the majority of railways use a GSM-R system for transmitting data between the train and TCC. GSM-R nowadays is used on conventional and ETCS networks for intercity and high-speed lines for the purpose of text messages, voice calls and/or data communication [89][90].

Communication latency in this context is the time required to transfer data between the train and the TCC. The communication latency of using cable, coded track circuit and WLAN systems is very small; for example, cable latency is up to several milliseconds and WLAN technology latency is up to several hundreds of milliseconds [55].

GSM-R latency is regulated according to the European Integrated Railway Radio Enhanced Network (EIRENE) project. The project specifies a radio system satisfying the mobile communications requirements of the European railways. First of all, the GSM-R system is composed of train antennas which can send and receive data to and from the Radio Block Centre (RBC) antennas placed alongside the track. EIRENE specifies that the time required to transmit 30 bytes of data between the train and RBC should be less than 0.5 s with 99%

confidence (i.e. there is no signal interference) [91]. If there is signal interference, the RBC handover process should not take more than 10 s according to EIRENE; however, it normally takes 5 s in cases of interference [29].

A train regularly sends its position and speed data to the RBC, a message which ranges in size between 60 and 120 bytes. Therefore, as specified by [29], the typical time required to transfer train position and speed data from the train sensors (on-board) to the TCC using GSM-R is 1 to 2 s if there is no signal interference [92], and 6 to 7 s if there is signal interference [93][94]; however, it should not be more than 10 s [42][29][95]. Fig. 2.6 shows the scheme leading to GSM-R communication latency for train position and speed data. The variance between t_1 and t_4 is the GSM-R latency.

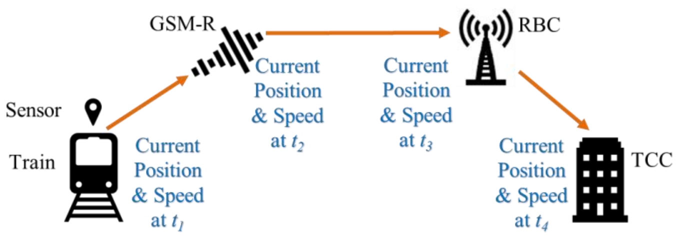


Fig. 2.6 Positioning data transmission using a GSM-R system, adapted from [96]

The impact of the time uncertainty on the accuracy of the train positioning data in real time depends on the train speed as shown in Table 2.3. The table shows the impact of increasing the train speed within four different communication latencies. The position uncertainty of low speed train is between ±4 and ±70 m while the uncertainty in position of a high-speed train is between ±42 and ±834 m. However, this positioning uncertainty could be mitigated at the TCC by identifying the communication latency from the time of the package sent; then the distance travelled during the communication latency can be estimated by assuming the train speed does not change during the transmission interval.

Table 2.3 Positioning uncertainty due to time uncertainty

Train speed	**Communication latency**			
	500 ms (0.5 s)	**2 s**	**5 s**	**10 s**
25 km/h	3.47 m	13.89 m	34.72 m	69.44 m
75 km/h	10.42 m	41.67 m	104.17 m	208.33 m
150 km/h	20.83 m	83.33 m	208.33 m	416.67 m
300 km/h	41.67 m	166.67 m	416.67 m	833.33 m

To sum up, there is a significant lag in the train positioning data in the TCC because of the communication latency. This positioning uncertainty, due to time uncertainty, is directly proportional to the train speed. Potential errors exist only if the positioning data are collected from on-train positioning sensors, as classified in Table 2.1. In contrast, the positioning data collected from off-train sensors do not have such problems with cable transmission systems.

2.3 Railway Network and Service Types

In order to fully understand and differentiate between railway positioning requirements, the whole variety of railway systems needs to be considered. Railway systems are varied and perform different duties; for instance, a metro line provides fast transportation for high passenger numbers within cities while a commuter line provides slower transportation for lower passenger numbers over a longer distance than a metro line. Generally, a railway consists of the rail infrastructure, rolling stock and the control and operation systems. The rail infrastructure can include the stations, rail tracks, junctions, sensing systems and power systems. The rolling stock can be considered to be any vehicle that can travel on the track, such as locomotives, carriage and wagons. The control system can include the trackside signalling, control centre, monitoring systems, communications systems, switches and interlocking. The design of all these systems is subject to the railway type and environment. For instance, WLAN and GSM-R can be used as a communication system between the train and TCC; however, WLAN is more practical for underground services while GSM-R is more practical for overground services.

Railways deliver different service types. Each railway service type has different requirements in terms of the rolling stock and infrastructure. This thesis classifies railway services into urban, intercity, freight, high-speed and mixed-traffic services. An urban service is generally carried out in metropolitan areas as a city’s internal public transportation. It could be a tramway, underground or overground service. An urban service is generally characterised by high frequency (short headway), low speed, short dwell time and short distances [97]. The service usually uses homogeneous rolling stock and runs on dedicated track. The track normally is unidirectional and without junctions.

An intercity service is used to move passengers between cities. This service can use diverse rolling stock types. Intercity services can be characterised as having lower frequency, higher speed and longer dwell time than urban services, with longer travel distances [98]. The services may be run on single track (bidirectional) or double track (unidirectional) lines, and the tracks generally contain junctions. In order to fulfil higher passenger demand on some lines, the line can include more than one track in parallel (i.e. multiple tracks in each direction).

A high-speed service is used to move a large number of passengers between two areas in a short time. The service usually runs on a dedicated high-speed track with few or no junctions. A service can be considered as high-speed if its speed exceeds 200 km/h [99]. This type of service is commonly characterised as long distance, with high permitted speed, relatively low frequency, long dwell time and long train length.

A freight service aims to transport a high quantity of goods over a long distance. In some countries, e.g. the US, freight services operate on dedicated freight lines for most of the travel distance but can be combined with other lines near cities. This type of service can be characterised as long distance, low speed, with long dwell time, low train accelerating and braking rates, high train weight, and long train length [97]. The frequency of the service is based on the demand, so in some seasons it can be relatively high frequency on some specific lines.

A mixed-traffic service consists of more than one type of service sharing the same infrastructure. Such railway lines are able to run different railway services using different rolling stock on the same track. For example, parts of an urban line can be used by urban, intercity and freight services, and also, in some countries, parts of a high-speed line can be used by high-speed, intercity and freight services [97][99]. Table 2.4 shows categories of railway services. It can be noted from the table that most extreme conditions are either in urban or high-speed services. On the other hand, most the medium conditions are in intercity service. The freight service has some similarities with either intercity or high-speed services.

Table 2.4 Diversity of railway services

Attributes	**Railway services**			
	Urban	**Intercity**	**High-speed**	**Freight**
Number of stops	high	medium	low	low
Distance between stops	short	medium	long	long
Line distance	short	long	long	long
Line speed	low	medium	high	medium
Frequency (traffic)	very high	high	medium	low
Dwell time	short	medium	long	very long
Rolling stock	homogeneous	different	homogeneous	different

It is clear that the aforementioned services are diverse and have different characteristics and perform different duties. Therefore, the positioning accuracy requirements could be different from one service type to another. Furthermore, the performance and properties of the proposed intelligent applications that are required for one service type may differ from those for another service type.

2.4 Position-Based Applications

Many intelligent applications have been developed in railway studies. The majority of them need to read the train positions in real time. However, the type of positioning data required for these applications may be different. For example, some applications may need an absolute position; other applications may need the train distance from a fixed point; and others may need a relative distance between two points [28]. This section will provide a review of the projects that have looked into the required positioning accuracies for several railway applications and indicate their strengths and drawbacks.

Due to the rapid rise in the development of satellite technologies in the last century, as mentioned in Section 2.3.2, the railway industry began to think about using GNSS to improve train detection systems. Therefore, some studies and projects have been carried out to introduce the new positioning technologies into railway systems. In 1999, the EU launched the Advanced Position Locator (APOLO) project which aimed to study the possible positioning accuracy that can be achieved by using GNSS in railways [100]. The project explored the railway applications that could gain an advantage from the use of GNSS technology. Then, the project classified railway application requirements into two classes of prototype: high accuracy requirement (5–10 m) and medium accuracy requirement (~50–100 m) with high integrity, coverage and availability of positioning. The verification of railway safety-related applications is not considered in the project aims. A standard GPS receiver is used for applications of medium accuracy requirement, and GPS with an EGNOS receiver is used for applications of high accuracy requirement [101]. This project has become a starting point for further research.

In 2000, the European GNSS Secretariat – European GNSS Rail Advisory Forum published the ‘Requirements of Rail Applications’ report [26]. It evaluates the benefit of using satellite technology in railway applications, especially when the Galileo service is involved. The railway applications are categorised into ten types within three groups: safety-related, operational and infrastructure applications. The report lists the application requirements of

Table 2.5 Positioning accuracy requirements according to [26]

ID	Application	Accuracy
Safety-related applications		
I	e.g. ATC on high-density lines/station/parallel track	1 m
II	e.g. train control on medium-density lines	10 m
III	e.g. train control on low-density lines	25 m
Mass commercial/information and management-operational applications		
IV	Tracing & tracking of vehicles	50 m
V	Cargo monitoring	100 m
VI	Dispatching	50 m
VII	Passenger information	100 m
Infrastructure & civil engineering, professional applications		
VIII	Positioning of machines	1 cm
IX	Infrastructure survey	1 cm
X	Fixed-point applications	5 mm

satellite services as accuracy, integrity, availability, interrupt threshold, continuity, coverage and fix rate. Table 2.5 presents the application requirements for positioning accuracy.

The report considers the diversity of railway networks and services for safety-related applications by dividing the requirements of positioning accuracy for train control systems into three levels for high-, medium- and low-density lines. In contrast, the diversity of railway networks and services is neglected in the operational and infrastructure applications. The report states that the figures proposed are based on the authors' experience on the application requirements and how Galileo services could contribute to these requirements. The report does not include a methodology to explain how the proposed figures have been derived.

In 2006, the European GRAIL (GNSS introduction in the RAIL sector) project considered the introduction of GNSS in ETCS systems and applications. The project reviewed the railway applications to which GNSS can contribute. The GRAIL project explores 44 railway applications that can benefit from utilising GNSS services. In order to recognise the application requirements, a list of application attributes was defined based on the authors' experience [102]. Then, the railway applications are classified into nine groups based on their requirements of positioning accuracy and integrity (accuracy guarantee). The project classifies the accuracy requirements into three scales: very high (0.01–1 m), high (1–10 m)

Table 2.6 Positioning accuracy and integrity requirements according to [102]

Accuracy requirement	Integrity requirement		
	Very high	**High**	**Low**
Very high (0.01–1 m)	**Group 1** • Digital route map creation • Odometer calibration	**Group 2** • Setting out (audit) • Construction (QA)	**Group 3** • Infrastructure survey • Structural monitoring • Gauging surveys
High (1–10 m)	**Group 4** • Calculation of end of movement authority • Train location • Speed profile calculation • Train integrity and train length monitoring • Train separation • Supervision to buffer stops • Cold movement detector • Level crossing supervision • Track identification	**Group 5** • Door control • Power control • Infrastructure charging • Hazardous cargo • Dispatching • Management of emergencies • Terminal operations • Worker protection • Train warning systems • Onboard train monitoring unit • Track condition	**Group 6** • Energy saving • Station stop advisor • Passenger comfort • Internet access points • Dispensing lubricants • Site management
Low (> 10 m)	**Group 7** • Low-traffic ATP	**Group 8** • Location of GSM-R reports	**Group 9** • Passenger information systems • Onboard displays • Travel assistants • LBS/POI • Fleet management • Cargo monitoring • Route atlas • Energy efficiency • Energy utilisation

and low (> 10 m), and the integrity requirements also into three levels: very high, high and low. Table 2.6 presents the project's classification for railway applications.

Although the project report reviewed 44 railway applications, all the reviewed applications are only concerned with the ETCS system, not all types of railway control systems. The project report also does not consider the differences in application requirements of intercity and high-speed lines within the ETCS control system. Moreover, the railway application attributes and requirements are set according to experts' opinions, without a clear classification procedure.

In 2012, RSSB published T892 report which focuses on providing an architecture for a positioning system (locator) that can satisfy the UK railway application requirements. The train locator is intended to be supported by a GNSS system. The report explores the requirements of each individual railway application by defining seven attributes for

Table 2.7 Positioning accuracy and integrity requirements according to [103]

ID	Application	Accuracy (m)	ID	Application	Accuracy (m)
Signalling and control application requirements			2.14	Pantograph Control	4
1.1	Automatic Train Protection (ATP)	2	2.15	Driver Route Knowledge Assistant	6
1.2	On-train ERTMS Interface	2	2.16	On-train ticketing, retail & authentication	6
1.3	Train Awakening	2	2.17	On-train reservations	6
1.4	Cold Movement Detector	2	2.18	On-train catering & services	6
1.5	Train integrity and train length monitoring	2	2.19	Train Crew Information Services	6
1.6	Location of GSM-R Reports	3	2.20	Infrastructure charges	17
1.7	User-Worked Crossings	33	2.21	Delay Attribution	17
1.8	Secondary line signalling	12	2.22	Incident Management Response	6
1.9	Trackside Personnel Protection	12	2.23	Logistics Planning and Monitoring	10
1.10	Possessions Management	19	**Customer application requirements**		
1.11	Track circuit diversity during leaf fall	12	3.1	Customer Information Systems	33
1.12	Alternative Temporary Block Working (ATBW)	12	3.2	Passenger Information Systems	33
1.13	Diverse Positioning Systems (COMPASS)	16	3.3	Personal Journey Assistant	6
1.14	Detonator Replacement ('Virtual Detonator')	9	3.4	Location-Based Services & Points of Interest	167
1.15	Tilting trains	11	3.5	Passenger Broadband	6
Operations application requirements			3.6	Train Approaching Warnings	24
2.1	Centralised clock	na	**Engineering application requirements**		
2.2	Traffic Management & Regulation	17	4.1	On-train Monitoring Recorder (OTMR)	14
2.3	Eco-Driving	6	4.2	On-train CCTV	14
2.4	Driver Advisory Systems (Stage 1)	33	4.3	On-train Monitoring	6
2.5	Fast and slow line discrimination	6	4.4	On-train automation	6
2.6	Automatic Train Operation (Stage 2)	17	4.5	On-train braking measurement probes	4
2.7	Driverless Trains (Stage 3)	2	4.6	Odometer Calibration	67
2.8	Temporary & Emergency Speed Restrictions	3	**Infrastructure application requirements**		
2.9	Fleet Management	83	5.1	Digital Route Map creation	0.3
2.10	Cargo Monitoring	600	5.2	Structural Monitoring	0.02
2.11	Terminal Management	13	5.3	Gauging surveys	0.2
2.12	Door operations	1	5.4	Automated Infrastructure Maintenance	0.2
2.13	Passenger Count	1			

positioning data and describes the levels of these attributes [103]. Then, based on discussions with railway stakeholders and the TSLG, the report divides 54 applications into five groups and sets the level of attributes required for each application. Based on the attributes set for each application considered, the report specifies the positioning requirements for applications, taking into account the characteristics of positioning and navigation systems [103]. Table 2.7 shows the accuracy requirements for 54 applications.

The report does not consider the variety in railway networks and services in evaluating the application attributes and requirements. Nevertheless, as can be seen from Table 2.7, very high positioning accuracies have been allocated for the applications. The report specifies the position accuracy required for each application whereas these requirements are built according to the application attributes that are themselves based on the opinion of the railway stakeholders and TSLG. Therefore, all the findings of this report are limited to the human point of view based on subject matter expertise.

From the studies mentioned above, it can be observed that the highest accuracy requirements are apparent in infrastructure-based applications, which are responsible for monitoring and maintaining work on the railway infrastructure. The infrastructure applications may require an accuracy greater than 1 m. The requirement for safety-related applications, which are responsible for the safety of the train and passenger movements, is between 1 and 25 m. Furthermore, it can be seen from the tables above that the majority of railway applications are operational applications, which are responsible for organising the use of routes, junctions, trains and crews efficiently. In other words, developing intelligent operational applications could significantly improve overall railway performance. The positioning requirements for the operational applications are in a wide range from 1 to 600 m. This means that a wide range of intelligent operational applications can be implemented to raise the performance of railways without the need for highly accurate positioning systems.

It is important to highlight that there are not yet railway standards that clearly specify the application requirements of positioning accuracy, and all the figures presented in Tables 2.5, 2.6 and 2.7 are recommended values. Moreover, all these studies have presented the requirements of positioning accuracy using expert knowledge, which was built through long periods of monitoring the railway performance and the data collected from the field. The requirements presented do not derive from technical studies showing how the positioning data are utilised within each application. In all these studies there is no mathematical or logical formula which represents how to assess the positioning data required for each railway application.

Therefore, the recommended values presented in the reports above might be over or under the actual requirement. The over specification case may increase the cost of implementing the railway application while the under specification case influences the application performance and could put the system in danger if the application is safety-related. Moreover, the reports mostly did not consider the variety of railway networks and services in their studies. This could either increase the implementation cost or render the application performance insufficient for the allocated type of service.

2.5 Conclusions

This chapter has reviewed first the railway positioning systems. The review presents the current railway positioning systems in addition to the positioning studies and projects promoted by governments and the railway industry. All these studies and projects have one goal to achieve, which is to attain more and more accurate positioning by designing integrated positioning systems with less or no focus on understating of the practical accuracy required.

Second, the chapter has introduced the complexity of the railway system which is composed of the rail infrastructure, rolling stock and controlling systems. The components making up the system are diverse depending on the railway network and service type. While different services have different duties and requirements, some positioning techniques may fulfil the requirement for one system but not necessary satisfy the others.

Lastly, the railway applications that rely on train position information are presented. There are few studies and projects that have put an emphasis on investigating the railway applications that can benefit from upgrading the current positioning system. Due to there being no standard for the positioning requirements, the studies proposed the positioning requirements for these applications. The positioning requirements proposed in these studies depend on the attributes of the applications and on discussions with railway experts. The studies indicate that the proposed positioning requirements should be prepared first to take advantage of these applications in railway systems. Therefore, governments and the railway industry push more and more investment into designing sophisticated positioning systems. Nevertheless, in many cases, the proposed requirements may not be optimal to efficiently achieve the desired application performance.

On the basis of this review, it can be seen that none of the reviewed application studies use a mathematical or logical formula to assess the positioning data required for each railway application. The proposed positioning requirements are based on experts' beliefs, which are built by monitoring the railway performance for long periods. Therefore, the practical positioning requirements could be less than the proposed values. Furthermore, the railway application studies do not consider the diversity of railway networks and services in the proposed positioning requirements. In addition, different railway networks and services may need different application performance: a high-speed service, for example, could need different application behaviour than a low-speed freight service. However, the application studies also do not consider the diversity of application performance in the proposed positioning requirements.

The review presented in this chapter clarifies the knowledge gaps in the literature. On one hand, there is a gap in the literature of railway application studies with mathematical analysis of railway performance requirements. On the other hand, there is a deficiency in the literature of railway positioning studies which aim to achieve one solution for all railway applications on all railway types. The aim of this thesis is to develop a simulation-based evaluation framework that can find the balance between railway service requirements, railway application requirements and railway positioning requirements. The framework outputs should be driven towards achieving the 4Cs strategies. For that purpose, the thesis framework will be developed, in the next chapter, according to the literature on railway services, railway applications and railway positioning that has been presented in this chapter.

3 Research Framework

3.1 Introduction

In response to the analysis of the literature presented in the previous chapter, this chapter demonstrates a methodology that combines the variables of railway systems, applications and positioning within one simulation-based framework for the purpose of evaluating the influence of positioning uncertainty on the performance of railway applications. The framework is developed to test the thesis hypothesis, which suggests that a railway application can be characterised in terms of positioning accuracy, for a specified performance quality, on the basis of the type of railway service. The chapter first presents a general evaluation framework. Then, the parameters of the input and the output modules, to be used in evaluating the required positioning accuracy for railway applications operating on any railway network or service, are populated in the framework. Before the framework is implemented for DAS and TMS applications in the following chapters, the framework requirements are discussed in terms of railway systems models. The chapter ends with a description of the microscopic railway network simulators used in this thesis.

3.2 Framework Description

There are many intelligent and automated applications that have been proposed in railway studies in order to improve system performance, cost, safety and maintenance. Most of these applications need to read train positions in real time in order to work and make judgements. In order to test the thesis hypothesis and understand the positioning requirements for a specific railway application, a general simulation-based evaluation framework is developed in this study. Due to the difficulty of carrying out experimental studies of railways in the real world, railway systems are usually modelled in virtual simulation environments. The simulation-based framework considers the railway parameters that have a non-negligible impact on the system. These parameters represent the diversity of railway networks and services, railway performance requirements, application performances and positioning system uncertainties which have been discussed in Chapter 2.

The developed simulation-based framework is inspired by the IDEF0 methodology which was developed by the US Air Force in the 1970s in order to improve the productivity of manufacturing by structuring the representation of the functions within a modelled system in the context of associated inputs, outputs, controls and resources, as shown in Fig. 3.1 [104]. The system functions are arranged in different levels, and the whole system is represented in the top-level context diagram. This study additionally needs to assess the resources of the railway service and network alongside the resources of the new automated subsystems and applications at the same level.

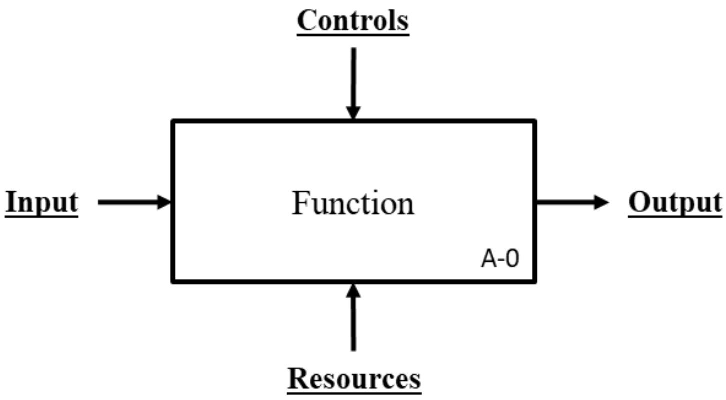


Fig. 3.1 IDEF0 block diagram [104]

In this study, the framework is constructed based on the thesis hypothesis, which indicates that the required positioning accuracy can be characterised for a desired level of application performance on specific railway network. The framework consists of five modules at one level, each containing parameters describing an aspect of the whole system according to the hypothesis. The framework includes four supplier modules and one output module. The first module represents the application being investigated; the second module represents the test variable, which is positioning data; the third module represents the static data of the railway model; the fourth module represents the operational data used in the railway model e.g. timetable; and the fifth (output) module measures the railway performance when the application runs under the test variable. Fig. 3.2 illustrates the general framework of the simulation-based evaluation methodology for positioning requirements. The data of the supplier modules are tested under railway control functions and the results are presented in the output module. The railway control functions in the framework reflect the modelled control functions within the supplier modules when they are put together and executed (run the simulator).

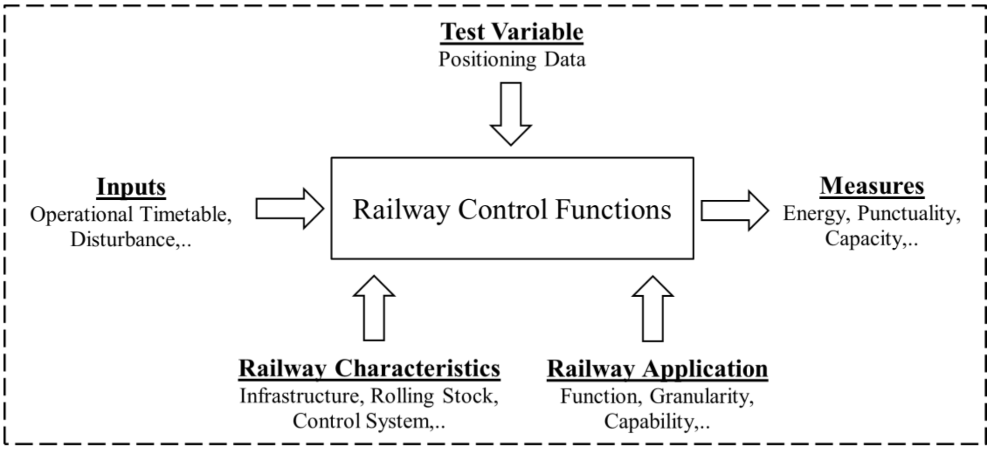


Fig. 3.2 General evaluation framework (top-level context diagram)

The following describes each framework module:

1. Railway Application Module

The railway application module represents the properties of the intelligent application that is proposed to improve railway performance. This is the module for which the impact of positioning accuracy is to be tested and for which its influence on the railway performance is to be assessed in the measures module. Examples include: DAS, CIS, TMS or ADO. This module focuses on the application's performance, response rate and capabilities. In other words, the module should consider all influential factors, such as the mathematical model, control loop, algorithms and optimisation function of the application.

2. Test Variable Module

In this study, the test variable is the uncertainty in train position information. All sources of train positioning data in real time should be considered, such as the signalling system, GNSS, train odometer, balises, etc. Each source of train positioning data has its own properties and parameters which need to be included. The integration method and the way of using these data in real time should also be considered.

3. Railway Characteristics Module

This module includes the static data that represent the type of railway service and network in terms of infrastructure and hardware equipment. Railway models should consider the necessary real field parameters in order to reflect the reality of railway traffic. Therefore, the railway characteristics module should consider the static data of the modelled case study, for instance, the infrastructure, rolling stock, control and safety system, communication system, environmental factors, operational rule, model granularity and model assumptions.

4. Inputs Module

The operational inputs module considers the railway operational parameters that interact with the application investigated, for example, the operational disturbances for investigating the TMS application. This module is also used to represent the type of railway services in terms of the operational parameters, for instance, the differences in operational timetables regarding the scheduled headway times and the allowance in train arrival times between railway services.

5. Measures Module

This module measures the impact of the investigated application on the performance of the railway. In other words, the benefits of using a particular application on a selected network and service in combination with a specific positioning system can be quantified using this module. In line with the UK's 4Cs strategies, the measurements of railway performance can be energy consumption, service punctuality and delay, capacity consumption or operational cost. This module can include one or more of these measurements depending on the application type and objective of the experiment.

In the base version of the experiment, all the parameters within the inputs module, the railway characteristics module and the railway application module should take fixed values while stochastic-valued variables are used in the test variable module. In this study, the test variable is always the uncertainty in train positioning data.

In a more complex experiment, to study the relationship between train positioning deviations and other railway parameters, all but one of the (inputs, railway characteristics and railway application) parameters should be fixed while the selected parameter is varied.

For example, to study the impact of uncertainty in the positioning data combined with uncertainty of train delay on an application, the same positioning deviations as used in the base experiment should be reused with different operational inputs representing different train delays; the other parameters retain their same fixed values. In this way, each parameter's influence can be assessed under positioning uncertainty. Fig. 3.3 illustrates all of the above parameters and variables in the framework.

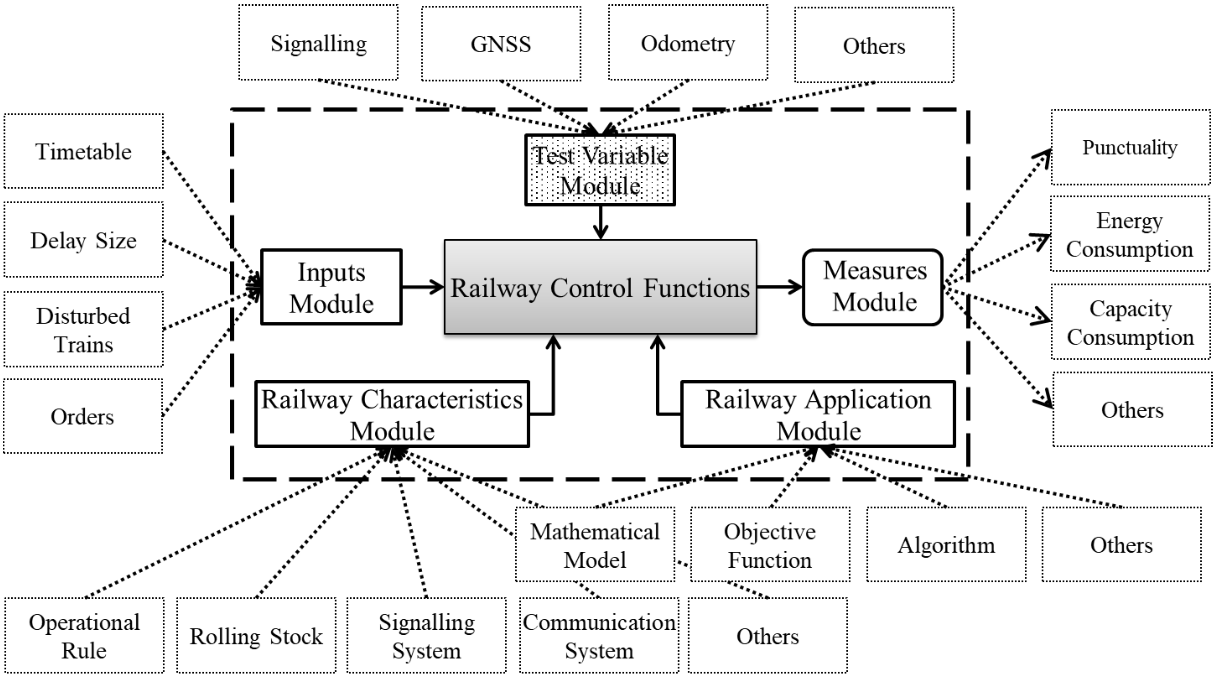


Fig. 3.3 Full representation of the framework

3.3 Framework Requirements

To put this framework into practice with respect to the thesis hypothesis, the railway system and railway application need to be modelled. The railway system can be modelled by setting parameters that represent the railway infrastructure, rolling stock, control and operational systems. Most of these parameters are considered in the railway characteristics module though some parameters are considered in the operational inputs module either because they influence the application investigated or to differentiate between railway services, as mentioned in Section 3.2. In order to emulate the positioning uncertainties in the test variable module, the train positioning system is considered as a separate model that interacts with the application and railway system models. The following provides more detail of the requirements for modelling the railway system, the application and the train positioning system.

1. **The railway system model:** there are various railway simulators that are able to simulate train movement on railway infrastructure [105][87]. It has been found that the requirements of simulators rely in part on the application being investigated with respect

to how the application interacts with the railway system [106][107]. Thus, different applications could have different requirements of a railway system simulator. The requirements for the purposes of this study are as follows:

- The simulator is able to insert operational events into the train journey and train traffic in real time, for instance, inserting system failure or train delays in real time.
- The output of the simulator is measurable in terms of what the application could contribute to, e.g. saving energy, punctuality of arrival times, etc.
- The simulator is able to provide the actual train positions (without uncertainties) to the train positioning model in real time.
- The simulator is able to support an Application Programming Interface (API) that can interface with the application models, in order to control some tasks in the railway systems.
- The simulator enables the API to read/write operational data in real time.

2. **The railway application model:** the application model is of the examined (sub-)system where the impact of varying test variables (i.e. variables related to positioning) is investigated. The model should support an API interface in order to join with the railway system simulator. It should also operate with the data exchange format supplied by the simulator.
3. **The railway positioning system model:** the positioning model is responsible for providing train positioning data to the application model. The model should be able to read the actual train positions from the simulator and then carry out a process to mimic positioning sensor deviations. Then, the model should provide positioning data to the application model according to the positioning sensor attributes. Fig. 3.4 shows a flowchart of the positioning model as proposed by [108].

After the models of the railway system, application and train positioning system are prepared, the models must be connected to each other in a way that allows the positioning information to be transferred between them. Fig. 3.5 illustrates a flowchart for interconnections between the models [109].

