SMART MAINTENANCE AND THE RAIL TRAVELLER EXPERIENCE

Deliverable 4.2/ Impact Assessment and Barriers Final Report

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REPORT CONTRIBUTORS

Name	Company	Details of Contribution
Andrew Smith	ITS	WP Leader, contributor to section 2, reviewer of sections 3 and 4
Thijs Dekker	UNIVLEEDS	Contributor to Section 3, reviewer section 4
Daniel Johnson	UNIVLEEDS	Contributor to Sections 4, reviewer sections 2 and 3
Xiaoxiao Ma	UNIVLEEDS	Contributor to Section 3 and 4
Adam Bevan	HUD	Contributor to Section 3
Antonio Andrade	IST	Contributor to Section 3

EXECUTIVE SUMMARY

The major purpose of SMaRTE is twofold. Firstly, SMaRTE aims to provide the methodology of implementing a Condition Based Maintenance (CBM) system that will allow maintenance to be tailored around the actual remaining life of key components. It is foreseen that CBM will reduce costs and improve reliability and availability. The second goal of SMaRTE is to understand the primary factors impacting on user decisions to choose rail (or an alternative) and to produce new quantitative evidence on the relative importance of those factors.

Most maintenance activities in the current railway system are carried out on a scheduled basis. This potentially means that components and sub systems are not replaced at the optimum time, such that components either fail between interventions or are replaced at a too early stage. In particular, the potential of CBM as a form of Smart Maintenance for passenger railways has been investigated in Work package 2 (WP2) and Deliverable 2.3 highlighted that there is significant scope for further optimisation of maintenance intervals as a first step towards CBM.

In terms of passenger experience, whilst there is substantial evidence on the impact of factors such as fares / journey time on rail usage, the impact of more subtle factors deterring passengers, also known as Human Factors, from using rail are less understood. WP3 of SMaRTE placed the focus on the customer, utilising an innovative multidisciplinary approach to understand and quantify factors influencing rail usability, and to recommend on how to decrease the cognitive effort and onward mobility for rail journeys.

The present deliverable is concerned with Task 4.2 in WP4 and presents an impact assessment of potential CBM and Human Factor interventions on a case study basis. Making use of the evaluation methods and metrics set out in Task 4.1, the impact of the referred interventions as developed in WP2 and WP3 is demonstrated through a set of KPIs and the establishment of a business and financial case.

In the context of CBM, the Portuguese Fertagus case study forms the core of reporting in this deliverable due to the high quality of the available data. For wheelset maintenance, as presented in D2.3, the use of condition-based data has illustrated that with limited risk of additional breakdowns, maintenance intervals can be prolonged and this can result in significant maintenance cost reductions. This deliverable highlights that in the long run maintenance costs can be reduced when maintenance of components is studied in isolation. However, when examining the opportunities within constraints in the context of a broader tactical maintenance scheme, the short (and most likely the long) run potential for maintenance cost savings is limited since the rolling stock has to come in for other scheduled maintenance activities. This result is confirmed by a second case study in the context of sliding doors also on the Fertagus data. The overall conclusion is thus that condition based data can be very helpful to further optimise existing tactical maintenance plans and thereby provide significant cost savings potential, but that the switch to full CBM based maintenance is still a large step. The research frontier is twofold. First, there is a need to extend the scope of optimised tactical maintenance plans based on condition-based data to all rolling stock components and to extend the length of the planning horizon of this tactical maintenance plan. Second, the potential maintenance cost reductions achieved through these optimised tactical maintenance plans should then be contrasted against the costs of a full CBM-based maintenance plan. This represents a very significant step up in complexity in terms of modelling but we consider this as necessary to being able to make more definitive statements about the costs and benefits of employment of full CBM based maintenance approaches.

As part of the human factors stream of work in SMaRTE, the aim of this impact assessment is to examine the demand, revenue and welfare implications of an improvement in rail passenger experience (within the context of a multi-modal journey).

The basis for these improvements is taken from D3.4, the Smart Journey Vision, which identifies the most significant factors and barriers influencing the rail passenger experience in order to best influence travel choices to maintain and increase passenger rail journeys. Based on the emerging key factors, we gather information from National Travel Survey and other key sources to gauge the impacts of improvements in these factors through 3 scenarios applied to 3 case studies based on Metropolitan areas within the UK's Yorkshire/Humberside and Northwest areas.

Associated with these factors (or attributes), we have used valuations and sensitivities from an extensive search of the literature to estimate how different passenger types would respond to these improvements.

Our basic scenario is to look at 10% improvements in quantifiable aspects of service quality where possible. A second scenario extends the improvements to include 10% reductions in Access and Egress costs/times and a third scenario examines the low cost solutions discussed in D3.4.

These scenarios are purely indicative, ie they do not identify specific measures, but allow us to look at the components of the emerging demand uplifts and make comparisons between the impacts of different attributes and the relativities of the welfare benefits within each case study and of the scale of impacts between the case studies.

Our results show us that there is scope for extensive benefits to be achieved through improvements in identified factors. Whilst demand uplifts are predictably driven by fare and GJT changes our findings suggest there is a role for a combination of improvements in 'softer' factors such as crowding, vehicle cleanliness, station environment and the first and last mile experience. The largest benefits and demand uplifts are found in our longer distance rail case study. Demand uplifts were lowest for light rail. For the lower cost scenario (excluding measures to improve crowding, rail journey time and reliability and access/egress times) we found demand uplifts of 9-12%.

When looking at overall monetised benefits, the largest share of the benefits in each case comes from consumer surplus effectively measuring the enhanced passenger experience from improvements across a range of attributes. Revenue improvements for operators are offset partially by the reductions in fares and the associated elasticities which are largely inelastic. External cost savings are also significant impact of the scenarios.

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1. INTRODUCTION

The overall purpose of SMaRTE is to develop the most suitable solutions for predictive and corrective maintenance in railway rolling stock based on a CBM approach (Smart Maintenance – as investigated in WP2) and to identify and quantify the key barriers inhibiting use of rail (Human Factors – as investigated in WP3).

As outlined in the S2R Multi-Annual Action Plan (MAAP), a technology and impact assessment plan is vital to ensure that the activities carried out under S2R are delivering the expected benefits. This should include the specific methods and metrics by which the impacts are measured. In this regard, WP4 Task 4.1 developed metrics to demonstrate the impact of the solutions developed in the project in line with achieving the relevant KPIs of the S2R JU. It also developed a methodology to present the business case for the proposed innovations to identify whether the solutions generate an overall net benefit to society, including the financial case to understand the viability of the innovations for the different parts of industry.

The present deliverable, concerned with Task 4.2, builds on the case study work done in WP2 and WP3 and conducts the necessary impact assessment using the framework presented in Task 4.1. The presented impact assessments cover the two core areas, Smart Maintenance and Human Factors over different case studies. This deliverable evaluates the relevant KPIs and presents the business and financial case of Smart Maintenance and Human Factors solutions. As noted in the description of work, this task applies a high-level methodology and data approach to keep within the budget envelope and to avoid specification of unnecessary detail.

With respect to Smart Maintenance, this deliverable assesses the CBM techniques and architecture proposed in WP2 to provide an overall socio-economic assessment of the shift towards a CBM regime. The basic approach is to compare the Do-nothing scenario, which is characterised by periodic maintenance, versus the Do-something scenario, which is moving towards the proposed CBM. This latter approach will involve more frequent and tailored maintenance of some components (relatively low cost activities); thus requiring the more expensive/major maintenance activity to occur less frequently. In particular, within the life of the asset, this approach may result in the removal of one or more major overhaul activities (i.e. pushing them beyond the end of the life of the train). It could also bring some reliability benefits resulting from reduced failures if faults are identified earlier, and improved availability of rolling stock as there is less need for the large maintenance activities that keep trains totally out of action for a long period. However, CBM is possibly associated with the risk that rolling stock may need to come in for maintenance more frequently but for shorter periods of time. The impact assessment of the CBM model covers two case studies specifically on “Wheelset maintenance” and “Vehicle systems and running gear”, specifically based on real data provided by Fertagus in Portugal and further supported by data from London Underground in the UK.

The overall purpose of the Human Factors work in SMaRTE is to identify and quantify the key barriers inhibiting use of rail. As part of this phase of the work, the aim of this impact assessment is to examine the demand, revenue and welfare implications of an improvement in rail passenger experience (within the context of a multi-modal journey). These improvements are implemented through a number of case studies based on Metropolitan areas within the UK’s Yorkshire/Humberside and Northwest areas.

The basis for these improvements is taken from D3.4, the Smart Journey Vision, which identifies the most significant factors influencing the rail passenger experience in order to best influence travel choices to maintain and increase passenger rail journeys.

Based on these chosen factors, we gather information from National Travel Survey and other sources where required to gauge the current cost, time, quality measure relating to fare cost, car parking cost, rail journey time, on-board security and safety, crowding, cleanliness and maintenance of the vehicles. The use of NTS also identifies the mix of the passenger types in each case study. We then look at enhancement scenarios which improve these measures and use valuations and sensitivities from the literature to estimate how different passenger types would respond using current levels of patronage on these networks as our base pivot point.
As identified in D4.1, benefits arising from these improvements are assessed on the basis of having the following components:

- Consumer surplus changes (as driven by Generalised cost changes)
- Revenue changes (producer surplus)
- In addition, we need to quantify the change in environmental costs and indirect tax revenue resulted from demand shifting. As part of this we use best available information to identify which modes passengers are diverted from.

As discussed in D4.1 the aim here is not carry out a full cost-benefit analysis featuring costs. This is principally because we are not identifying specific ways to improve passenger experience per se, ie identifying innovations: rather we are looking at aspects of the journey experience that could be improved. Through this deliverable we aim to understand the nature, scale and relativities of the impacts of such improvements and thus to guide where operators and policy makers could focus their efforts in improving the rail passenger experience.

Section 2 summarises the business case framework, Section 3 details the information and data needs in order to assess the impact of Smart Maintenance, and Section 4 specifies the data requirement associated with Human Factors.

2. IMPACT ASSESSMENT FRAMEWORK

Since Deliverable 4.1 was not a public facing document, this section summarises the developed impact assessment framework in the respective deliverable. The impact assessment framework was setup generically to enable developing separate business cases for both Smart Maintenance and Human Factors interventions.

2.1 THE BUSINESS CASE FRAMEWORK

The SMaRTE project proposes an innovative CBM model and identify attrition factors in rail use. These innovations and factors will have impacts (in terms of changes in costs and benefits) on rail operators, rail users, and third parties (i.e., infrastructure managers of rail and competing modes, users of the alternative modes, the government, and the environment as a whole). As part of the Business Case, we need to identify and quantify the impacts. See the table below for a generic description of impacts and groups considered.

	Groups		
	Rail operators	**Rail users**	**Third parties**
Impact	Changes in costs and revenues	Changes in costs and benefits for rail users (e.g. improvements in reliability, mobility, etc.)	Changes in external costs (i.e., infrastructure cost of rail and competing modes, congestion in alternative modes, indirect tax revenue, and environmental costs)

Table 1 – Business Case – Impacts table

The aim here is simply to identify and quantify all impacts. The construction of the Business Case deals with the expected changes in costs and net benefits for society and for the different stakeholders, particularly for the rail operators and users. Two main components identified are:

- A socio-economic analysis, covering all affected parties (i.e. societal effect).
- A financial analysis, investigating the impacts on each of the relevant stakeholders.

In general, all impacts mentioned above can be summarised into five categories that will determine the output of the assessment:

Costs	Benefits
• Investment costs	• Life cycle cost reductions • Operator revenue increases • User benefits • External cost reductions

Table 2 – Costs and benefits in the impact assessment

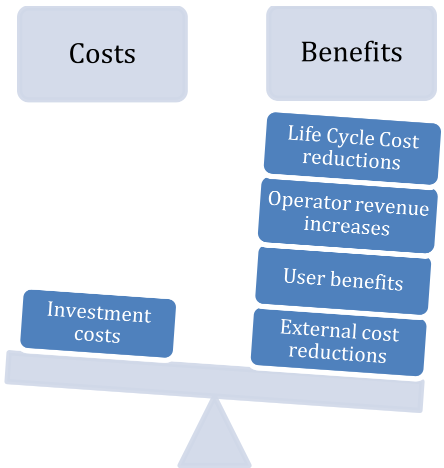

Figure 1. Costs and Benefits in the impact assessment

In order to be more specific about the benefits and costs from this project, the following table, as presented in Task 4.1, broadly summarises the expected impacts of proposed innovations.

Benefit/Cost	Relevant to WP2	Relevant to WP3

Life cycle cost	Change in maintenance regime	√	
	Reduction in rolling stock maintenance costs	√	
	Reduction in up-front component costs	√	
	Reduction in component failure and replacement costs	√	
Operator revenue	Increase in revenue resulting from change in service (due to improved availability of rolling stock)	√	
	Increase in revenue resulting from demand growth		√
User benefits	Improved reliability (fewer delays / cancellations)	√	
	Improved accessibility		√
	Improved usability		√
	Improved comfort		√
	Improved waiting time experience		
	Reduction in generalised travel cost	√	√
External costs	Reduction in infrastructure cost of rail and competing modes	√	√
	Reduction in congestion in alternative modes		√
	Change in indirect tax revenue		√
	Reductions in environmental costs (i.e., air pollution, noise pollution, greenhouse gases)	√	√

Table 3 – List of costs and benefits

A CBA recommends the implementation of innovation or change of practice where its benefits outweigh its costs. Task 4.1 highlighted that most of the benefits of CBM are expected to emanate from Life Cycle Costs (LCC) reductions, associated with reduced and cheaper maintenance strategies. Therefore, the rail operators are expected to be the direct beneficiary of CBM; users would also benefit from improvements in reliability. There may also be knock-on effects for users if some of the cost savings are passed through in fare changes or if increased availability permits new services. For Human Factor interventions, the main benefits are expected to arise to the users and operators. Instead of explicitly considering types of technology, the goal of the Human Factors case study is identifying the potential for rail if certain barriers in the journey process can be addressed.

Task 4.1 also translated the expected impacts into a set of KPIs for the Smart Maintenance and Human Factor case studies, which are presented separately below respectively:

Smart Maintenance:

- Reduction in annual rolling stock maintenance costs (measured as a percentage cost reduction and also incorporated into a LCC assessment, KPI1 in the S2R JU call document);
- Reduction in up-front component cost to reflect less frequent replacement of components (incorporated into a life cycle cost assessment);
- Reduced component failure through improved tailoring of maintenance to actual component condition and earlier identification of faults;
- Increase in rolling stock reliability (converted into an impact on delays to services, KPI3 in the S2R JU call document);
- Increase in availability of rolling stock due to a reduction in unplanned maintenance and less set down time for inspecting of component condition;
- Reduced track forces and infrastructure damage due to improved condition of rolling stock and reduction in the frequency of failed components;
- Environmental benefits relating to noise and reduced use of materials.

Human Factors:

- Reduction in passenger cognitive effort using rail;
- Reduction in generalised cost of rail travel;
- Increase of number of passenger journeys for different types of journeys;
- Increase of rail operator revenues;
- Changes of the transport costs using the alternatives;
- Changes of environmental costs associated with mode shift.

Measuring the KPIs and translating the impact results into a business case requires a significant amount of data from the train operators in the respective case studies. Hence, despite the full list of data requirements set out in Task 4.1, it was not possible to present a complete business case for all case studies on all impact categories and KPIs. The information presented in the present deliverable acknowledges these limitations and provides the most complete picture given the available data.

3. IMPACT ASSESSMENT SMART MAINTENANCE

At the time of writing D4.1, it was proposed that the impact assessment would be carried out on the case studies completed during WP2 (and detailed in D2.3), specifically “Wheelset maintenance” and “Vehicle systems and running gear”. However, as WP2 progressed it was evident that reliable data to support the “Vehicle systems and running gear” case study on the London Underground was not available. Therefore, within WP2 the respective case study was adjusted to make use of diagnostic data provided by the IMPACT-2 project partners, but available data from the London Underground was used to strengthen the Fertagus wheelset maintenance case study. The final case studies as presented in D2.3 are summarised below:

- Case study 1 (IMPACT-2): various systems and running gear – in this case study condition data was collated in the form of diagnostic data relating to a range of vehicle systems and components. Prognosis techniques were developed using historic data to train a neural network model to predict the sequence / patterns in diagnostic events which would provide an early warning of impending failures with sufficient response time to allow remedial action to be planned before the failure becomes terminal.

- Case study 2 (Fertagus): wheelset maintenance – a range of techniques were applied to demonstrate the full CBM process for the wheelset. Wheelset condition data was collated and analysed to support maintenance decision making and optimisation. This included statistical modelling of wheelset degradation, survival modelling and a Markov Decision Process. The condition based data highlighted that with relatively little risk of additional breakdowns, the maintenance interval of wheelsets can be prolonged offering potential for successful implementation of CBM and cost savings.

The key distinction between the two case studies undertaken in WP2 (other than the analysis techniques) is mainly the input data used to support the maintenance decisions. Case study 1 makes use of on-train diagnostic data (event-based system that is already available on most modern rolling stock), whilst Case study 2 uses data which describes the actual condition of the component in question (e.g. wheelset). The input data for Case study 1 originated from a variety of train operators involved in IMPACT-2. Presenting a business and financial case for CBM interventions requires to compare the Do-nothing scenario, which is characterised by periodic maintenance, versus the Do-something scenario, which is the proposed CBM. For Case study 2, the Do-nothing scenario was feasible to establish due to the detailed information on the full tactical maintenance plan of Fertagus. For Case study 1, however, the available information was very sparse beyond the provided on-train diagnostic data. Hence, it was not possible to establish the Do-nothing scenario in this context. As a result, the present deliverable covers two business cases on the Fertagus data covering respectively Wheelset maintenance and Sliding doors as case studies. The respective Fertagus case studies follow after reflections on the potential benefits to implementation of CBM based on the outcomes of the IMPACT-2 case study.

3.1 CBM AND THE IMPACT-2 CASE STUDY

The key element of a rolling stock maintenance regime is the vehicle maintenance instructions or maintenance plan. Typically, the current maintenance regime for rail vehicles is characterised by a mixture of scheduled *preventive* and *corrective* maintenance. This includes details of all the preventive maintenance tasks scheduled for the vehicle and its components and the planned interval for these tasks as well as the quality criteria to be met or achieved, limiting dimensions or desired conditions.

The key elements of the maintenance plan for each vehicle, in particular the maintenance interval, service limiting values and resulting maintenance activities to be carried out, are based on the manufacturer specifications or operator/maintainer experience. Specifying limit values and scheduled preventive maintenance steps demonstrates the advantages of this maintenance system as well as its disadvantages and limitations.

The primary advantage of such a preventive maintenance regime is the high degree of predictability regarding the maintenance work. This is particularly important when considering the overall maintenance and operation of the vehicle, for example scheduling, inventory control and availability. However, one of the disadvantages of this approach is that the actual condition of individual vehicles and components remains unknown. This means that it not possible to determine the specific maintenance actions required for each vehicle and the necessary time. The availability and quality of condition data become a key to the success of CBM because the lack of condition information makes it difficult to predict and therefore prevent unplanned corrective maintenance.

Therefore, applying a condition-based maintenance regime provides the opportunity to target maintenance activities based on the actual condition of individual components. The aim is to either replace or optimise the planned preventive maintenance activities by a maintenance interval limit through intelligent analysis of condition data. Additionally, recognising patterns and trends in the data we can predict the evolving condition of components and ultimately move from a condition-based to a predictive maintenance regime.

In the first WP2 case study, on-train diagnostic data supplied by IMPACT-2 for a traction and braking system were analysed. This case study demonstrated the feasibility of the techniques for identifying trends/patterns in the data and how these might be used to predict impending failures with sufficient response time to allow remedial action to be planned before the failure becomes terminal. Due to challenges in obtaining data from operators/maintainers to link maintenance activities and costs it has not been possible to fully quantify the benefits of the approaches assessed in this case study. However, end users have identified some of the intangible benefits and challenges of implementing the CBM techniques, as reported in deliverables D2.2 and D2.3. The IMPACT-2 case studies conclude that one of the most significant benefits in implementing the CBM strategies is that accurate, efficient data from failures and maintenance activities can enable informed and optimal management decision making:

- The Siemens case study (Section 2.4.7 in deliverable D2.3) showed that CBM techniques provide sufficient time and information to enable fleet maintainers to prepare the vehicle for arrival at the appropriate maintenance depot and therefore respond to the event in a more pro-active manner rather than the current reactive method.

- In the IMPACT-2 case study from DB it was shown that that the maintenance plans and inspection intervals can be adjusted based on the prediction of failure events. We further work this out in the impact assessment of the Fertagus case study.

Application of similar techniques in other industries have identified cost benefit and performance indicators include time savings, direct cost benefits and intangible benefits as summarised below:

- Time savings – e.g. reduced days in maintenance, reduced time between failures and days pending repair, increased in-service hours.
- Tangible benefit – e.g. reduced/eliminate premature component failure and unnecessary replacement, reduced corrective maintenance, increased operational readiness.
- Associated benefits – e.g. improved safety, increased confidence in early diagnosis, and operational performance.

Unfortunately, due to the lack of information to quantify the benefits of the techniques developed during the IMPACT-2 case studies it is not possible to present a business and financial case for this case study. More generally and as discussed further below, the research frontier is to find a way of optimising across multiple component types, which also requires a detailed model of how maintenance is scheduled and delivered in the depot.

3.2 WHEELSET AND SLIDING DOORS MAINTENANCE CASE STUDIES

This section presents the outcomes of two impact assessments of CBM in the context of Wheelset and Sliding doors maintenance activities for the Fertagus case study. Fertagus is a Portuguese train operating company, which is part of Grupo Barraqueiro, and became the first private train operator to guarantee the commercial concession of a railway line in Portugal. This company is responsible for ensuring the suburban passenger transportation between Roma-Areeiro (Lisbon) and Setúbal.

Fertagus trains run on a line of 54 kilometres that cross the “25 de Abril” bridge; and stop at 14 stations. Total travel duration between Roma-Areeiro (in Lisbon) and Setúbal is 57 minutes. No train can be pulled out of service to go to maintenance if there is no backup train available, and thus Fertagus owns 18 train units of which only 17 are necessary to perform the current operation.

The wheelset maintenance data analysed in D2.3 came from wheelset turning maintenance operations, of a fleet of EMU trains of a single type or class, and dated between October 2000 up and June 2015 (i.e. a 16-year interval). Each EMU train unit has four vehicles and each vehicle has eight wheels (i.e. four wheelsets). One of the key conclusions of the D2.3 was that one of the key factors in determining failure and thus the need for maintenance was the number of kilometres since the last turning operations. More specifically, statistical analysis on the loss in wheel diameter and the change in flange height and thickness due to wear since the last turning operation highlighted that the number of kilometres was the primary driver. This result was supported by similar condition based data on the wheelsets for the London Underground.

3.2.1 LONG RUN WHEELSET MAINTENANCE LIFE-CYCLE COST

Section 3.1 already highlighted that a first step to implementation of CBM is that of further optimisation of the tactical maintenance plan of a train operator. Hence, the purpose of the present case study is to study the business and financial case for such CBM interventions. Given that London Underground already runs a more optimal planned preventative wheel re-profiling regime compared to Fertagus, the London Underground case study was not further considered in the remainder of Deliverable 2.3 (see p.64 of D2.3). This deliverable will follow the same approach and only conduct an impact assessment of an improved preventive wheel re-profiling regime at Fertagus using inputs from D2.3.

A survival analysis with the aim of better predicting wheelset damage was conducted in D2.3. A key output of statistical survival analysis is that hazard rates and survival probabilities for wheelsets can be derived, i.e. the probability of components failing or not failing respectively. The survival analysis was based on condition (e.g. wheel diameter, flange height and thickness) and component failure data and highlighted that key factors in the prediction of wheelset damage are i) the kilometres since the last turning operation, and ii) the loss in the diameter. The survival analysis highlighted that interactions between wheelset diameter and the kilometres since the last turning operation are relevant and that accordingly the use of condition-based data (i.e. wheelset diameter loss) could be beneficial for wheelset maintenance schemes (see Section 3.3 in D2.3).