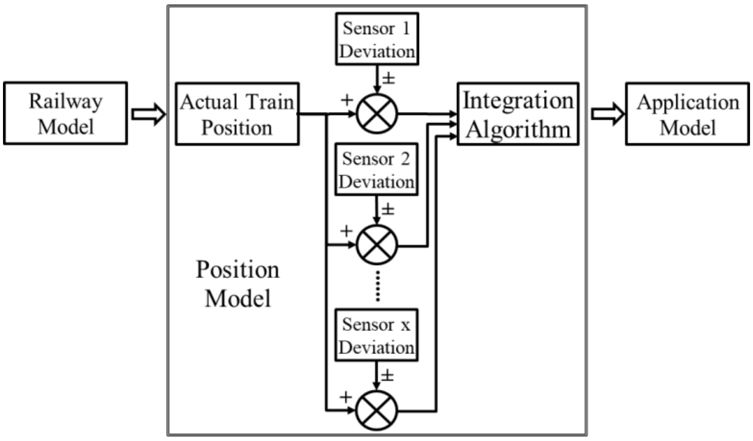


Fig. 3.4 Position model, adapted from [108]

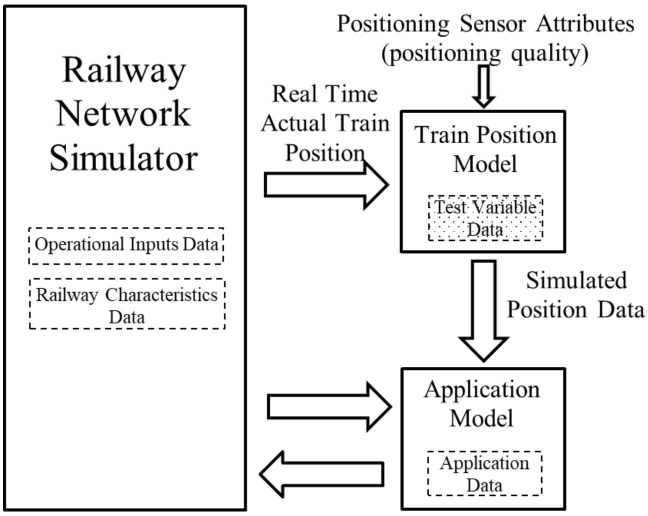


Fig. 3.5 Flowchart of system interconnections

3.4 Framework Implementation

To implement the framework, it is recommended that the following procedure is taken. First, select the railway application to be investigated. The application functions, objectives and capability need to be specified. Consequently, all the application units should be considered, such as the mathematical model, algorithms and optimisation function. This is because any change in these units may have a direct or inverse proportionality with the accuracy of the positioning system.

Second, select the measures on which the performance of the application will be evaluated. If more than one measure is chosen, a formula should define the relationship between the measures for the application's performance evaluation, for example, energy consumption and railway punctuality. Third, select the test variable. The types, methods and characteristics of the positioning system(s) available should be identified. Fourth, define the model of the railway system and the operational parameters in detail. As has been mentioned in Section 3.2, the parameters of the railway model and operation should be defined as fixed values because any change in these parameters may have different impacts on the measures module and thus on the evaluation of application performance.

To implement the framework in this study, the railway simulator, application and position models need to be prepared first. Following is a description of modelling the railway system, while modelling of the investigated applications (DAS and TMS) and their associated positioning systems will be described in Chapters 4 and 5 respectively. There are various railway simulators that are able to simulate train movements on railway infrastructure. For example, OpenTrack is a commercial railway simulator developed by the Institute for Transport Planning and Systems at ETH Zürich [106], and RailSys is a railway simulator developed by Rail Management Consultants (RMCon) and the Institute for Transport, Railway Construction and Operation (IVE) at Leibniz Universität Hannover [110]. OpenTrack supports an API, which allows the user to send standardised commands to OpenTrack and gets defined status messages back, while RailSys does not. Both simulators model the railway track, rolling stock and signalling systems. However, neither simulator is flexible enough to allow rapid editing of the train position data between the simulator and the application in real time. In this study, two railway applications were chosen in order to validate the proposed framework: DAS and TMS. A Single Train Simulator (STS) [111] was chosen to investigate the impact of positioning uncertainty on the DAS application with respect to energy saving. This is because STS calculations are based on distance steps and so it is easy to track the impact of position deviation on the calculation of train traction and energy in each step. A Railway Network Simulator (RNS) has been developed to understand the impact of positioning uncertainty on the TMS application with respect to minimising the train delay. The RNS calculations are based on a time step, so it is easy to ascertain the impact of position deviation on the calculation of train journey time and delay in each step. The two simulators have been written in MATLAB [112]. The following is a description of the two simulators used in this study.

3.4.1 Single Train Simulator

The STS was developed at the University of Birmingham [111] and it is commonly used in research projects [113][114][115][116]. The simulator was developed specifically for the purpose of calculating the power and energy consumption for a specific train class on a specific railway line. It calculates train movement on the railway line using a predefined route and vehicle information. The simulator also calculates the journey time based on the calculated train speed profile and distance. The simulator calculations are carried out for discrete distance steps of 1 metre.

3.4.2 Railway Network Simulator

An RNS simulator has been developed especially for the purpose of this study. It is built based on the design scheme of a Multi-Train Simulator (MTS) [117]. In this study, the RNS software was developed to consider the railway control systems, tracks and trains. The simulator consists of different modules which are combined and controlled by the simulation core, as shown in Fig. 3.6.

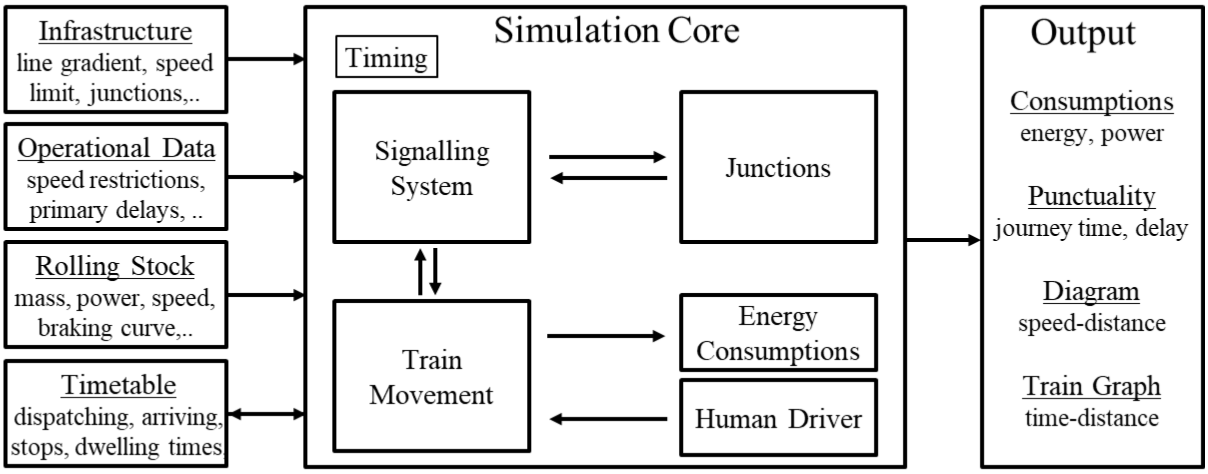


Fig. 3.6 RNS architecture of the simulation modules

The following is a description of the simulation modules.

3.4.2.1 Infrastructure module

The infrastructure module provides the track data and station attributes. It contains the line gradient, speed limit, block section length, signalling system type, junctions and switching points, and station platforms and terminals. The module is used by the train movement module to calculate the trains' motion.

3.4.2.2 Operational data module

The operational module provides railway operational data such as operational disturbances and temporary speed restrictions due to maintenance work for example. However, the RNS considers the operational timetables in a separate module. This module is used to model and insert a primary delay (entrance delay) in the train journeys. The module also provides information about railway services and routes which are used by the simulation core module to define the train route and line sections considering the junctions on the line.

3.4.2.3 Rolling stock module

The rolling stock module models the passenger and freight train attributes. It includes tractive effort, Davis coefficients, speed, acceleration and braking curves, and total train mass [118]. To represent different type of services, four types of train are modelled in this study, three passenger trains (Class 150, Class 375 and Class 373 for urban, intercity and high-speed services respectively), and one freight train (F2-mixed). Table 3.1 shows the values for each rolling stock parameter.

Table 3.1 Modelled rolling stock

Train Class	**Class 150** [119]	**Class 375** [120]	**Class 373** [118]	**F2-mixed** [119]
Maximum speed, km/h	120	160	300	110
Davis parameters				
A:	2.09	2.90	5.77	11.50
B:	0.0098	0.0180	0.2941	0.2580
C:	0.0065	0.0090	0.0156	0.0370
Mass, tonnes	76.4	186.3	867.0	1041.0
Power, MW	0.374	1.500	12.000	2.036
Braking, m/s^2	0.78	0.78	0.78	0.18
Train length, m	60.18	163.20	394.00	355.00

3.4.2.4 Timetable module

The RNS timetable module includes the scheduled dispatch and arrival times for each train. The intermediate stations are defined by their distance from the first dispatching station with the scheduled dwell times. The module is designed to be able to archive, after the train has arrived at the terminal station, the actual dispatch and arrival times and train delays, for analysis purposes.

The scheduled dispatch and arrival times are calculated in this study according to the railway timetabling rules of respecting safe train separation combined with additional time [121]. The timetabling parameters, such as running time, headway time, recovery time and buffer time, are measured in seconds in the calculations of dispatching and arriving times [17]. In addition, the timetable times are calculated based on blocking time theory that includes 10 s sight and reaction times [12] and 1 s setup and release times [122]; see [121] for more details.

3.4.2.5 Signalling system module

Railway signalling is a fundamental part of any railway control and operation system that provides movement authority to the driver to proceed safely considering the train braking distance. The RNS includes models of three- and four-aspect signalling systems. The three-aspect signalling system includes green, red and yellow signals. The green signal indicates that the train can be driven at the permitted line speed. The red signal indicates that the next block section is occupied by another train. The yellow signal indicates that the train should start slowing down until it reaches ‘approaching speed’ [123]. The approaching speed is the speed permitted with a yellow signal, which enables the train to stop within the sighting distance of the next signal [123]. The four-aspect signalling system uses two block sections for train braking, i.e. it divides the braking distance into two short block sections [124]. This is achieved by using a double yellow signal which indicates that the train should start slowing down to stop safely before the red signal. Commonly on UK main lines, an overlap distance is added beyond the block section as an additional safety feature [47]. The overlap distance must be released by the first train before allowing the next train to enter the block section. In the design of the RNS, 40 km/h approaching speed [123], 200 m sighting distance [124] and 180 m overlap distance [47][125] have been used.

3.4.2.6 Train movement module

The movement of the train is calculated in this module based on a 1-second time step, i.e. for each second of a train journey. It calculates the tractive effort required for train movement based on Lomonossoff's equation [126]:

$$M_{tr}\,(d^2\,s)/(d\,t)^2 = F_{tr} - F_{res} - F_{grad} \tag{3.1}$$

where M_{tr} is the effective mass; F_{tr} is the tractive effort; F_{res} is the vehicle resistance; F_{grad} is the force due to the gradient; and s is the vehicle position. M_{tr} can be determined by:

$$M_{tr} = M\,(1 + \lambda) + M_L \tag{3.2}$$

where M is the train mass; λ is the rotary allowance; and M_L is the freight or passenger load [127]. F_{res} is the aerodynamic resistance, which can be determined using the constants a, b, c, in the Davis equation [128][129]:

$$F_{res} = \mathrm{a} + \mathrm{b}\,v + \mathrm{c}\,v^2 \tag{3.3}$$

where v is the train speed. F_{grad} is the force due to the gradient, which can be calculated by [115][127]:

$$F_{grad} = M_{tr}\,g\,\sin(\alpha) \approx M_{tr}\,g\,\alpha \tag{3.4}$$

where g is the acceleration due to gravity and α is the slope angle in radians.

In a train's speed profile, there are four possible modes: accelerating, cruising, coasting and braking. The coasting mode might not be used, and full train braking can be applied straight away. In each step, the RNS calculates F_{res}, F_{grad} and F_{tr}. The train acceleration, speed and distance are then calculated. To determine the braking points, where the train starts braking, the distance required to stop is evaluated for each step. If the braking distance is less than the remaining distance to the destination, the train starts its braking operation [130].

3.4.2.7 Junction module

The signal of the railway junction is controlled by the junction module. To set a route for a train through the junction in the RNS, that train must have the priority to pass the junction according to the planned (in the timetable) train order for that junction. The tracks either converge or diverge at the junction. To set the junction signal for a train, both sides of the junction should be free. The junction signal needs to be set when a train enters a junction area which is two blocks away from the junction signal according to a three-aspect signalling system. It assumed that the switching time for a set of points at the junction is 4 s [105][131].

3.4.2.8 Energy consumption module

In this study, the train traction is estimated to use 85% of the power supplied, and 15% of total traction energy is considered lost due to the drive chain [99]. The power required to realise the calculated speed profile, P, can be determined by [127]:

$$P = F_{tr}\, v \tag{3.5}$$

The energy consumption E to realise the calculated speed profile can be determined by [113]:

$$E = P\, t \tag{3.6}$$

where t is the time required to travel the calculated distance, which is always 1 s in the RNS.

3.4.2.9 Driver module

A driver is modelled in the RNS by considering the driver behaviour of following the line speed limit with a 5% uncertainty up to the speed limit. For example, if the speed limit is 100 km/h, a cautious driver drives at 95 km/h while a risky driver drives at 100 km/h. The behaviour of each train driver is randomly chosen within 5% of the speed limit. However, the driver behaviour model is applied only when the line speed limit is more than 50 km/h, i.e. if the line speed limit is less than 50 km/h, all the drivers will drive at the speed limit.

3.4.2.10 Simulation core

After all the static data has been loaded from the infrastructure, rolling stock, timetable and operational modules, the simulator starts defining its variables, setting the routes and time step. The simulator timing is the summation of the simulator time steps as ($t = t_{-1} + \Delta t$), where Δt is the calculation time step of 1s. The RNS is an asynchronous simulator in which each train journey is modelled separately. The simulator calculates the train journey, taking into account the traffic plan and the schedule in the timetable. The first train is modelled, and the train path is recorded according to its time event. The latter train considers the position of the first train based on time-position record. This means that the latter train, in each time step, reads the position of the first train at that time; thus, the last train can read the position of all the previous trains.

In each time step, the simulator first evaluates the signal state by considering the train position related to the leading train and to the next signal. Based on the signal state, train speed is calculated as $v(t) = v(t_{-1}) + v(\Delta t)$, taking into account the speed profile mode, i.e. acceleration, cruising, coasting or braking. Subsequently, the train position is calculated as $s(t) = s(t_{-1}) + s(\Delta t)$. Afterwards, the consumed power and energy are calculated. All the train data are recorded and saved. The following train reads the data recorded for the leading train. In short, the simulation core manages data transference between the simulator modules and delivers the results to the output modules, as shown in Fig. 3.6.

3.4.2.11 Simulation outputs

After the simulation core has calculated the train journey time, speed, distance, energy and power, the output module calculates the train delays depending on the scheduled arrival times in the timetable. The module presents the outcome of the simulator in different forms as follows:

1. Train speed profile, km/h
2. Train time–distance profile, m
3. Train journey time and delay, s
4. Power consumption, kW
5. Energy consumption, kWh

Moreover, the module provides the speed–distance diagram and the train graph of time–distance, as shown in Fig. 3.7. These graphs help us to understand train delays and the impact of operational disturbance on train journeys.

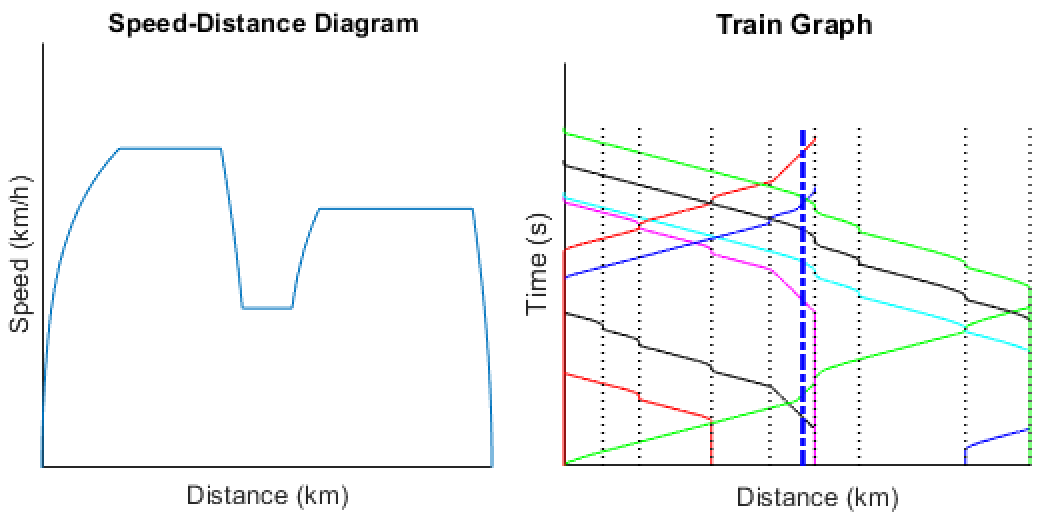


Fig. 3.7 Examples of RNS graphs

3.5 Conclusions

This chapter presents the proposed methodology for investigating the impact of train positioning uncertainty on the performance of railway applications. A general framework has been developed to test the thesis hypothesis which can be used with any railway network, service or application. The framework considers the variety of performance requirements for railway networks and services, uncertainties in positioning systems, and in the performance of application types. The framework requirements have been discussed, to help understand how the railway systems and applications need to be prepared before implementing the framework. The STS and RNS were then presented in order to fulfil the framework requirements. The other requirements will be discussed in the following chapters in terms of railway applications and positioning systems. Two applications are implemented in the following chapters: DAS in Chapter 4 and TMS in Chapters 5 and 6. The following three chapters will cover the implementation of the framework for three measurements which are energy consumption, punctuality and capacity, respectively.

4 Impact of Positioning on Energy Efficiency

4.1 Introduction

This chapter presents the first implementation of the framework proposed in Chapter 3 for DAS application. The impact of positioning uncertainty on DAS performance is investigated. The chapter sets out to verify the first sub-hypothesis, which states that energy consumption in the railway sector can be reduced by using a DAS application with a low-cost low-accuracy positioning system. The chapter first provides a review of the relationship between railway energy efficiency and driving strategy. Then, how the framework is populated with the DAS-related parameters is discussed. The chapter describes how the hypothesis is tested, how the framework is implemented and how Stand-alone DAS (S-DAS) is considered in terms of its optimisation algorithm and the system structure, followed by the way in which the impact of positioning uncertainty on the total energy consumption and journey time is evaluated when using a DAS. Then, the influence of uncertainty in train position is evaluated and the experiment results are discussed. The advantages of applying the framework are discussed in the conclusion. The work of this chapter has been published in part as a conference paper [132] DOI: 10.1109/ICIRT.2016.7588769, of which I am the primary contributor and lead author.

4.2 Introduction to Railway Energy Saving

In recent years, the demand for rail transport has increased from both passengers and freight carriers. Energy efficiency in railway systems has become a global concern and it is a subject being explored with the purpose of reducing energy consumption as a result of rising energy prices as well as environmental concerns [9][10][11]. On the other hand, auxiliary facilities on new trains may consume more energy than the old ones as a result of new facilities added such as air-conditioning [133].

The movement of trains is regulated by signalling systems. The signalling system provides the train driver or automatic driving system with movement authority which delivers limited information about the route ahead. The signalling system only indicates the permitted distance and speed that the train can travel safely. However, a complete view of the status of the forward line and the network is not provided to the driver. Therefore, the driver tries to utilise the information available and route knowledge to arrive at the scheduled time.

However, the issue is that drivers are not usually trained on energy-efficient driving (or Eco-driving) [99][134]; drivers drive the train at the highest permitted speed and using full braking force. This can avoid train delays; however, the train could arrive before the scheduled time.

Trains can also arrive before their scheduled time if margin times that have been added to the timetable are not used. The statistics show that, in some seasons, up to 50% of trains in the UK arrive before their scheduled arrival time [135][136]. In the process of building the timetable, margin times are added for several reasons such as covering the uncertainty in estimating running time, covering minor delays and mitigating against conflicts around junctions and stations. Mitchell [137] states that reducing energy consumption is not a target in the process of building train timetables in Britain. Unused margin times can be utilised by reducing the braking force. As stated by Douglas et al. [99], large amounts of energy (typically up to 50% of the traction energy) are dissipated through conventional mechanical braking; however, some may be returned if regenerative braking is used. Therefore, energy consumption can be reduced by avoiding unnecessary braking. Furthermore, increasing train speed increases the aerodynamic resistance to movement, leading to proportionally more energy loss, which is based on kinetic energy = 1/2 mass * velocity^2 [118]. Reducing the train speed, at the cost of increased journey time, has a large effect on traction energy consumption because traction energy is directly proportional to the square of its velocity [138].

The energy consumption from traction can be improved by optimising the train speed throughout the journey. To reduce train energy consumption, unnecessary braking should be avoided, and the train must be driven at the lowest appropriate maximum speed while taking into account the required journey time. The application of efficient driving by following an optimised train trajectory contributes to reducing the energy consumption. An optimised train trajectory is a planned speed profile that typically reduces energy consumption while maintaining passenger comfort and acceptable running times. The cost function of efficient driving is a trade-off between the journey time and energy consumption [99][120][139][140][141]. An optimised train trajectory can be realised either using a DAS or applying it in Automatic Train Operation (ATO). A DAS is a system that provides the advised speed profile information to the train driver. ATO is a system that automatically controls train movements without the need for human driver intervention [142].

To obtain the benefits of efficient driving, the train driver or ATO system should be instructed to follow an optimised train trajectory. Guiding the train driver can be achieved by installing trackside coasting signs [134] or by dynamically displaying the optimised speed requirement in-cab via the Driver-Machine Interface (DMI) of a DAS [143]. A DAS is a tool which can provide dynamic advice on the optimised trajectory as a function of the current train position and/or time [99][137]. Fig. 4.1 shows the application of optimised train trajectory on a train operating system where v is the train speed and s is the train position.

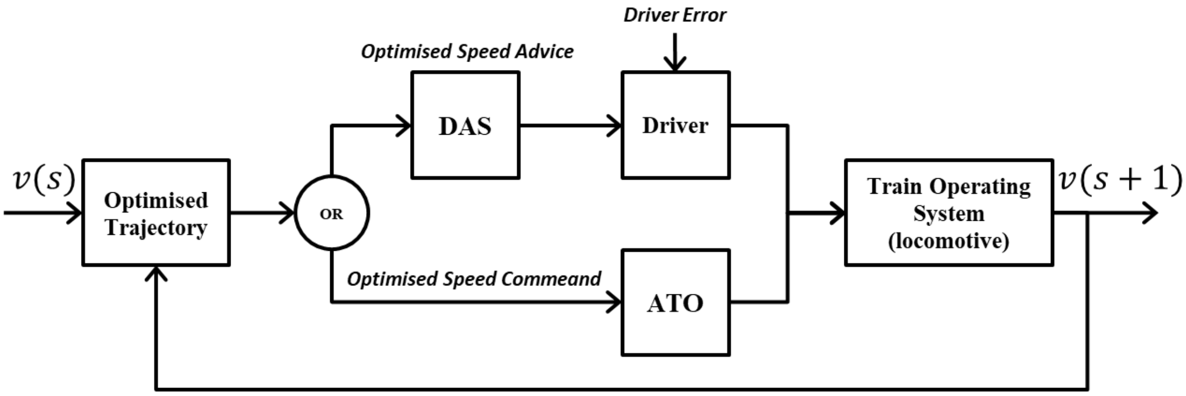


Fig. 4.1 Application of optimised train trajectory

DAS can be classified into three types: S-DAS, Networked DAS (N-DAS) and Connected DAS (C-DAS) [138][144]. S-DAS is an on-board system which aims to advise the train driver about how to follow an efficient driving strategy; it delivers an optimised speed profile that is calculated based on the static infrastructure information, vehicle characteristics and a pre-defined timetable. Several research projects claim that S-DAS can save energy consumption by up to approximately 25% [145][146]. C-DAS offers advice to the train driver that may be updated throughout a journey. The in-cab component is connected to the TCC for updating the timetable and route in real time when disturbances occur. C-DAS dynamically updates the re-planned timetable and recalculates the trajectory with the aim of optimising traffic flow by, e.g., avoiding junction conflicts, and then advises the train driver to follow the new plan [144][147]. In this regard, scientific research [148] shows that additional energy savings might be possible by applying C-DAS over S-DAS, particularly on high-capacity routes when a service is perturbed. N-DAS is an intermediary system between S-DAC and C-DAS that can communicate with one or more railway undertakings in order to receive some data related to the train journey such as an update of the train schedule and route. However, these data usually are not in real time [144].

The information delivered to the driver by a DAS can take various forms. These forms must be recognisable and easy to apply by the driver. The following are the three main forms of information that are used in DAS systems [147][149]:

- Suggested speed: the DAS provides target advisory speed or the difference between the target speed and the current speed.
- Timekeeping: the DAS presents the difference between the target and current time for the current position on the route.
- Action on controls: the system provides the optimum advisory as instructions, for example: traction power, coasting instruction and braking force.

To calculate an optimised trajectory, a variety of input data is required. The input data consists of the maximum speed allowed under normal conditions, temporary speed restrictions, line gradient profile, dwell time, stations, vehicle characteristics and timetable data. A DAS system needs a means of determining train position in real time to define and display the correct speed advice [149]. A GNSS is used in some DAS systems to specify the current train position and speed [138][147][149]. The general GNSS accuracy is about ±15 m with a confidence of 95% [29][28], and due to deep cuttings and high-rise buildings, the absolute accuracy is about 100 m [53][101][150][151][152]. A number of DAS systems use ERTMS level 2 position measurement as a positioning technique [138][149]. Other DAS systems use fixed-block signalling train detection information from the TCC to predict the train position [138][147]. With both ERTMS and signalling detection techniques, the train speed can be estimated by inference, from the time between successive reporting points [138][147][149].

Human factors can have a large effect on energy consumption if a driver does not follow the DAS advice in an ideal manner. Fig. 4.2 shows the energy consumption resulting from different train drivers following the same optimised trajectory using the same train type, track and timetable [137][153]. The results show that driver behaviour is very diverse in terms of understanding and applying the DAS advice. In contrast, driver errors can be avoided by implementing ATO to obtain accurate matching of driving with an optimised train trajectory.

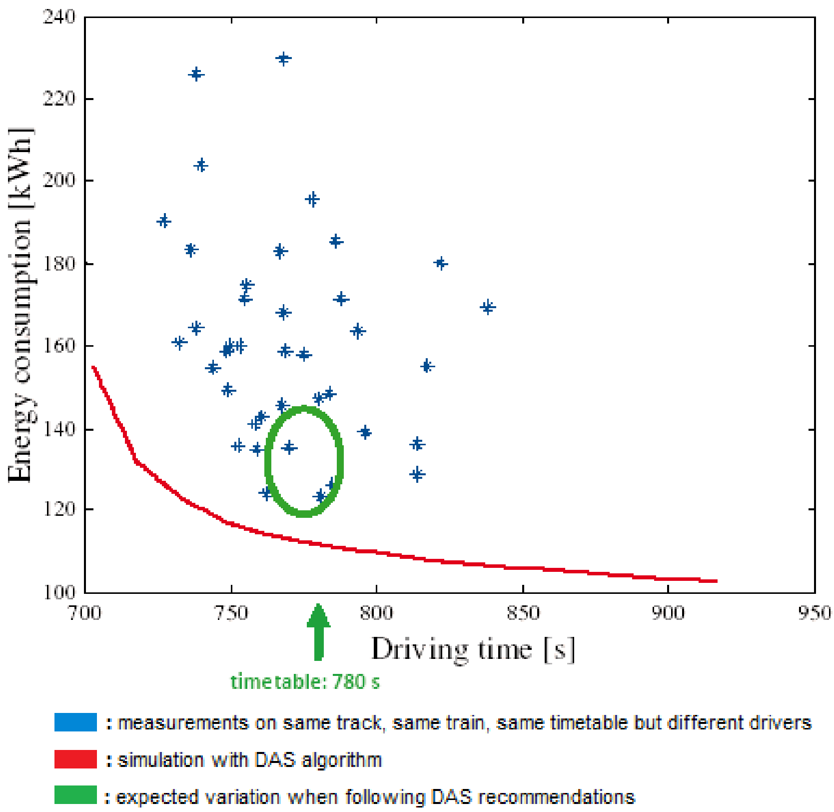


Fig. 4.2 Variability in journey time and energy consumption for different drivers following the same DAS trajectory, adapted from [153]

4.3 Application of the Framework to DAS

The sub-hypothesis related to energy consumption, mentioned in Section 1.4, states that energy consumption in the railway sector can be reduced by using a DAS application with a low-cost low-accuracy positioning system. To test this sub-hypothesis, the framework developed in Chapter 3 is applied for DAS application. The framework is populated with the application-related parameters, as follows. The three positioning systems mentioned in Section 4.2 should be included with their attributes in the test variable module. A DAS mostly focuses on improving energy consumption and journey times; therefore, energy and punctuality are in the measures module. The attributes of the type of the railway network and service should be included in the railway characteristics module. A DAS considers the scheduled arrival time in its calculations; therefore, it needs the timetable in the inputs module. These are in addition to the characteristics of the DAS itself and should be considered in the application module. All these parameters can be placed in the framework as shown in Fig. 4.3. In the following sections, the experiment conducted throughout this study will be described, with details of how this framework is implemented.

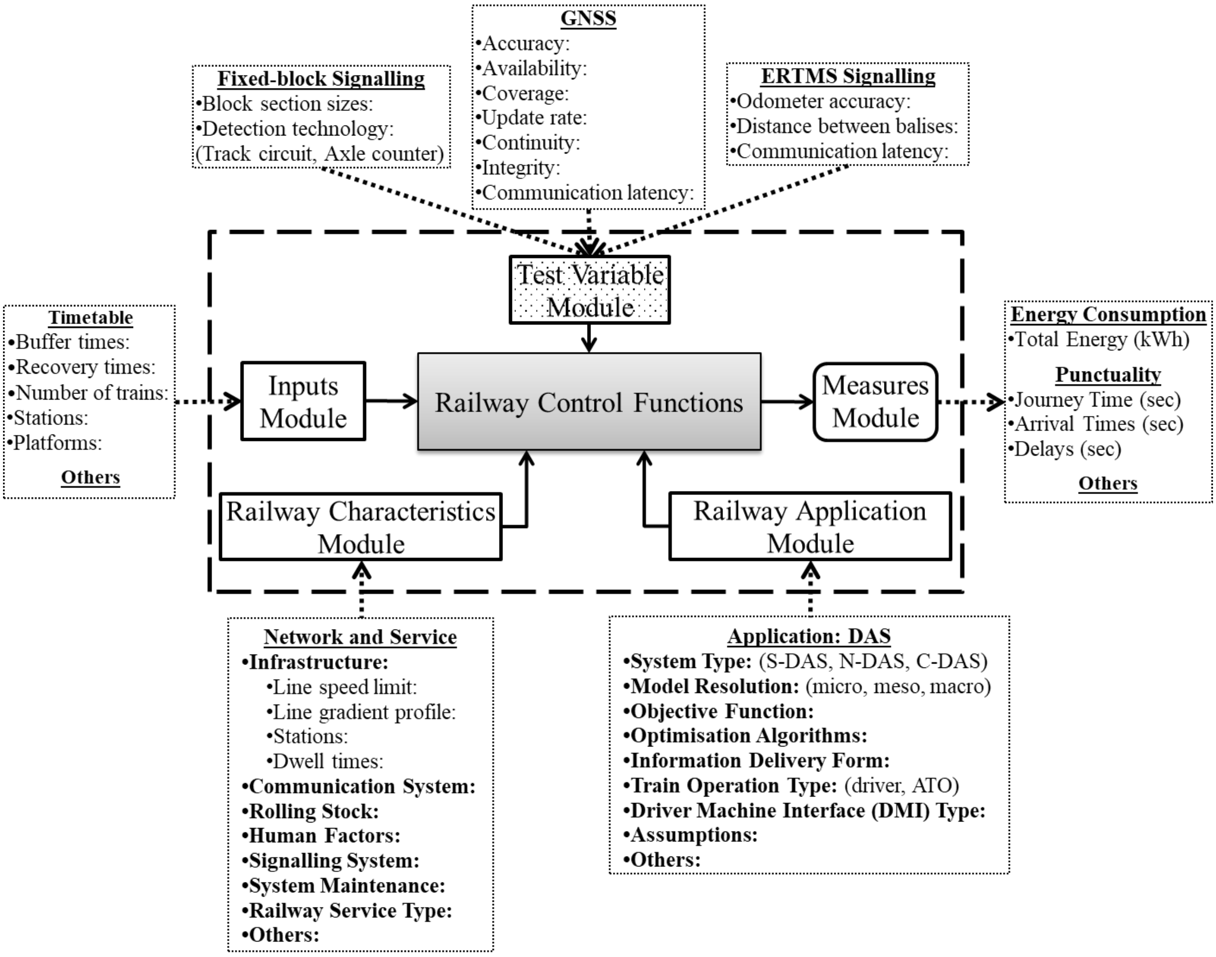


Fig. 4.3 General framework to evaluate the impact of positioning uncertainty on DAS application

4.4 Implementing the Framework

This section describes how the framework proposed in Section 4.3 is implemented for DAS application. This case study was conducted to test the hypothesis and investigate how much energy can be saved if the train is supported with a DAS and a low-cost low-accuracy positioning system. The whole experiment is presented in Section 4.6. The simulation tools required to carry out this study, as described in Section 3.3, are a railway network model, a train position model and a DAS application model. The following is a description of the railway, positioning and DAS simulation tools that are modelled in this study.

4.4.1 Railway Simulator

The train movement is simulated in this study by using a single train simulator STS, which is discussed in Section 3.4.1. This simulator was chosen for this study because it was designed especially for the purpose of calculating train power and energy consumption. Moreover, the simulator valuations of the train parameters are based on distance step. This helps to track the impact of positioning deviation in each step. The simulator distance step in this study is 1 m. The simulator models a Class 375 ‘Electrostar’ Electric Multiple Unit (EMU), whose parameters are given in Section 3.4.2.3, travelling on parts of the East Coast Main Line. The simulator is used in two parts of this experiment, first in calculating the optimised train trajectory for that specific rolling stock and railway line which is an off-line process. The result is uploaded to the DAS tool. Second, the STS is used to model the train movement on the track while using DAS, i.e. the train operating system of Fig. 4.1.

4.4.2 Train Position Model

The STS calculation is a function of discrete distance steps; therefore, the distance step is an input to the simulator functions and the output is the train speed and the time required to pass that distance step. The train position in each step is the sum of the discrete distance steps. The train position is used in the simulator to read the line speed limit and the line gradient, related to that distance step, from the infrastructure files.

A positioning deviation, as defined in Section 2.2.1, is the difference between the positioning sensor data and the actual position. The train position model is used in this study to mimic the deviation of the positioning sensor by artificially inducing positioning deviations. They are modelled in two ways. The first is by shifting the values in the actual (calculated) position by a constant distance, e.g., a constant shift in front of or behind the calculated position. For instance, the train positioning system reports the train position with a constant 25 m backward deviation (−25 m deviation) from the actual position. The altitude of an actual train position profile and an incorrect position profile is illustrated in Fig. 4.4 (a). The second way is by dividing the actual train path into 50 m segments. Then, ±50 m deviation can be randomly inserted into each segment of the positioning system profile, i.e. each segment’s position reading can be shifted by either +50 or −50 m from the actual path. As a result, after adjusting the overlaps, the positioning deviation could be 0, ±50 or ±100 m. Fig. 4.4 (b) shows three examples of the altitude of random positioning deviations inserted into the position profile.

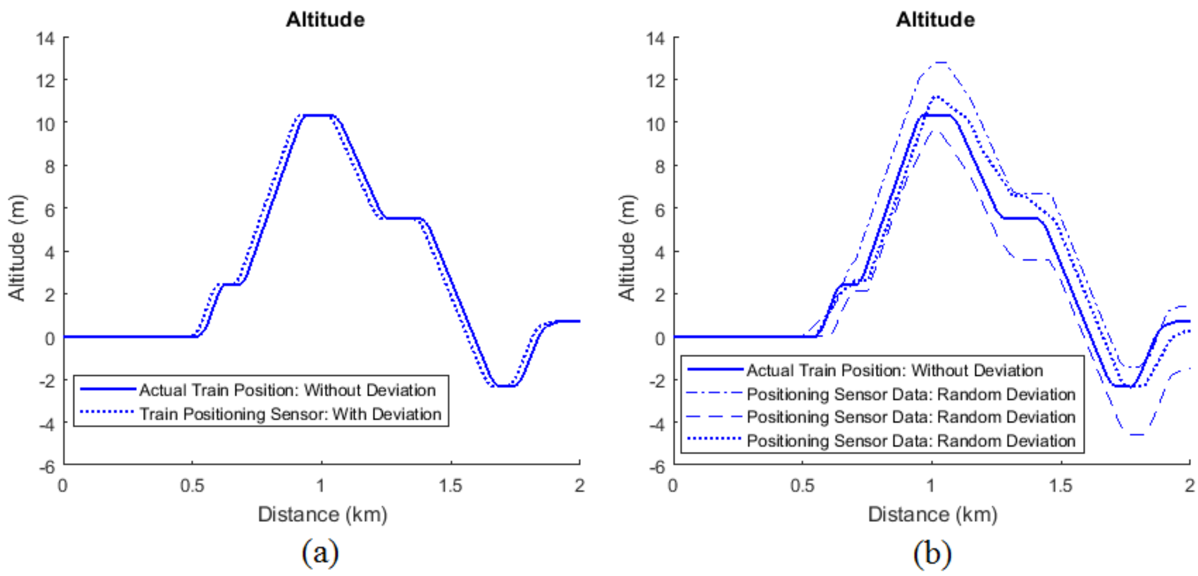


Fig. 4.4 Altitude of actual and sensor positioning profile: (a) constant deviation, (b) random deviation

The effect of this deviation with regard to the force due to the gradient F_{grad} along the line can be calculated using Equation (3.4). Fig. 4.5 (a) and (b) show F_{grad} of the deviations shown in Fig. 4.4; more details on how Fig. 4.5 is calculated are in Section 4.5.1.

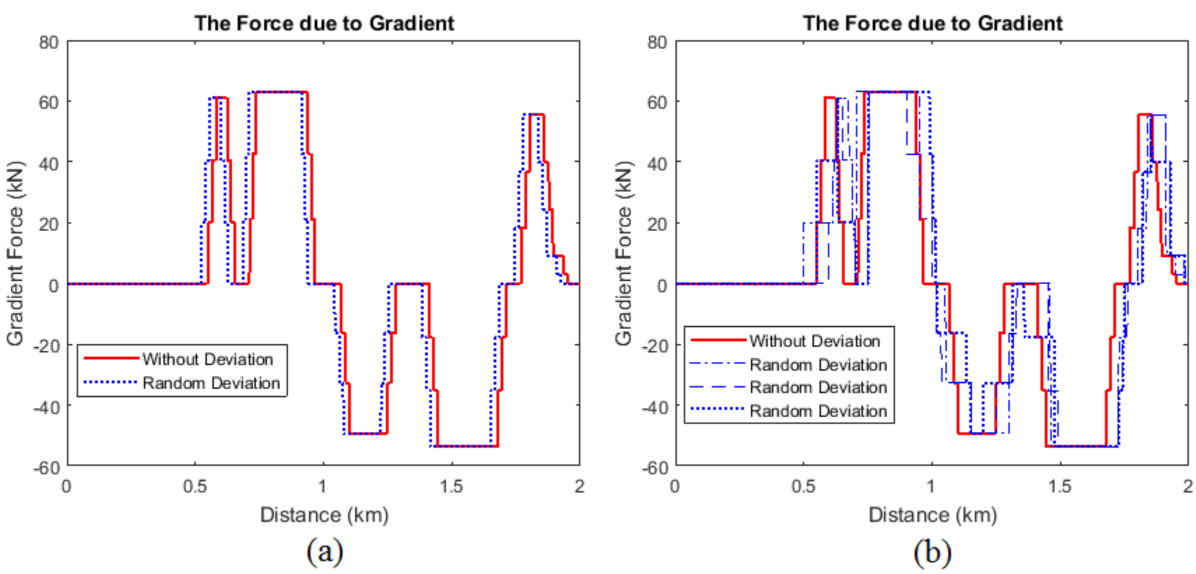


Fig. 4.5 Force due to the gradient

4.4.3 DAS Application Model

This study was conducted to investigate how much energy can be saved if the train is supported with a portable DAS as a PDA (Personal Digital Assistant). The PDA includes S-DAS, DMI and GNSS systems. The optimised train trajectory is calculated and uploaded off-line. The DAS delivers the advised speed profile as a function of train position. The advised speed and operation mode (traction, coasting and braking) are offered to the train driver through the DMI. The following is a description of how the optimised train trajectory and the train operation are calculated.

4.4.3.1 Optimised train trajectory

In general, an optimised train trajectory is composed of three modes [10][117][145][146][154]: traction mode, coasting mode and braking mode, as illustrated in Fig. 4.6. The traction mode consists of acceleration and cruising parts; in cruising mode, the acceleration is zero – other studies use a multi-coasting mode rather than a cruising mode [115][140][142]. The braking mode decelerates the train. The coasting mode is when no power is applied, and train movement relies on the train's momentum [146]. Consequently, the train speed is decreased gradually based on resistance to motion and the force due to the gradient [99][115].

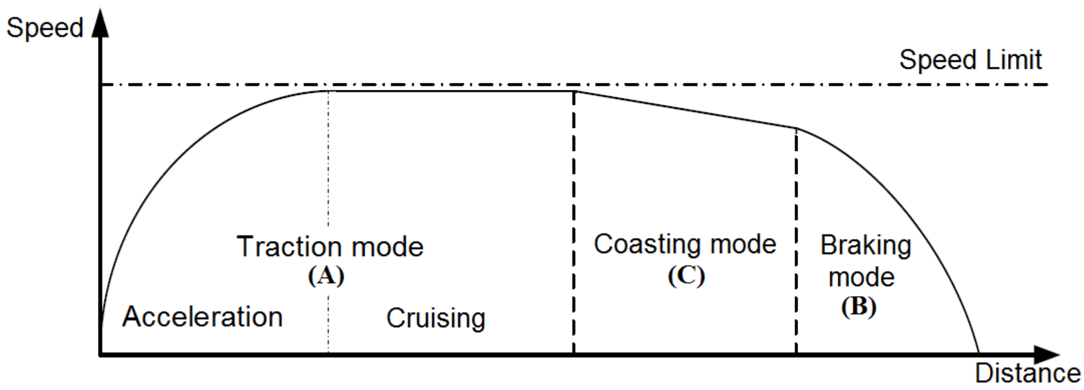


Fig. 4.6 Train operation modes [132]

An optimised train trajectory is the best combination of these modes. To find the optimum train trajectories, a number of search methods have been used in the literature, including: Genetic Algorithm (GA) [115][120][130][139][140][155][156][157]; particle swarm optimisation [142]; a direct searching method [158][159]; Artificial Neural Networks (ANN) [160][161]; a combination of ANN and GA techniques [162]; Ant Colony Optimisation (ACO) [130][139]; an enhanced brute force algorithm [10][117]; a fuzzy control model [163]; a max-min ant system [164]; and a Pontryagin maximum principle application [165]. The most common search method employed to obtain an optimised trajectory uses GAs, and earlier studies show promising solutions in this area. Therefore, a GA is an appropriate method for the purposes of this study, which requires a robust off-line trajectory optimisation method. The following is a description of the GA developed in this study.

There are static and dynamic input parameters to the GA optimisation programme. Static parameters consist of all train movement simulation inputs as well as the minimum and maximum journey time between two stations that are allowed by timetabling constraints. The dynamic parameters are the acceleration rate, deceleration rate and minimum coasting speed. The train acceleration rate (a_r) is determined by $a_r = A * (F/M_{tr})$, where F is the train traction force, M_{tr} is the effective mass, and A is the control factor for the train acceleration rate. The train deceleration rate (a_{br}) is determined by $a_{br} = B * a_{br\text{-}max}$, where $a_{br\text{-}max}$ is the maximum train deceleration rate available; B is the control factor for the train deceleration rate. The minimum coasting speed ($V_{c\text{-}min}$) is the minimum speed that a train is permitted to run at in coasting mode. The minimum coasting speed is determined by $V_{c\text{-}min} = C * V_{c\text{-}max}$, where $V_{c\text{-}max}$ is the maximum coasting speed, which is the cruising speed, and C is the control factor for the minimum train coasting speed [115]. Briefly, the factors A, B and C are used in this study to control the train traction force (acceleration), braking and coasting speed. The procedure followed to initialise, assess and evolve the GA generations is as follows:

Initialisation: since the GA dynamic parameters are the acceleration rate, deceleration rate and minimum coasting speed, the GA chromosome consists of three genomes containing the control factors A, B and C. Each genome may take values in the range 1 to 0.5. For example, if $A = 1$, this means that the train applies full traction force, and if $C = 1$, it means there is no coasting. As recommended by [166], the number of GA chromosomes should be at least five times the number of genomes; therefore, the population has been chosen to consist of 16 chromosomes. The initial values of genomes are chosen randomly for each chromosome.

Assessment: the GA chromosomes of each generation need to be assessed and ranked to identify the best solution. The genomes (control factors) of each chromosome are assessed using the STS. The STS outputs (energy and time) are assessed in the fitness function. The fitness function uses two fuzzy sets (for time and energy) in order to achieve an intelligent and selective search and reflect the search objectives. Typically, applying the maximum value of traction and braking and no coasting (A, B, C = 1, 1, 1) results in maximum energy consumption (E_{max}) and minimum journey time (T_{min}). In this study, the scheduled journey time in the timetable is assumed to be 1.1 T_{min} and the maximum allowed journey time is assumed to be 1.2 T_{min}. Therefore, the fuzzy membership function of the train journey time μ (T) is between T_{min} and 1.2 T_{min}, where T is the running time. The fuzzy membership function of the energy consumption μ (E) minimises the energy consumption up to 0.6 of the maximum consumption E_{max} [115]. Fig. 4.7 shows the membership functions of the fuzzy sets used in this study.

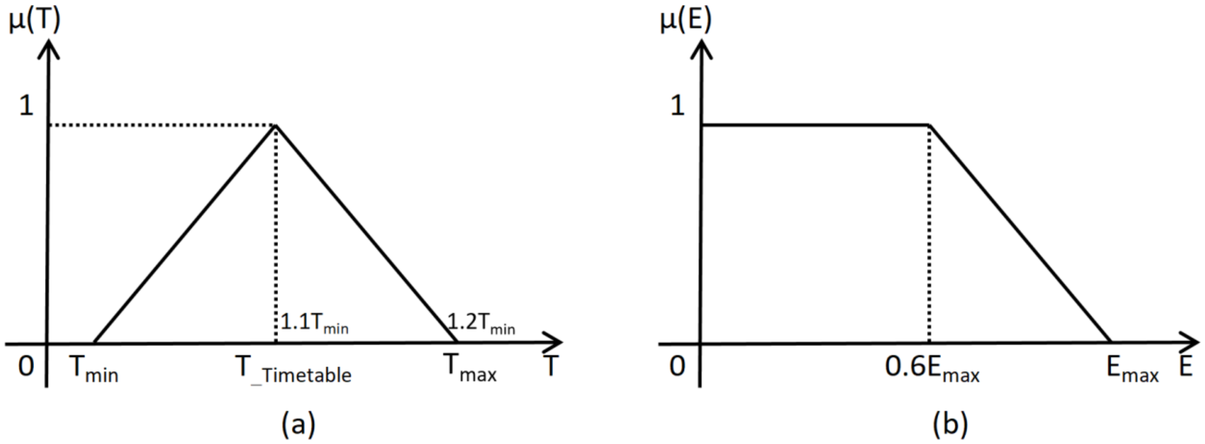


Fig. 4.7 Shape of fussy membership functions: (a) journey time (b) energy consumption

The GA fitness function combines the fuzzy sets of the journey time and energy consumption as follows:

$$Fitness\ Function = \mu\,(E).\omega_E + \mu\,(T).\omega_T \tag{4.1}$$

where ω_E and ω_T are weightings associated with energy consumption and journey time, respectively. In this study, ω_E = 0.5 and ω_T = 0.5 are applied; however, railway operators or infrastructure managers may use other more appropriate weightings to suit their purposes. The journey time and energy are assessed in the fitness function where 1 refers to the most desired answer and 0 refers to an inapplicable answer. This assessment is carried out for all generations of the population (chromosomes).

Selection: based on the fitness of the generation of chromosomes, it is evolved to create the next generation. The best three chromosomes are taken forward to the next generation. The remainder is set using tournament selection, as suggested by [167]. This is achieved by repeatedly selecting two chromosomes randomly; then, the highest rank (fitness) of them will appear in the next generation until the population is filled.

Crossover: after the selection operation, the crossover operation is used on the output of the selection process. The crossover is carried out by randomly selecting two chromosomes and then randomly crossing over parts (one or two genomes) between them. The crossover process is performed on the chromosomes with a probability of 0.7, while the others are taken forward to the next generation.

Mutation: after the crossover operation, the mutation operation takes place on the crossover outputs. The mutation operation replaces a genome in the chromosome with a new random value (within the permissible range). The mutation process is implemented with a probability of 0.4.

After the assessment, selection, crossover and mutation operations have been successively applied to the first generation, a new generation is said to have evolved. These operations are repeated until the termination condition is reached. The loop condition is either when the population provides the desirable solution i.e. Fitness Function = 1 or the number of generations reaches 250 because it has been observed in multiple runs to 1000 generations; there is rarely a change after 250 generations. The flowchart in Fig. 4.8 shows the steps of the GA to find the optimised parameters for the train speed profile.

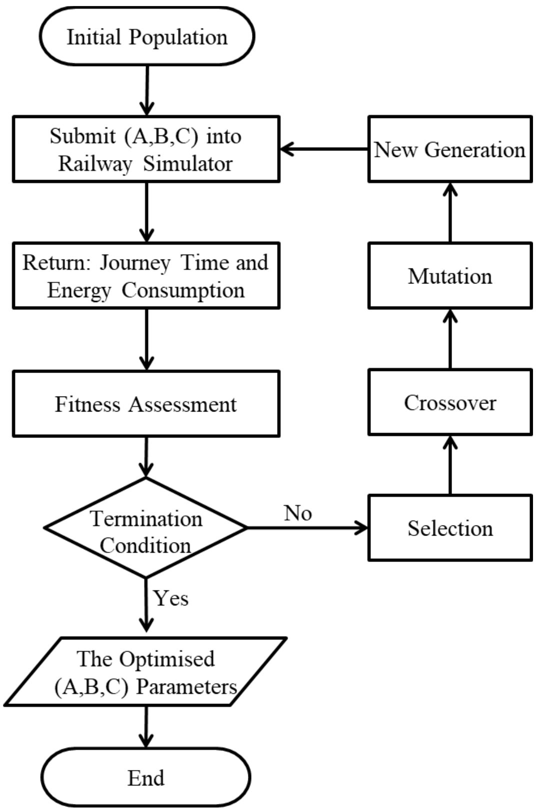


Fig. 4.8 Genetic algorithm flowchart [132]

4.4.3.2 DAS on-board

After the optimised train trajectory is identified, it should be uploaded to the S-DAS PDA which can be carried on-board the train. The DAS DMI presents the advised speed and the operation mode to the train driver based on the positioning data which could be in the wrong place. In this study, human errors are not considered (i.e., an ideal driver is assumed). This means that the train speed matches the optimised train trajectory. The power required to achieve the train speed (optimised speed) may not be as expected by the DAS application due to position deviation; more details on how to assess the difference in power, and therefore energy use, are in Section 4.5.

When these steps have been taken, the framework in Section 4.3 has been implemented. The data, mathematical model, control functions and algorithms considered in Sections 4.4.1, 4.4.2 and 4.4.3 are populated in the railway characteristics module, test variable module and application module, respectively, while the timetables are populated in the inputs module, and the journey time and energy consumption in the measures module. The following sections will illustrate how this assessment is conducted on the case studies.

4.5 Evaluating the Impact of Positioning Uncertainty on DAS

Some train positioning systems, as mentioned earlier, have a large uncertainty associated with them. Therefore, the positioning system's accuracy may cause erroneous reporting of a train's position, potentially leading a DAS to give advice on the trajectory in an incorrect position. This error affects the implementation of efficient driving, as the driver (or instructions in an ATO system) will apply DAS advice in the wrong position.

Initial investigations carried out in this study have shown that the impact of the positioning deviations is dependent on the railway line characteristics and geometry. Some railway lines were affected while other lines were not affected by positioning deviations. When the gradient profiles of railway lines were almost flat, the impact of positioning deviations on implementing DAS was limited. Based on the studies that have been completed, the impact of the positioning deviations is mainly confined to two points, incorrect calculation of the braking distance, and the effect of force due to the gradient. The braking distance calculation depends on the train position and speed, in order that the train stopping process is applied in the right position in an optimised trajectory. The force due to the gradient depends on the train position and is used to calculate the traction force required by the train. The following are the principles of the positioning impact on the force due to the gradient and braking operation.

4.5.1 Positioning Impact on the Force Due to the Gradient

A positioning uncertainty reduces the amount of energy that can be saved by following the optimised train trajectory. In this case, the actual traction force used will not match the total traction force determined in the optimised trajectory calculation. In general, the total traction force can be described, based on Equation (3.1), as $F_{total} = F_{tr} - F_{res} - F_{grad}$, where F_{total} is the total resultant force on a train. F_{tr} is the traction force provided at the wheels. F_{res} is the train aerodynamic resistance and it is a function of the train speed, so it does not directly rely on the train position. Therefore, the positioning impact on F_{res} is insignificant since the train driver always endeavours to follow the advised speed. However, F_{grad} is the force due to the gradient and it depends on the slope angle of the track. When a driver applies the power required to realise the advised speed at a given position, more or less energy will be consumed than was calculated in the optimised trajectory computation. This is because of the change of F_{grad} during deviations in position. If a train is going up a steep incline, it will consume more energy than assumed. Conversely, if a train is going down a steep incline, it will consume less energy than assumed.

To calculate the difference in power, and therefore energy, when there is a positioning deviation, an actual train operating system was simulated. The train is forced to follow the (off-line) optimised trajectory in the wrong place. The real-world processes are simulated to calculate the actual force due to gradient and thus the actual power and energy consumed. Fig. 4.9 demonstrates the scheme of the real-world processes which this study considers.

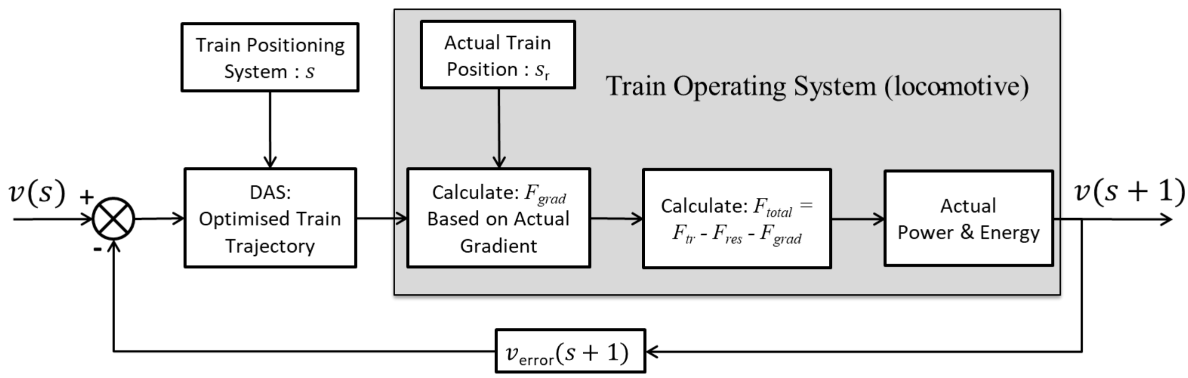


Fig. 4.9 Real-world process scheme of using DAS [132]

The positioning deviation (s_d) is the difference between the positioning system data (s) and the actual position (s_r). As mentioned in Section 4.4.2, the train position model in this study mimics the positioning deviation (s_d) which can be used by the simulator to read the gradient angle of the railway track, and therefore to calculate the F_{grad} of each distance step. In this way, the actual position of the train is used with respect to the F_{grad} which reflects the real-world situation.

4.5.2 Positioning Impact on Train Stopping Process

Train positioning uncertainty could influence the DAS so that it advises the driver to initiate the stopping process in the wrong position. The stopping process with respect to an energy-efficiency strategy usually consists of coasting and braking modes, as mentioned in Section 4.4.3. The impact of positioning deviations on the DAS leads the driver to start coasting either earlier or later than he or she is supposed to. Because most of the stopping distance is utilised in a coasting operation, the braking operation is usually a short distance. This problem is usually handled by the driver by ignoring the DAS advice and applying braking in an appropriate place based on his or her experience. If the train is driven by ATO, the train will be forced to apply braking by railway safety and protection systems such as ATP. However, this would consume more energy or journey time than expected.

4.6 Experiment

The differences between railway services are discussed in Section 2.3. The thesis hypothesis indicated that different types of railway networks need a different quality of application performance and thus require different positioning accuracy. Table 2.4 shows the diversity of railway services in some relevant railway parameters. It is expected that the highest application performance required is in urban and high-speed services, while it is expected the lowest performance required is in intercity service and thus the lowest positioning accuracy. Therefore, in this study, the experiments are conducted mainly on intercity services and then the expected translation of results for the other railway services is discussed.

To quantify the impact of positioning uncertainty in a realistic case on the train stopping process and the force due to the gradient, the following experiment was carried out. The case study and the optimised trajectory are presented first; the impact on the train operation (the force due to the gradient) and stopping process are then discussed.

4.6.1 Case Studies

To discover the influence of train positioning system uncertainty on energy consumption, three case studies with different gradient profiles were investigated: uphill, downhill and changing gradient routes. All these case studies are taken from different sections of the East Coast Main Line route, an intercity line between London and Edinburgh, as shown in Fig. 4.10 (a) and (b). The distance axis in the Fig. 4.10 (b) starts at 0 m from London King's Cross

Station. For this experiment, data with the following characteristics were selected: the maximum line speed is 130 km/h; the line length of each case study is 20 km; train movement starts from position zero and stops after 20 km; all are plain line sections with no stations; trains run without regenerative braking, and the distance of the calculation step (s) is 1 m. The first case is an uphill section of line, which rises approximately 85 m. The second case is a downhill section of line, whose altitude falls approximately 75 m along the line section. The third case is an undulating section of line, which rises and falls over a maximum of 6.5 m at a time.

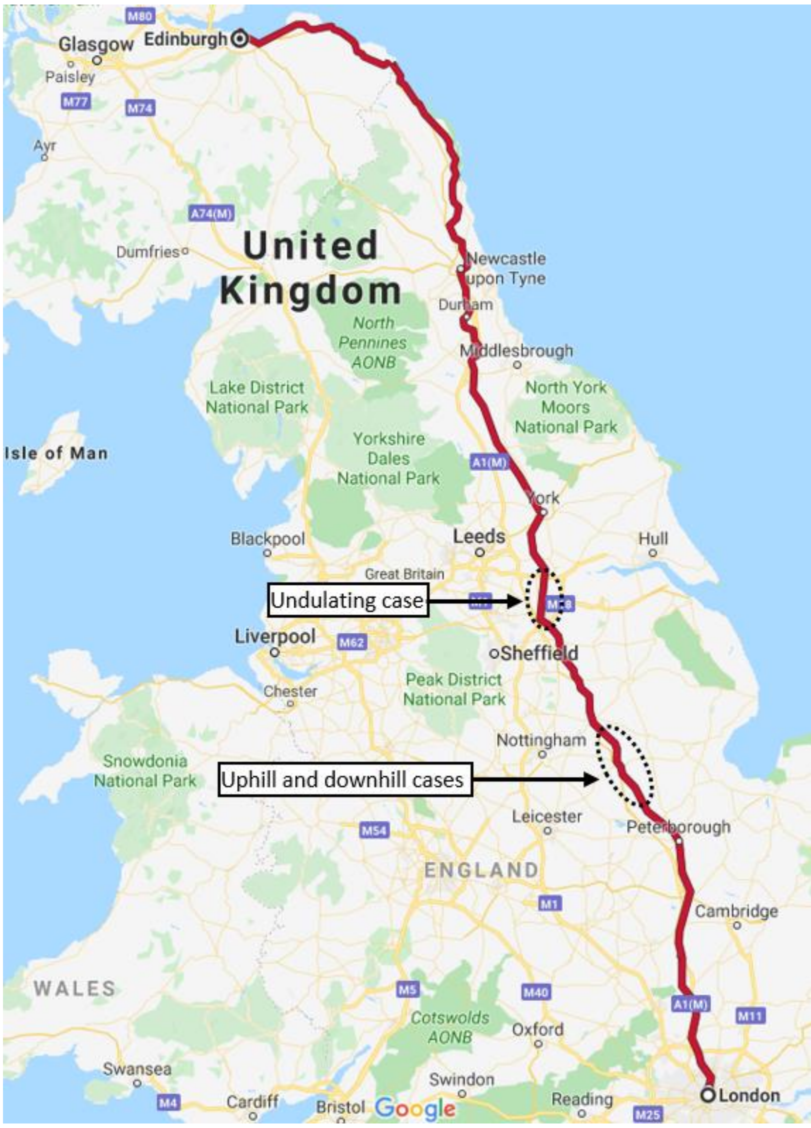


Fig. 4.10 (a) The considered sections of the East Coast Main Line route (from Google map)

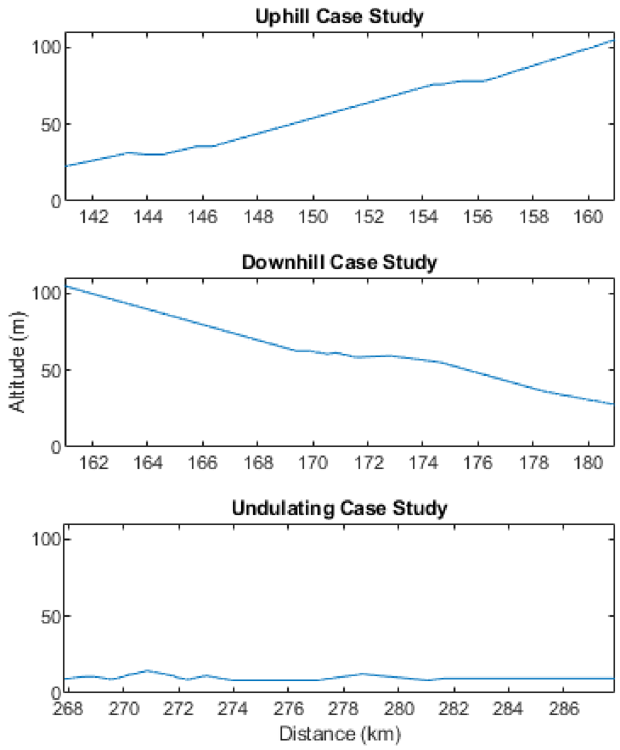


Fig. 4.10 (b) Altitude of sections of the East Coast Main Line route [132]

4.6.2 Optimised Train Trajectory

The optimised train trajectories for each case study were found with regard to (A, B, C) parameters by utilising the GA described in Section 4.4.3.1. Table 4.1 shows the results of the train movement simulation using the GA in each case. The table shows the E_{max} and T_{min} which are obtained when the train applies the maximum value of traction and braking and no coasting (A, B, C = 1, 1, 1). The results in the table show the optimisation parameters and the percentage energy saving and increased time which are expected to be achieved if the driver follows the DAS advisory for the optimised trajectory. It can be noted that the T_{min} of all cases are very similar while E_{max} varies. This is because in all cases the trains travel with almost the same speed for the same distance while the line gradients are different. The increase in the journey time, as described in Section 4.4.3.1, is to realise the time in the timetable, which is

Table 4.1 Optimised train trajectory results, adapted from [132]

Cases	**E_{max} (kWh)**	**T_{min} (s)**	**Optimisation parameters**			**Energy (kWh)**	**Energy saving (%)**	**Journey time (s)**	**Increased time (%)**
			Traction A	Braking B	Coasting C				
Uphill	172.02	658.1	0.91	0.50	0.50	140.84	18.12	726.4	10.4
Downhill	85.83	654.1	1.00	0.98	0.72	55.10	35.81	720.2	10.1
Undulating	127.88	659.9	1.00	1.00	0.55	92.09	27.98	730.8	10.7

assumed to be at least 1.1 T_{min}, and not more than 1.2 T_{min}. The optimised train trajectories for the three cases are shown in Fig. 4.11.