The implementation of a maintenance regime that solely depends on condition-based data was considered not to be sufficiently realistic since such an optimal strategy/policy requires train operating companies to have exceptional maintenance management and control over their assets. Instead, the preventive maintenance regime was optimised in Section 3.3 of D2.3 for the kilometres since the last turning operation (*kst*). Currently, in the "*Do nothing scenario*" Fertagus runs turning operations every 120,000 *kst*. The survival analysis indicated there is scope to extend the *kst* interval. Such prolonged maintenance intervals come at the risk of increasing the risk of component failures and thereby wheelset damage occurring before the end of the increased *kst* period. To account for such uncertainty a Markov Decision Process (MDP) was conducted in Section 3.3 of D2.3.

Simply put, the MDP uses simulation methods to track long-run (discounted) maintenance costs for different *kst* policy regimes. Across the different *kst* policy regimes the reduced preventive maintenance costs are traded-off against the increased risk of failure and thus corrective maintenance cost.[1] During each simulation run wheelset components randomly breakdown in between scheduled maintenance activities (i.e. every 120K *kst* or more) inducing preventive and corrective maintenance costs throughout the lifetime of the wheelset components. The breakdown pattern follows the estimated survival curves and by repeating the simulation a large number of times an (average or expected) life cycle costs for wheelset maintenance activities can be established. Due to the discounting that takes place during the MDP, the expressed costs are already in net present values.

It should be noted that the life-cycle cost (LCC) analysis presented only looks at the predicted and corrective wheelset maintenance in isolation and does not consider other preventive and corrective maintenance activities. Namely, that would require running similar survival analyses and simultaneous simulations on different components of the rolling stock. This was considered out of scope for the current project and more importantly the necessary condition-based data would currently not be available for most components other than wheelsets.

Figure 1 summarises the results of the LCC analysis (i.e. the MDP) across different policy regimes. Compared to the "Do nothing scenario", i.e. Fertagus' current preventive maintenance scheme of turning at every 120K *kst*, significant long run wheelset maintenance cost savings can be achieved up to 35%. Note that this does take into account for increased failure risk. The optimal level of 35% cost reductions would, however, only occur when the *kst* would be tripled compared to the current preventive maintenance regime. Noteworthy is, however, that the largest incremental benefits occur by relaxing the *kst* close to the current preventive maintenance regime. For example, by increasing the *kst* by 25% from 120,000 km to 160,000 km would already result in a reduction of long run wheelset maintenance cost of 15%.

[1] Note that this does not include any costs arising as a result of delay to the users on the train network as such information was not available.

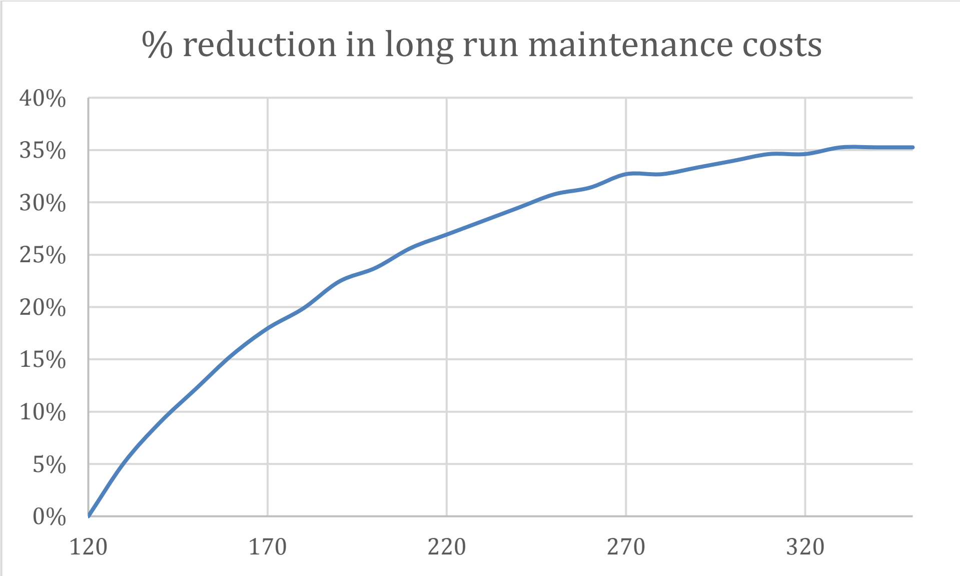

Figure 2: Reduction in present value LCC relative to 120K kst "Do Nothing" scenario

In relation to the other benefits discussed in Table 3, the LCC analysis is unable to provide information on benefits arising to operators, user benefits and reductions in external costs. That is, since Fertagus has a spare train on the network it can be assumed that the increase in availability due to a tactical maintenance plan improved by CBM is only limited. Moreover, for the Fertagus case study there was insufficient information to quantify the benefits to users and impacts on external costs as a result of changes to the wheelset maintenance plan. As a result, the presented LCC thus covers both the business case and the financial case since the analysis was unable to augment the analysis with benefits of CBM to society beyond the benefits to the train operator in the form of reduced (long-run) maintenance cost. Nevertheless, with relatively cheap and easy measurement of wheelset conditions substantial cost reductions can be achieved as indicated by Figure 2. The cost savings / trade-offs we have modelled all occur within the train operator and there is therefore no need to consider incentive arrangements between for example the operator and the infrastructure manager.

3.2.2 OPTIMISATION OF THE ANNUAL TACTICAL MAINTENANCE PLAN

The presented reductions in the present value of long-run life-cycle costs for wheelset maintenance do not take into account that wheelset maintenance is only a subset of Fertagus' preventive maintenance regime. Hence, increasing the *kst* levels to, for example, every 300,000 km might not be beneficial since failures can be prevented by maintaining wheelsets alongside other scheduled maintenance activities, i.e. when the rolling stock has to come in for an alternative maintenance activity.

As indicated in Section 3.2.1, the MDP providing the long run LCC could only be conducted on the wheelset maintenance activities due to having the necessary condition-based data to estimate survival curves for this particular rolling stock component. To acknowledge the importance for other maintenance activities and the corresponding constraints this puts on scheduling individual maintenance activities, Section 3.4 of D2.3 optimised Fertagus' current tactical maintenance plan for the '*do nothing scenario*' of 120,000 *kst*.

The optimisation minimised the preventive maintenance costs associated with the different maintenance activities within a one year planning horizon. Only preventive maintenance activities were included here since the necessary wear and tear; and break down data (inducing corrective maintenance activities) was not available. Moreover, due to the complexity of the optimisation problem, the tactical maintenance plan only works with a planning horizon of one year. As such, only short-run preventive maintenance cost reductions can be studied in this context and thereby only cover part of the LCC. Since component failure, i.e. the additional risk of break downs is not taken into account in this subsection, the results below may be slight over-representations of the potential costs savings.

For the purpose of this deliverable, the optimisation conducted in Section 3.4 of D2.3 was re-visited and re-optimised by relaxing the wheelset *kst*, as suggested by Figure 2. Due to updates of the software used for the optimisation process, the results for the '*do nothing*' scenario as presented in Table 16 (p.95) of D2.3 changed slightly. The updated annual costs associated with the reference optimal tactical maintenance plan are presented in Table 4. From Table 4 it can be observed that planned maintenance activity costs and shunting costs (components A and B) form the most substantial part of Fertagus' annual maintenance costs.

Table 4: Updated annuals costs for Fertagus' optimal tactical maintenance plan at 120,000 km kst

Cost Components	Scenario 0 – 'do nothing' (120,000 km *kst*)
A (maintenance activity costs)	669,880.00
B (shunting costs)	1,000,000.00
C (spare part costs)	5,300.00
D (penalty costs)	15.67
Total	1,675,195.67

In similar fashion to Section 3.2.1, different scenarios were optimised gradually prolonging the wheelset turning interval, i.e. increasing the *kst* from the 120,000 km *kst* 'do nothing scenario'. Table 5 presents the annual costs associated with four alternative optimised tactical maintenance plans varying in the *kst* for wheelsets. Scenarios 1-4 increase the *kst* for wheelset maintenance activities in a stepwise fashion by 30,000 km *kst* relative to the 'do nothing' scenario.

Due to the limited time horizon of one year considered by the tactical maintenance plan, preventive maintenance cost reductions are not observed when the wheelset turning interval is increased beyond 210,000 km *kst*. This is a direct result of the wheelsets not covering such long distances during a given year and thereby not having to come in for more than one wheelset turning interval maintenance activity. Note that this should not be considered as a restriction, since Figure 2 highlighted that the largest marginal cost reductions would be achieved at small relaxations of the turning interval.

Table 5: Potential short run preventive maintenance cost reduction due to relaxing the turning interval for wheelsets

Cost Components	Scenario 1 (Wheelset turning every 150,000 km)	Scenario 2 (Wheelset turning every 180,000 km)	Scenario 3 (Wheelset turning every 210,000 km)	Scenario 4 (Wheelset turning every 240,000 km)
A (maintenance activity costs)	661,699.00	649,088.00	623,810.00	623,810.00
B (shunting costs)	995,000.00	995,000.00	995,000.00	995,000.00
C (spare part costs)	2,650.00	2,650.00	0.00	0.00
D (penalty costs)	15.15	15.05	14.44	14.44
Total	1,659,364.15	1,646,753.05	1,618,824.44	1,618,824.44
Reduction compared to base scenario (%)	0.94%	1.70%	3.37%	3.37%

Wheelset preventive maintenance costs are only a subset of the overall preventive maintenance costs. Hence, we do not observe potential cost reductions of the same order of magnitude as compared to Figure 2. Cost component A (i.e. maintenance activity costs), however, does show potential for reductions in planned maintenance activity costs and together with the results from Figure 2 that these benefits are likely to outweigh the increased risk of failure, we can conclude there is potential for cost reductions. For example, Cost component A reduced by 6.9% relative to Scenario 0 under a 210,000 km *kst* on an annual basis.

The need for maintenance activities other than wheelset turning still requires trains to come in for maintenance and accordingly the reductions in shunting costs (Cost component B) are only minimal (0.5%), suggesting that further cost reductions can possibly be achieved when other maintenance intervals are being relaxed together with increasing wheelset turning interval periods.

Spare parts costs (cost component C) are highest in the 'do nothing' scenario and half when moving to scenarios 1 and 2 and further reduce to zero. Only spare parts for wheelset maintenance costs are taken into account here and that in the 'do nothing' scenario two planned turning operations are scheduled per vehicle per year. Increasing to respectively 150,000 km and 180,000 km kst per turning operation would reduce this to only one per year. If a longer planning horizon would be taken into account than one year, spare parts would be expected to decrease more gradually since some of the planned maintenance might just fall outside of the one year planning period. We therefore treat the results for cost component C with a significant degree of caution. Given the limited contribution to the overall costs (0.3%), we do not consider this to be a matter of concern. In similar vein, penalty costs (Cost component D) are negligible in the overall tactical maintenance plan. Reductions in penalty costs are observed across the scenarios, but don't increase beyond the 201,000 km *kst*.

Overall, increasing the interval between wheelset turning operations can lead to reductions in total planned maintenance cost up to 3.37% every year. These cost reductions primarily arise due to reduced planned wheelset maintenance activities, but does not significantly reduce the frequency by which trains have to be serviced (as evidenced by the limited decrease in shunting costs). Firstly, 3.37% may sound like a small number, but with an annual maintenance cost of around 1.7 million this accounts for annual costs savings of 55,000 which are likely to outweigh the small costs of installing condition-based monitoring equipment. A similar point was also indicted, though not proven, in the NeTIRail-INFRA project (see Deliverable D1.8: Final Business Case Synthesis Report)[2]. Secondly, larger cost reductions are possible if multiple maintenance activities are optimised based on their respective condition based data simultaneously. As highlighted by the current case study, such revisions of the tactical maintenance plan are relative simple and only require relaxing maintenance intervals instead of shifting to a fully CBM-based maintenance regime. Any such revisions to the tactical maintenance plan should be based on analyses comparable to those conducted for wheelset maintenance in D2.3, using survival analysis to establish whether the benefits outweigh the risk of increased failure. Further, a full analysis of all components together would be needed to obtain a deeper and complete understanding of the cost savings that may be possible and subsequently contrasted against a full CBM approach, which may suffer from suboptimal occurrence of maintenance intervals due to the unscheduled approach to maintenance activities.