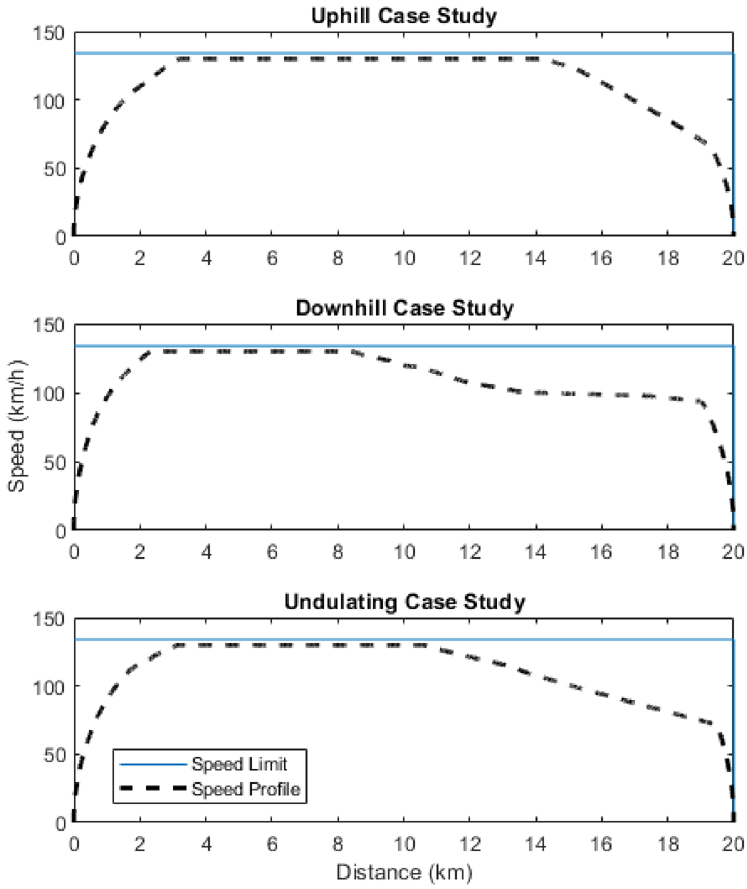


Fig. 4.11 Optimised train trajectory for each case study [132]

4.6.3 Train Traction Force

4.6.3.1 Constant deviations scenario

The actual energy consumption depends on the accuracy of the DAS advice relative to the train's position. To calculate the actual energy consumption, a constant deviation was added to the train position that was used to read the line gradient profile, as illustrated for the example of −25 m in Fig. 4.4 (a). In this experiment, the positioning deviations ranged between −500 and 500 m, in multiples of 25 m. These deviations influenced the calculation of the force due to the gradient, F_{grad}, as demonstrated in Fig. 4.5 (a). Consequently, the tractive force, F_{tr}, compensates. The actual power applied and energy consumed were calculated using Equations (3.5) and (3.6), respectively.

The results for each case study are shown in Tables 4.2 to 4.4. Each table contains the total energy consumed for the various positioning deviation cases (column 2), the difference in energy consumption from the zero positioning deviation case (column 3), the energy saving over the non-optimised trajectory case (column 4) and the difference in energy saving from the zero positioning deviation case (column 5). To reduce the size of the tables, the results of

Table 4.2 Results for uphill line [132]

Positioning deviation (m)	Energy consumption (kWh)	Energy difference from zero deviation (kWh)	Energy saving (%)	Difference in energy saving from zero deviation (%)
-500	141.59	0.74	17.69	0.43
-100	141.13	0.29	17.96	0.17
-75	141.05	0.21	18.00	0.12
-50	140.98	0.14	18.04	0.08
-25	140.91	0.07	18.08	0.04
0	140.84	0.00	18.12	0.00
25	140.90	0.06	18.09	0.03
50	140.95	0.11	18.06	0.07
75	141.01	0.17	18.03	0.10
100	141.07	0.23	17.99	0.13
500	141.97	1.13	17.47	0.66

Table 4.3 Results for downhill line [132]

Positioning deviation (m)	Energy consumption (kWh)	Energy difference from zero deviation (kWh)	Energy saving (%)	Difference in energy saving from zero deviation (%)
-500	59.53	4.44	30.64	5.17
-100	56.13	1.04	34.60	1.21
-75	55.87	0.77	34.91	0.90
-50	55.61	0.51	35.22	0.59
-25	55.34	0.25	35.52	0.29
0	55.10	0.00	35.81	0.00
25	55.33	0.24	35.53	0.28
50	55.57	0.48	35.25	0.56
75	55.81	0.72	34.98	0.83
100	56.05	0.95	34.70	1.11
500	59.04	3.95	31.21	4.60

Table 4.4 Results for undulating line [132]

Positioning deviation (m)	Energy consumption (kWh)	Energy difference from zero deviation (kWh)	Energy saving (%)	Difference in energy saving from zero deviation (%)
-500	92.53	0.44	27.64	0.34
-100	92.34	0.25	27.79	0.19
-75	92.28	0.18	27.84	0.14
-50	92.21	0.12	27.89	0.09
-25	92.15	0.06	27.94	0.04
0	92.09	0.00	27.98	0.00
25	92.18	0.09	27.91	0.07
50	92.28	0.18	27.84	0.14
75	92.37	0.27	27.77	0.21
100	92.46	0.37	27.70	0.29
500	93.93	1.83	26.55	1.43

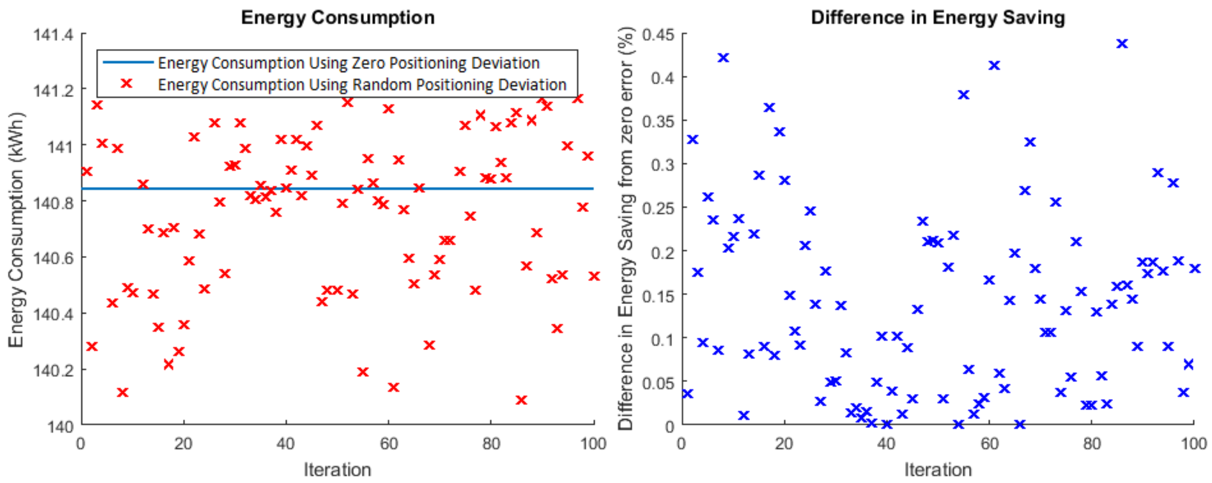
using positioning deviations from 25 to 100 m and 500 m are presented in the tables.

Of these three case studies, it is clear that the highest potential energy saving is in the downhill case and the lowest energy saving is in the uphill case, as shown in Table 4.1. From Tables 4.2, 4.3 and 4.4, it can be noted that the difference in energy consumption from the zero deviation base case increases gradually as the size of the positioning deviation increases. However, the differences are not equal in all cases. The positioning deviations have the greatest impact in the downhill case. The difference in energy consumption is 4.44 and 3.95 kWh, when the positioning deviations are −500 and 500 m, respectively.

In the uphill and undulating cases, the impact of a positive (after actual position) deviation is more than that of a negative (before actual position) deviation. Conversely, in the downhill case, the impact of a negative deviation is more than that of a positive deviation. This is because a positive deviation increases the distance travelled in accelerating mode; however, in the downhill case, the train is already accelerating because of downhill travel. In the uphill and undulating cases, the impact of a position deviation of less than 100 m is approximately less than 0.3% and the impact of a position deviation of less than 500 m is less than 1.5%. Moreover, in the downhill case, the impact of a position deviation of less than 100 m is approximately less than 1.3% and the impact of a position deviation under 500 m is less than 5.2%. Even though in the downhill case the loss of energy saving could reach up to 1.3% with 100 m deviations, the total energy saving in the downhill case is very high (35.81%) compared with uphill and undulating cases (18.12% and 27.98% respectively). To this end, the overall results show that the reduction in energy saving with a positioning deviation of less than 100 m is less than 2%.

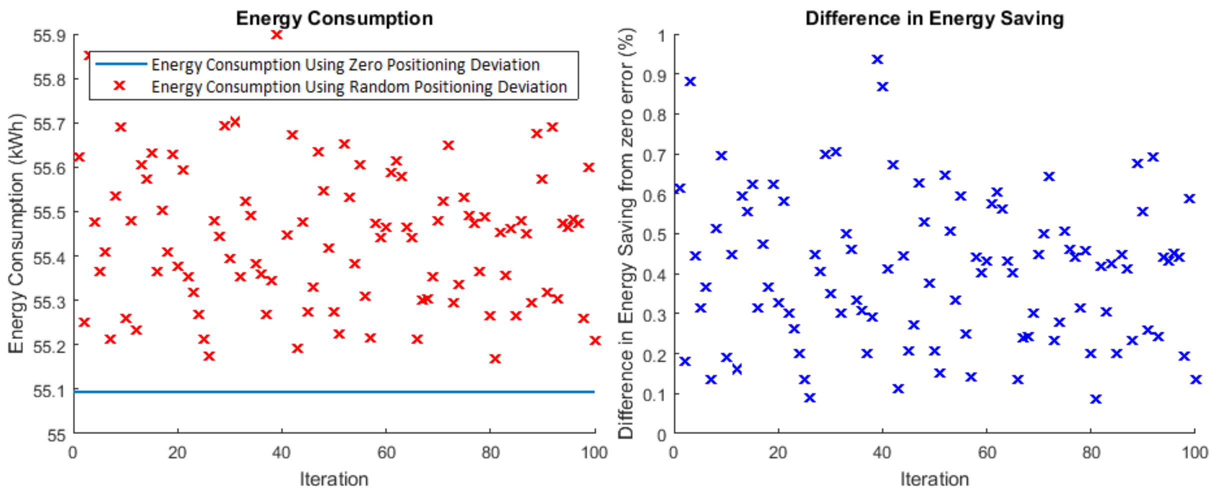
4.6.3.2 Random deviations scenario

In the random (0, ±50 or ±100 m) deviations scenario, the positioning deviations are modelled as demonstrated in Fig. 4.4 (b). These deviations influenced the calculation of the force due to the gradient, F_{grad}. Due to this scenario being based on a random function, the experiment was repeated 100 times. The energy consumed for the random positioning deviation scenario and the percentage difference in energy saving from the zero positioning deviation case are presented for the three case studies in Figs. 4.12, 4.13 and 4.14.



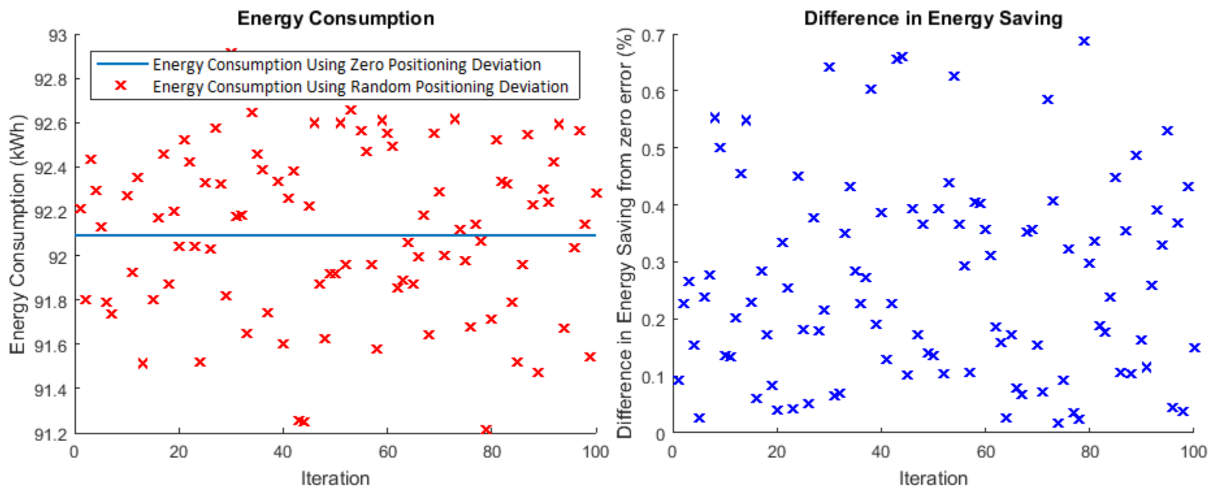
(a) (b)

Fig. 4.12 Impact of random positioning deviations on the uphill case study: (a) energy consumption, (b) percentage difference in energy saving from zero positioning deviation



(a) (b)

Fig. 4.13 Impact of random positioning deviations on the downhill case study: (a) energy consumption, (b) percentage difference in energy saving from zero positioning deviation



(a) (b)

Fig. 4.14 Impact of random positioning deviations on the undulating case study: (a) energy consumption, (b) percentage absolute difference in energy saving from zero positioning deviation

It can be noticed from the above that the results of the random deviations scenario are different to those of the constant deviations scenario. The results in Section 4.6.3.1 show that all the positioning deviations (positive or negative deviation) increase the energy consumption. Conversely, Figs. 4.12 and 4.14 show that the energy consumption could be increased or decreased by the random deviations scenario. This is because the constant deviations scenario shifts the line gradient right or left without changing the altitude, while the random deviations scenario divides the line into 50 m segments and inserts deviation in each segment and thereby distorts the altitude slightly, as shown in Fig. 4.4 (b).

Of these 100 iterations of random ±100 m positioning uncertainty, it is clear that the greatest absolute difference in energy saving is in the downhill case, up to 1.00%; the lowest impact is in the uphill case, up to 0.45%, while 0.70% is observed in the undulating case. However, the differences are not equal in all cases. In the uphill and undulating cases, the impact of the random deviations on energy consumption is almost equivalent between up and down for the zero positioning deviation (optimised train trajectory). On the contrary, in the downhill case, the energy consumption for all 100 iterations is higher than for the zero positioning deviation. This is because most of the changes in the line gradient profile are in the second half of the line where the train is in coasting mode (no power). The lowest range of the variation in energy consumption is in the downhill case, about 0.8 kWh, while the highest is in the undulating case where it is about 1.8 kWh. In the uphill case, the range of variation in energy consumption is about 1.4 kWh.

4.6.4 Train Stopping Process

The DAS can provide incorrect advice to start the coasting or braking driving mode in the wrong place. The DAS could get a position correction from the positioning system during the coasting operation. Depending on the correction, the DAS can advise an early braking operation (to handle later coasting) or application of power to carry on with the current train speed (to handle earlier coasting) but not to accelerate, as shown in Fig. 4.15. This is because re-acceleration will consume a lot of energy and has an insignificant impact on reducing the journey time due to the short distance. However, if the DAS does not get a position correction from the positioning system, the train will be forced to stop by safety and protection systems such as ATP, or the driver will apply the braking operation in an appropriate place based on his or her experience (ignores the DAS advice). To discover the influence of train positioning uncertainty on energy consumption in the stopping process, it is assumed in this study that the train will stop anyway in the right place at the platform.

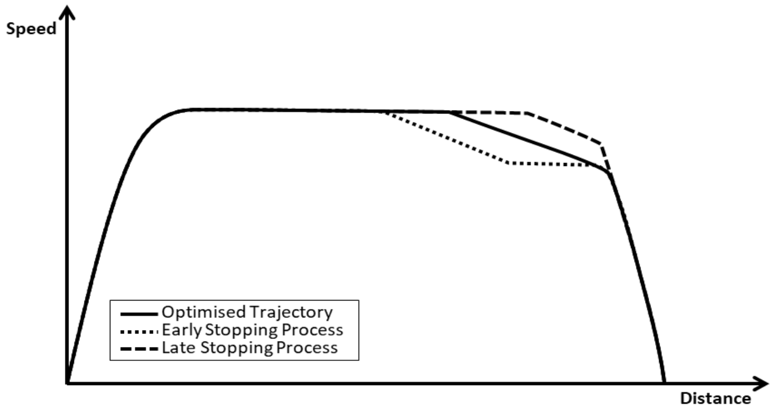


Fig. 4.15 Impact of positioning uncertainty on the stopping process

In this study, the impact of ±100 m uncertainty on the stopping process of the undulating case study was investigated, as illustrated in Section 4.6.1. For the case where the DAS advises the driver to start coasting 100 m earlier than it supposed, the DAS gets a correction of the current position and so advises the driver to drive in cruising mode (keeping the current speed) for 100 m. After that, the DAS advises the driver to start coasting again. It is assumed that at 15 km from the departure station, the DAS receives the position correction; see Fig. 4.11. For the case where the DAS advises the driver to start coasting 100 m later than it is supposed to, the train driver starts the braking operation at the appropriate position based on his or her experience. The impact of this positioning uncertainty on energy and journey time is presented in Table 4.5. The results of applying maximum power and optimised train trajectory have been added to the table for comparison purposes.

Table 4.5 Impact of positioning uncertainty on journey time and energy in stopping process

Speed profile	**Energy consumption**	**Journey time**
Max. power	127.88 kWh	659.9 s
Optimised trajectory	92.09 kWh (27.98%)	730.8 s (10.7%)
Early stopping process (−100 m)	91.83 kWh (28.19%)	731.6 s (10.9%)
Late stopping process (+100 m)	92.97 kWh (27.30%)	728.6 s (10.4%)

As mentioned in Table 4.1, the optimised train trajectory saves about 27.98% of the energy consumed while increasing the journey time by 10.7%. The impact of positioning uncertainty on the stopping process compared to the optimised trajectory and maximum power cases is as follows. The early stopping case increases the energy saving by 0.26 kWh (0.21%) and increases the journey time by 0.8 s (0.2%). The late stopping case decreases the energy saving by 0.88 kWh (−0.68%) and decreases the journey time by 2.2 s (−0.3%).

It is clear from the above that the impact of ±100 m positioning uncertainty on the journey time in the stopping process is insignificant (increased by less than 1 s). The impact on energy consumption can be considered even though it is less than ±1% of the optimised trajectory. This is because it could have a notable impact when it is added to the impact of the positioning uncertainty on the force due to the gradient throughout the train journey. Moreover, this ±1% could consume a notable amount of energy on different types of railway services such as high-speed or freight services.

4.7 Discussion

The thesis sub-hypothesis, related to energy consumption, states that using a DAS application with a low-cost low-accuracy positioning system can improve energy consumption in the railway system. As discussed in the beginning of Section 4.6, it is expected that intercity service require the lowest quality of application performance. The results of this chapter clearly demonstrate that more than 98% of the optimised energy consumption can be achieved with a positioning system that has ±100 m uncertainty on an intercity line. Therefore, the above results have met the sub-hypothesis on intercity services. The RSSB T892 report indicates that DAS system needs ±33 m positioning accuracy, see Table 2.7. Based on the results of this chapter, it is expected that using the RSSB T892 proposed accuracy will improve the application performance on an intercity line. However, providing positioning data with less than ±33 m uncertainty, will significantly increase the service initial costs and so the operational cost compared to using a low-cost positioning system achieving 98% of the optimised energy consumption.

This chapter investigates the impact of positioning uncertainties on the force due to the gradient and the train stopping process. The results of this chapter are based on the data populated in the framework, i.e. changing the service length, the rolling stock, etc. can change the results. It is expected the impact on the force due to the gradient among the different railway service types will be similar in manner to the above results while the impact on the train stopping process will vary. The urban service usually has low speed and a high number of stops with short distances between stops, as shown in Table 2.4. For example, a tram service stops approximately every 500 m [168]. The high-speed service usually has low number of stops but needs a very long braking distance. The freight service usually has low speed and low number of stops but has a low braking rate leads to a very long braking distance too. Therefore, each service may need a different positioning accuracy to apply an optimised coasting and stopping processes. The positioning uncertainties could lead to safety issues as well as reduce the efficiency of applying an optimised train trajectory.

Based on the results of this chapter, it is expected that using RSSB T892 report proposed accuracy, ±33 m, can fulfil the positioning requirements for the freight and high-speed services. However, it is expected more accurate positioning system is required to achieve an optimised coasting and stopping processes on urban services due to the short distances between stops. To test the thesis hypothesis on urban, high-speed and freight services, and determine the required positioning accuracy for DAS application at specified performance quality, the thesis framework needs to be populated with the parameters of the type of the service as demonstrated in Fig. 4.3. The parameters of the railway service type should be included in the railway characteristics module and operational inputs module.

4.8 Conclusions

Saving energy consumption in railway systems has become an important subject. With regard to this, optimised train trajectories are used to save energy consumption in railway networks. An optimised train trajectory can be implemented via either a DAS or within ATO. This research has been concerned with discovering the impact of train positioning systems' uncertainty on implementing an optimised train trajectory. This uncertainty affects the starting point of brake operation and affects the force due to the gradient.

The framework proposed in Chapter 3 has been upgraded with the general dynamic DAS-related variables. Then, the framework has been fulfilled with the parameters of the modelled S-DAS and the case studies. That is to say, the results of this implementation of the framework are restricted to the specific railway infrastructure and service type which are modelled, as well as the type of DAS. Different DAS types and different railway infrastructure could have different parameters and so need a different framework implementation.

A GA has been used to optimise the train trajectory for a section of the East Coast Main Line. The results have shown that any train positioning uncertainty reduces the benefits of implementation of the optimised train trajectory. The uncertainty of positioning systems has been simulated in two different ways: constant deviations throughout the line, and random deviations. In general, the impact of constant deviations is higher than that of random deviations in terms of energy consumption. The results show that a deviation under 100 m increases the energy consumption by less than 0.3% and a deviation under 500 m increases the energy consumption by less than 1.5% for specific uphill or undulating lines and by 1.3% and 5.2%, respectively, for a downhill line. The impact of a deviation under 100 m on the train stopping process is less than ±1% of the optimised energy consumption and less than 1 s of train journey time. However, the results of this study are based on assumptions of using an ATO system or an ideal driver who applies the DAS advice in an ideal manner, as well as DAS advice that is updated every metre.

The results of this chapter clearly demonstrate that more than 98% of the optimised energy consumption can be achieved with a positioning system that has ±100 m uncertainty on an intercity line. By comparing the impact of positioning uncertainty with the impact of human driver behaviour in following the DAS advice shown in Fig. 4.2, the impact of positioning uncertainty is obviously far less significant than that of human errors on energy saving. Therefore, high-accuracy positioning systems are not always required, and thus the most cost-effective solution for some railways may be a low-accuracy solution. It can be concluded that using a basic GNSS system with a 100 m uncertainty is sufficient to gain most of the benefits of optimised train trajectories in combination with a DAS on intercity lines. This is in case the line passes through deep cuttings, high-rise buildings, bridges and also possibly short tunnels.

The results of this chapter demonstrate the advantage of implementing the thesis framework. The framework specifies the requirements of the significant figures, measurements and influential parameters that can have an impact on the results. Moreover, the framework delimits the study outcomes and how they should be considered in real-life railway systems.

5 Impact of Positioning on Railway Punctuality

5.1 Introduction

Railway punctuality is a general expression that is concerned with the deviation in practice from the scheduled departure or arrival times of train services [12]. It is usually used as an indicator of railway system performance [169]. An intelligent traffic management system, TMS, as stated by [82], has the potential to improve railway punctuality by at least 10%. This chapter is conducted to test the thesis sub-hypothesis related to punctuality, which states that railway punctuality can be improved by using a TMS application with a low-cost low-accuracy positioning system. The chapter will present an implementation of the framework proposed in Chapter 3 of an intelligent TMS application. The framework was implemented in three case studies to demonstrate the impact of positioning accuracy on TMS performance. Case study 1 was carried out to demonstrate the concept of positioning deviation threshold and compare it between First Come First Served (FCFS) and optimised rescheduling strategies. Case study 2 was carried out to demonstrate the impact on TMS performance of positioning uncertainties combined with other railway data uncertainties. Case study 3 was carried out to demonstrate the impact of positioning uncertainties on the TMS applied on different railway service types. Lastly, the chapter concludes with a summary of the benefits of the framework in the investigation of a TMS. The work of this chapter has been published in part as a conference paper [170] DOI: 10.1049/cp.2018.0073, of which I am the primary contributor and lead author.

5.2 Introduction to the Traffic Management Process

In recent years, the demand for rail transport from both passengers and freight carriers has increased. Rail infrastructure managers and operators have been put under pressure to make more of existing resources. This may motivate them to move towards using automated subsystems and intelligent traffic management in order to make more effective use of available capacity. A traffic conflict can arise when two or more trains approach a railway junction at the same time from different lines, making one train, or more, wait behind the signal [105]. Currently, railway traffic conflicts are usually handled by the signaller (called the dispatcher in some countries) in the TCC, based on their experience with the help of some rules or ready-made alternative plans for each type of disturbance [14]. These solutions may require train cancellations and, even in less severe cases, knock-on delays cannot always be avoided. The traffic control system needs to be combined with a real-time automated TMS in order to improve the reliability of dispatching decisions and to automatically manage the train routes. When implemented, a railway TMS is responsible for handling railway traffic once a disturbance happens. The TMS is generally focused on monitoring the trains' movement through the railway network, taking into account the planned timetable, and recovering a disrupted train or trains by retiming, reordering and/or rerouting in order to return trains back to the original timetable as soon as possible. This is done by reading dynamic railway operations data in real time to evaluate the current traffic status. Based on the current traffic, the TMS predicts the future traffic state. From the predicted future traffic, the TMS provides an optimised solution that can reduce the severity of potential traffic conflicts.

Many studies have developed models and methods for building an intelligent TMS that can provide improved dispatching decisions taking into account targets of saving energy, increasing capacity use and reducing delays [96][171][172]. There are also studies investigating the impact of some parameters on TMS performance; for instance, the impact of using a flexible timetable on TMS results [173], and the impact of local versus global optimisation strategies [174].

From TMS studies, it can be observed that many factors can affect the performance of a traffic management strategy. These factors can be divided into two categories: the robustness of the TMS plan and the input data accuracy. The robustness of the traffic plan relies on the accuracy of the method of predicting future traffic [175]. According to [175], the most common mathematical models that have been used in recent traffic management studies are Alternative Graph (AG) [176] and Mixed Integer Linear Programming (MILP) [172]. Good predictive methods are capable of predicting accurate values for uncertain parameters such as train speed and position, driver behaviour, equipment delay and train running, waiting, dwelling and arrival times.

However, the discrepancy between the actual and predicted traffic conditions over time has a direct impact on the efficiency of the TMS plan. Few studies have been conducted on evaluating the robustness of the TMS in terms of the impact of uncertainties in railway data. Meng and Zhou [177] assessed the robustness of a TMS by studying the impact of uncertainties associated with predicting running times and disruption duration. A rolling horizon framework was proposed to optimise single-track train schedules in terms of meet-pass plans, under random variations in both running time and disruption duration. The robustness of the TMS was assessed to understand the effect of a dynamic and stochastic environment on the quality of the solution. The study shows that TMS under stochastic environment provides a better solution than the human signaller solution. Quaglietta *et al.* [178] considered the stability of TMS plans against incomplete knowledge of the perturbation progress. Rescheduling plans were calculated under a set of randomly inaccurate train dwell times using a Monte Carlo scheme. Also, TMS plans for different prediction horizons with incomplete knowledge were compared. The assessment shows that the stability of TMS plans decreases with increasing magnitude of stochastic disturbances. Larsen *et al.* [179] assessed the degree of sensitivity of rescheduling algorithms to stochastic disturbances. The study aimed to minimise the propagation of train delay and increase the robustness of TMS plans when using inaccurate information. The robustness of three different TMS algorithms was evaluated under variations in running and dwell times, in a large railway network. The evaluation indicates that small stochastic variations in running and dwell times have a critical impact on TMS performance. Pellegrini *et al.* [180] evaluated the robustness of a TMS by studying the impact of inaccurate information for train entrance delays on TMS performance. The system aimed to reduce the overall delay to trains by reordering and rerouting within a control area. The study evaluated the usefulness of TMS algorithms against an FCFS management strategy, using imperfect information on train entrance delays (primary delay). The evaluation indicates that the use of a TMS outperforms an FCFS strategy even when imperfect information is used by the TMS algorithms.

The second category is the input data accuracy. A TMS needs a variety of static and dynamic input data in order to calculate an optimised traffic plan. The static data are the train characteristics such as train mass, traction and braking rates, and the track characteristics such as line speed limit, line gradient profile and junction characteristics. The dynamic data are the train data: train position and speed, and the signalling and control systems data such as route state, signal state and switch position. The accuracy of these data has a direct impact on the TMS results. The train speed is usually estimated by inference, from the time between successive reporting positions [138][149]. The signalling and control systems data are usually available in real time in the TCC [29]. As a result, the accuracy of the train positions, among other dynamic data, is the vital factor that can affect the TMS evaluation process.

Train positioning systems have been reviewed in Section 2.3, in terms of technology and relative accuracy. The train position information can be based on one or more positioning systems. In the literature on TMS, some studies assume that accurate train position information is available at the TCC in real time [123][181]. Other studies assume that the train position information can be obtained from on-board sensors, and thus the transmission time of the train position and speed data must be taken into consideration [96][182]. Others assume the position information can be estimated from fixed block occupation/release data [19][183].

As mentioned in Section 2.3.3, Train Positioning Deviations (TPDs) cannot be avoided in a real-time TMS system. TPDs may have a different impact on TMS functions depending upon the values of other railway parameters. The parameters whose values could have significant interaction with TPDs are the timetable buffer and recovery times; the variety/uniformity in capability of the rolling stock (speed, length, accelerating and braking rates); driving behaviour (human or ATO); the infrastructure of the lines (gradient, speed limit, block section length, overlap and signalling aspect); the size of the communication system latency; the method used for prediction of future traffic status; the cost function of the TMS; the TMS control loop (open or closed); the variety/uniformity of railway services; the accuracy of the speed data in real time; the types of operational disturbance (system failures, single or multiple delays) and the railway network capacity constraints.

To the best of the author’s knowledge, the full impact of TPDs on the effectiveness of a TMS is still unclear. However, TPDs can mislead the TMS functions and then the TMS may provide suboptimal solutions. This study was carried out to understand the potential impact of TPDs on the performance of a TMS and to evaluate the impact of applying suboptimal TMS solutions on railway network performance. The thesis framework proposed in Chapter 3 is implemented in this chapter to assess TMS performance when using inaccurate knowledge of train positions.

5.3 Application of the Framework to TMS

As mentioned earlier, several input parameters can influence TMS performance. Traffic management studies use many assumptions and fixed values reflecting real-world values. To the best of the author’s knowledge, in the literature, all traffic management studies use real-time train position information, but do not use positioning data containing uncertainties reflecting the capabilities of real-world technology.

The sub-hypothesis related to punctuality, introduced in Section 1.4, states that railway punctuality can be improved by using a TMS application with a low-cost low-accuracy positioning system. To test this sub-hypothesis, the framework developed in Chapter 3 is applied for TMS application. The framework was populated with non-negligible parameters of the railway and application. The TMS mostly focuses on improving operational performance and reducing train delays; therefore, connectivity, reliability, traffic flow, punctuality and Public Performance Measure (PPM) can be used to evaluate TMS performance. PPM is a UK industry measurement for service performance which indicates the percentage of trains that arrived at the scheduled time or with a delay of not more than 5 minutes for urban services and 10 minutes for intercity services [133]. All the parameters considered for this TMS investigation can be placed in the framework as shown in Fig. 5.1. In the following sections, the experiments conducted throughout this study will be described with details of how the hypothesis is tested and how the framework is implemented.

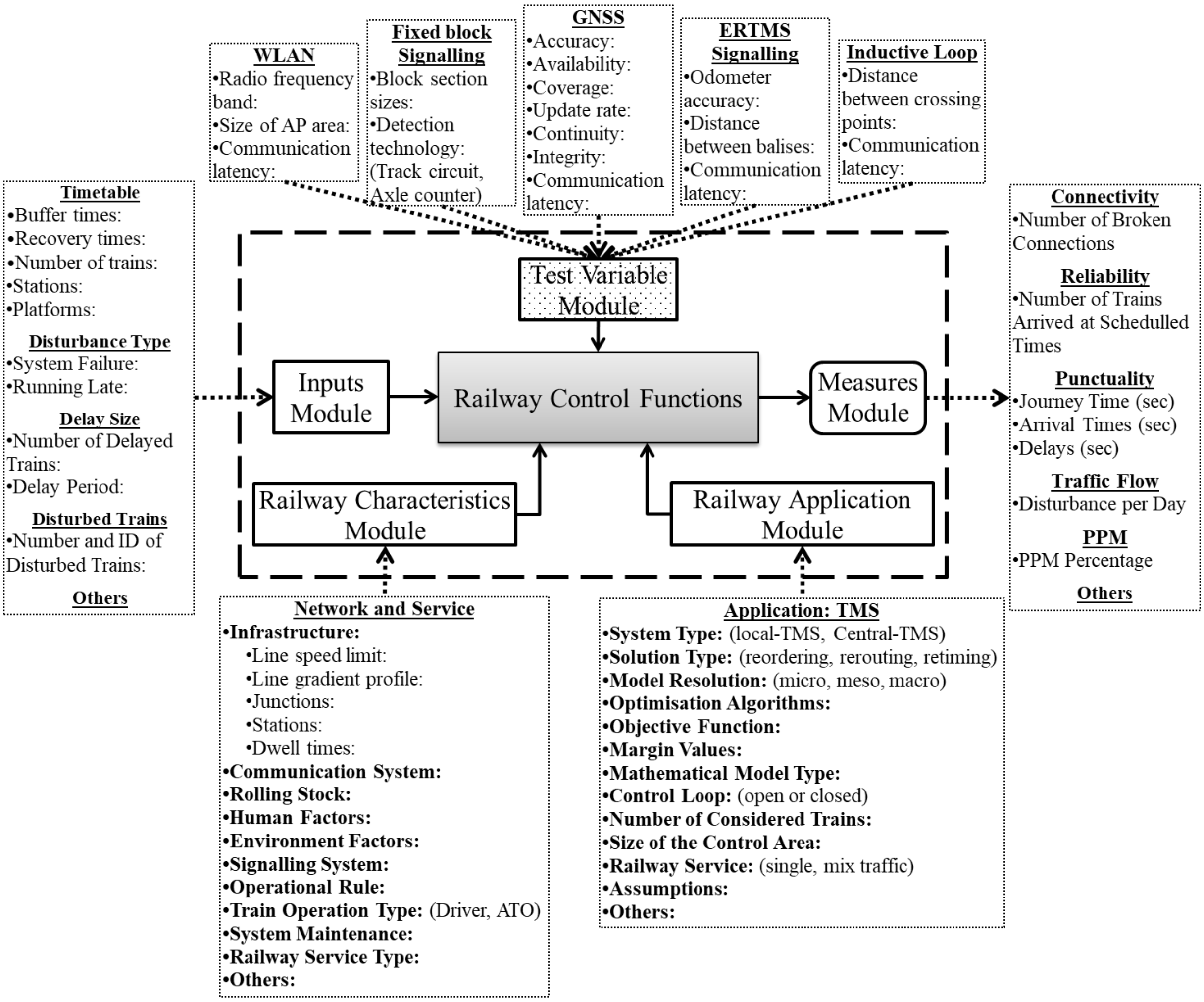


Fig. 5.1 General framework to evaluate the impact of positioning uncertainty on TMS application

5.4 Implementing the Framework

This section presents the models that have been used to implement the framework in this chapter. A case study was conducted to test the hypothesis and investigate the performance of a local TMS under a low-cost low-accuracy train positioning system; the experimental details are given in Section 5.6. The difference in TMS performance, in terms of overall train delays, when using accurate train positions and inaccurate train positions is considered. This means that the outcomes after the railway system applies the TMS solutions based on using accurate/inaccurate train positions are assessed. The simulation tools required to assess the TMS performance and therefore railway punctuality, as described in Section 3.3, are the railway network model, train position model and TMS application model. The following is a description of the railway, positioning and TMS simulation tools that are modelled for the purpose of this chapter.

5.4.1 Railway Simulator

The railway system is simulated in this chapter by using an RNS, which is discussed in Section 3.4.2. The simulator valuations of the railway parameters are based on a time step of 1 s. This helps to track the impact of position deviation on the calculated train journey time and delay in each step.

5.4.2 Train Position Model

The train positioning information in this study is assumed to consist of conventional fixed block occupation data with the assistance of an on-board positioning sensor such as a GNSS, INS or odometer. A fixed block signalling system is used to ensure safety while the on-board positioning system is used to provide the TMS with real-time train positions [96]. The on-board reported position is transmitted to the TCC by GSM-R. The impact of the communication system on the positioning accuracy is based on the latency period and train speed. As an example, if the speed of a train is 130 km/h, the train will travel between 36 and 360 m during a GSM-R latency period of between 1 and 10 s. If the on-board positioning sensor uncertainty is ±100 m, the uncertainty of the positioning data in the TCC will be up to ±460 m. By considering ±25 m and 2 s as typical sensor uncertainty and communication latency, respectively, the positioning uncertainty will be around ±100 m. Consequently, this study uses ±100 m positioning uncertainty to represent the usual uncertainty in the TCC, and

±500 m positioning uncertainty to represent the worst-case scenario of TPDs in the TCC, which indicates positioning system uncertainty combined with the impact of the communications latency.

The TPDs in this study are modelled between 0 and ±500 m using a Monte Carlo simulation with two different probability density functions. In order to investigate the impact of increased deviations, the peaks of the two probability density functions are ±100 and ±450 m, as shown in Fig. 5.2. Probability function 1 increases the probability of deviations being allocated towards ±100 m, and probability function 2 towards ±450 m. The inaccurate positioning data is the accurate current train position data plus the simulated TPDs. The TPD is inserted into the data for each train position when the TMS collects the trains' data in order to find an optimal train order.

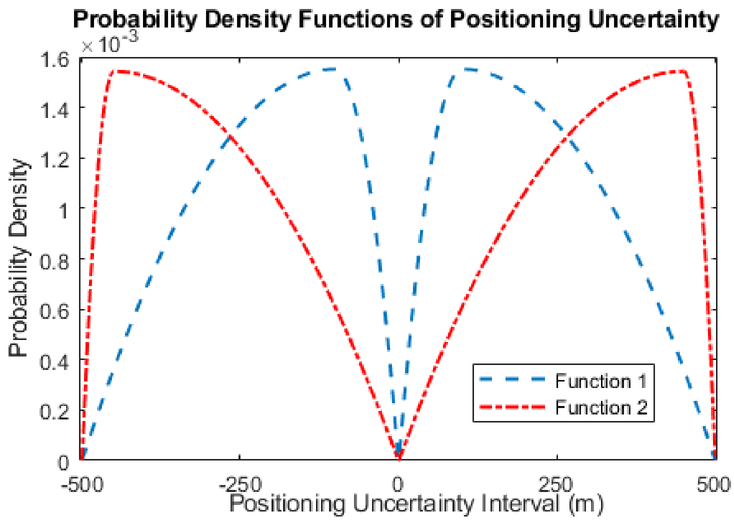


Fig. 5.2 Probability density functions

5.4.3 TMS Application Model

This study uses a model that includes the basic conceptual functions of an intelligent TMS in order to investigate the impact of TPDs on these functions. The strategy of the prototype TMS (train rescheduling) implemented in this study is to minimise the overall arrival delays of all the trains in the control area measured at destination stations. The control area is the part of a railway network that the TMS considers and usually includes one or more junctions. To return the disturbed trains to their original timetable, a temporary traffic plan is needed that endeavours to keep the overall delay to a minimum. The temporary plan, in this study, is achieved by changing the order in which trains pass the junction(s) within the control area. Calculation and the search for a new traffic plan (train order) can be triggered either by a specific traffic event or can be carried out periodically at specific time intervals [29]. In this study, the search for a new train order is triggered when the presence of potential conflicts is detected. Potential conflicts are detected when a scheduled train is delayed by more than a pre-defined delay threshold at the entrance to the control area [19]. The expected time of entry to the control area is calculated based on the original conflict-free timetable. The delay threshold is subject to debate between infrastructure managers; for example, in Germany the delay threshold is 3 minutes while in Italy it is 5 minutes [19]. In this study, the TMS delay threshold is assumed to be 60 s.

After the rescheduling process has been triggered by a train delayed by more than the delay threshold, the RNS is paused and the TMS requests the static and dynamic data from the TCC (from the simulator). Consequently, based on the data collected, a list of all feasible plans (train orders) that can solve this traffic conflict is produced. A decision tree mechanism [184] is utilised to obtain the feasible train orders. Next, an optimisation algorithm is employed to find the optimal train order that solves the traffic conflict with the shortest overall delay to trains. Fig. 5.3 shows the outline TMS process for rescheduling that is considered in this study.

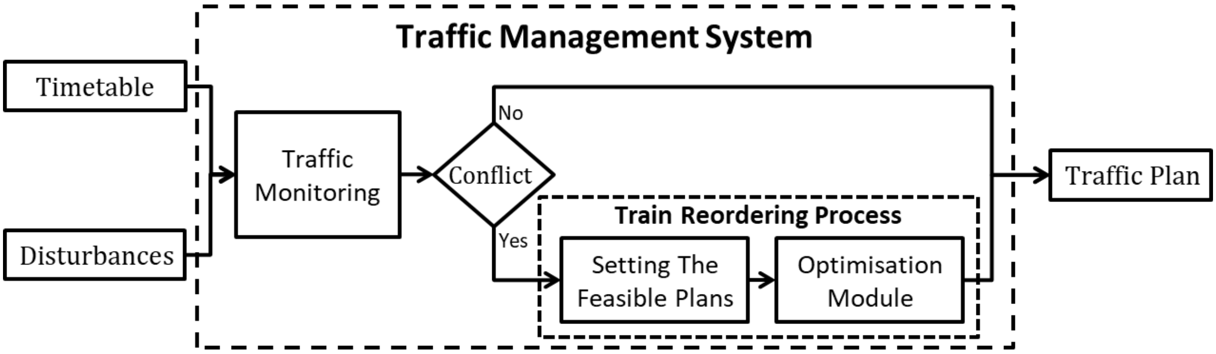


Fig. 5.3 Data flow within TMS [170]

The TMS process time depends on the optimisation algorithm and the complexity of the railway network and is usually restricted by process time limit, between 60 s [181][185] and 300 s [186][187]. TMS typically predicts changes in the train dynamic data for the average process time. Since reducing the process time is not the target of this study, an exhaustive search (or Brute Force (BF) search) has been used in the TMS optimisation module. The advantage of this method is that finding the optimal answer is guaranteed. The optimal result is assumed to be instantaneously found and applied in the railway network. The BF search evaluates the overall delay for all feasible train orders. This is realised by predicting the trains' journey time, according to each feasible train order, from their current reported positions (when rescheduling is triggered) to their last scheduled station stop in the timetable. This journey is predicted, based on equation (3.1), with the assumption that all trains travel at the line speed limit and with maximum acceleration and braking rates. The signalling states are predicted based on the feasible train orders, taking into account the waiting and dwell times. The accuracy of the prediction calculation, in this study, depends on the Prediction Update Rate (PUR). In order to design a TMS model that can be used to test the impact of accuracies in the predicting running times, PURs of 1, 5, 10, 15 and 20 s are used. The lowest prediction accuracy is obtained by using PUR20 and the highest by using PUR1, which can give granularity similar to that of the RNS calculations.

After predicting the required travel time, the delay for each train at the last scheduled stop point is assessed based on the scheduled arrival time in the timetable. After that, a cost function is used to identify the result with the shortest overall delay. The train order that has the shortest overall delay is submitted to the RNS. In this stage, it is assumed that the new train order is applied immediately and does not need to be approved by a human signaller/dispatcher. The RNS applies the optimal train order by setting the routes for each train and setting the junction points according to the order of each train. The pseudocode of the reordering procedure using BF is shown in Fig. 5.4.

5.5 Evaluating the Impact of Positioning Uncertainty on TMS

Train positioning sensors provide the train positioning data in near-real time to the TCC. In this study, the simulated TMS uses the train position information in three different functions: traffic monitoring, setting the feasible train orders, and the optimisation module, as depicted in Fig. 5.3. The traffic monitoring function needs the train position in real time to identify the expected delay to the train at the entrance to the control area and trigger a rescheduling if the delay threshold is exceeded. The impact of TPDs on the monitoring function is that if the train delay is within a few seconds of the delay threshold, the TPD can mislead the TMS by reporting that the train has entered the control area and so no potential conflict will arise. The amount of uncertainty caused by the TPD depends on the train speed. For example, if the train speed is 100 km/h and the TPD is ±100 m, the uncertainty around the delay threshold is ±3.6 s. In addition, the threshold itself, as mentioned in Section 5.4.3, is not fixed and is subject to debate between infrastructure managers.

```
Waiting for the expected trains at the entrance of the control area
If the expected train delays more than the delay threshold
    Trigger TMS to reschedule the traffic plan
    Call the current position of all trains
    Set a list of all feasible train orders to pass the junction
        While (feasible orders list is not empty)
            Read one train order from the feasible orders list
            Set the sequence of trains on tracks before the junction (based on the current train positions)
            Set the sequence of trains on tracks after the junction (based on the feasible order)
            Set a list of the intersected train routes
            For train =1 to N number of trains (based on the feasible order)
                Calculate the remaining journey time to destination
                Calculate the train delay based on the scheduled arrival time
                Save the train data and will be available for the next train
            End
            Calculate the total train delays (the overall delay of order)
            Save the order of trains with its overall delay
        End
        Pick out the solution based on the cost function
    Set the solution as the optimised train order for the TMS traffic plan
End
TMS traffic plan
```

Fig. 5.4 Pseudocode for TMS procedure

The ‘setting feasible train orders’ function requires the train positions in order to find all the feasible configurations for dispatching trains through the junction, regardless of the distance between trains (i.e. high accuracy is not necessary). Also, it needs to know whether the junction signal has been set for a train (i.e. once a train is within two blocks from the junction, with three-aspect signalling) to excluded it from the feasible train orders since it cannot be rescheduled. This information, depending on the type of TMS model, can be obtained either from an on-board positioning systems or from traffic status data which is based on a fixed block system.

The optimisation module needs the train position to predict the remaining journey time, from the current train position to the last scheduled stop in the timetable, based on each feasible train order. In this study, the traffic monitoring function and setting feasible train orders function use accurate real-time train position data from the simulator. However, the impact of positioning uncertainty on the train rescheduling process in the optimisation module is investigated in this study.

To put this framework into practice, the railway network, a TMS and a railway positioning system need to be simulated. The methodology for evaluating the impact of positioning uncertainty on TMS performance is as follows. Step 1: the trains must be dispatched according to scheduled running in the original timetable plan. Step 2: a realistic operational disturbance must then be inserted into a train journey to cause a potential traffic conflict. Step 3: the TMS identifies the conflict and requests a rescheduled traffic plan. Accurate information (i.e. the accurate train positions without deviation) is gathered directly from the railway network. The TMS uses this accurate information to evaluate the feasible plans and provides an 'optimal solution' (an optimised traffic plan based on the accurate train positions) which minimises the impact of potential conflicts around the junction areas. Step 4: the railway systems apply the new plan. Based on the TMS cost function, the TMS performance must be evaluated. For example, if the TMS cost function is to minimise overall train delays, the overall train delays must be measured at the last stop for each train in the timetable. The results of step 4 should be used as a reference for the following stages.

Step 5: this experiment is then repeated with the TMS being provided with positioning information that contains TPDs. The TMS uses this inaccurate positioning data to evaluate the feasible plans. Then, the TMS provides an 'experimental solution' (a traffic plan optimised based on the inaccurate train positions). The experimental solution may be the same as the optimal solution (i.e. the TPDs do not affect the TMS) or suboptimal (i.e. the TPDs mislead the TMS). Step 6: the railway systems apply the experimental solution and evaluate the TMS performance. The impact of TPDs on TMS performance is registered by comparing the evaluation measure values for the optimal solution and the experimental solution and examining the TMS traffic plan for both solutions. If the optimal and experimental solutions are equal, the TPD has no impact on the TMS performance in that case. If the optimal and experimental solutions are different, the impact of the TPD is measured based on the difference between the overall delays resulting from their implementation. The experiment should be repeated using different values of uncertain data in order to assess the relationship between the magnitude of position deviations and the affected TMS results. The following section describes how the above methodology has been applied to the case studies within this chapter.

5.6 Experiments

This section presents the experiments that have been conducted to validate the effectiveness of the proposed framework for three case studies. The framework is implemented to attain a preliminary understanding of the influence of positioning uncertainty on the fundamental

TMS functions. In each application of the framework, the framework modules were populated with the parameters of different case studies. Case study 1 was carried out to demonstrate the concept of a positioning deviation threshold and compare FCFS and optimised rescheduling strategies. Case study 2 was carried out to investigate the impact on the TMS of using different positioning deviations. Case study 3 was carried out to investigate the impact of TPDs on the TMS applied to different railway service types.

5.6.1 Case Study 1

In the first case study, a network with one junction and two running trains was studied to demonstrate the effects of a TPD on the TMS. More precisely, the study clarifies how TPDs can mislead TMS functions. The study verified the relationship between the trains' speeds, positions and section crossing times and quantified the magnitude of positioning deviation that can affect TMS outputs. Two cases for train rescheduling are considered: using an FCFS strategy that gives priority to the first train arriving at a junction area, and using a prototype TMS with a cost function that minimises overall delay. The strategies are investigated under the same simulated level of disruption.

5.6.1.1 Setup parameters and assumptions

The network has three stations, marked A, B and C. A conflict-free timetable contains two trains, one travelling from A to C and the other from B to C. The minimum headway after the junction is 160 s, as shown in Fig. 5.5. The length and speed limit of both (A-C and B-C) lines are 15 km and 70 km/h, respectively. The experiment was carried out based on assumptions that the timetable is without buffer and recovery times; both trains travel at the same speed; both trains have the same rolling stock (speed, length, accelerating curve and braking curve); both drivers have the same behaviour; both lines have the same infrastructure (speed limit, block section length, overlap and signalling system); and the predictions of future traffic are absolutely true (the RNS is run forward as a prediction of future traffic). The following sections calculate how the TMS (based on an FCFS or optimised overall delay strategy) can be affected by the TPDs and submit a suboptimal train order.

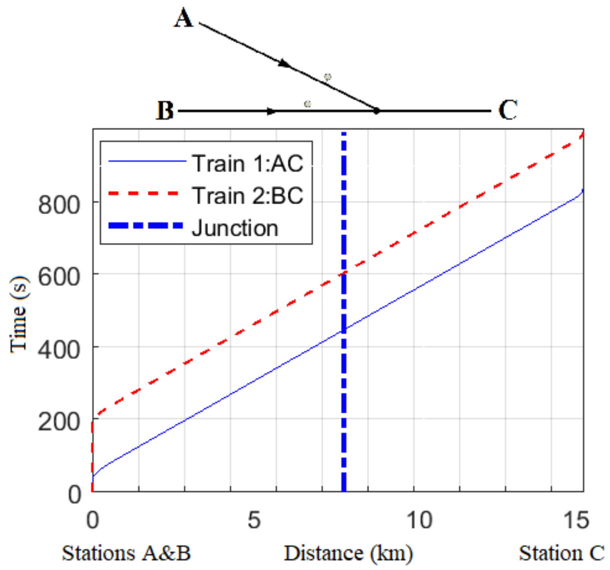


Fig. 5.5 Conflict-free timetable of two trains crossing a junction area (A, B, C)

5.6.1.2 FCFS strategy

A simulated delay scenario, in which Train 1 is delayed by 135 s, is used to illustrate a situation where deviated positioning could have an impact on a TMS solution. The traffic scheduling process, under FCFS, can be misled if the relative positioning inaccuracy (absolute value of 'Train 1 deviation − Train 2 deviation') is greater than the interval between the trains' entry times to the junction area multiplied by the train speed, i.e. a distance value. This is denoted as the relative positioning deviation threshold. In the delay scenario, Train 1 enters the junction area 25 s before Train 2. In this case, the relative positioning deviation threshold is 25 s × 70 km/h × (1000/(60 × 60)) = 486.1 m. The TPDs can mislead the TMS under FCFS by reporting that Train 2 entered the junction first, either by reporting that Train 1 entered the junction area later than the actual time or that Train 2 entered the junction area earlier than the actual time. If Train 1 has more than −486.1 m (backward) TPD, the TMS can be misled and provides a suboptimal order. If Train 2 has more than 486.1 m (forward) TPD, the TMS can also be misled and provides a suboptimal order. TPD less than −486.1 m for Train 1 or 486.1 m for Train 2 does not affect the TMS performance. Moreover, the TPDs can be distributed between the trains, for example −200 and 286.1 m in Trains 1 and 2, respectively, and so can mislead the TMS.

5.6.1.3 Optimised rescheduling strategy

Using a more sophisticated rescheduling strategy, a TMS which sets the train order based on an estimation of which order will cause the least overall delay is now demonstrated. In this case, the relative positioning deviation threshold between Trains 1 and 2 is different due to considering the impact of predicted future traffic. Consider again the scenario of Train 1 delayed by 135 s and entering the junction area 25 s before Train 2. Using actual train positions (without TPDs), the overall delay for order {1,2} predicted by the TMS is 314 s (Train 1: 135 s, Train 2: 179 s) while for order {2,1} it is 364 s (Train 1: 364 s, Train 2: 0 s). The difference between the two orders' predicted overall delay is 50 s. This difference, which is denoted the predicted rescheduling cost difference, sets the relative positioning deviation threshold. In this case it is 50 s × 70 km/h × (1000/(60 × 60)) = 972.2 m. The TMS can be misled if the TPD is more than this threshold, i.e. if the TPDs cause the predicted rescheduling cost difference to be greater than 50 s.

The TPDs can mislead the TMS by either causing: an increase in the predicted delay for the order {1,2}, a decrease in the predicted delay for {2,1} or increasing the former and decreasing the latter at the same time. A backward TPD in Train 1, in evaluating the cost of order {1,2}, causes the predicted junction section occupation time for Train 1 to be longer than the reality. As a result, Train 2 will be predicted to wait in front of the junction signal for longer than in reality; see Fig. 5.6 (a). Therefore, a backward TPD in Train 1 increases the predicted delay of both trains in evaluating the order {1,2}, while it does not affect the predicted delay in evaluating the order {2,1}; see Fig. 5.6 (b). On the other hand, a forward TPD in Train 2, in evaluating the order {2,1}, decreases the predicted waiting time for Train 1 in front the junction signal and so decreases Train 1's predicted delay, while it does not affect the evaluated cost of the order {1,2}. In short, a backward TPD in Train 1 can increase the predicted delay of both trains in evaluating the order {1,2} while a forward TPD in Train 2 can decrease the predicted delay of only Train 1 in evaluating the order {2,1}. Therefore, the threshold for positioning deviation for Train 1 is half that for Train 2.

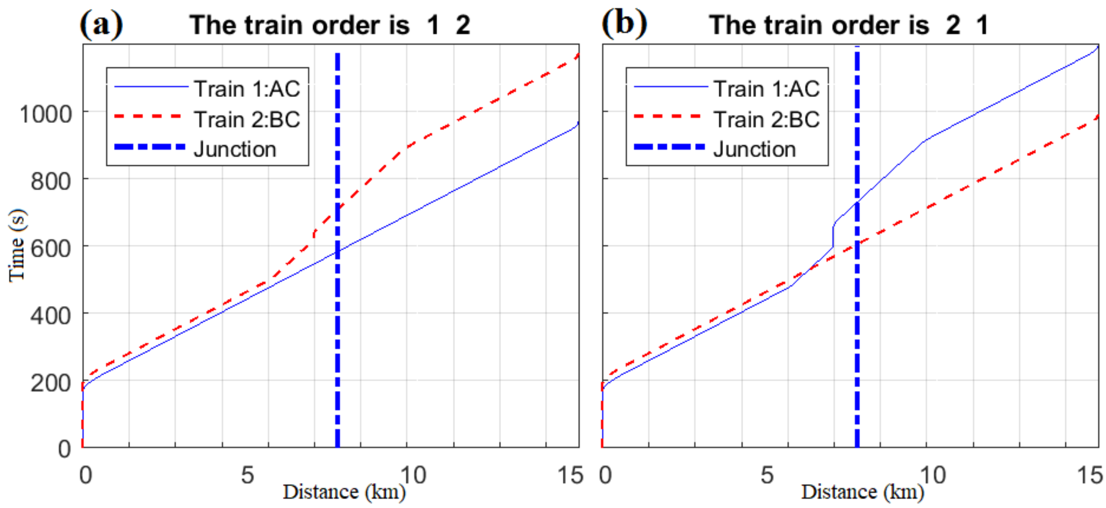


Fig. 5.6 (a) Train order {1,2}, (b) train order {2,1}

When this example was applied in the RNS, it was found that a reporting deviation of −488 m or more in Train 1's positioning data can mislead the rescheduling system and lead it to choose order {2,1}, while one of +991 m or more in Train 2's positioning data can also mislead the rescheduling system and lead it to choose order {2,1}. These values are very similar to those calculated theoretically (972.2 m for Train 2 and 972.2/2 m for Train 1).

The timetable used in the above example has no buffer time. If a buffer time of 60 s is added between Train 1 and Train 2, the interval between the two orders' predicted overall delay will increase and thus increase the relative positioning deviation threshold. However, if Train 1's delay is increased by 60 s, the interval and the threshold will again be 50 s and 972.2 m, respectively. Therefore, it can be concluded that increasing the buffer time reduces the risk of propagating a train's delay, but it does not prevent TPDs from influencing TMS performance.

Obviously, based on the assumptions of this case study (in Section 5.6.1.1), if the speed of the trains is altered, the relative positioning deviation threshold will also change. If the interval between the trains' entry times to the junction area is altered, the threshold for positioning deviations will change too. Each TMS uses different methods and tools, for different rolling stock and infrastructures and for different railway services. Therefore, each TMS process has its assumptions and formats; and the deviations in the positioning data could have a different impact on TMS associated with each one of these assumptions and formats. For further analysis, the impact of TPDs on a train rescheduling system for a realistic junction area based on a section of the UK network will be studied in the next section.

5.6.2 Case Study 2

This experiment was considered to evaluate the influence of positioning uncertainty on the performance of a prototype TMS (train rescheduling) in a junction area with an operational disturbance. More precisely, the experiment illustrates the influence of different magnitudes of positioning deviations on the TMS under different operational disturbances and prediction accuracies. The study verifies the relationship between positioning deviation, operational disturbances and prediction accuracy.

5.6.2.1 Setup parameters

A simplified version of the Stenson and North Stafford junctions, in the UK, was studied in this experiment; see Fig. 5.7 (a) and (b). The bottleneck area considered is composed of two double flat junctions. The modelled network is a 104 km long; it consists of section of the line between Birmingham and Derby and the intersecting line between Nottingham and Uttoxeter.