3.2.3 SLIDING DOORS CASE STUDY

The results of Section 3.2.2 are promising and warrant further research into the potential benefits of CBM from a long run LCC analysis at the individual component level, but also in relation to further optimising the short run tactical maintenance plan. Whilst recognising that only data on wheelset maintenance was available for the Fertagus case study; that the alternative case study on sliding doors, as presented in D2.3, was obtained using data from IMPACT-2 case studies; and that transferring such results across train operators is not a straightforward exercise, we perform such a transfer of results to form a second case study. That is, without loss of generality the promising results for the IMPACT-2 case studies in the context of sliding doors can be translated into similar relaxations of the scheduled maintenance interval relative to the “do-nothing” scenario, as was conducted for the wheelset maintenance Fertagus case study in section 3.2.2.

Therefore, the presented analysis used the tactical maintenance model with a one year planning horizon for the Fertagus case study as the reference case (Scenario 0) in which it was assumed that the sliding doors would be inspected every 150,000 km. Four other scenarios (scenarios 5-8) were tested with corresponding intervals of 165000 km, 180000 km, 195000 km and 210,000 km, whilst keeping the wheelset turning periodicity at 120,000km *kst*. In other words, these scenarios are testing whether or not a better maintenance plan can be achieved when looking at other components than wheelsets. Any future analysis would benefit from running joint scenarios relaxing the intervals for both maintenance activities.

[2] That project used the “switching values approach” and indicated that very small annual savings would be required to make the initial investment in monitoring equipment worthwhile in net present value terms.

Table 6 shows that compared to the wheelset maintenance plan, potential preventive maintenance cost reductions are much smaller in the case of sliding doors. Primarily, reductions in preventive maintenance costs (Cost component A) are observed, but not in shunting costs (Cost component B) resulting in cost reductions of less than 1% across all four scenarios. Relaxing a certain maintenance activity may result in more separate servicing activities, hence increasing shunting costs (e.g. Scenario 5) or keeping shunting costs constant (e.g. Scenarios 6-8) since the rolling stock need to be serviced for other maintenance activities.

Table 6: Potential cost reduction due to relaxing the periodicity for sliding doors in Fertagus' tactical maintenance plan

Cost Components	Scenario 5 (Doors inspection every 165,000 km)	Scenario 6 (Doors inspection every 180,000 km)	Scenario 7 (Doors inspection every 195,000 km)	Scenario 8 (Doors inspection every 210,000 km)
A (maintenance activity costs)	665,672.00	665,734.00	664,291.00	661,916.00
B (shunting costs)	1,005,000.00	1,000,000.00	1,000,000.00	1,000,000.00
C (spare part costs)	2,650.00	2,650.00	2,650.00	2,650.00
D (penalty costs)	14.98	14.93	14.86	15.31
Total	1,673,336.98	1,668,398.93	1,666,955.86	1,664,581.31
Reduction compared to base scenario (%)	0.11%	0.41%	0.49%	0.63%

3.3 SUMMARY OF SMART MAINTENANCE IMPACT ASSESSMENT

In the railway industry, the current maintenance strategies are generally characterised by a combination of both corrective (condition-based) and scheduled (interval-based) maintenance. However, the selection of an optimum strategy can often be subjective with little reference to scientific proof. The selection of an appropriate strategy will have a significant impact on the life cycle costs and benefits to the system and should be analysed in a scientific manner. Therefore, techniques and methods to find the optimum solutions has to be implemented in order to improve the maintenance of railway systems.

In this section, the Fertagus case study was used to perform an impact assessment of moving towards more condition-based wheelset maintenance activities. This move was operationalised by relaxing the wheelset turning interval. Namely the survival analysis conducted in D2.3 based on wheelset condition data had indicated that such relaxations were viable and associated with a limited increased risk of component failures.

A long-run life cycle cost analysis indicated that a business and financial case can be made for implementing such CBM (i.e. Smart Maintenance) interventions. In terms of the KPI1, long run cost reductions can be achieved up to 35% on preventive and corrective wheelset maintenance costs over the full life time of the wheelsets. These potential cost reductions, however, do not take into account that the rolling stock will have to come in for alternative maintenance activities and hence optimisation of the maintenance interval can be different when multiple maintenance activities can be relaxed jointly, which would save both maintenance and shunting costs due to further optimisation of the tactical maintenance plan.

It is not possible to make an indication of KPI1 across all the maintenance activities since that would require condition based data on all respective rolling stock components, which was not at our disposal. The only option at hand was to show the potential for optimisations to the tactical maintenance plan with a one year planning horizon. This highlighted that in terms of total preventive maintenance costs annually up to 3% can be saved, but that such interventions had limited impact on the frequency at which the rolling stock has to come in for maintenance activities. Moreover, the potential for cost reductions depends on the rolling stock component under consideration. In an alternative analysis, cost reductions of annual preventive maintenance costs up to 1% were identified when the maintenance interval for sliding doors was relaxed. Ideally, we would have extended the time period of the tactical maintenance plan analysis, but that was impossible given the complexity of the optimisation problem.

In relation to two other KPIs, the Fertagus case study has shown that CBM maintenance activities do result in reduced up-front component costs to reflect less frequent replacement of components, but that these only form a small share of the overall maintenance activities. Moreover, the survival analysis conducted in WP2 has shown that CBM has the potential to reduce component failure through improved tailoring of maintenance to actual component condition and earlier identification of faults and in the long run this is one of the key causes of cost savings.

It is not possible to make complete statements generalising the presented result across railway operators in Europe due to the varying nature of their rolling stock and tactical maintenance plans. However, if each individual train operator could save up to 3% of its annual preventive maintenance costs, the benefits would easily add up to large figures. It is also difficult to obtain figures for train maintenance costs as these are often grouped in with other categories. In Great Britain in 2017/18, Britain's train operators spent £6.4bn on rolling stock charges and other costs[3]. These include capital lease elements and also other costs such as fuel, so they only give a broad indication. More widely across several European operators, however, in a report for the rail regulator, Civity estimated that roughly 25% of train operation costs is made of up of rolling stock operating costs (which in their report are broadly equated with train maintenance[4]). Thus train maintenance is a substantial element of cost and thus savings on this category can be substantial in economic terms.

Given the limited costs of installing CBM monitoring devices, we can say that there appears to be a clear business and financial case to make use of condition based data. Namely, we have shown that condition based data provides valuable information on optimisation of tactical maintenance plans, resulting in substantial cost reductions. The research frontier at this point is to study further improvements to tactical maintenance plans by making use of condition-based data on multiple (or preferably all) rolling stock components. Namely, only making use of condition-based data on single components limits the scope for cost maintenance cost reductions since the rolling stock has to come in for other scheduled maintenance activities. Hence, further costs reductions are deemed to be possible when condition-based data is used for all components in the optimisation of the tactical maintenance plan. The next step would then be to implement processes similar to the Markov Decision Process as applied in D2.3 to study whether a full CBM based maintenance regime would save costs beyond the cost savings obtained from optimisations applied in the context of a condition-based tactical maintenance plan.

With reference to the grant agreement, the two case studies presented in the present deliverable are based on the Fertagus data. For the IMPACT-2 case study as presented in D2.3, there was insufficient information available about the tactical maintenance interval of individual operators to conduct a similar analysis as presented for the Fertagus case study. The results of the IMPACT-2 case study have, however, been transferred and analysed in the context of the Fertagus case study.

We have presented a long and short run life-cycle cost analysis for the Fertagus case study, but were unable to quantify any benefits to operators, users and externalities beyond the savings in maintenance costs as discussed above. Partly this was a result of Fertagus having a spare train to cover for any unavailability, but also due to lack of understanding on how prolonged use of wheelsets would affect user comfort (e.g. generalised cost) and external costs (e.g. safety and environmental benefits).

[3] https://orr.gov.uk/__data/assets/pdf_file/0013/40351/uk-rail-industry-financial-information-2017-18.pdf
[4] https://orr.gov.uk/__data/assets/pdf_file/0004/3658/civity-toc-benchmarking-201112.pdf

4. IMPACT ASSESSMENT FOR HUMAN FACTORS

4.1 CHOICE OF CASE STUDIES

Given the structure of the passenger survey in Task 3.3 we categorised the conventional rail journeys undertaken by respondents into longer distance (>30 km) and short distance (<30km). Also, we collected information on journeys conducted on light rail/metro systems.

Given the diversity of the journeys undertaken by rail we decided to conduct these three case studies to represent these three different types of rail journeys. Our survey areas for the passenger survey in D3.3 were Brussels and Rome metropolitan areas and the Leeds/Manchester area in the UK. However, it is very difficult to obtain detailed operating information for rail networks given commercial confidentiality issues but we were aware that the UK has a number of sources of data for passenger operations at the aggregate level of franchises and light rail networks. Also given our experience using UK National Travel Survey data we were aware we could establish a level of match between the data, the available operating statistics and the evidence from our passenger surveys. For this reason, our case studies are all based on the Leeds/Manchester areas. However, through the coarse spatial zoning in the NTS we are only able to collect journey data on passengers who made journeys in metropolitan areas in North Yorkshire/Humberside and the North West. This means that as well as for Leeds and the Greater Manchester area, there will be some journey information from Merseyside too for conventional rail.

Our findings should not be taken as a literal estimation of what would happen if our improvements were applied to these particular case studies, but more to explore the scales and scope of benefits that might be realised from improvements in the passenger experience on different kinds of rail networks. For an accurate estimation of specific impacts on these case study networks we would have required more detailed and extensive passenger journey information than was available to us from the NTS or publicly available operator level data. We discuss the finalised choice of the case studies below:

4.1.1 LIGHT RAIL: MANCHESTER METROLINK LIGHT RAIL

Manchester Metrolink has geographic scope covering Greater Manchester (GM) area. The Metrolink represents a large scale transport investment in light rail which has been developed over a number of stages over the last 25 years and currently has a network of 57 miles, 93 stops spread over seven lines (Airport, Altrincham, Bury, South Manchester, East Manchester, Eccles, Oldham/Rochdale) radiating from Manchester City Centre. Most services run at 12 minute frequency intervals.

Transport for Greater Manchester set the Service Specification and the operation is run under contract for them. Since January 2017, a consortium between Keolis/Amey have been in charge of operations and maintenance under this contract.

4.1.2 SHORT DISTANCE CONVENTIONAL RAIL: ARRIVA NORTHERN FRANCHISE

The Northern Franchise is the second-largest train franchise in the United Kingdom: its trains call at 528 stations. Since 1st April 2016, Northern franchise has been run by Northern, a subsidiary of Arriva UK Trains. The routes operated by under the franchise in Northern England serve Leeds, Liverpool, Manchester, Newcastle upon Tyne and Sheffield and counties of Cheshire, Cumbria, Greater Manchester, Lancashire, Merseyside, Durham, Tyne and Wear, Northumberland and Yorkshire, plus some services further north and south. These services account for a larger proportion of local short distance rail operations in the Leeds/Manchester area so were chosen as indicative of the services running short distance journeys for the purpose of our case studies.

4.1.3 LONGER DISTANCE PASSENGER RAIL: FIRST TRANSPENNINE EXPRESS FRANCHISE

TransPennine Express, often abbreviated to TPE, is a British train operating company owned by FirstGroup operating the TransPennine Express franchise. It runs regional and intercity rail services between the major cities of Northern England and Scotland.

The franchise operates all its services to and through Manchester covering three main routes. The service provides rail links for major towns and cities such as Edinburgh, Glasgow, Liverpool, Sheffield, Hull, Leeds, York, Scarborough, Middlesbrough and Newcastle.

The franchise operates 51 three-carriage Class 185 diesel units and 10 four-carriage Class 350 electric units with plans to replace most of the fleet by 44 new-built five-carriage units, in addition to retaining a number of Class 185 DMUs.

4.2 IMPROVEMENTS IN PASSENGER EXPERIENCE

From D3.4, the Smart Journey Vision, we identified the most significant factors influencing the rail passenger experience. These are shown in Table 7.

From an extensive review of the available literature we establish the appropriate valuations and demand elasticities for a range of service quality attributes and softer factors associated with the waiting and on-board experience. In many cases we were unable to find supporting evidence by which to estimate the impact of improvements. For this reason, these attributes were not included in the case studies as indicated in Table 7.