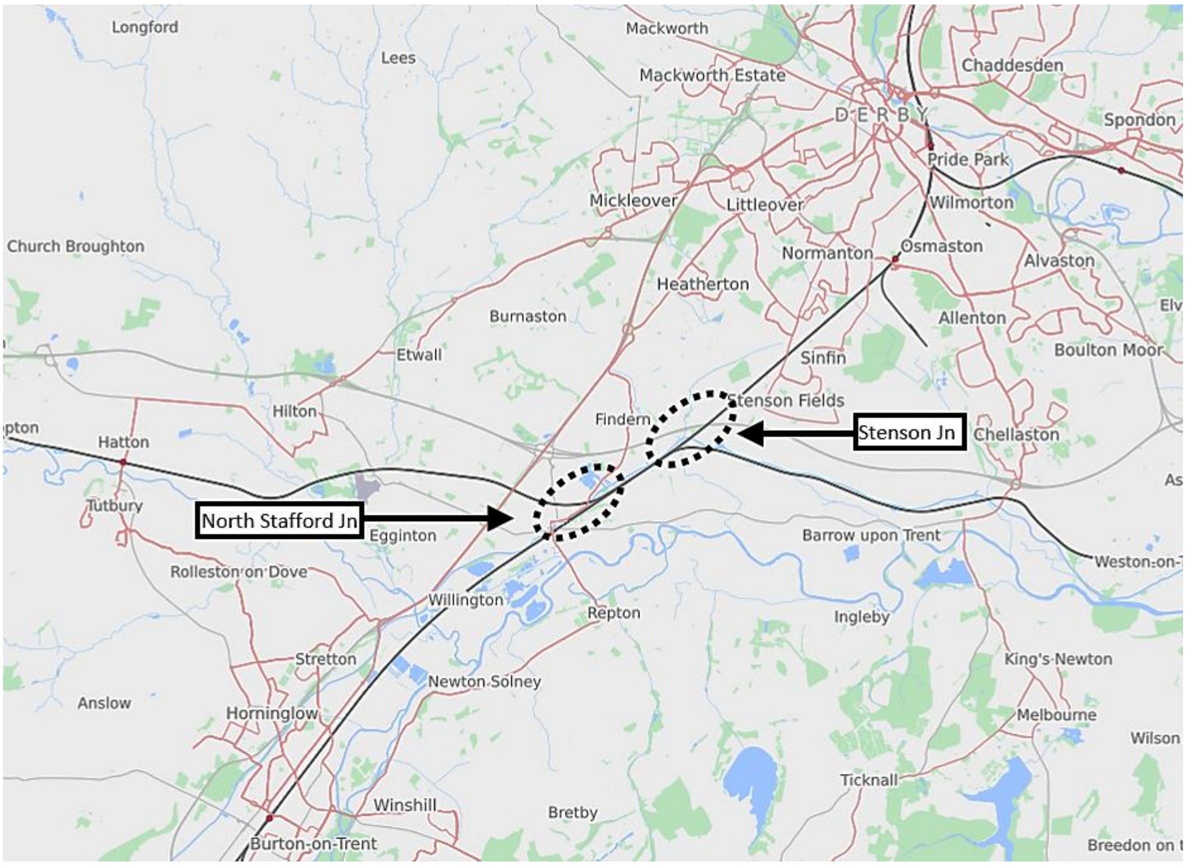


Fig. 5.7 (a) Stenson and North Stafford junctions (from OpenStreetMap)

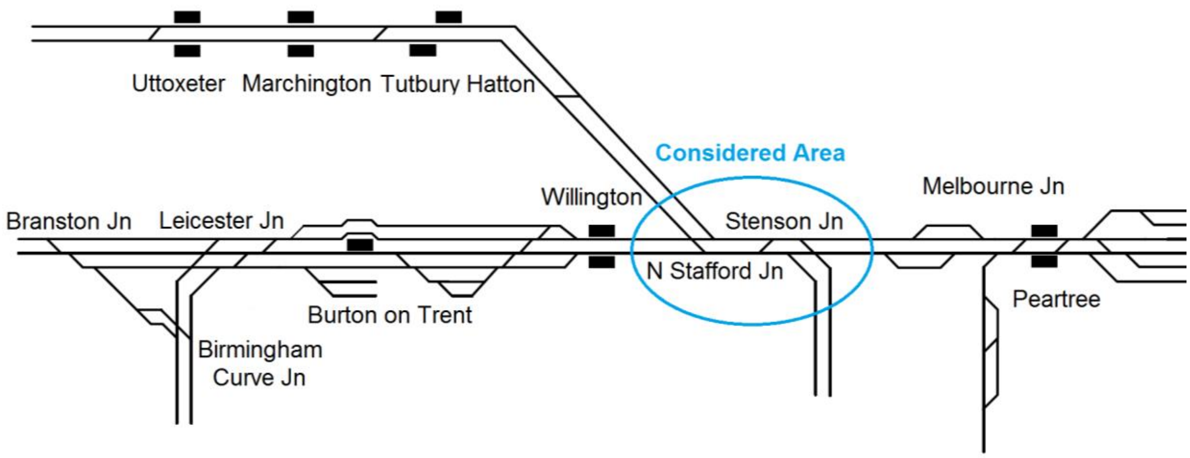


Fig. 5.7 (b) Part of the Birmingham–Derby railway line [188]

It is assumed that trains can arrive at and depart from stations A, B, C and D. Each of the stations is located 24.7 km from its corresponding junction signal. The length of the block sections in the area considered is around 1.3 km; therefore, this length is used as the fixed block length in this simulated network. The diameter of the control area is 13 km. Therefore, the boundary of the control area is 5.2 km from the entrance signal of each junction. A three-aspect lineside signalling system is used to regulate the train movement. The line speed limits are considered based on the actual route data [189]. Further, a 40 km/h approach speed limit for yellow signals, a 200 m sighting distance and a 180 m overlap distance are used. The track in this study is assumed to be flat.

The timetable is composed of six trains, which are dispatched from four stations: Train 1: AC, Train 2: BD, Train 3: DA, Train 4: CB, Train 5: BD and Train 6: CA, where the trains are labelled as 'train ID: departure station destination station'. The timetable for each train includes 60 s buffer time in addition to the minimum headway, with running time supplements (recovery time) of 5%. The train order at the junction of the conflict-free timetable is {1,2,3,4,5,6}. There are two types of passenger train used in this study: the Class 150 'Sprinter' whose maximum speed is 120 km/h and the Class 375 'Electrostar' whose maximum speed is 160 km/h. The Class 150 is used to model Trains 1, 3 and 6 and the Class 375 is used to model Trains 2, 4 and 5. Fig. 5.8 shows the time–distance diagram of the conflict-free timetable of the six trains crossing the bottleneck area. The x-axis is the distance between stations in opposite directions, with station A and B on the right side and stations C and D on the left side. The y-axis represents the train journey times.

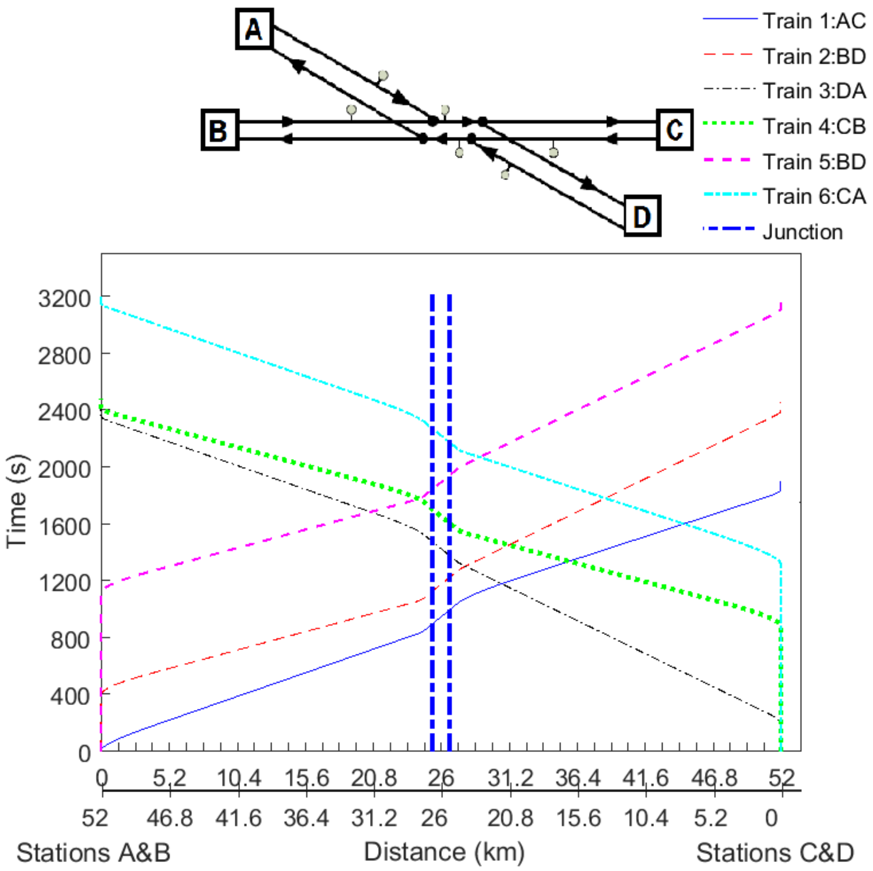


Fig. 5.8 Time–distance diagram of the conflict-free timetable

5.6.2.2 Experimental parameters

Operational disturbances, driver behaviours and TPDs were simulated and prepared for use in the experiment. One hundred and fifty operational disturbance scenarios were created. Each scenario was composed of two train delays chosen from a uniform probability distribution in the interval |180, 720| seconds for the first delay and |60, 240| seconds for the second delay [190][191]. The first delay was allocated an equal number of times to Trains 1 to 5; each one suffered 30 of the 150 delay scenarios. The second delay was applied to one of the trains that follows the first delayed train (chosen from a uniform distribution). For example, if the first delay was in Train 3, the second delay could be in Train 4, 5 or 6. All the operational disturbance scenarios were simulated and saved to be used in the experiments.

Six drivers with different behaviours were modelled for the six trains; see Section 3.4.2.9. The driver behaviours were randomly chosen. Each train was assumed to always have the same driver in this experiment. The TPDs were simulated using a Monte Carlo simulation. The TPDs for six trains were gathered in a TPD list, for example, {-75, 352, 186, -129, -213, 94} for Trains 1, 2, 3, 4, 5 and 6 respectively. In order to represent a wide range of potential positioning deviations, 100 lists were generated for each operational disturbance (of 150) and for each probability density function (of two) (see Fig. 5.2); the total number of TPD lists generated was 100 × 150 × 2 = 30000. Fig. 5.9 shows the density of the modelled positioning deviations. Each time the experiment runs, it loads the six simulated drivers, one simulated operational disturbance and one TPD list.

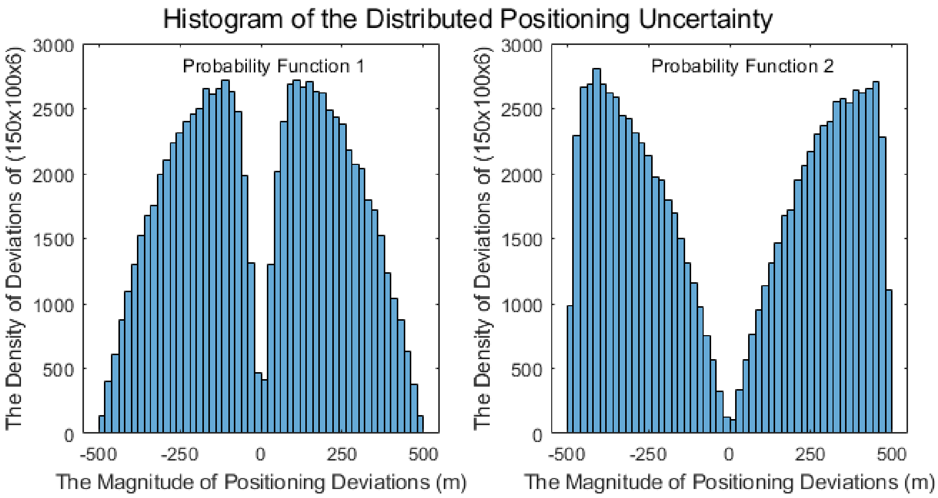


Fig. 5.9 Density of the modelled positioning deviations

The steps of the experiment, following the method outlined in Section 5.5, are as follows. The simulator runs using a timetable of six trains (step 1). An operational disturbance scenario is inserted into the relevant train journey(s) as a delay in train departure (step 2). When the TMS detects the operational disturbance, the RNS is paused, the TMS is triggered and a decision tree for all feasible train orders across the junctions is created. By using accurate positioning information, an accurate optimal train order to reduce the effect of the operational disturbance is produced (step 3). Thereafter, the RNS is resumed and applies the optimal order. After all the trains arrive at their destinations, the overall train delay is calculated (step 4). This corresponds to the accurate optimal solution obtained with accurate positioning provided to the TMS and is the basis for comparison with the inaccurate positioning data results obtained in the remaining steps. Steps 5 and 6 of the experiment are a repetition of steps 3 and 4 using positional information containing simulated TPDs. Steps 5 and 6 are repeated for each list of TPDs. The results of these steps are called the experimental solutions and will be compared with the optimal solution of steps 3 and 4.

In case of studying the relationship between train positioning uncertainty and other railway parameters, for example TMS prediction (predicting running time), the experiment should be repeated as follows: first, change the prediction accuracy in the application model, then repeat the above six steps and finally compare the results of the two experiments.

In the following sections, the results of the experiments are analysed based on positioning deviations, probability functions, operational disturbances and prediction accuracies. The first section will demonstrate the impact of TPDs on the TMS with one operational disturbance. The second section will discuss the impact of increasing the deviations in the positioning data on the TMS under different operational disturbances. The third section will discuss the impact of TPDs on the TMS under different prediction accuracies. In terms of the proposed framework in Fig. 5.1, the parameters examined are located in the test variable module, TMS module and inputs module. Table 5.1 shows a summary of the parameters examined in the following sections.

Table 5.1 Parameters examined in the following sections

Section	No. of operational disturbances	TPI		TMS prediction
		Prob. Fun.	No. of lists	
5.6.2.3 Analysis based on positioning deviations	1	1	100	PUR1
5.6.2.4 Analysis based on probability functions	150	1 & 2	150x2x100	PUR1
5.6.2.5 Analysis based on prediction accuracies	150	1	150x100	PUR:1,5,10,15&20

5.6.2.3 Analysis based on positioning uncertainty

The impact of the TPDs was assessed independently from the impact of prediction uncertainty. This TPD assessment is achieved by using a 1-second PUR (PUR1), which provides highly accurate traffic prediction. The outcome of the simulated 100 TPD lists, based on probability function 1 shown in Fig. 5.2, was investigated. In the following, the experimental result of the one operational disturbance will be elaborated upon qualitatively and quantitatively. The operational disturbance examined consists of Train 2 suffering from 410 s delay and Train 5 suffering from 217 s delay at their respective departure stations. In this case, the TMS detected the potential junction conflict and provided the optimal train order {1,3,4,2,5,6}, using accurate positioning data. When the RNS applied the optimal train order and all the trains had reached their destination, the arrival delays of Trains 2, 5 and 6 were 567, 208 and 81 s, respectively, while the other trains arrived without delay. The overall delay was 856 s. Then, the experiment was repeated 100 times using the simulated TPD lists.

The result shows that 34 of the TPD lists affect TMS performance. All these TPD lists led the TMS to choose the same suboptimal order, {1,3,2,4,5,6}. When the RNS applied the suboptimal train order, Trains 2, 4, 5 and 6 were delayed by 451, 211, 208 and 81 s, respectively. The overall delay was 951 s. The overall delay error is therefore 951 s – 856 s = 94 s. This means that the TPDs increase the overall delay by 11.1%. Fig. 5.10 shows a boxplot containing the TPDs, i.e. the input values, of the 100 lists divided into those that did not mislead the TMS (a) and those that did (b). In the figure, the boxes show the values between the first and third quartiles, the line within the box shows the median, and lines outside the box show the spread of values.

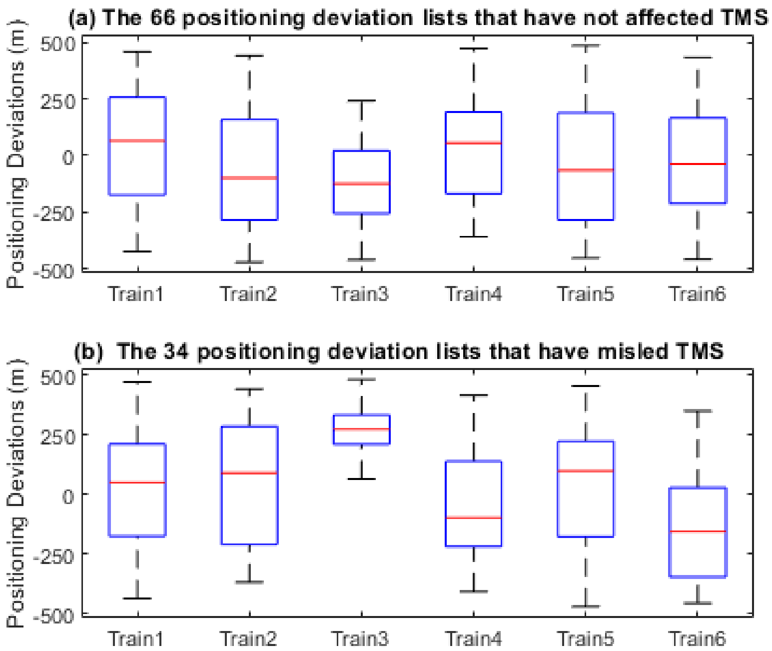


Fig. 5.10 (a) TPD lists that did not affect TMS, (b) TPD lists that misled TMS

As can be seen from Fig. 5.10, all 34 affected results are when Train 3 is reported to have a forward TPD (positive deviation). The explanation is that when the order {1,3,2,4,5,6} is evaluated in the TMS optimisation module, forward TPD3 causes Train 3 to be predicted to release the junction section earlier than in reality and so there is less waiting time for Trains 2 and 4 in front of the junction signal. Therefore, the predicted delays for Trains 2 and 4 are less than in reality. The forward TPD5 can also reduce the predicted Train 5 delay. Therefore in 34 cases, the predicted overall delay of the order {1,3,2,4,5,6} was less than the predicted overall delay of {1,3,4,2,5,6}. Consequently, the TMS was misled and chose the suboptimal order {1,3,2,4,5,6} which increased the overall delay by 95 s (11.1%).

On the other hand, there is no tangible impact of TPD2, TPD4 and TPD6 because they only cause Trains 2, 4 and 6 to be predicted to reach the junction signal later or earlier than in reality and do not significantly impact the predicted delays. The impact of TPD1 causes Train 1 to be predicted to reach its destination earlier or later than in reality, and this short impact is covered by the scheduled recovery time.

5.6.2.4 Analysis based on probability functions

The experiment in this section was carried out with 150 simulated operational disturbance scenarios. To assess the TPDs separately from prediction uncertainty, a high prediction accuracy of PUR1 was used. To analyse the impact of increased positioning deviation, steps 5 and 6 of each experiment were repeated 200 times, 100 each based on the two positioning deviations probability functions.

Even though TPDs of up to ±500 m were used with each experiment, only 10 of the 150 operational disturbance scenarios showed suboptimal train orders in their results. Table 5.2 shows these 10 experiments affected by TPD. It shows the number of affected cases, in which a suboptimal train order is presented, separately for each probability function (i.e. the number of affected cases out of 100). It also shows the impact of the suboptimal orders on the overall train delays when the RNS applies them.

Table 5.2 Experiments affected by TPDs

No.	Operational disturbance Train ID (delay s)		Optimal solution		Affected cases in experimental solutions					
			Optimal Train order	Overall delay s	Number of affected cases of 100		Suboptimal Train order	Overall delay s	The impact of suboptimal order	
	First delay	Second delay			Prob. Fun. 1	Prob. Fun. 2			Delay error s	Delay error %
1	Train 2 (368)	Train 4 (211)	[1,2,3,4,5,6]	744	13	26	[1,3,2,4,5,6]	801	57	7.66
2	Train 2 (410)	Train 5 (217)	[1,3,4,2,5,6]	856	34	37	[1,3,2,4,5,6]	951	95	11.1
3	Train 2 (619)	Train 4 (160)	[1,3,4,2,5,6]	1177	2	2	[1,3,2,5,4,6]	1232	55	4.67
					7	18	[1,3,2,4,5,6]	1258	81	6.88
4	Train 2 (630)	Train 4 (214)	[1,3,2,4,5,6]	1302	24	20	[1,3,2,5,4,6]	1272	-30	-2.3
5	Train 3 (339)	Train 4 (64)	[1,2,4,3,5,6]	591	32	33	[1,2,3,4,5,6]	671	122	20.64
6	Train 3 (410)	Train 6 (238)	[1,2,4,3,5,6]	732	1	0	[1,2,4,5,3,6]	716	-16	-2.19
7	Train 3 (412)	Train 4 (215)	[1,2,3,4,5,6]	1005	0	8	[1,2,4,5,3,6]	980	-25	-2.49
8	Train 3 (413)	Train 6 (176)	[1,2,4,3,5,6]	676	1	2	[1,2,4,5,3,6]	654	-22	-3.25
9	Train 4 (323)	Train 6 (198)	[1,2,3,4,5,6]	636	18	25	[1,2,3,5,4,6]	570	-66	-10.38
10	Train 4 (489)	Train 5 (176)	[1,2,3,5,4,6]	1038	0	2	[1,2,3,4,5,6]	1078	40	3.85

Experiment no. 2 in the table was the one demonstrated in detail in Section 5.6.2.3 (for probability function 1, 34 affected cases). However, when this experiment was repeated with probability function 2, the number of affected cases was slightly increased. This is because probability function 2 increases the probability of deviations being allocated towards ±450 m rather than probability function 1 towards ±100 m, as can be seen from Fig. 5.9, in addition to the impact of the deviations of the other trains. In experiment no. 3 in Table 5.2, two suboptimal orders appears in the experimental solutions, {1,3,2,5,4,6} and {1,3,2,4,5,6}. This is because the predicted overall delay of the optimal order and these two suboptimal order were very close and so TPDs misled the TMS, in some cases, by choosing one of the above two orders. Experiments no. 4 and 6, in Table 5.2, show a decline in the number of affected cases from function 1 to function 2. This is because, in some cases, increasing the magnitude of the TPDs can increase/decrease the predicted overall delay in both optimal and suboptimal orders, and so the optimal order keeps providing the shortest predicted delays.

It can be seen in Table 5.2 that there are some suboptimal orders that reduce the overall delay. After conducting a deeper analysis to understand this situation, it was found to be due to the RNS driver module; see Section 3.4.2.9. The drivers are modelled to have different behaviours. Due to the use of high prediction accuracy in this experiment (PUR1), the difference between the prediction and RNS is mainly due to the drivers' behaviour. Because the difference in overall delay between the optimal and suboptimal orders was very small, the impact of driver behaviour was higher than the impact of the suboptimal order on the overall delay. Experiment no. 9 in Table 5.2 can be taken as an example. The predicted overall delays for optimal and suboptimal orders in step 3 (without positioning deviation) were 481 and 498 s, respectively. When these orders were applied in the RNS, the overall delays were 636 and 570 s, respectively. This is because the drivers of Trains 5 and 6 were driving cautiously, at 5% less than the maximum speed, while the other drivers were less cautious.

From Table 5.2, though 15,000 experiments were conducted, for each probability function, only 132 experiments were affected by TPDs using probability function 1, and only 173 experiments were affected by TPDs using probability function 2, providing suboptimal solutions. Therefore, the percentage of cases affected by the TPDs around ±100 and ±450 m is 0.88% and 1.15%, respectively. If suboptimal orders resulting from modelled driving behaviour are ignored, the total affected cases by probability function 1 and 2 will be 88 (0.59%) and 116 (0.77%) respectively.

To summarise the results of this section, the increase in overall delay, when the TMS chooses a suboptimal order, is only between 40 and 122 s. The TPDs around ±100 and ±450 m mislead the TMS results respectively for only 0.88% and 1.15% of the investigated cases. Using a different magnitude of TPDs, through different probability functions, does not affect the overall delay size of the suboptimal orders. In addition, an increase in the magnitude of the TPDs does not necessarily increase the probability of affected cases.

5.6.2.5 Analysis based on prediction accuracies

This experiment assesses the impact of positioning deviations in combination with the impact of inaccurate TMS prediction for future traffic. The experiment was repeated using PUR5, PUR10, PUR15 and PUR20 for the 150 disturbance scenarios to mimic inaccurate TMS prediction. The results of all scenarios are summarised in Table 5.3. In steps 3 and 4 of the experiment, the impact of prediction uncertainty on TMS was assessed without TPDs, shown in Table 5.3 (a), then in step 5 and 6 it was assessed with TPDs of probability function 1, shown in Table 5.3 (b). The table presents the number of affected cases, meaning those where the TMS chose a suboptimal order due to the impact of deviations, and the range of the extra delays caused by the suboptimal orders. The outputs of using PUR1 without TPDs, in Table 5.3 (a), are used as a reference for all the other results in both Table 5.3 (a) and (b). Suboptimal orders resulting from modelled driving behaviour are ignored in Table 5.3, as discussed in Section 5.6.2.4.

Table 5.3 Experiments affected by: (a) PUR, (b) PUR and TPD

(a) Prediction	The impact of prediction uncertainty			
	No. of affected cases of 150 scenarios	Proportion of affected cases of 150	Lowest delay error s	Highest delay error s
PUR1	--	--	--	--
PUR5	24	16%	40	753
PUR10	18	12%	57	753
PUR15	18	12%	42	753
PUR20	20	13.33%	86	624

(b) Prediction	The impact of prediction & positioning uncertainty			
	No. of affected cases of 15000	Proportion of affected cases of 15000	Lowest delay error s	Highest delay error s
PUR1	88	0.59%	40	122
PUR5	2079	13.86%	40	773
PUR10	2140	14.27%	40	754
PUR15	2037	13.58%	19	802
PUR20	2556	17.04%	19	755

It can be seen from the above table that the majority of the experiments (84% to 88%) of the 150 scenarios are not affected by prediction uncertainty. Furthermore, the overall delay is increased by up to 753 s without including the impact of the TPDs. Besides that, 83% to 86% of the 15000 experiments are never affected by the combined effect of prediction and positioning uncertainties together, i.e. in steps 5 and 6 of the experiments. Moreover, from Table 5.3, the value of highest overall delay error is increased by the combined effect by up to 131 s. This means that the impact of low prediction accuracy increased the overall delay of the studied scenarios by about 12.5 minutes while the greatest impact of low positioning accuracy was less than 2.2 minutes. To further understand the results in Table 5.3, the results for the operational disturbance that showed the biggest effects are elaborated below. Table 5.4 shows that the results of one operational disturbance consisting of Train 3 suffering from

706 s delay and Train 4 suffering from 118 s delay; the optimal order and overall delay for PUR1 are {1,2,4,5,3,6} and 811 s, respectively.

Table 5.4 Impact of different PURs on a scenario of Trains 3 & 4 delayed by 706 and 118 s, respectively; the optimal order and overall delay are [1,2,4,5,3,6] and 811 s, respectively

Prediction	The impact of prediction uncertainty				The impact of prediction & positioning uncertainty				
	Train order	Overall delay s	Delay error s	Delay error %	Train order	Overall delay s	Number of appearance of 100 lists	Delay error s	Delay error %
PUR5	[1,2,5,3,4,6]	1435	624	76.94	Optimal order		(02)	0	0
					[1,2,5,3,4,6]	1435	(98)	624	76.94
PUR10	[1,2,5,3,4,6]	1435	624	76.94	Optimal order		(12)	0	0
					[1,2,5,3,4,6]	1435	(81)	624	76.94
					[1,2,4,5,6,3]	1030	(07)	219	27
PUR15	[1,2,5,3,4,6]	1435	624	76.94	Optimal order		(17)	0	0
					[1,2,5,3,4,6]	1435	(72)	624	76.94
					[1,2,4,5,6,3]	1030	(11)	219	27
PUR20	[1,2,5,3,4,6]	1435	624	76.94	Optimal order		(42)	0	0
					[1,2,5,3,4,6]	1435	(36)	624	76.94
					[1,2,4,5,6,3]	1030	(15)	219	27
					[1,2,4,3,6,5]	1441	(02)	630	77.68
					[1,2,4,3,5,6]	1566	(05)	755	93.09

It can be seen from the impact of prediction uncertainty that the TMS under all PURs provides a solution which is not the optimal one for PUR1. Compared to PUR1, the suboptimal order provided by all PURs increased the overall delay by 624 s which is 76.94% of the optimal overall delay. Under the combined impact of prediction and positioning uncertainties, the optimal order appears in some cases of the 100 TPD lists. However, the proportion of the optimal order is different between the PURs, the lowest being 2% in PUR5 and the highest 42% in PUR20. The numbers of suboptimal orders are not equal between the PURs. In the PUR5 case, 98% of the results provided a suboptimal order. In PUR10 and PUR15 cases, 88% and 83% of the results, respectively, provided one of two suboptimal orders. In the PUR20 case, 58% of the results provided one of four suboptimal orders. This means that by decreasing the accuracy of prediction, the impact of TPDs on the results increases. This is why the proportion of the optimal order increased for the combined effect of prediction and positioning uncertainties from PUR5 to PUR20, while the results for the individual effect of prediction uncertainty were all suboptimal orders. Moreover, only when using PUR20 did the TPDs severely affect the TMS and lead it to provide train orders that increased the overall delay by 6 and 131 s over the prediction effect (630 s – 624 s = 6 s and 755 s – 624 s = 131 s).

It can be concluded that the impact of the train position uncertainties on TMS depends to a large extent on the circumstances of the operational disturbance; some train delays can put the traffic in such a way that is very difficult for data uncertainties to mislead the TMS processes. This is because the difference between the highest ranked (shortest delay) train orders – the predicted rescheduling cost difference – is very high and so the threshold for positioning deviation is high too. Decreasing the prediction accuracy increases the number of affected cases, the number of suboptimal orders and the overall delays. The impact of prediction and positioning uncertainties together can increase the percentage of affected cases compared to the impact of prediction uncertainty individually. However, the impact of prediction and positioning uncertainties together usually does not increase the overall delay of the suboptimal orders compared to the impact of prediction uncertainty individually (unless the prediction is severely deviated). Finally, the results of this experiment have clearly demonstrated that the impact of positioning uncertainty is far less than the impact of prediction uncertainty.

5.6.3 Case Study 3

In this experiment, the impact of positioning system uncertainty on the effect of a TMS was investigated for different railway service types. More precisely, the study evaluated the impact of the same positioning deviations on the traffic management of urban, freight, intercity, high-speed and mixed-traffic systems. The study elucidated the relationship between positioning deviations and service types.

The performance of railways is varied, and each railway service type has different requirements for infrastructure, rolling stock and control and operation systems. The parameters of railway systems are diverse due to the diversity of railway networks and services, as mentioned in Section 2.2. Railway services can be classified into three groups which represent the differences in infrastructure, rolling stock and the operational timetable, as shown in Fig. 5.11 [170]. To model a specific railway service, several parameters need to be considered. To allow a clear comparison between a TMS applied to different railway service types, some railway parameters need to be fixed. For this reason, all the services have been assumed to run on the same infrastructure, with differences in the line speed limit, operational timetable and rolling stock. Therefore, the line length, number of stations, inter-station distance, signalling and communication systems, number of rolling stocks, service distance and dwell time are the same. Although some other railway parameters also vary, they have no direct impact on the application investigated in this study which is a local TMS. Therefore, the power supply, number of parallel tracks, number of seats, number of passengers, platform pattern and number of operators are not considered in this study, as shown in Fig. 5.11.

Railway Systems	Infrastructure	Power supply
		Number of parallel tracks
		Line speed limit
		Line length
		Number of stations
		Inter-station distance
		Signalling system
		Lineside/In-cab signalling
		Communication system
		Number of rolling stock
	Rolling stock	Number of seats
		Number of car
		Maximum speed
		Mass
		Aerodynamics
		Power
		Acceleration
		Braking
		Train length
	Timetable	Number of passengers
		Number of operators
		Platform pattern
		Journey time
		Minimum headway
		Recovery time
		Allowance times
		Capacity (trains per hour)
		Service distance
		Dwell time

	Not considered
	Modelled as a variable
	Modelled as a fixed value

Fig. 5.11 Railway network and service parameters considered in this experiment, adapted from [170]

5.6.3.1 Setup parameters

The railway services were modelled using the same infrastructure but with different speed limits. The infrastructure is the same bottleneck area used in Section 5.6.2, based on Stenson and North Stafford junctions. In order to maintain enough braking distance for all service types used in this experiment, a four-aspect lineside signalling system has been used. The line speed limits were adapted for each type of railway service taking into account the trains' braking rate. Fig. 5.12 shows the bottleneck area considered. Table 5.5 shows the line speed limits assumed for each service, where Jn refers to junction.

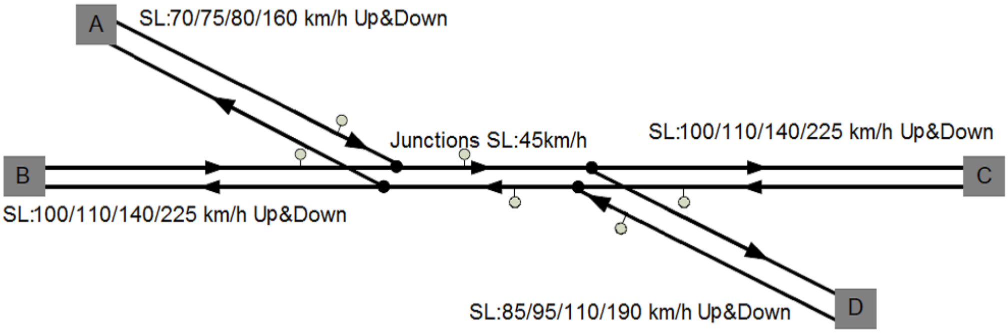


Fig. 5.12 Bottleneck area considered; the line Speed Limit (SL) is sorted for unban/freight/intercity/high-speed services, respectively [170]

Table 5.5 The line speed limits assumed for each service (km/h)

Line section / Service	A-Jn and Jn-A	B-Jn and Jn-B	Jn-C and C-Jn	Jn-D and D-Jn	Jn Area
Unban	70	100	100	85	45
Freight	75	110	110	95	45
Intercity	80	140	140	110	45
High-Speed	160	225	225	190	45

One train class was used for each service category, and two train classes were used for the mixed-traffic service category. It is assumed that the urban services use Class 150 trains, the intercity services use Class 375 trains, the high-speed services use Class 373 trains and freight services use F2-mixed trains. The parameters used to represent the differences in rolling stock are shown in Table 3.1. In addition to the line speed limit and rolling stock parameters, the trains' timetable is built for each service type based on blocking time theory with running time supplements (recovery time) of 5% and 60 s buffer times [121].

This study was carried out in seven experiments, one for each service type. The services investigated were urban, freight, intercity, high-speed, mixed urban and intercity (U/I), mixed freight and intercity (F/I), and mixed high-speed and intercity services (H/I). Each experiment was performed for six trains crossing the bottleneck area as presented in Section 5.6.2.1 and in the order shown in Fig. 5.8. The trains' scheduled departure and arrival times are different between the timetables of the services investigated. The mixed-traffic services are mixed between an intercity service and either an urban, high-speed or freight service; stations A, C and D can serve all service types while station B serves only one type of service, the intercity service.

5.6.3.2 Experimental parameters

The same 15000 TPD lists based on probability function 1, the six simulated drivers and the 150 operational disturbance scenarios developed in the previous experiment (see Section

5.6.2) were used for these experiments. To assess the positioning uncertainty separately from prediction uncertainty, a 1-second PUR (PUR1) is used. The methodology steps shown in Section 5.5 are applied in the experiments for different railway service types. In terms of the proposed framework, the parameters examined are located in the inputs module (different timetables and operational disturbances) and railway characteristics module (different speed limits and rolling stocks) in addition to the test variable module.

5.6.3.3 Analysis based on predicted delays

This section looks into the TMS prediction function for future traffic in terms of how TPD can impact different services. After the TMS has detected a potential conflict, it starts the rescheduling process. In this process, the TPDs cause an error in predicting the journey time and so in the predicted delay of the feasible train orders evaluated. This error, compared to using accurate positioning data, was measured for each train order. Then, the average of the absolute value of the error, caused by all TPD lists, was calculated. Fig. 5.13 shows a boxplot containing the average of the errors in the predicted delay for different railway service categories.

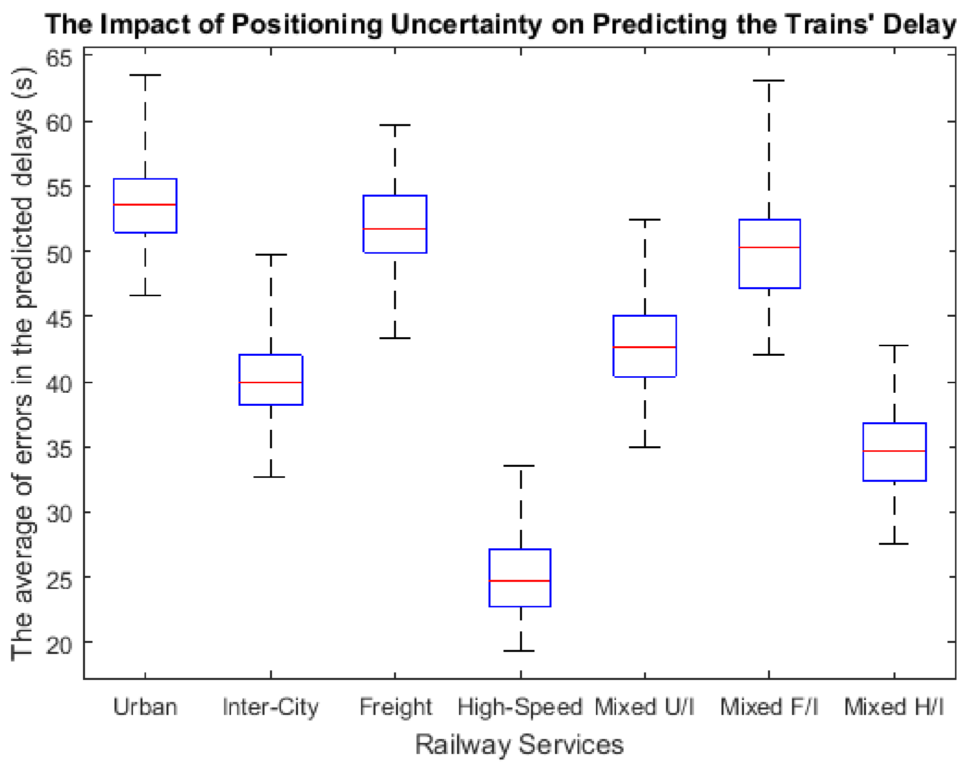


Fig. 5.13 Impact of TPDs on predicting the overall delay on different railway services

As can be seen from Fig. 5.13, the impact of the TPDs on the average of errors in the predicted delay, caused by 15000 TPD lists, is high in the urban, intercity, freight, mixed U/I and mixed F/I service cases, at 54, 40, 52, 43 and 51 s, respectively. However, it is significantly lower in the high-speed service at about 25 s. The impact on the mixed H/I service is about 33 s, which falls between the values for intercity and high-speed services. This can be explained by considering the trains' speed and its relationship with TPD. A high-speed train can cover the deviation in the reported position in less time than other types of train. Therefore, it is expected, according to Fig. 5.13, that the impact of TPDs on the TMS of high-speed and H/I services will be different from that on other services.

5.6.3.4 Analysis based on overall arrival delays

This section looks into the results of applying the TMS experimental solutions (with TPDs) in the RNS in terms of the overall delay compared to the optimal solution without TPDs. The errors in train delay predictions, due to TPDs, misled the TMS in some cases and so it provided a suboptimal train order. The results show that the TMS solutions for all the services investigated are affected by the TPDs and provide suboptimal solutions but in different proportions. Fig. 5.14 shows the impact of each suboptimal order produced by the TMS in terms of the overall delay error with respect to the optimal solution without TPDs. The horizontal bars in the figure show the overall delay errors in ascending order. It is clear from the figure that the service least affected by TPDs is the high-speed service, followed by the H/I service. This is because the average of the errors in the predicted overall delay, caused by TPDs, is low compared to other services. It can also be seen that the highest number of decreasing delays, due to driver behaviour, appears in the urban and U/I services. The explanation is that the urban service has the lowest speed among the services studied. Due to the low speed, any slight change in train speed can have a big impact on the train arrival time. Although the RNS driver module does not work under a speed of 50 km/h, the results show it has a high impact on urban and U/I services.

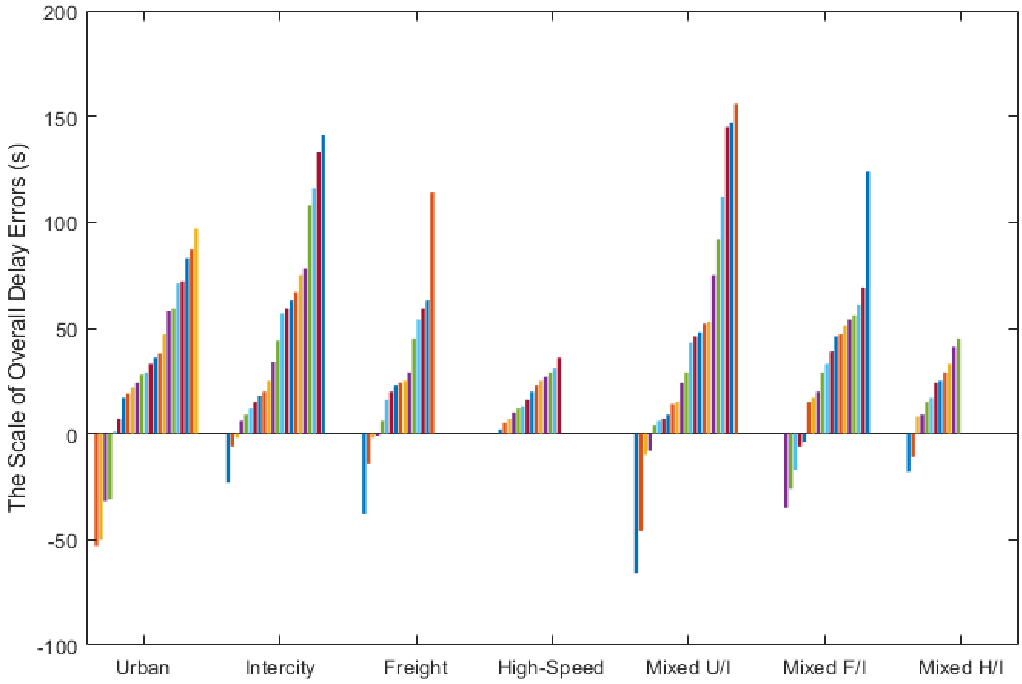


Fig. 5.14 Impact of each suboptimal order on overall delay

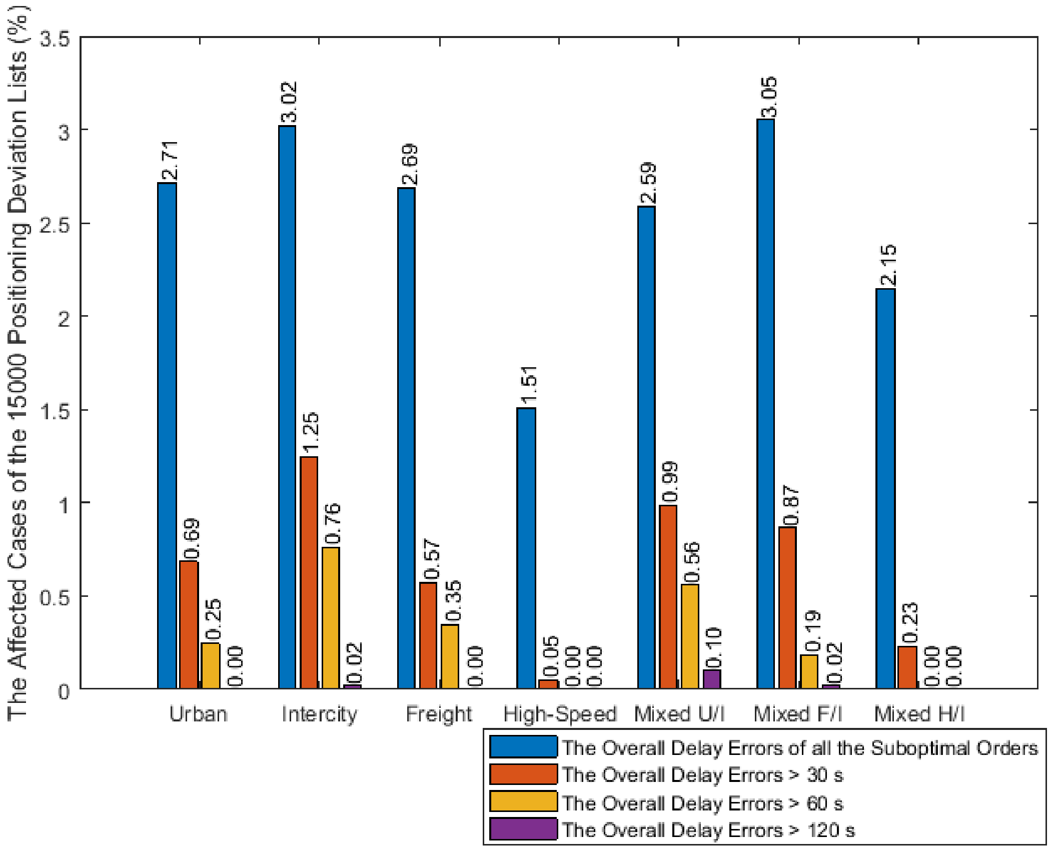


Fig. 5.15 Percentage of cases affected with different increased delay scale

The percentage of cases affected by TPDs distributed by different scales of delay errors are shown in Fig. 5.15. In general, the figure shows that there is little difference in affected cases between the services except for high-speed and H/I services. The intercity and F/I services show the highest number of affected cases, at about 3%; however, the majority of them are less than 30 s and only 0.02% are more than 120 s. The results for urban and freight services show a high similarity; 0.25% and 0.35%, respectively, of the delay errors are located between 60 and 120 s. The U/I service shows the highest impact of TPD: 0.1% of the results are misled with more than 120 s delays. The high-speed and H/I services show the lowest impact: only 0.05% and 0.23%, respectively, of the delay errors are between 30 and 60 s.

By considering that an urban service requires the highest performance, mixing an urban service with an intercity service leads to a service sensitive to the TPD, which could increase the sum of the trains' delay (overall delay error) to more than 120 s (up to 156 s in Fig. 5.14). Therefore, the speed of the train has an impact on TMS performance using a non-systematically inaccurate train positioning system. The TMS for low- and medium-speed services requires more accurate positioning data than that for high-speed services in order to deliver a reliable prediction of future train traffic and so an accurate traffic plan. The TMS of high-speed services is more capable of using a less accurate positioning system to provide a reliable solution. However, in general, the results of this experiment clearly demonstrate that more than 97% of the accurate optimal TMS solutions can be achieved with a positioning system that has uncertainty of ±500 m with high probability distribution around ±100 m, regardless of railway service type.

5.7 Discussion

The experiments described in this chapter were conducted to test the thesis sub-hypothesis related to punctuality, which states that railway punctuality can be improved by using a TMS application with a low-cost low-accuracy positioning system. The hypothesis has been formed in the context of the TMS evaluation framework shown in Fig. 5.1. The chapter shows that the TMS of all types of railway services are somewhat vulnerable to the influence of positioning uncertainties. The results of this chapter demonstrate that for the cases studied more than 97% of the accurate optimal TMS solutions can be achieved with a positioning system that has uncertainty of ±500 m with high probability distribution around ±100 m, regardless of railway service type. The extra delays caused by TMS choosing a suboptimal order due to the impact of positioning uncertainties were up to 156 s. Therefore, the above results have met the sub-hypothesis. The results also indicated that the low-speed services are affected more by positioning uncertainties than the high-speed services.

The RSSB T892 report indicates that TMS system needs ±17 m positioning uncertainty, see Table 2.7. Based on the results of this chapter, it is expected that using the RSSB T892 proposed accuracy will improve the application performance on all railway lines in the case studies used. From Table 2.4, the most extreme conditions are either in urban or high-speed services. Accordingly, it is expected that the highest application performance required is in urban and high-speed services. The results of this chapter clearly demonstrate that the high-speed services are less affected by positioning uncertainties among other services. Therefore, RSSB T892 proposed positioning accuracy, ±17 m, is potentially an over specification for the most railway services. This over specification of positioning accuracy will significantly increase the service initial costs and so the operational costs. Because the urban service requires high application performance and the above results shows it is highly affected by positioning accuracy, RSSB T892 proposed positioning accuracy, ±17 m, could be required for TMS applications to cover all conditions experienced by an urban service.

5.8 Conclusions

Punctuality is a key topic for the railway industry. Railway systems frequently encounter unpredictable disturbances that can lead to traffic conflicts and, consequently, train delays. This chapter has pointed out the relationship between the accuracy of train positioning data and train delays when using an intelligent TMS. The framework, which is described in Chapter 3, has been populated with general TMS-related variables. Then, the framework has been implemented with the parameters of the modelled TMS in three case studies. The framework is used to test the thesis hypothesis and demonstrate the impact of different scenarios of positioning uncertainty on the TMS outcome. After that, the desired position resolution associated with acceptable TMS performance can be characterised.

The study indicates where the positioning uncertainty has a great impact and how this uncertainty can influence TMS functions. The results indicate that the accuracy of train positioning data influences the prediction function of future traffic state in two ways. The first is that positioning uncertainty can influence the prediction of trains' remaining journey time and so the trains' delay. The second is that positioning uncertainty can influence the prediction of the state of the signalling system.

Increasing the magnitude of the positioning deviation increases the probability of the TMS providing suboptimal solutions. The impact of positioning uncertainty on the TMS can be increased when combined with uncertainties in other railway parameters. The impact of positioning uncertainty is far less than the impact of prediction uncertainty. The impact of prediction and positioning uncertainties together can increase the probability of a TMS providing suboptimal solutions compared to the impact of prediction uncertainty individually; however, it usually does not increase the overall delay errors of the suboptimal orders, except when the prediction severely deviates.

The size of the impact of positioning uncertainty depends on the speed of trains and the magnitude of the deviation in train positions. Therefore, this influence varies among railway service types. The results show that the TMS of low- and medium-speed services is affected by the train position uncertainty more than high-speed services. Therefore, for each specific network, a TMS might need to have a positioning system reporting at a specific accuracy level to perform at an agreed quality level. On the whole, more than 97% of the accurate optimal TMS solutions are achievable with a positioning system that has uncertainty of ±500 m with high probability distribution around ±100 m for all railway services.

The three implementations of the framework demonstrate how the framework can be utilised and how the application outputs can be understood. In other words, it helps to understand the relationship between the input parameters and the output behaviour. Different TMS types and different railway services could have different parameters and so need different framework implementation.

6 Impact of Positioning on Railway Capacity

6.1 Introduction

Demand for passenger and freight railway services has increased rapidly in recent years [192]. This puts the railway system under pressure to maximise the use of available capacity, which leads to saturated routes and stations and increased train delays. As stated by [82], the target of increasing capacity by 10% can be achieved by implementing an intelligent TMS. This chapter is carried out to test the thesis sub-hypothesis related to capacity, which states that the capacity consumption of railway lines can be increased without negatively affecting the railway punctuality by using a TMS application with low-cost low-accuracy positioning system. This chapter presents a test of the hypothesis by the implementation of the thesis framework for railway capacity when using an intelligent TMS. The framework was implemented on a TMS application using timetables with different levels of capacity. The chapter first provides a review of railway capacity concepts and measurements, followed by a description of how different levels of capacity are considered in this study. The framework was implemented on a case study of Dundee Central Junction, in Scotland, UK. Then, based on the experimental results, conclusions about the impact of railway capacity on an intelligent TMS using inaccurate positioning data were made. The work of this chapter has been published in part as a conference paper [193] DOI: 10.1109/ICIRT.2018.8641580, of which I am the primary contributor and lead author.

6.2 Introduction to Railway Capacity

In urban public transport, the demand for passenger and freight services generally is growing more than the capacity of the existing railway system. The term ‘railway capacity’ can have two different meanings: the capacity to carry passengers, and line capacity. Passenger capacity is the number of passengers that can be accommodated in a passenger train [3]. Line capacity can theoretically be indicated by the maximum number of trains that can be included in a timetable without conflict [84][194]. Railway timetables are designed to be conflict-free, and are typically based on a pre-set deterministic headway times between stations [20]. Line headway time is the interval between the departure times of two successive trains, which includes the minimum headway and some additional buffer time. The minimum headway time is calculated based on (fixed) blocking time theory which incorporates the signal set-up time, sighting and reaction time, approach time, running time, clearing time and release time

[121]. Buffer time is an additional time added to the minimum headway in order to prevent minor train delays from propagating to following trains [121].

The characteristics of the railway control system, especially signalling system design, have a substantial impact on railway line capacity. One way to improve railway capacity is to upgrade the control system to one that allows a closer headway between successive trains, i.e. increase the signalling aspect or adopt a moving block control system. Another way is to trim the trains' headway by reducing the additional times incorporated in the timetable. The second solution could increase railway traffic sensitivity and the potential for conflicts, thereby increasing train delays in the case of disturbance. In order to help cope with this issue, an intelligent TMS can be introduced.

Line capacity is measured in diverse ways in the railway industry [195]. However, generally there are two main concepts used to evaluate railway line capacity. The first concept expresses the traffic volume, describing the number of trains passing a point over a time period, typically trains per hour (tph). The second concept expresses the track occupation volume, which represents the percentage of track usage over a time period. The International Union of Railways (UIC) has formulated these two concepts in methods UIC 405 and UIC 406, respectively.

In this study, UIC 406 was used to evaluate the capacity of a railway network, based on compressing the timetable. In this method, the railway capacity consumption can be presented as a percentage describing the actual infrastructure occupation for a given period of time [196]. The first step in evaluating the capacity of a railway line is to divide the railway line into several sections on the basis of any change in infrastructure and timetable characteristics. The next step is to calculate the occupancy times of the infrastructure by pushing all the train paths together, using only the minimum headway between trains. In this step, all the buffer times are eliminated from the original schedule. The capacity consumption is calculated as follows [196]:

$$Capacity\ consumption\ (\%) = \frac{occupancy\ time * (1 + additional\ time\ rate)}{defined\ Time\ Period} * 100 \qquad (6.1)$$

The additional time rate is based on the type of line and services and whether the defined time period is in peak hours or not [196]. If the capacity consumption is less than 100%, the line capacity is not fully utilised and there is a possibility of adding extra trains. For a junction area, the occupancy time of all intersecting trains should be measured without overlap and considering the scheduled junction passage order. UIC 406 considers a different additional time rate for the switching area (junction), which should be taken into account with junction occupancy time. The highest capacity consumption value among the line sections is presented as the line capacity of a whole train path (the train service). Extra trains can be added until the capacity consumption reaches 100%. Moreover, extra trains might be added to specific line sections whose capacity is still less than 100%, without affecting the capacity consumption of the whole train path.

However, increasing the number of trains, and so decreasing the additional times, in a railway timetable leads to saturated routes and stations. Decreasing the additional times in the trains' practical headway increases the likelihood of conflicts between services and the number of red signal approaches. An intelligent TMS can be introduced to help cope with traffic conflicts and return the trains back to the scheduled timetable, thus reducing delays. In this study, the impact of different passenger timetable capacities on the effect of TMS was investigated using inaccurate positioning data.

6.3 Application of the Framework to Capacity

To investigate the impact of different levels of capacity on a TMS with positioning uncertainty, the general framework for TMS application shown in Fig. 5.1 can be used. The experiment reuses the framework with timetables representing different levels of capacity utilisation. The difference between the timetables focuses on the number of extra trains and the allowance times between the extra trains, in each implementation. The same railway simulator, train position model and TMS application model as in Chapter 5 were used in this experiment.

Timetables with different capacities need to be prepared before carrying out the experiment. The capacity consumption of the working timetable of the studied area should be calculated first. If there is a possibility to add an extra train to the number of trains (Tn) in the working timetable, a new timetable will be designed for (Tn+1) trains. If still there is a possibility to add extra trains, new timetables should be designed by adding one extra train to the prior timetable. In this case, the headways are different between the timetable of one extra train and the timetable of two extra trains, etc. Another way to design different timetables is by using the same number of extra trains but with different headways; the experimental details are given in Section 6.4. The experiment should be carried out on the case study timetable first. Then, the experiment should be repeated for each new timetable. The impact of adding trains to the original timetable can be observed by comparing the outputs of the experiments in terms of the suboptimal orders that have been produced and the overall delay caused.

6.4 Experiments

This chapter is carried out to test the thesis sub-hypothesis related to railway capacity, which states that the capacity consumption of railway lines can be increased without negatively affecting the railway punctuality by using a TMS application with low-cost low-accuracy positioning system. As discussed earlier, the intercity service may require the lowest application performance among the other services based on the information presented in Table 2.4. In this chapter, the experiments are conducted mainly on a low traffic density intercity service because it is expected that TMS application can handle disturbances resulting from increased operational capacity of a low traffic density service. Afterwards, discussion is made on how the results of intercity service would translate to the other railway services. To quantify the impact of positioning uncertainty in a realistic case on timetable capacity, the following experiment was carried out. The case study and the capacity consumption are presented first; the experimental parameters and the results are then discussed.

6.4.1 Case Study

A case study was used to demonstrate the impact of train positioning uncertainty on the traffic management system, using timetables with different levels of capacity consumption. The case study is based on Dundee Central Junction in Scotland, UK. The junction joins the route between Ladybank and Arbroath with the route between Perth and Arbroath. Fourteen stations are modelled, as shown in Fig. 6.1. Perth station contains five through platforms and two terminal platforms; Dundee station contains two through platforms and two terminal platforms; the other stations contains two through platforms. The line length for both routes is around 60 km, the block section size is around 1.5 km and the gradient profile is almost flat. The movement of the train on the track is regulated by a conventional three-aspect lineside signalling system.

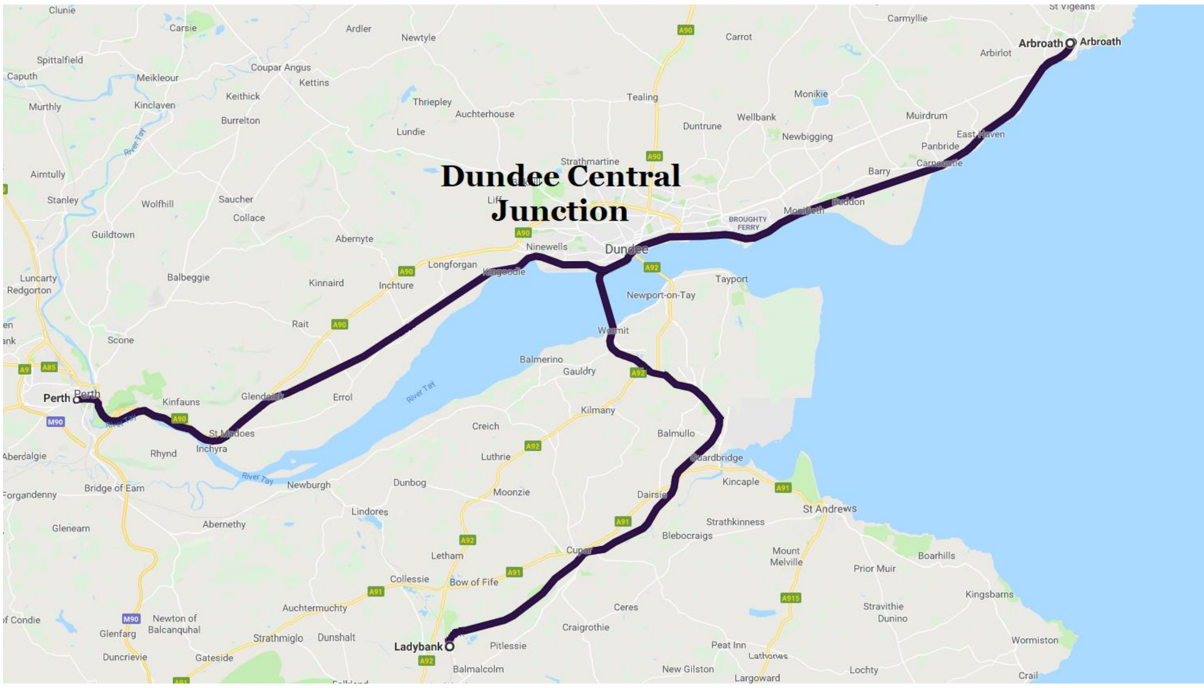


Fig. 6.1 (a) Routes considered (from Google map)

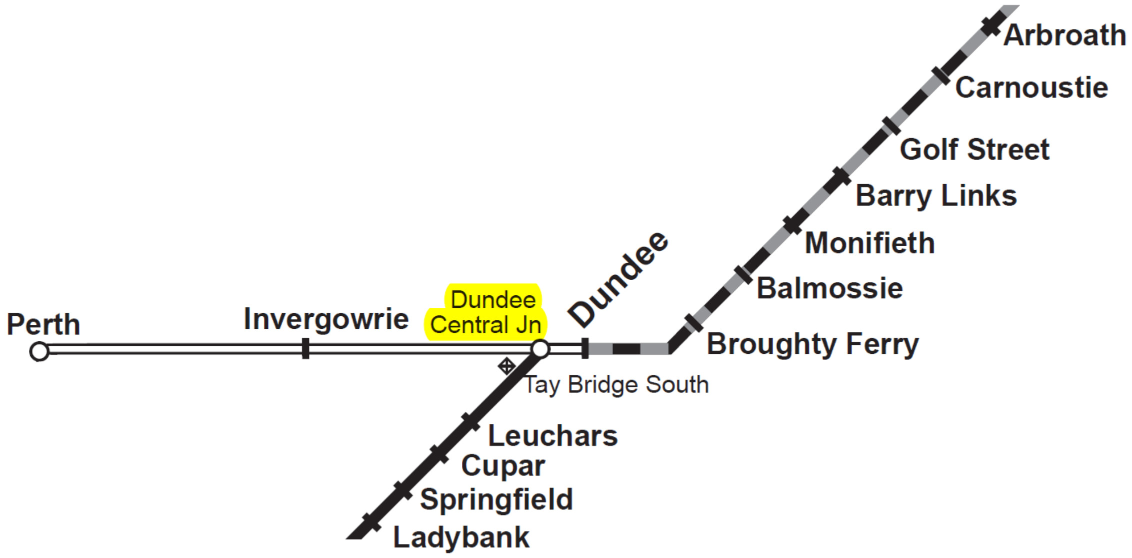


Fig. 6.1 (b) case study infrastructure [5]

The morning peak hour timetable, 7:00 am to 8:00 am for a normal working day was used. There are eight passenger trains dispatched through the studied area during this time. Fig. 6.2 shows the space–time diagram representing the traffic in the studied area during this time period, where A refers to stations in the direction of Perth, B refers to stations in the direction of Ladybank and C refers to stations in the direction of Arbroath. In Fig. 6.2, Perth and Ladybank are at the same point because the distance is the same. Two classes of passenger train are used: Class 150 is used for Trains 1, 4 and 6 and Class 375 is used for Trains 2, 3, 5, 7 and 8.

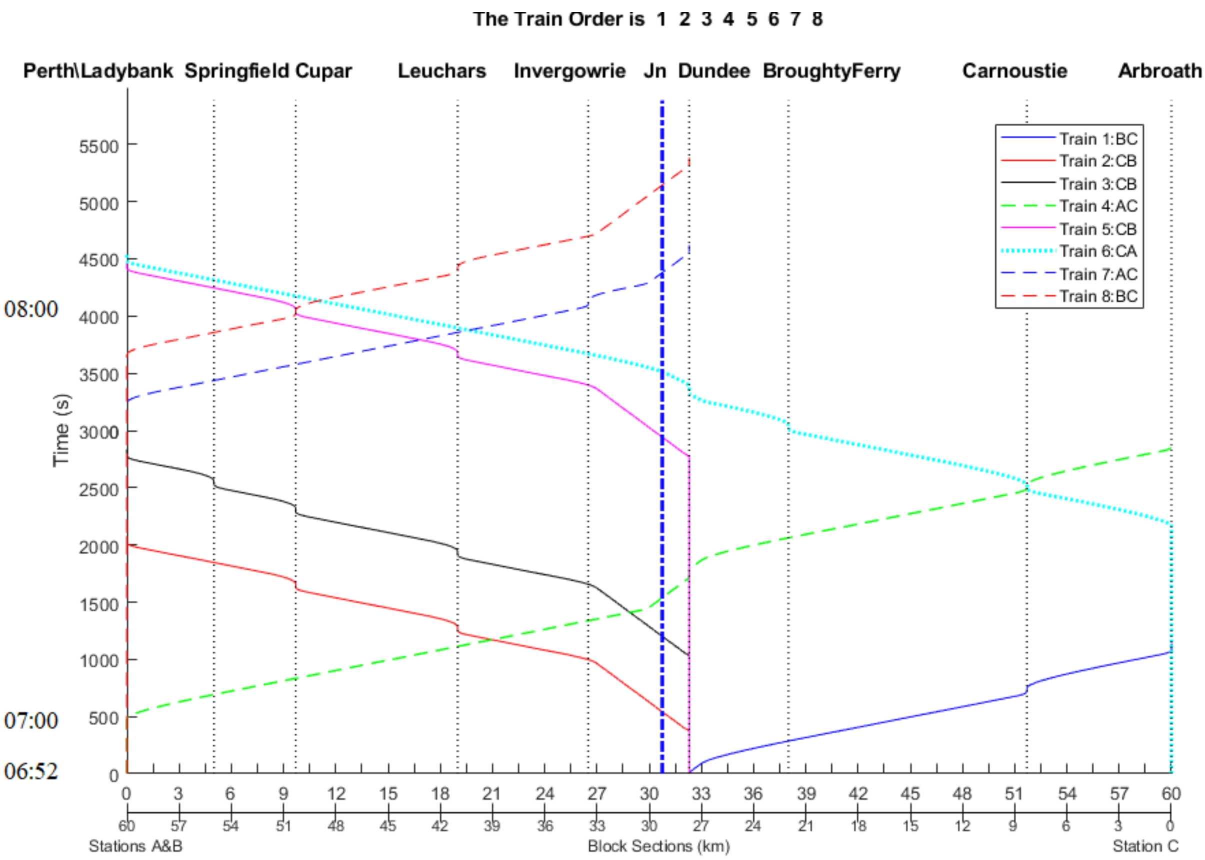


Fig. 6.2 Space–time diagram of the working timetable [193]

6.4.2 Capacity Consumption

The UIC 406 procedure was used to evaluate the capacity of the working timetable. First, the routes were divided into the junction area Jn-D and three line sections, A-Jn, B-Jn and D-C, where Jn refers to Dundee Central Junction and D refers to Dundee station. Each line section was evaluated in both directions separately. The junction area was evaluated by considering all the intersecting paths. Due to the peak hour of the timetable segment used, the UIC 406 recommended additional time of 18% was considered in calculating the capacity of the line section, and 33% was considered for the junction area [196]. The capacity of the working timetable is the maximum value of the line section capacities as shown in Table 6.1.