Table 7: Potential sources of demand uplift

Improvements	Included in case studies	Note
Improved affordability and ticket flexibilty	√	Fare issues quantifiable but flexibility does not have sufficient evidence.
On board security and safety	×	Full CCTV coverage realised
Ability to find a seat	√	
The ability to book the journey in advance	×	Lack of data and measurement
Improved rail journey time	√	
Reliability of rail service	√	
The ability to use one of more tools to plan journey	×	Lack of data and measurement
Car parking availability & Car parking cost	√	
Accessible and comfortable rolling stock to improve in-vehicle service quality (comfort, on board security/safety, capacity, cleanliness)	√	
Improved first and last mile travel experience	√	Not within the remit of rail operators, but included as a sensitivity
Security and safety around the station	×	Most of the stations are CCTV covered, other attributes lack data and measurement.
Improved Wifi/Power Connectivity	×	Lack of data and measurement
Improved service availability (more lines, more frequency)	×	Lack of data and measurement
More digitalization, to enable end users to view rail as part of Mobility as a Service where they can configure the available resources into their own package	×	Lack of data and measurement
Utilisation of digital tools to improve coordination between operators and across modes to create a 'whole mobility experience'	×	Lack of data and measurement
Design for the needs of the elderly and disabled	×	Lack of data and measurement
Improved Facilities/ ambience in waiting environment	√	
Better tools to plan trips and for accessing travel information through online systems	×	Lack of data and measurement
Simplified ticket buying processes (such as improved online flows and more usable machines)	×	Lack of data and measurement
Improved service availability (more lines, more frequency)	×	Lack of data and measurement

As seen from Table 7, the cases studies will look at eight factors which were applicable to the case studies and where supporting evidence exists. The results will show the resultant demand uplift and revenue and consumer surplus changes from improvements in these aspects. Given the different sensitivities, values and distances regarding these attributes between different passengers, we stratify our analysis into commuter, business and 'other' (i.e. the remainder) passenger groups.

The impacts for the Human Factors (WP3) aspects of the project is measured by the number of passengers added through addressing perceived barriers to rail travel. These measures are expressed in numbers of passengers shifting from other modes to rail (both light rail and conventional rail). The benefits are computed based on revenues, transport costs (generalised journey time cost) associated with mode shifts. Specifically, we focus on passengers from "Yorkshire/Humberside, Metropolitan" and "Northwest, Metropolitan" areas.

The case study analysis is structured as follows. Section 4.3describes the data, section 4.4 describes the attributes, Section 4.5 the scenarios that were evaluated, section 4.6 the attribute values and elasticities needed to assess changes in attributes, and section 4.7 describes the results.

4.3 DATA

4.3.1 PATRONAGE DATA

The scale of patronage on the three case study networks are outlined in Table 8 below:

Table 8: Case study passenger journeys (2018/19 figures)

Case Study Network	Annual Passenger journeys (M)	Source
Conventional rail (longer distance) Transpennine Express	29.25	https://dataportal.orr.gov.uk/statistics/usage/passenger-rail-usage/passenger-journeys-by-train-operating-company-table-1212/
Conventional rail (short distance) Northern	101.34	https://dataportal.orr.gov.uk/statistics/usage/passenger-rail-usage/passenger-journeys-by-train-operating-company-table-1212/
Light rail Manchester Metrolink	43.70	https://www.gov.uk/government/collections/light-rail-and-tram-statistics

4.3.2 NATIONAL TRAVEL SURVEY

The National Travel Survey (NTS) is an individual and household based survey commissioned by the Department for Transport (DfT, 2017a) to monitor long-term changes in travel behaviour and understand the use of transport by different sectors of the population in Great Britain and to provide a nationally representative picture of travel behaviour. It is used extensively by DfT and is one of its main sources of data on personal travel patterns in Great Britain.

Individuals in sampled households are interviewed face-to-face to collect personal background information, and are also asked to complete a seven day travel diary to provide detailed information on travel undertaken. Data is held about households, individuals, trips and stages in various linked datasets.

The NTS covers travel by all age groups, including children. The NTS has an annual issued sample size of over 15,000 addresses. Each year diary data is collected from over 8,000 households which collects detailed information on trips including component times, distances, fares of the various associated stages of the trip. For example, whilst we are interested in rail trips, a trip where the main mode is rail may have access or egress journey elements conducted through other modes. Due to the level of detail of some of our analysis we felt it appropriate to pool the NTS data from 2002 and 2017 to ensure robust sample sizes throughout.

The structure of the NTS data is hierarchical and consists of several record types. The information is held about households, vehicles, individual trips and stages; and they are linked with each other to make cross-level analysis possible. For the purpose of our case studies, we focus on trips made by individuals travelling from/towards metropolitan areas in Yorkshire/Humberside and the North West to encapsulate trips involving Leeds or Manchester, where the main mode of travel is rail.
The case studies mainly took information from a number of datasets in NTS. The PSU (Primary Sampling Units) provides a list of postcode areas while Trip contains all the journeys made by individuals where a trip is defined as a one-way course of travel having a single main purpose. A trip consists of one or more stages. Stage decomposes each trip into different stages where a new stage is defined when there is a change in the form of transport or when there is a change of vehicle reacquiring a separate ticket.

Each level is uniquely identifiable by a specific identifier. We thus link different levels together using the identifier variables. After merging PSU and Trip, we are able to filter out the trips made from both Leeds and Manchester where the main mode of the travel is conventional rail or light rail. We can also make conventional rail trips distinct by dividing them into different distances ("short" distance of 30km or less or "longer" distances above that). Individual contains basic information of travellers. By linking Individual, Trip and Stage, we get an insightful view on trips made by different traveller groups and the relevant costs incurred.

4.3.3 NTS SAMPLE CHARACTERISTICS

The working sample contains individual level response from 2002 to 2017 NTS surveys. We focus on the trips made by individuals from Metropolitan areas in Yorkshire/Humberside and the North West the main mode of the trip is by conventional rail or light rail. Table 9 contain the composition of our final sample.

Table 9: NTS sample summary

Traveller Type	Conventional rail		Light Rail	Total
	Longer distance	Short Distance		
Commuters	704	2,085	798	**3,587**
Business Travellers	432	140	39	**611**
Others	1,874	3,084	1,701	**6,659**
Total	**3,010**	**5,309**	**2,538**	**10,857**

The figures in the table above show that among the trips we are interested in, most of them (76.6%) are made by conventional rail and among all the travellers, commuting takes a significant proportion (33%). Other traveller type include education, shopping, personal business and leisure. Regarding different distance of travel, short distance trips dominates, which also supports the fact that more people use rail service between Leeds and Manchester to commute.

4.4 CALCULATION OF KEY ATTRIBUTES

Built on the results from Work Package 3, we are able to define the influence of key factors behind the choice, or otherwise, of rail, which will be analysed in through implementing scenarios which improve financial cost, generalised journey time and other aspects of service quality or 'soft factors'. In order to operationalise the case studies we require an estimation of 'base-level' mean values of these attributes for the selected trips by different traveller types.

Whilst the NTS provides us with base level data on journey times and fares we have to rely on other sources for measures of crowding, reliability and other soft factors. Each attribute is discussed in the following sections.

4.4.1 FINANCIAL COSTS

When considering a rail journey, the cost of tickets is the principal consideration for all types of journeys. However, besides rail ticket costs, there are many other financial costs incurred in order to complete one single rail journey. We thus start from Stage level data from the NTS where each trip is decomposed into different stages and the financial cost related to each stage is recorded.

In order to keep the financial cost consistent and comparable among different years, we need to adjust the price levels to account for inflation. The pooled data set we are looking at starts from 2002 until 2017. We therefore adjust the cost to 2019 level using Consumer Price Inflation (CPI) index (ONS, 2019). After adjusting for inflation using CPI index, NTS dataset provides us with the average fare cost for each case study and traveller type.

By adding up all the financial costs incurred within a single journey, we obtain the total financial cost of every trip. Table 10 presents an overall view on financial cost for different types of travellers and different distance travelled. Short distance rail fares look low but include costs per trip where season or return tickets are involved.

Table 10: Financial cost per trip (£)

Traveller Type	Average rail ticket cost per trip	Average car parking cost	Overall financial cost
Conventional rail (longer distance)			
Business travellers	£ 36.03	£ 0.61	£39.79
Commuters	£ 5.95	£ 0.44	£6.64
Others	£ 10.61	£ 0.49	£12.30
Conventional rail (short distance)			
Business travellers	£1.43	£ 0.38	£2.20
Commuters	£ 1.67	£ 0.37	£1.93
Others	£ 1.27	£ 0.34	£1.53
Light rail			
Business travellers	£ 1.60	£ 0.30	£1.74
Commuters	£ 1.68	£ 0.31	£1.78
Others	£ 0.94	£ 0.29	£1.06

Whilst ticket costs for rail and access public transport journeys are reported there are many missing values in the data. Also for access journeys involving car we imputed fuel costs as part of access costs. These calculations are detailed in the Appendix.

4.4.2 GENERALISED JOURNEY TIME

When choosing travel modes, journey time is a key metric of the level of service provided by rail system, especially to commuters. Timetable-related service quality attributes undoubtedly have an important influence on rail demand. The measurement of journey time related costs consists of three parts and is dealt with together in a single measure that is termed *Generalised Journey Time* (GJT).

The DfT appraisal guidance (2017c) follows the Passenger Demand Forecasting Handbook (2017) approach based on Generalised Journey Time (GJT) incorporating in and out of-vehicle time, frequency and interchange elements in the following way:

$GJT = T + S + I,$

where:

T is the total station to station journey time (including interchange time),

S is the service interval penalty,

I is the sum of the interchange penalties for any interchanges required.

We use total travel time from NTS data to measure total station-to-station journey time.

NTS provides stage time which we use to estimate the total travel time from station to station, including interchange time. Penalty for interchange penality is calculated separately for different types of travellers based on the number of service intervals in minutes and trip distance (miles). Using the Stage and Trip dataset, we are able to have a rough measurement of the average waiting time before passengers start their rail journey. Finally, by adding up three factors, we get the generalised journey time (GJT) for each trip as shown in Table 11 below.

Table 11: Generalised journey time per trip (minutes)

Conventional rail (longer distance)					
Traveller type	**Station-to-Station time(mins)**	**Interchange penalty**	**Waiting time**	**Waiting time penalty**	**GJT**
Business travellers	126.05	25.25	14.05	28.09	179.39
Commuters	59.00	7.06	9.84	19.67	85.73
Others	107.02	23.93	6.97	13.93	144.89
Conventional rail (short distance)					
Business travellers	30.89	2.79	8.73	17.45	51.13
Commuters	30.34	1.76	11.68	23.35	55.45
Others	28.63	2.13	7.87	15.75	46.51
Light rail					
Business travellers	26.04	2.05	5.32	10.63	38.72
Commuters	32.84	1.81	7.93	15.86	50.51
Others	27.72	2.29	12.91	25.83	55.83

4.4.3 CROWDING LEVELS

Crowding is a major concern to many passengers, especially during peak time. The passenger survey undertaken in WP3 also shows that “ability to find a seat” ranks as the third necessary consideration for undertaking a rail journey.

For the conventional rail case study, crowding levels are based on passengers standing per square meter following Whelan and Crockett (2008) based on occupancy levels from a statistical release by Department for Transport (2018) and dimensions based on Class 185 Trans Pennine Express. An example calculation is shown in Table 12 below.

Table 12: Basic information of Trans Pennine Express Coach

Class 185 Trans Pennine Express	
Car length	23.763m
Width	2.673m
Rows of seats	20
Number of cars	3
Seats	167
Total area (per car)	63.518 m^2
Seating area (per car)	27.1068 m^2
Standing area (per car)	36.4116 m^2
Passenger standing per square meter (Manchester)	0.1958
Crowding factor base	*1.263*
Crowding factor new	*1.08*

Given the statistical information on Trans Pennine Express services, crowding factors are calculated. For Manchester, there are about 0.19 passengers per square meters standing. We applied these crowding levels to all case studies, given the complexity and lack of other available data on rolling stock and loadings but not to ‘other’ passenger type who we assume are predominantly off-peak travellers. We are aware that many Northern Services and Metrolink services are also similarly densely crowded in the peak.

4.4.4 RELIABILITY

Unreliability causes great inconvenience to travellers and is recognised as a fundamental impact factor to rail demand. In the passenger survey carried out in D3.3, rail reliability was a factor in the Top Ten considerations necessary for undertaking a rail journey. Reliability was also in the Top Ten necessary improvements required to consider use of train in future.

The standard measurement of reliability is defined in terms of Average Performance Minutes, which consists of average minutes late that relate to train punctuality and train cancellations. However, we did not have supporting data on cancellations for this calculation.

According to the Tram Passenger Survey (Transport Focus, 2018) for Manchester Metrolink[5] , in 2018, 89% of the services provided by Metrolink were punctual, 1% higher than the previous year. According to the survey, 6% of the passengers experience a delay to their journey and the average length of delay (perceived) is 10 minutes. The average minutes of lateness per journey we used is thus 0.6 minutes.

The National Rail Passenger Survey (Transport Focus, 2017) provides details on the distribution of delays experienced by surveyed passengers on Transpennine express services. From this, we calculated an average delay per journey of 3.6 minutes for our longer distance case study.

From Northern Rail punctuality figures (Northern Rail, 2019) we imputed an average delay per journey of 3.3 minutes per journey for use in our short distance case study.

4.4.5 ROLLING STOCK CLEANLINESS AND MAINTENANCE

When passengers consider travelling by rail, their perception of the trip, and hence the overall level of demand, is also influenced by several attributes of the journey itself. When considering undertaking a rail journey, cleanliness and maintenance of the vehicles is an important factor to passengers, especially to commuters. Cleanliness and maintenance of the vehicle ranked the third on the list of necessary improvements to consider use of train in future in D3.3. Therefore, improving the rolling stock quality will undoubtedly make passengers’ in-vehicle experience more comfortable and lead to more journeys made by rail.

For rolling stock services, in D3.3 we found the average satisfaction level for cleanliness and maintenance of the vehicles show that rail passengers are neither satisfied nor dissatisfied about the current maintenance level. This shows there is clearly scope for improvement in these aspects of service quality. Although we cannot pivot from a quantifiable base level of cleanliness and maintenance, following Wardman (2014b) in section 4.6.5 we will look at GJT equivalent improvements in related attributes.

[5] The TPS provides a consistent, robust measurement of passenger satisfaction with tram services in Britain.

4.4.6 STATION FACILITIES

From the passenger survey in D3.3, security and safety were found to be in the Top Ten considerations necessary for undertaking a rail journey. Provision of waiting facilities, cleanliness and maintenance of stations, Wi-Fi and power connectivity were all found to be in the Top Ten key factors with which passengers expressed dissatisfaction. For non-rail users security and safety were in the Top Ten necessary improvements required for them to consider use of train in future. It is for this reason that we attempt to include some of these attributes in our case studies. Again, here we follow Wardman (2014b) in section 4.6.5 and estimate GJT equivalent improvements in Station Facility related attributes.

4.4.7 CAR PARKING

Providing better access to rail stations is another way to increase rail use. Findings from WP3 indicate that the accessibility of the railway station can be a factor in determining if rail is chosen as a travel alternative. In D3.3, Car parking cost and availability were found to be key factors which passengers expressed dissatisfaction with (both in the top three). Both these aforementioned factors were considered as in the Top Ten necessary improvements required to consider use of train in future.

Given the current capacity constraints around stations, it is difficult for rail operators to expand parking spaces while parking cost is a more accessible option to affect the overall journey cost to travellers. Further, we found the evidence base here to be very weak. We were able to measure car parking cost from the NTS and explore the impact of reductions in this for Longer Distance but assumed it was not a particular issue for short distance or light rail.

4.4.8 ACCESS/EGRESS TIME AND COSTS

In the passenger survey in D3.3, station access and egress issues emerged as important with access journey time in the Top Ten considerations necessary for undertaking a short rail journey. Given the cost implications and the lack of control operators have over this attribute it is examined in a separate scenario along with reductions in access and egress financial cost. The baselines estimations of these from the NTS are detailed in Table 13 below.

Table 13: Access/Egress times and costs

Conventional rail (longer distance)		
Traveller type	**Average Access/Egress time (mins)**	**Average Access/Egress cost (£)**
Business travellers	27.28	3.76
Commuters	17.87	0.69
Others	24.81	1.69
Conventional rail (short distance)		
Business travellers	11.53	0.77
Commuters	10.30	0.26
Others	9.18	0.26
Light rail		
Business travellers	7.50	0.14
Commuters	6.46	0.10
Others	5.54	0.12

4.5 SCENARIOS

We have undertaken to investigate the demand uplift from reducing ticket cost and improving service quality and rolling stock based on findings from D3.4 and the available evidence. The aim is to reduce financial cost and journey-time related cost, i.e. generalised cost, in order to attract more travellers consider rail as their main mode of travel when planning a journey. Our basic scenario is to look at 10% improvements in quantifiable aspects of service quality where possible. With crowding this was difficult but we examined a reduction from current levels by 10% of standing and seated passengers per train. With rolling stock quality and station facilities no baseline data was available but we were able to use figures from Wardman (2014b) which looked at GJT equivalent reductions from improvements in vehicle cleanliness and maintenance from 60%-70% level and from improvement in station facilities from 50%-60% level.

A second scenario extends the improvements to include 10% reductions in Access and Egress costs/times to represent improvements in the first/last mile elements. These are not necessarily in control of operators.

A third scenario examines the low cost solutions discussed in D3.4 which means excluding measures to improve crowding, rail journey time and reliability and access/egress times.

Table 14:Case studies scenarios

Necessary improvements	After improvements	Scenario 1 Rail specific	Scenario 2 All measures	Scenario 3 Low cost
Cost of tickets	***10%*** reduction in average fare cost.	√	√	√
Crowding	***10%*** reduction in standing and seated passenger loads	√	√	
Rail journey time	***10%*** reduction in average generalised journey time.	√	√	√
Reliability	***10%*** *reduction in average minutes of delay.*	√	√	
Rolling stock cleanliness and maintenance	*From* ***60-70%*** *level*	√	√	√
Station facilities	*From* ***50-60%*** *level*	√	√	√
Car parking	***10%*** reduction in average car parking cost.	√	√	√
Access/egress time	***10%*** reduction in access/egress times.		√	
Access/egress cost	***10%*** reduction in access/egress costs.		√	√

We apply these to the baseline NTS data and show how the impacts differ across the different traveller types.

4.6 ATTRIBUTE VALUES AND ELASTICITIES

In order to calculate the demand uplifts and value the benefits resulting from these improvements we require detailed information on attribute values and elasticities. To make in-depth analysis the case studies look further into scenarios with regard to different traveller type (commuters, business travellers and the others), as valuations and sensitivities are typically disaggregated by these dimensions. Where possible we vary by type of network too.

In Table 15 we describe the supporting evidence on elasticities used as the basis to calculate the resultant demand uplifts when fare reductions are examined.

4.6.1 FARES

Table 15: Rail fare elasticities and data source

	Traveller Type		
	Commuters	Business	Others
Conventional rail (short distance)			
	-0.36	-0.2	-0.73
Source	*Wardman (2014a) Short PTE Season*	*Balcombe et al (2004) Business Rail Fare*	*Wardman (2014a) Short PTE Non-Season*
Conventional rail (longer distance)			
	-0.57	-0.2	-1.14
Source	*Wardman (2014a) Interurban non London Season*	*Balcombe et al (2004) Business Rail Fare*	*Wardman (2014a) Interurban non London Season*
Light rail			
	-0.65		
Source	*Balcombe et al (2004), Metro fares Elasticities*		

4.6.2 CROWDING

The measurement of crowding and its impact on demand is implemented through the change in In-Vehicle-Time (IVT). The crowding penalty effectively provides an addition to IVT which is a major component of GJT. Without any specific elasticity for crowding available, the impact on demand can be calculated by the computation of an uplift factor by applying the GJT elasticity to the adjusted GJT figure, j, in the following way:

$$U_{crowding} = \left(\frac{GJT + (Crowding\ Factor_{Scenario} - 1) * IVT}{GJT + (Crowding\ Factor_{Base} - 1) * IVT}\right)^{j}$$

where IVT is the in-vehicle time and j is the GJT elasticity. The crowding factor applies to IVT and serves as a penalty on GJT. Based on the crowding levels sourced from Department for Transport (2018) , we have calculated the crowding factors for our case studies based on figures shown in Table 16. We use linear interpolation to impute the appropriate crowding factor from these two levels.

Table 16: Crowding factors from Whelan and Crockett (2008)

Crowding level	Traveller Condition	
	Sit	Stand
0 Pass/m2	1	1.34
1 Pass/m2	1.24	1.61

4.6.3 JOURNEY TIME

Demand response from changes generalised journey time are based on rail GJT elasticities taken from a meta-analysis study by Wardman (2012) who provided long run rail GJT elasticities varying with distance. We used the GJT elasticity for 10 miles of -0.91 to represent our short distance rail case and light rail studies and a value of -1.26 for the longer distance case study based on 50 miles.

4.6.4 RELIABILITY

To keep the analysis consistent, the case study follows the approach proposed by Transport Analysis Guidance (DfT, 2017c). We can deduce the implied late time elasticity (η_{AML}) from η_{GJT} as:

$$\eta_{AML} = \eta_{GJT} \frac{W_{AML} AML}{GJT},$$

where AML is average minutes of lateness relative to the public transport schedule and W_{AML} is the valuation of late time. The valuation of W_{AML} has been changing over time and we take W_{AML} of 3 based on Wardman and Batley (2014). The late time elasticity η_{AML} is then calculated for different types of travellers and shown in Table 17.

Table 17: Late time elasticity values

Case study	Commuters	Business Travellers	Others
Conventional rail (longer distance)	-0.160	-0.0766	-0.095
Conventional rail (short distance)	-0.161	-0.174	-0.191
Light rail	-0.032	-0.042	-0.029

4.6.5 ROLLING STOCK QUALITY:CLEANLINESS AND MAINTENANCE

Given a distinct lack of supporting evidence apart from in the commercially confidential PDFH, we follow a simplistic approach based on a recent report by Wardman (2014b) who identified the following GJT reductions associated with an improvement from the 60% level to the 70% level in various vehicle quality attributes associated with TfL rolling stock as shown in Table 18.

Table 18: GJT reductions from improvement in vehicle cleanliness and maintenance from 60%-70%

Attribute	Generalised Journey Time reduction (mins)
Train outside appearance	0.15
Cleanliness	0.26
Graffiti	0.08
Total	**0.49**

As these are absolute reductions in GJT we applied them in the same way to each case study and traveller type and applied the respective GJT elasticities.

4.6.6 STATION FACILITIES

Here we again use recent information from Wardman (2014b) based on improvements in Station ambience and Station Security/Safety, Facilities from TfL(2013) shown in Table 19.

Table 19: GJT reductions from improvement in station facilities from 50%-60% level

Attribute	Generalised Journey Time reduction (mins)
Station lighting	0.03
Cleaning	0.13
Safety	0.06
Staff	0.09
Retail	0.05
Telephone	0.01
Toilets	0.01
Seating	0.04
Building	0.01
Lifts/Escalators	0.03
Total	**0.55**

4.6.7 CAR PARKING

Car parking cost, as a type of financial cost, is considered together with ticket cost when evaluating demand uplift. To decompose the demand uplift of reduced car parking cost from reduced general financial cost of the journey, a specific demand elasticity is calculated based on the appropriate Fare elasticity and the ratio of average car parking cost to fare cost and shown in Table 20.

Table 20: Car parking elasticity values

Case study	Commuters	Business Travellers	Others
Conventional rail (longer distance)	-0.09272	-0.0528	-0.17439

4.7 ECONOMIC VALUATION

4.7.1 DEMAND UPLIFT

CBA Explanation

Here we measure the demand uplifts from the improvements in components of generalised cost described in the scenarios.

Following the previous section where the demand uplifts from different attribute improvements are obtained, we derive the compound demand uplift in each case study for each different traveller type and then an average uplift weighted by NTS sample sizes in each type/case study.