Table 6.1 Capacity consumptions of the case study, adapted from [193]

Line	Capacity consumption of line sections			Capacity consumption of the line
Perth to Arbroath (A-Jn, Jn-D, D-C)	A-Jn = 41%	Jn-D = 45%	D-C = 43%	45%
Arbroath to Perth (C-D, D-Jn, Jn-A)	C-D = 39%	D-Jn = 36%	Jn-A = 36%	39%
Ladybank to Arbroath (B-Jn, Jn-D, D-C)	B-Jn = 49%	Jn-D = 45%	D-C = 43%	49%
Arbroath to Ladybank (C-D, D-Jn, Jn-B)	C-D = 39%	D-Jn = 36%	Jn-B = 66%	66%

Since the capacity of the working timetable in all cases is less than 100%, more trains could be added to the timetable until the capacity reaches 100%. For the purpose of this study, the impact of adding two trains to the original working timetable with different practical headways was investigated. The timetable was extended by inserting two extra trains from Arbroath to Perth, which are the same as Train 6 in Fig. 6.2. The two additional trains increase the capacity of the Arbroath to Perth and Ladybank to Arbroath paths to 59%. The capacity of the ⇐ Arbroath to Ladybank path is still 66% due to the capacity of the last line section being higher than the junction area. The additional trains do not affect the capacity of the Perth to Arbroath path.

Since train headway is inversely proportional to timetable capacity, in this experiment, the impact of adding trains with three different headways was investigated, first with 480 s headway (305 s minimum headway and 175 s buffer time), second with 365 s (305 s minimum headway and 60 s buffer time) and third with only the 305 s minimum headway. A recovery time supplement of 3% of the train running time was used for all trains in all timetables in this experiment.

The study investigated the impact of uncertainty in the train positioning data on the TMS applied to four different timetables (the working timetable of eight trains and the three extended timetables of 10 trains). Comparing the outcomes of the four experiments indicates the impact of the differences in timetable capacity on the TMS under a stochastic operating environment.

6.4.3 Experimental Parameters

For the purpose of this study, 150 operational disturbance scenarios were created. Each scenario was composed of a single train delay chosen from a uniform probability distribution in the interval |300, 800| seconds. The delay was allocated an equal number of times to Trains

5 to 9, i.e., each train was allocated 30 of the 150 scenarios. All of the operational disturbance scenarios were simulated and saved to be used in the experiments. For the experiment using a working timetable of eight passenger trains, the scenarios for Train 9 were ignored and the experiment was carried out only with 120 scenarios. To assess the positioning uncertainty separately from prediction uncertainty, a 1 s prediction update rate, PUR1, was used; see Section 5.4.3 for more details. A hundred lists of train positioning deviations TPDs were simulated for each operational disturbance using probability function 1; see Section 5.4.2 for more details. Each list contains TPDs for 10 trains; in the first experiment with a working timetable of eight trains, the last two TPDs were ignored. For each timetable, the operational disturbance scenarios were repeated 100 times using the 100 simulated TPD lists.

6.4.4 Results and Analysis

The 150 scenarios were studied for the four timetables (the working timetable and the three developed timetables). In a similar way to what is illustrated in Chapter 5, the deviations in the train positioning data cause errors in predicting the trains' future movement and so can lead the TMS to provide a suboptimal train order. The results show that in only seven scenarios of operational disturbance is the TMS is affected and provides suboptimal solutions. In all of these seven scenarios, the disturbed train is Train 5. All initial disturbances to Trains 6, 7, 8 and 9 do not affect the TMS when it runs with inaccurate train positioning data. This is because the difference between the highest ranked (shortest delay) train orders – the predicted rescheduling cost difference – is very high and so the ±500 m positioning uncertainty are not enough to mislead the TMS.

The highest impact of TPDs on TMS, among the seven scenarios of operational disturbance, is when Train 5 departs 610 s late from Dundee station. This scenario will be discussed and then compared with the results of the other suboptimal scenarios. The details of the working timetable experiment are as follows. Firstly, Train 5 was delayed by 610 s at departure from Dundee station. The TMS detected the potential conflict and provided the optimal solution, {1,2,3,4,6,5,7,8} train order, which was based on using accurate positioning data. The RNS applied the optimal solution which caused a delay of 666 s at the final destination of Train 5, while all the other trains arrived at their scheduled times. Secondly, the experiment was repeated using the 100 combinations of TPDs. Eighty percent of the experimental solutions gave the optimal solution train order {1,2,3,4,6,5,7,8}. However, 20% of the experimental solutions gave the suboptimal {1,2,3,4,5,6,7,8} train order. When the RNS applied this suboptimal train order, the train delays were 561 and 162 s for Trains 5 and 6, respectively. The trains' overall delay was 723 s. This means that 20% of the TPD lists misled the TMS and thereby increased the overall delay by 8.56% compared to the optimal solution. Table 6.2 shows a summary of the experimental results of each timetable in a column.

For the second experiment when two trains were added to the timetable with 480 s headway, the result was exactly the same as for the first experiment. This is because the buffer time stops the extra delay that was caused by the suboptimal order from propagating to Trains 9 and 10. In contrast, in the third experiment, once the buffer time is only 60 s, Train 9 was affected and suffered a 33 s delay. In the fourth experiment, once only the minimum headway was used for the added trains, the extra delay caused by the suboptimal order propagated to Train 9 (93 s) and Train 10 (24 s).

Table 6.2 Impact of positioning uncertainty on TMS with different capacity consumptions

Experiment	**1**	**2**	**3**	**4**
Railway timetable	**8 trains** ***(working timetable)***	**10 trains** ***(2 extra trains with 175 s buffer time)***	**10 trains** ***(2 extra trains with 60 s buffer time)***	**10 trains** ***(2 extra trains with minimum headway)***
Disturbed train	5	5	5	5
Disturbance time	610 s	610 s	610 s	610 s
Optimal solution				
Optimal order	{1,2,3,4,6,5,7,8}	{1,2,3,4,6,5,9,10,7,8}	{1,2,3,4,6,5,9,10,7,8}	{1,2,3,4,6,5,9,10,7,8}
Overall delay	666 s	666 s	666 s	666 s
Experimental solutions (100 solutions)				
Affected cases	20%	20%	16%	2%
Suboptimal order	{1,2,3,4,5,6,7,8}	{1,2,3,4,5,6,9,10,7,8}	{1,2,3,4,5,6,9,10,7,8}	{1,2,3,4,5,6,9,10,7,8}
Overall delay	723 s	723 s	756 s	840 s
Overall delay error	57 s	57 s	90 s	174 s
Overall delay error	8.56%	8.56%	13.51%	26.13%

It can be noticed from Table 6.2 that the difference between the optimal and experimental solutions, in terms of overall delay, is increased by decreasing the train headways. Due to the increase in the difference between the overall delay of the optimal and suboptimal train orders, the volume of TPDs capable of influencing TMS increases, i.e. increasing the positioning deviation threshold, as shown in Section 5.6.1.3. This explains why the percentage of cases affected decreased in experiments 2, 3 and 4, respectively, where only a high TPD is capable of misleading TMS solutions. The details of why the percentage decreased are as follows. It has been observed from the experimental data that the TMS is highly influenced by the positioning deviation of Train 5, TPD5. When the TMS evaluates the optimal order, TPD5 does not affect the delay prediction since Train 5 waits for Train 6 to clear the junction. Whereas when the TMS evaluates the suboptimal order, the forward TPD5 decreases the predicted delay of Train 5 and subsequently Train 6. Therefore, it was found in the first two experiments that every time TPD5 is above +245 m, the TMS is affected and provides a suboptimal train order. In experiment 3, it was found that the TMS is affected only when TPD5 is above +315 m. In experiment 4, the TMS is affected only when TPD5 is above +467 m.

As mentioned earlier, only seven scenarios of operational delays showed suboptimal train orders in their results. Table 6.3 shows these seven experiments affected by TPDs; it shows the percentage of cases affected, in which a suboptimal train order is presented, and the impact of the suboptimal orders on the overall train delays when the RNS applies them. It can be noticed from Table 6.3 that the difference between all the disturbance times of Train 5 is only within 78 s, between 540 and 618 s. This is where the difference in overall delay between the optimal and suboptimal orders is not very high (less than 3 minutes). In the 540 and 556 s scenarios, the optimal order gives priority to Train 5, to pass the junction before Train 6, {1,2,3,4,5,6,7,8}. In the 597, 605, 610 and 618 s scenarios, the optimal order gives the priority to Train 6 before Train 5, {┅,**6,5,**┅}. In the 578 s scenario, the optimal order gives the priority to Train 5 in experiments 1, 2 and 3 while in experiment 4 the priority is given to Train 6.

When the optimal order is {┅,5,6,┅}, decreasing the headway increases the number of affected cases and decreases the amount of delay errors, for instance no. 2 in Table 6.3. When the optimal order is {┅,**6,5**,┅}, decreasing the headway decreases the number of affected cases and increases the amount of delay errors, for instance no. 4 in Table 6.3. In no. 5 and 7 of Table 6.3, the difference between optimal and suboptimal increased to a point where the modelled TPDs (±500 m) were not enough to mislead the TMS. In general from Table 6.3, the impact of TPDs on the percentage of the overall delay error increases by decreasing the trains' headway. The TPDs increased the overall delay by around 11% in experiments 1 and 2, by 17% in experiment 3 and by 26% in experiment 4. Furthermore, the results of experiments 1 and 2 are exactly same in all the affected cases, even though two trains have been added to the timetable for experiment 2.

Table 6.3 Scenarios affected by positioning uncertainty

No.	Operational Disturbance		Experiment 1			Experiment 2			Experiment 3			Experiment 4		
	Train ID	Delay s	Affected cases %	Delay error s	Delay error %	Affected cases %	Delay error s	Delay error %	Affected cases %	Delay error s	Delay Error %	Affected cases %	Delay error s	Delay error %
1	Train 5	540	0	0	0	0	0	0	0	0	0	16	58	9.54
2	Train 5	556	7	51	8.29	7	51	8.29	12	49	7.94	51	10	1.52
3	Train 5	578	39	7	1.06	39	7	1.06	44	5	0.76	26	56	8.41
4	Train 5	597	36	31	4.65	36	31	4.65	34	50	7.51	7	115	17.27
5	Train 5	605	20	47	7.06	20	47	7.06	18	75	11.26	0	0	0
6	Train 5	610	20	57	8.56	20	57	8.56	16	90	13.51	2	174	26.13
7	Train 5	618	10	73	10.96	10	73	10.96	8	114	17.12	0	0	0

It was noticed from the experimental data that the impact of TPDs on the delay prediction of train order varies between the experiments. The predicted overall delay of all the feasible train orders in experimental solutions was compared to the same predicted overall delay in the optimal solution. The ranges of the errors in predicted delays caused by the same TPDs are ± 90, ± 110, ± 130 and ± 170 s for experiments 1, 2, 3 and 4, respectively. The range of errors is increased by decreasing the train headways. This does not necessarily mean that the number of affected cases increase, because the error could still be increased for both optimal and suboptimal train orders in a way that still the actual lowest overall delay is predictable. Besides that, increasing the number of trains in the conflicted area increases the number of data uncertainties, which are input to the TMS, and so increases the errors in the predicted delay of train orders.

Overall, of (15000 × 4) cases investigated, only 132 (0.88%) cases were affected in experiments 1, 2 and 3 by a TPD around ± 100 m while only 102 (0.68%) cases were affected in experiment 4; and the highest increased in overall delay caused by suboptimal orders was less than 3 minutes. To conclude, for this case study, increasing the timetable capacity by decreasing the train headway increases the difference in overall delay between the train orders and so increases the overall delay errors. By increasing the difference between the train orders, low TPDs might not be able to mislead the TMS.

6.5 Discussion

The thesis sub-hypothesis, related to capacity consumption, states that capacity consumption of railway lines can be increased without decreasing the railway punctuality by using a TMS application with a low-cost low-accuracy positioning system. This chapter shows how the hypothesis has been tested. The results of the chapter demonstrate that railway capacity can be improved on a low traffic density line using TMS supported by a low-cost low-accuracy positioning system. The results also show that more than 99% of the accurate optimal TMS solutions can be achieved with a positioning system that has uncertainties of ±500 m with high probability distribution around ±100 m, on a low traffic density intercity service. The extra delays, caused by the less than 1% suboptimal orders chosen due to the impact of positioning uncertainties, were less than 3 minutes. Therefore, the above results have met the sub-hypothesis.

The experiment conducted in this chapter was on a low traffic density intercity service. It is expected based on the results of this chapter that by using the RSSB T892 proposed accuracy for TMS, which is ±17 m uncertainty, the capacity consumption of all types of railway services can be improved without negatively affecting the railway punctuality by using a TMS application. The expectation is that a TMS of high performance quality (by using the RSSB T892 proposed accuracy, ±17 m) can handle traffic disturbances caused by increased trains in the timetable and thus improve the system capacity of different types of railway services. However, building such a system needs high investment in trackside infrastructure and control systems. It is important to indicate that the positioning and communication systems are different between the railway services; see Section 2.2.5 for more details. This makes the cost of developing a system to provide the RSSB T892 proposed accuracy, ±17 m different between the service types. For instance, the time uncertainty of WLAN (one of the urban communication system) can be up to several hundreds of milliseconds [55] while the timing uncertainty of GSM-R (intercity and high-speed communication system) can be up to 10 s [42][29][95]. As has been seen in Table 2.3, the impact of these time uncertainties on the positioning data accuracy is very diverse. High-speed services could need a communication system with very low communication latency compared to a WLAN system.

This thesis aims to bring the attention of the railway industry to the fact that many automated and intelligent applications can be used on wide range of railways with acceptable performances with low-cost low-accuracy positioning systems.

6.6 Conclusions

This chapter demonstrates how the hypothesis can be tested and how the proposed framework can be adapted to be used for the purpose of different investigations and measurements on a TMS with inaccurate positioning. Moreover, the study demonstrates how changing one parameter of the input module of the framework can influence the TMS output. This chapter also provides a preliminary study on the impact of TPDs on a TMS with different timetable capacities. The results indicate that the timetable capacity has a direct impact on the magnitude of overall delays that are caused by the same suboptimal solution. The suboptimal solution has a different impact on the railway network based on the number of trains in the network considered. By increasing the number of trains, the buffer time of each train will be decreased. Therefore, the impact of a suboptimal solution could propagate to more trains and cause more delays. On the other hand, decreasing the buffer times does not necessarily mean increasing the number of affected cases because that is subject to the positioning deviation threshold which is itself subject to the difference between the predicted overall delays of train orders. Finally, majority of railways design the timetables typically based on a pre-set deterministic headway times between the stations. The results of this study shows that using a TMS with low-accuracy positioning systems can provide the same performance as one with high-accuracy positioning systems, where adequate buffer times are included in the timetables. Therefore, finding the adequate buffer times for each railway system, by implementing the framework proposed in this study, can significantly improve the railway capacity when railway systems are supported by TMS with low-accuracy positioning systems on non-high density railway routes.

7 Conclusions and Further Work

7.1 Conclusions

7.1.1 Summary

This thesis set out to develop a framework that enables a structured investigation into the positioning accuracy required for new automated and intelligent railway subsystems and applications. In order to do so, in Chapter 2, a review was carried out on railway service types, current train positioning methods, proposed future positioning systems and the railway applications that use train position data. The review indicates the gap in understating the balance between the accuracy of the required positioning and the quality of application performance required on different types of railway networks. After that, a framework was presented in Chapter 3 that enables consideration of the combined performance of a particular railway application, railway positioning system and railway infrastructure. To validate the suitability of the framework developed, it was implemented for DAS and TMS applications, and the impact of positioning uncertainties on railway performance was evaluated in terms of energy, punctuality and capacity in Chapters 4, 5, and 6, respectively.

7.1.2 Thesis Hypotheses

This thesis started with three sub-hypotheses, each of which relates to a specific assessment measure for railway performance, with respect to the positioning requirements.

- *Energy consumption in the railway sector can be reduced by using a DAS application with a low-cost low-accuracy positioning system.*

In order to investigate the above hypothesis, a simulated stand-alone DAS was developed, which is presented in Chapter 4. A genetic algorithm GA was developed to calculate the optimised train trajectory by finding the optimal acceleration and deceleration rates and optimal coasting and braking points. Its aim was to reduce train energy consumption whilst maintaining journey time. The experiment was carried out on three different model sections of an intercity line, the East Coast Main Line, with different track gradients, characterised as uphill, downhill and changing gradient routes. The GA identified the optimised train trajectory for each of the three sections considering their geometry. It was found that by using highly accurate positioning data, the optimised train trajectory could save 18% to 35% of the train energy consumption, depending on the gradient of the track.

The DAS developed used a simulated low-cost GNSS to advise the train driver of the optimised speed and driving mode for that position. Two scenarios of positioning deviations were investigated. Analysis of the results showed that an uncertainty of under ±500 m in the train positioning data increased the energy consumption by less than 0.7%, 5.2% and 1.5% for the specific uphill, downhill and undulating lines, respectively, compared to a perfect positioning system. Therefore, within the scope of the research, the analysis has shown that the first hypothesis is achievable.

- *Railway punctuality can be improved by using a TMS application with a low-cost low-accuracy positioning system.*

A prototype TMS was developed in Chapter 5 to test the hypothesis. The TMS objective was to minimise the overall arrival delay of all trains at their destinations. This was done by providing an optimal train order to pass the conflicted area. A BF search method was employed to find the optimal train order that mitigates the impact of an operational disturbance. The TMS was applied on models of Stenson and North Stafford junctions in the UK. Urban, intercity, high-speed and freight services were considered. Three- and four-aspect signalling systems were used to regulate the train movement. A Monte Carlo simulation scheme was used to model positioning deviations of between 0 and ±500 m. The investigation was carried out in three different experiments. Analysis of the results of Chapter 5 demonstrated that train positioning uncertainty could only reduce the TMS performance slightly. The results of the 15000 experiments (Section 5.6.3.4) indicated that only 0.88% of the experiments were affected when the majority of positioning deviations were around ±100 m, and only 1.15% of the experiments were affected when the majority of positioning deviations were around ±450 m. The results also show that the impact of positioning uncertainty is far less than the impact of uncertainties associated with predicting running times. The impact of positioning uncertainty on the TMS can be increased when combined with uncertainty of TMS prediction. The highest impact of the positioning uncertainty on the TMS was shown with mixed-traffic services, which reached 3.05%. Therefore, within the scope of the research, the analysis has shown that the second hypothesis can be met.

- *The capacity consumption of railway lines can be increased without negatively affecting railway punctuality by using a TMS application with a low-cost low-accuracy positioning system.*

In order to justify the third hypothesis, a low traffic density intercity service was investigated. The case study was on the routes that meet at Dundee Central Junction in Scotland, UK.

There are 14 stations in the area investigated. Capacity consumption of the working timetable during the morning peak hour (7:00 am to 8:00 am) was assessed using the UIC 406 compression method. Two extra trains were added to the working timetable. In order to represent different traffic densities, the two trains were added with three different headways in three different timetables. Through (15000 × 4 experiments) cases investigated, only 0.88% of the cases were affected by a positioning uncertainty of ±500 m with high probability distribution around ±100 m when the train headway includes additional times; while only 0.68% of the cases were affected when the train headway does not include additional times. However, the latter caused a higher increase in overall delay compared with the former. Analysis of the results indicates that the number of trains in a timetable can be increased without reducing railway punctuality by using a TMS with a low-accuracy positioning system on non-high density railway routes, thus agreeing with the third hypothesis.

7.1.3 Key Achievements

A number of key results and achievements were obtained in this thesis, which are based on the case studies investigated, as follows:

- A general framework for evaluating the impact of train positioning uncertainty on railway applications has been developed.
- This thesis populated the framework with general dynamic DAS-related variables. The DAS framework has been successfully applied to specific case studies with an S-DAS application. From this the following points were achieved:
    a. Demonstration of the significant differences in traction energy-saving solutions regarding line gradient (uphill, downhill and undulating);
    b. Evaluation of the impact of positioning accuracies on the optimised train trajectory applied by DAS in terms of energy saving;
    c. Evaluation of the impact of positioning accuracies on the optimised train stopping process in terms of energy consumption and journey time;
    d. Introduction of a comparison between the impact of human driver behaviour in following the DAS advice and the impact of positioning uncertainty in terms of energy saving.

- In this thesis, the framework was filled with general dynamic TMS-related variables. The TMS framework has been successfully applied to a prototype TMS (train rescheduling) application on specific case studies, and the following points were achieved:
    a. Introduction of the accuracy of positioning data in real time at the TCC as a function of positioning sensor accuracy and communication latency;
    b. Introduction of the concept and relevance of the positioning deviation threshold;
    c. Demonstration of the difference in the effect of positioning uncertainty between FCFS and optimised TMS strategies;
    d. Demonstration of a way to assess the influence of uncertainties in train positioning information in real time on the TMS rescheduling process;
    e. Demonstration of the influence of operational disturbances on the TMS rescheduling process;
    f. Demonstration of the influence of prediction uncertainty on the TMS rescheduling process;
    g. Comparison of the impact of positioning uncertainty with the impact of prediction uncertainty;
    h. Demonstration of the influence of driver behaviour on applying the optimised TMS solutions;
    i. Demonstration of the impact of diversity in railway networks and services on the TMS rescheduling process;
    j. Introduction of the impact of positioning uncertainty on the TMS rescheduling process regarding mixed traffic in addition to the urban, intercity, freight and high-speed lines.
- This thesis successfully applied the TMS framework with variables related to timetables with different levels of capacity consumption in a case study, and achieved the following:
    a. Demonstration of the influence of uncertainties in train positioning information on traffic rescheduling with different timetable capacities;
    b. Comparison of the impact of different timetable capacities on the magnitude of overall delays with the same circumstances of TMS solution;

c. Introduction of the effect of increasing timetable capacity on TMS performance under the same circumstances of positioning uncertainty;
d. Introduction of the relationship between railway capacity, positioning accuracy and TMS performance.

7.1.4 Findings and Contributions

The experiments conducted in this thesis indicate some important findings that can be summarised as follows:

- It was found that the magnitude of energy saving, through applying an optimised train trajectory, varies depending on the gradient of the line. The highest energy saving can be obtained on downhill lines and the lowest on uphill lines. Uncertainty of the positioning data decreases the efficiency of the DAS performance. The impact of positioning uncertainty is higher on a downhill line than on uphill or undulating lines. The whole analysis of the results of Chapter 4 demonstrated that more than 98% of the optimised energy consumption saving can be achieved with a low-cost low-accuracy positioning system that has around ±100 m uncertainty.
- It was found that train positioning uncertainty can reduce the TMS performance. Analysis of the results of Chapter 5 demonstrated that train positioning uncertainty can affect the TMS prediction of train arrival times. The magnitude of the impact depends on the speed of trains and the size of the positioning deviation. Therefore, this impact varies among railway service types. Analysis of the results showed that the TMS of low- and medium-speed services is affected by uncertainty of the train position more than those of high-speed services. Furthermore, analysis of the results demonstrated that the impact of train driver behaviour might be more than the impact of positioning uncertainty in terms of overall train delays. Moreover, the granularity of the prediction method for future traffic has a much higher impact than the accuracy of the positioning data on TMS performance.
- It was found that train positioning uncertainty can have a different impact on TMS under timetables with different levels of capacity consumption. However, analysis of the results showed that low-accuracy positioning systems have a similar effect on TMS applied to timetables containing a different number of trains per hour provided they are separated with adequate buffer times. The adequate buffer time can be

estimated by taking into account the relation between the number of trains, positioning uncertainty and the average speed of the trains.

7.2 Further Work

This study opens the door for further possible investigations that can be undertaken as future work. The further research can be on the framework, applications and case studies.

7.2.1 Framework

A framework has been developed in this study for the purpose of investigating the impact of train positioning uncertainties on railway applications that can be used to improve railway performance in terms of cost, carbon, capacity and customer satisfaction. Moreover, the framework helps in evaluating the cost-benefit of upgrading railway systems with new technologies. More than 50 applications, presented in Chapter 2, can be investigated under low-cost low-accuracy positioning systems by populating the application variables into the framework developed. The framework can be adapted for further investigations on different parameters, for example, the impact of uncertainties in condition monitoring sensors or in predicting future traffic events. To identify an optimised balance between the required performance and positioning accuracy, in future work, the framework can be extended to include a semi-automated optimisation and evaluation process.

7.2.2 Energy

This study investigates the impact of simulated positioning uncertainties on a simulated S-DAS system on an intercity train service. In the first instance, a practical application of this study with a low-cost low-accuracy positioning system in real field conditions is required. Further work can be undertaken on different types of railway service such as urban, freight and high-speed services. It is expected that less benefit can be obtained from implementing S-DAS with a low-cost low-accuracy positioning system on urban, freight and high-speed services than intercity services. This is because of the difficulty of applying an optimised coasting and stopping processes on these services with low-accuracy positioning system. Urban services have a high number of stops with short distances between them; freight and high-speed services need high safety performance due to the low braking rate and long braking distance. A GA has been used to optimise the traction, braking and coasting parameters in this study; in the literature, more parameters could be considered and so could require different positioning accuracy. C-DAS system has additional parameters and objectives such as reducing the traffic and delays at specific places. Therefore, further study on C-DAS is needed to find the balance between the implementation cost and required performance. Moreover, it would be beneficial, if it is possible, to collect a record of the practical positioning data for a low-cost sensor from the real field and then use it in an investigation on a modelled DAS and network. The positioning data record should consider all the railway geometry, for example, deep cuttings, high rise buildings, bridges and tunnels.

7.2.3 Punctuality

A prototype of a local TMS was used as an example of implementing the framework developed in this study. A BF search has been used to guarantee the optimal TMS solution and so it can be used as reference for the following stages with positioning uncertainty data. Further work can be undertaken on different types of optimisation method used in the TMS literature. It is expected that the uncertainties in the results of the optimisation method have a higher impact than positioning uncertainties.

The investigation in this study was carried out on a conventional fixed block signalling system which is usually based on a track circuit or axle counter train detection and localisation. A moving block signalling system uses a different positioning system, which is usually by odometry with balises, WLAN or inductive loop; therefore, a more dedicated investigation could be carried out on a moving block signalling system and its variables and uncertainties.

This study considered an open-loop local reordering TMS. A sophisticated closed-loop TMS with local/centralised retiming, reordering and rerouting of the trains on the railway network needs to be considered. It is expected that the impact of positioning uncertainty on a closed-loop system would be less than that on an open-loop system, given the possibility of improving the accumulated positioning information with short periodic calculation times. A simplified version of the Stenson and North Stafford junctions has been considered in this study. More practical work can be undertaken to compare the positioning requirements of high-density lines on a large network compared to low-density lines on regional and rural networks.

7.2.4 Capacity

The levels of different capacity consumption were considered by adding two trains with different headways. For further work, the capacity consumption could be considered by adding one train to each new timetable until the consumed capacity reaches 100%. However, it is not expected that a significant change in the conclusions can be drawn due to the similarity between the cases. The timetable of the case study was evaluated using the UIC 406 compression method. There are different methods to assess the capacity consumption and ways of adding additional trains; the framework would be appropriate for assessing these methods. The case study was conducted with a timetable of one hour on a low-density line. Further work can be carried out with a timetable of a whole working day on an intercity line with mixed traffic of freight services. It is expected that the mixed traffic of freight services would give different results due to the low braking rate.

On the whole, the aim of this thesis was to develop a general framework to understand the required positioning accuracy for new proposed automated and intelligent subsystems and applications. Implementation of the framework to the problem of energy consumption, punctuality and capacity has demonstrated the following: (i) application performance is the main factor in the evaluation of the required positioning system; (ii) different railway services and networks have different requirements for application performance; (iii) there is no single solution for all railways; (iv) each application needs to be evaluated in the framework separately for a specific network; (v) a low-accuracy positioning system, such as the block occupation/release data or GNSS, is good enough for a wide range of non-safety-related applications on a wide range of railway networks.

Appendix: Metrology-Related Terminology

In the glossary below, there are a few metrology-related terms defined. Although the definitions are mainly based on the International Vocabulary of Metrology (VIM) [197], they have been adapted/complemented based on references [198][199][200][201].

Measurement is an experimental or computational process that, by comparison with a standard, produces an estimate of the true value of a property of a material, or of a process, event, etc., together with an uncertainty associated with that estimate.

Measurement result is the outcome of any measurement activity generally expressed as a single measured quantity value and a measurement uncertainty.

Measurand is the quantity intended to be measured or the particular quantity subject to measurement. The measurand cannot be specified by a value but only by a description of a quantity.

True value of a measurand is the value of the quantity that would ideally reflect both qualitative and quantitative, the corresponding property of the object according to the purpose of the measurement, which is in practice unknowable.

Reference value is the value that serves as an agreed-upon reference for comparison. It has an associated measurement uncertainty usually provided with reference to a calibration certificate, a reference measurement procedure, or a comparison to a standard. In practice, a reference value substitutes the unknown 'true value'.

Error is represented by the difference between the measurement result and the true value of the measurand. The component of the total error of measurement, which varies in an unpredictable way, is called *random error*. The component that tends to shift all measurements in a systematic predictable way is known as *systematic error*.

Bias or offset is the estimate of the total systematic measurement error. It can be computed as the difference between the average value of a large series of measurement results and the true value of the measurand.

Trueness is the closeness of agreement between the average value of an infinite number of replicate measurement results and an accepted reference quantity value. This is a hypothetical indication because an infinite number of measurements cannot be made in practice, and thus trueness is not a quantity and therefore cannot be expressed numerically. Trueness is essentially 'absence of bias'.

Precision is a measure of how close independent results are to one another when the same measurement is made repeatedly. It is related to random measurement errors only. Precision is usually expressed numerically as a standard deviation or variance for the results obtained from replicate measurements, which describes the spread of the results.

Accuracy is the closeness of agreement between a measured quantity value and the true value of the measurand. It is related to both, trueness and precision, as a quality indicator of an unbiased and precise measurement result. Accuracy is not a quantity, it is a quality associated with the correctness of a result, relative to an expected outcome. A measurement is said to be 'more accurate' when the measurement errors and the measurement uncertainty, are reduced. Accuracy is essentially 'absence of error'.

Uncertainty is the doubt about the true value of the measurand that remains after making a measurement. It is a quantitative measure of the likely range of values within which the true value is asserted to lie with some level of confidence. At a minimum, uncertainty could be described approximately by a quantitative indication of the dispersion of quantity values being attributed to the measurand.

Maximum Permissible Error (MPE) defines a maximum limit value of measurement deviation, with respect to a known reference quantity value, that a measuring instrument or system must not exceed for a certain measuring task.

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