Table 21: Demand uplifts from Scenario 1 (Rail mesasures)

Traveller Type	Fare Cost	GJT	Crowding	Cleanliness	Station Env	Reliability	Car parking cost	Demand Uplift
Conventional rail(LD)								
Business	1.021	1.14	1.025	1.004	1.005	1.008	1.000	**1.216**
Commute	1.062	1.14	1.025	1.008	1.011	1.017	1.004	**1.293**
Others	1.128	1.14		1.005	1.006	1.010	1.006	**1.322**
Average	**1.097**	**1.14**	**1.025**	**1.005**	**1.007**	**1.011**	**1.005**	**1.300**
Conventional rail (SD)								
Traveller Type	**Fare Cost**	**GJT**	**Crowding**	**Cleanliness**	**Station Env**	**Reliability**		**Demand Uplift**
Business	1.021	1.10	1.016	1.010	1.013	1.019		**1.189**
Commute	1.039	1.10	1.014	1.009	1.012	1.017		**1.204**
Others	1.080	1.10		1.011	1.014	1.020		**1.243**
Average	**1.062**	**1.10**	**1.014**	**1.010**	**1.013**	**1.019**		**1.226**
Light Rail								
Traveller Type	**Fare Cost**	**GJT**	**Crowding**	**Cleanliness**	**Station Env**	**Reliability**		**Demand Uplift**
Business	1.071	1.10	1.016	1.013	1.017	1.004		**1.239**
Commute	1.071	1.10	1.014	1.010	1.013	1.003		**1.227**
Others	1.071	1.10		1.009	1.012	1.003		**1.207**
Average	**1.071**	**1.10**	**1.014**	**1.009**	**1.012**	**1.003**		**1.214**

The scale of the overall uplifts from Scenario 1 as shown in Table 21 is around 30% (ie a factor of 1.3) for longer distance conventional rail, 23% for short distance conventional rail and 20% for light rail. These increase to 37%, 29% and 24% respectively for Scenario 2 as shown in Table 22, which builds on the Scenario 1 measures. The largest drivers of demand growth in our scenarios are from 10% improvements in GJT and fare elements. The higher elasticities for longer distance GJT and Fare elements drive the differences in the uplifts in the case studies. The lower figures for short distance conventional rail vs longer distance also reflect a higher concentration of commuters in this case study; commuters generally have lower sensitivities to changes given their constraints regarding travel arrangements (e.g. to be at work for specific times). The slightly lower uplifts for light rail reflect the smaller demand uplifts from improvements in reliability which is already a lower base level of delay than the other case studies.

The lower cost scenario (Table 23) yields demand uplifts of 12% for longer distance conventional rail and 9% for the short distance and light rail case studies, most of which is driven by the fare change.

Table 22: Demand uplifts from Scenario 2 (All measures)

Traveller Type	Demand Uplift Scenario 1	Access costs	Access time	Demand Uplift Scenario 2
Conventional rail(LD)				
Business	**1.216**	1.002	1.041	**1.269**
Commute	**1.293**	1.007	1.006	**1.309**
Others	**1.322**	1.019	1.047	**1.410**
Average	**1.300**	**1.010**	**1.031**	**1.367**
Conventional rail (SD)				
Traveller Type	**Demand Uplift Scenario 1**	**Access costs**	**Access time**	**Demand Uplift Scenario 2**
Business	**1.189**	1.011	1.044	**1.256**
Commute	**1.204**	1.006	1.036	**1.255**
Others	**1.243**	1.016	1.039	**1.312**
Average	**1.226**	**1.011**	**1.040**	**1.288**
Light Rail				
Traveller Type	**Demand Uplift Scenario 1**	**Access costs**	**Access time**	**Demand Uplift Scenario 2**
Business	**1.239**	1.006	1.038	**1.294**
Commute	**1.227**	1.004	1.025	**1.263**
Others	**1.207**	1.009	1.021	**1.243**
Average	**1.214**	**1.006**	**1.028**	**1.250**

Table 23: Demand uplifts from Scenario 3 (Low cost)

Traveller Type	Fare Cost	Cleanliness	StationEnv	Car parking cost	Access costs	Demand Uplift
Conventional rail(LD)						
Business	1.021	1.004	1.005	1.000	1.002	**1.031**
Commute	1.062	1.008	1.011	1.004	1.007	**1.087**
Others	1.128	1.005	1.006	1.006	1.019	**1.146**
Average	**1.097**	**1.005**	**1.007**	**1.005**	**1.014**	**1.116**
Conventional rail (SD)						
Traveller Type	**Fare Cost**	**Cleanliness**	**StationEnv**		**Access costs**	**Demand Uplift**
Business	1.021	1.010	1.013		1.011	**1.045**
Commute	1.039	1.009	1.012		1.006	**1.060**
Others	1.080	1.011	1.014		1.016	**1.107**
Average	**1.062**	**1.010**	**1.013**		**1.012**	**1.087**
Light Rail						
Traveller Type	**Fare Cost**	**Cleanliness**	**StationEnv**		**Access costs**	**Demand Uplift**
Business	1.071	1.013	1.017		1.006	**1.103**
Commute	1.071	1.010	1.013		1.004	**1.096**
Others	1.071	1.009	1.012		1.009	**1.093**
Average	**1.071**	**1.009**	**1.012**		**1.007**	**1.094**

4.7.2 REVENUE UPLIFT

The rail operator annual revenues predicted from the scenarios are shown in Table 24. Here we see revenue uplifts of 15%, 21% and -1% (ie factors of 1.15, 1.21 and 0.99) from scenarios 1,2 and 3 respectively in the longer distance rail case study. The revenue losses in scenario 3 stems from the lower demand uplift and the low fares elasticities. For the short distance rail case study we see revenue uplifts of 10%, 16% and -2% from scenarios 1,2 and 3 respectively and a similar pattern of 9%, 12% and -2% across the scenarios for light rail.

Table 24: Annual Revenues

Conventional rail(LD)				
Traveller Type	**Revenue Base (£M)**	**Revenue Scenario (£M)**	**Change (£M)**	**Proportional Uplift**
Scenario 1	385.08	442.77	57.69	1.15
Scenario 2	385.08	465.91	80.83	1.21
Scenario 3	385.08	379.38	-5.70	0.99
Conventional rail (SD)				
Traveller Type	**Revenue Base (£M)**	**Revenue Scenario (£M)**	**Change (£M)**	**Proportional Uplift**
Scenario 1	145.22	159.96	14.74	1.10
Scenario 2	145.22	167.84	22.62	1.16
Scenario 3	145.22	141.69	-3.53	0.98
Light Rail				
Traveller Type	**Revenue Base (£M)**	**Revenue Scenario (£M)**	**Change (£M)**	**Proportional Uplift**
Scenario 1	51.79	56.71	4.92	1.10
Scenario 2	51.79	58.41	6.62	1.13
Scenario 3	51.79	51.02	-0.77	0.99

4.7.3 CONSUMER SURPLUS

Besides demand and revenue uplift, another measurement of the improvements from rail service would be through the reduction in generalised cost of travel and the calculation of consumer surplus.

The financial cost for each journey, which consists of mainly two parts, 1) costs of tickets and 2) car parking costs and access costs where relevant, have been calculated and adjusted for inflation and GDP growth. The other attributes are all measured by generalised journey time (GJT), which is converted into a monetary measure using to values of travel time savings following Transport Analysis Guidance (Department for Transport, 2017b).

The value of travel time (VTT) is an important concept in the transport sector, since savings in travel time typically account for a large proportion of the benefits. It reflects the amount of money a traveller is willing to pay to save time and is measured in pounds per hour. Given that the price level used by TAG is from 2014, a new valuation is calculated using CPI index. A GDP per capita growth rate has also been applied to correctly evaluate the new value of travel time. To be consistent with the previous analysis, the valuations are undertaken separately for different traveller groups. For business travellers, they would pay £ 11.33 to save one hour of journey time, commuters would pay £ 12.56 and others would pay £ 5.74, as shown in Table 25.

Table 25: Adjusted value of travel time

Valuation	Business Travellers	Commuters	Others
2014 price level	£ 10.11/hr	£ 11.21/hr	£ 5.12/hr
2019 price level	*£ 11.33/hr*	*£ 12.56/hr*	*£ 5.74/hr*

The case study in concerned with consumer surplus change after rail services have been improved. Generalised cost of travel is computed as follows:

$GC_i = FC_i + GJT_i * VTT_i$,
where
$i = business\ travellers, commuters\ or\ others$,

GC denotes the monetized measurement of travel cost,

FC represents financial cost which consists of costs of tickets and car parking and access costs,

VTT denotes value of travel time.

The change of GC is then expressed as:

$\Delta GC_i = \Delta FC_i + VTT_i * (\Delta GJT_i)$.

Table 26: Change of generalised journey time and cost for different types of travellers

	Scenario 1		Scenario 2		Scenario 3	
Traveller type	**Monetised GJT attributes change (£)**	**Total GC change (£)**	**Monetised GJT attributes change (£)**	**Total GC change (£)**	**Monetised GJT attributes change (£)**	**Total GC change (£)**
Conventional rail (LD)						
Business	-13.040	-16.704	-15.995	-20.035	-0.682	-4.723
Commute	-2.658	-3.297	-3.406	-4.114	-0.264	-0.972
Others	-1.610	-3.732	-2.084	-4.375	-0.120	-2.411
All	**-3.496**	**-5.492**	**-4.390**	**-6.561**	**-0.235**	**-2.406**
Conventional rail (SD)						
Business	-1.563	-1.744	-1.999	-2.257	-1.563	-0.496
Commute	-1.820	-2.024	-2.251	-2.481	-0.264	-0.493
Others	-0.659	-0.820	-0.834	-1.021	-0.120	-0.308
All	**-1.139**	**-5.492**	**-1.422**	**-1.627**	**-0.180**	**-0.386**
Light Rail						
Business	-1.151	-1.341	-1.292	-1.497	-0.238	-0.442
Commute	-1.565	-1.765	-1.701	-1.910	-0.264	-0.473
Others	-0.671	-0.794	-0.724	-0.859	-0.120	-0.255
All	**-0.960**	**-1.108**	**-1.040**	**-1.199**	**-0.167**	**-0.327**

As seen from Table 26, given all the improved rail services and reduced financial cost, there are reductions in generalised cost for all passenger groups across all scenarios. The largest reductions are in the long distance case study – in particular the longer distances travelled by business passengers in this case study leads to markedly higher reductions in GC for this group.

Based on the demand uplift information from Table 23 we have derived in the previous section and the reductions in generalised cost shown in Table 26, improvements in consumer surplus could be calculated.

$$\Delta CS_i = \frac{1}{2} * \Delta GC_i * (D_{b,i} + D_{scenario,i}),$$

where

ΔCS_i denotes the change in consumer surplus,

D_i denotes the journey demand.

Thus, the consumer surplus brought by improving light rail services is shown in Table 27. The magnitudes between the case studies reflect the overall levels of patronage costs and distances travelled. However it is interesting to note the consumer surplus changes from scenario 2 are 3-4 times bigger than those from the low cost scenario 3. These improvements in passenger welfare are much larger than the revenue changes for operators shown in Table 24.

Table 27: Consumer surplus for scenarios and case studies

Scenario	Total Consumer surplus change (£M PA)
Conventional rail (LD)	
Scenario 1	182.5
Scenario 2	223.9
Scenario 3	74.2
Conventional rail (SD)	
Scenario 1	148.0
Scenario 2	187.6
Scenario 3	37.8
Light Rail	
Scenario 1	53.7
Scenario 2	59.1
Scenario 3	14.4

4.7.4 EXTERNAL COST CHANGES

External costs comprise those costs imposed on non-users by rail itself when usage changes, and those imposed by other modes of transport whose volumes are changed by the change in rail demand.

For external costs and benefits of other modes of transport we use values from the study of Sansom et al (2001). It should be noted that strictly these values were estimated for 1998 so we uplifted them to 2015 prices using the Consumer Price Index (ONS,2019). To apply these values we need to know how much traffic transfers to or from road and the types of road and time of day in question.

Diversion Factors & Passenger Trips

The change in rail passenger trips can be used to calculate the modal shift between rail, car, coach and not travel or new journeys. An integral part of these calculations are the application of diversion factors to the change in passenger trips. For example, if the number of rail trips are assumed to have increased by 10,000 per year, diversion factors can be used to ascertain where those journeys have come from. The following diversion factors (Table 28) were used to estimate the sources of new rail journeys and vice versa.

Table 28: Diversion factors

Diversion Factors	Passenger%	Vehicle%
Car (passenger)	68%	42.5%
Coach (passenger)	24%	2%
New	8%	

Source: Train Operating Company Figures (1998) as used in Johnson and Nash (2008)

To calculate the modal shift in terms of car and coach vehicle kms requires the average loadings of both car and coach vehicles to be taken into account, alongside the length of the trips made by both modes. In the case of car a loading factor of 1.6 (taken from the Transport Economics Note, DfT, 2003) has been used and in the absence of any supporting data, we have assumed for coach a loading factor of 25. This allows the number of car and coach journeys to be calculated.

External Factor Costs

This information can be taken forward and used in conjunction with passenger and vehicle km estimates to calculate the net external cost changes over all modes. All the factors used for the calculation of the environment have been taken directly from a report carried out by ITS for the DETR which examined surface transport costs and charges for Great Britain for 1998 (Sansom et al., 2001). We used the mid-points of the reported costs per vehicle kilometre for road and rail travel. The UK average values for environmental factors, infrastructure costs and congestion costs, and tax are presented in Table 29. These values were implemented by uplifting by 52% to 2019 prices using the CPI (ONS, 2019).

Table 29: UK average values of external factors per vkm (£s in 1998 prices and values)

Impact Type	Coach	Car	Passenger Rail
Noise	0.021	0.0027	0.122
LAQ	0.093	0.0053	0.279
Greenhouse Gases	0.014	0.0030	0.067
Safety	0.052	0.011	
Infrastructure costs	0.060	0.0006	1.116
Congestion costs	0.1671	0.0971	
Tax	0.0757	-0.0386	See below
Mohring effect	1.47		1.55

Road Infrastructure costs are based on the average values for vehicle kms, vehicle type and road types. We assume that infrastructure costs have already been charged to the train operator through the variable access charge.

For car and coach travellers the change patronage leads to a change in congestion costs imposed on non-users.

The impact of indirect tax directly affects government revenues. For cars the government levies fuel duty and VAT on fuel duty. Rail and coach travel are not subject to VAT, so VAT not paid on fares expenditure which would have otherwise incurred VAT has to be calculated as a cost of these modes. Values per average UK vehicle kms have been taken from the Sansom et al. (2001) publication are also presented in Table 29. VAT is charged at 20%, so changes in VAT payments from Rail are directly derived from the change in rail revenues.

We have assumed there will not be any effect on subsidy payments. We have also included average benefits to existing users from increased frequencies (the Mohring effect), taken from Sansom et al, as shown in the final row of Table 29.

In the absence of sufficient revenue data, we took fares information from previous work (Johnson and Nash 2008), which allowed us to approximate a marginal profit figure of 1.6 pence per passenger kilometre for changes in coach patronage. We assumed coach service costs would expand, maintaining existing load factors. This will increase external costs, but there will be benefits to existing users from increased frequencies (the Mohring effect), taken from Sansom et al, of 14.7 pence per vehicle km.

External Cost Valuations

The resultant calculations are shown in Table 30. As expected the largest external cost reductions emerge from scenario 2, which has the largest demand and modal share shift.

Table 30: External cost savings results

Scenario	Total External Cost Change (£M PA)
Conventional rail (LD)	
Scenario 1	27.2
Scenario 2	31.1
Scenario 3	16.1
Conventional rail (SD)	
Scenario 1	36.0
Scenario 2	45.7
Scenario 3	13.8
Light Rail	
Scenario 1	6.0
Scenario 2	7.0
Scenario 3	2.6

4.7.5 SUMMARY

Table 31 summarises the changes in welfare benefits that would accrue to society via passenger benefits (consumer surplus), operator benefits (revenue) and society (external costs). Over scenarios 1 and 2 the revenue increases amount to over 20% of the benefits for long distance travel and below 10% for the shorter distance case studies.

Table 31: Summary of welfare benefits

	Scenario 1		Scenario 2		Scenario 3	
Welfare Category	**Change (£M)**	**%**	**Change (£M)**	**%**	**Change (£M)**	**%**
Conventional rail (LD)						
Revenue	57.69	21.58	80.83	24.07	-5.70	-6.75
Consumer surplus	182.45	68.26	223.93	66.67	74.18	87.74
External cost savings	27.16	10.16	31.09	9.26	16.07	19.01
Total	**267.31**	**100.00**	**335.85**	**100.00**	**84.54**	**100.00**
Conventional rail (SD)						
Revenue	14.74	7.42	22.62	8.84	-3.53	-7.34
Consumer surplus	148.02	74.48	187.63	73.30	37.80	78.57
External cost savings	35.98	18.10	45.74	17.87	13.84	28.77
Total	**198.74**	**100.00**	**255.99**	**100.00**	**48.11**	**100.00**
Light Rail						
Revenue	4.92	7.62	6.62	9.10	-0.77	-4.75
Consumer surplus	53.68	83.12	59.06	81.27	14.43	88.58
External cost savings	5.98	9.26	7.00	9.63	2.63	16.17
Total	**64.59**	**100.00**	**72.68**	**100.00**	**16.29**	**100.00**

4.8 CONCLUSIONS FOR HUMAN FACTORS

As part of the human factors stream of work in SMaRTE, the aim of this impact assessment is to examine the demand, revenue and welfare implications of an improvement in rail passenger experience (within the context of a multi-modal journey). These improvements are implemented through three case studies based on Metropolitan areas within the UK's Yorkshire/Humberside and Northwest areas.

The basis for these improvements is taken from D3.4, the Smart Journey Vision, which identifies the most significant factors and barriers influencing the rail passenger experience in order to best influence travel choices to maintain and increase passenger rail journeys. Based on the emerging key factors, we gather information from National Travel Survey and other key sources to gauge the impacts of improvements in these factors through 3 scenarios applied to 3 case studies. .

Associated with these factors (or attributes), we have used valuations and sensitivities from an extensive search of the literature to estimate how different passenger types would respond to these improvements.

Our basic scenario is to look at 10% improvements in quantifiable aspects of service quality where possible. This was chosen as representative of achievable improvements in these dimensions rather than complete step changes in provision necessitating large scale infrastructure investment and re-organisation of how rail services are delivered. Whilst demand uplifts are predictably driven by fare and GJT (including reliability) changes our findings suggest there is a role for a combination of improvements in 'softer' factors such as crowding, vehicle cleanliness, station environment and the first and last mile experience. A second scenario extends the improvements to include 10% reductions in Access and Egress costs/times to represent improvements in the first/last mile elements. These are not necessarily in control of operators. A third scenario examines the low cost solutions discussed in D3.4 which means excluding measures to improve crowding, rail journey time and reliability and access/egress times.

These scenarios are purely indicative, ie they do not identify specific measures, but allow us to look at the components of the emerging demand uplifts and make comparisons between the impacts of different attributes and the relativities of the welfare benefits within each case study and of the scale of impacts between the case studies. We are aware that there are many limitations to this assessment. We have not been able to identify measures or sensitivities for a number of attributes identified in WP3. For a number of others we are missing measures such as load factors. Where we have supporting data, there is often conflicting (or dated) evidence available (eg on fares and GJT elasticities). We have used a very aggregate approach for our case studies given the lack of commercially confidential data. We have applied generic factors and diversion factors for external cost calculations.

Our results show us that there is scope for extensive benefits to be achieved through improvements in identified factors. The largest benefits are found in our longer distance rail case study, although this is principally driven by higher distances meaning larger absolute reductions in generalised cost. We found demand uplifts between 25-37% where all identified improvements are implemented. Demand uplifts were lowest for light rail – this was due to not considering improvements in car parking costs (as many light rail travellers do not use car as access), better underlying levels of reliability (ie less scope for improvement), and lower sensitivities with respect to GJT and fare changes than those travelling longer distances by conventional rail. For the lower cost scenario (excluding measures to improve crowding, rail journey time and reliability and access/egress times) we found demand uplifts of 9-12%.

When looking at overall monetised benefits, the largest share of the benefits in each case comes from consumer surplus effectively measuring the enhanced passenger experience from improvements across a range of attributes. Revenue improvements for operators are offset partially by the reductions in fares and the associated elasticities which are largely inelastic. External cost savings are also significant impact of the scenarios although a much lower proportion for light rail.

4.9 APPENDIX: IMPUTATION OF PUBLIC TRANSPORT MISSING FARE VALUES AND PETROL COSTS

Conventional rail cost

Conventional rail ticket cost is reported but there are many missing values in the data. To impute these, we estimated based on the travel distance as well as traveller types (business travellers, students, the retired, full-time commuters and other commuters). We estimate the linear relationship between train ticket cost and distance for different traveller groups, adjusting the price to 2019 level based on CPI index. Table 32 summarizes the regression results[6].

Table 32: Conventional rail fare-distance relationship

Traveller Type	Fare-Distance regression
Retired	$TicketCost = -1.221 + 0.107Dist$
Business Travellers	$TicketCost = -2.629 + 0.272Dist$
Students	$TicketCost = -0.048 + 0.122Dist$
Commuters (full time)	$TicketCost = -1.709 + 0.205Dist$
Commuters (others)	$TicketCost = 0.150 + 0.120Dist$

Light rail cost

The same approach is applied to impute the missing value of light rail ticket costs.

Table 33: Light rail fare-distance relationship

Traveller Type	Fare-Distance regression
Retired	$TicketCost = 0.458 - 0.012Dist$
Business Travellers	$TicketCost = 1.799 + 0.067Dist$
Students	$TicketCost = 0.415 + 0.102Dist$
Commuters (full time)	$TicketCost = 0.822 + 0.1Dist$
Commuters (others)	$TicketCost = 1.009 + 0.127Dist$

Table 33 presents the estimation results. However, the estimation results for the retired imply a negative correlation between distance travelled and the ticket cost. Moreover, the coefficient for business traveller is not significant, which means that we cannot impute missing values using the estimated linear regressions. To address this, we calculate the average light rail ticket cost and impute the missing values with the mean value.

Table 34: Light rail imputation for business and retired travellers

Business Travellers	Total Cost	Retired Travellers	Total Cost
74	£ 159.81	528	£ 184.55
Average cost	*£2.16*	*Average Cost*	*£ 0.35*

Public transport

[6] All of the estimated coefficients are significant under significance level 0.01.

Besides conventional rail and light rail, there are other modes of travel and they fall into either public transport ("*Other stage bus*", "*Public express bus/coach*" and "*Other public transport*") or private vehicles. We apply same methodology to estimate public transport cost to travellers.

Table 35 presents the linear relation between ticket cost and distance travelled using public transport. Note that the coefficient for business traveller is negative and insignificant. We thus calculate the average cost for business travellers as imputed value. Besides the aforementioned public transport modes, there are three other travelling modes, which fall into the regime of public transport. We calculate the average cost as imputation for missing values.

Table 35: Public transport fare-distance relationship

Traveller Type	Fare-Distance regression
Retired	$TicketCost = -0.008 + 0.044Dist$
Business travellers	$TicketCost = 1.317 - 0.01Dist$
Students	$TicketCost = 0.294 + 0.114Dist$
Commuters (full time)	$TicketCost = 0.428 + 0.086Dist$
Commuters (others)	$TicketCost = 0.56 + 0.059Dist$

Table 36: Public transport imputation

Public transport (business)	Total cost
1,378	£ 19,115.18
Average cost	*£ 13.87*
London underground	**Total cost**
266	£ 613.87
Average cost	*£ 2.31*
London stage bus	**Total cost**
47	£ 35.2
Average cost	*£ 0.75*
Taxi & mini cab	**Total cost**
726	£ 2,791.54
Average cost	*£ 3.85*

As shown in Table 36, we use £13.78 as the imputation for business travellers using public transport. For three other public transport modes ("*London underground*", "*London stage bus*" and "*Taxi & mini cab*"), their average costs, £2.31, £0.75 and £3.85, are also used as imputation for missing values.

Private vehicle costs

When households travel using private vehicles, there are two costs incurred: parking cost and fuel cost. Households do not customarily consider driving cost when they plan their journeys and those implicit costs are very important when it comes to choosing rail or not. For parking cost, we use the average cost to impute the missing values. For fuel cost, we apply the methodology proposed in Transport Analysis Guidance (DfT, 2017c).

Fuel costs are estimated using a function of the form:

$$L = \frac{a}{v} + b + cv + dv^2$$

where L measures the cost and is expressed as in pence per kilometre, v is average speed in kilometres per hour and a, b, c, d are parameters defined for different vehicle type. For parameters a, b, c, d, we use the values from average vehicles in the handbook. Two types of vehicles are presented in the data: 1) cars and 2) large good vehicles (LGV) where different parameters are applied:

Table 37: Private vehicle costs

Vehicle Type	Fuel Cost (pence/km)
Average cars	$L = 38.881/v + 6.829 - 0.072v + 0.0005v^2$
Average LGV	$L = 42.069/v + 10.424 - 0.151v + 0.0013v^2$

We can obtain average speed from *Stage* data by dividing travel distance with driving time. Given households' reported travel diary, we also quantify the average cost travellers spend on parking:

Table 38: Average car parking cost

Number of trips	Total car parking cost
334	£ 69.9
Average car parking cost	*£ 0.209*

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