INVESTIGATING THE OPERATIONAL ENERGY CONSUMPTION OF A TRAIN – UNDERSTANDING THE FACTORS WHICH AFFECT IT, AND THE POTENTIAL OF RAIL TO BE A SUSTAINABLE MODE OF TRANSPORT

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ABSTRACT

Online journey planners, such as the UK website www.transportdirect.info, often provide information about the carbon footprint of a proposed journey. When it comes to driving, calculations can be quite sophisticated, taking into account fuel type, journey type and even predicted levels of congestion. When it comes to catching the train, however, the estimated carbon footprint typically relies on average data. Although average carbon emissions from rail travel tend to be much lower than those from alternative modes, there will be cases where such carbon calculators overestimate the benefits of travelling by train. Furthermore, widespread uptake of new technologies can happen faster in the motor industry than in the rail industry, and there are already some cars which, on paper, produce fewer carbon emissions per passenger than some trains.

It is therefore desirable to develop an understanding of carbon emissions arising from railway operations. A good place to start is by considering energy consumption, which is directly linked, although even then existing data are scarce and inconsistent. Work has been undertaken to model train energy consumption, and some empirical data has been obtained. Results from the modelling suggest that operational energy consumption and emissions can depend on a number of factors, including service-type and driving style, whilst features of the infrastructure such as tunnels may also have a very significant effect.

Keywords: Energy, Carbon, Efficiency, Rail, Infrastructure

INTRODUCTION

The UK Climate Change Act 2008 includes a legally binding target to reduce greenhouse gas (GHG) emissions relative to 1990 levels by 34% by 2020 and by 80% by 2050 (Department of Energy & Climate Change, 2012a). Progress so far has not been encouraging; according to the UK Department for Transport (2011), total GHG emissions from UK domestic transport (excluding international aviation and shipping) were around the same level in 2009 as they were in 1990, and accounted for 22% of total UK domestic GHG emissions in 2009. From the transport sector, carbon-dioxide (CO_2) is, in terms of levels emitted, the most significant GHG (Department for Transport, 2009).

It is noted that although technological innovation could help towards achieving a reduction in emissions (Banister, 2010), it will not on its own be able to help meet the targets set. Indeed, Banister claims that "significant reductions of CO_2 emissions in transport in the EU can only be achieved through behavioural change." Such behavioural change may include modal shift from highly polluting modes to those which pollute less

Rail has the potential to be a suitable target for such modal shift, away from driving and flying. As Armstrong & Preston (2010) put it, "rail's specific strengths in the context of climate change include its general environmental friendliness relative to competing modes." The basis for this includes the fact that for steel wheels running on steel rails there is comparatively little rolling resistance, which results in greater energy efficiency.

However, when modal comparisons are made, the case for rail is often made using average data, which may not be appropriate for a specific journey. This paper comprises an initial investigation in to the energy consumption of and emissions from rail travel, in order to understand the key factors which might affect them and how they might vary in reality. As well as providing an idea of how energy consumption and emissions could best be reduced, the findings from the investigation may be useful for developing better modal comparisons.

Methodology

The paper begins with an overview of the background to the research, including a brief review of existing data and an introduction to the factors which may affect energy consumption and emissions. This is followed by a description of some basic modelling and simulations, and the analysis of empirical data from on-train monitoring (OTMR) systems, as well as some theoretical predictions concerning the energy consumption of a train in a tunnel.

BACKGROUND

Making modal comparisons

When making comparisons between different modes, it is common to standardise and consider energy and emissions data on a per passenger-kilometre basis. This requires data about the vehicle itself (either in terms of energy and emissions on a per vehicle-km or per seat-km basis) and about the number of occupants (the load factor).

Some typical data for car travel, rail travel and domestic aviation in the UK are given in Table 1. Data in italics are inferred from the other data given.

At the end of 2012, the Hyundai i20 CRDi was claimed to produce the lowest CO_2 emissions of any internal-combustion engine car on sale in the UK (carpages.co.uk, 2012). Currently, it is not particularly representative of the UK car fleet as a whole and the manufacturers' data given is based on standard test-cycles rather than real—world driving. However, the operating life of a train is around 30 years, which is significantly higher than that of a car; in 2010, the average age of UK National Rail rolling stock was 17 years (Department for Transport, 2011b), whilst the average age of a car on UK roads is given to be 7 years (SMMT, 2012). Furthermore, cars over about 5 years in age tend to have low-mileage uses (RSSB, 2007).

This means that the motor industry is likely to close the gap on the rail industry; the RSSB suggest that "as the efficiency of cars increases, under the influence of progressive EU legislation, the difference in emissions between cars and trains such as the Class 221 will be narrow, making it difficult to make a case for transferring people onto diesel-powered railways" (RSSB, 2007, p.6)

Although electric trains generally fare better, the upshot is that it should not be automatically assumed that – as far as reducing GHG emissions is concerned – the train makes the best modal choice. Several websites, such as Transport Direct (www.transportdirect.info), offer journey planning and emissions comparison tools, but their reliance on average data may result in misleading results for a specific journey, and makes them of limited use.

Table 1 - Emissions data for different modes of transport

Mode		CO_2 per vehicle km (g)	CO_2 per seat km (g)	Typical Load Factor (%)	CO_2 per passenger km (g)	Notes
Car	2009 UK New Car Average	149.5 (SMMT, 2010)	*29.9*	32 (RSSB, 2007)	*93.4*	Assumes 5 seats/car
	2012 EU Target	120 (RSSB, 2007)	*24.0*		*75*	
	Hyundai i20 1.1 CRDi	84 (carpages.co.uk, 2012)	*16.8*		*52.5*	
Rail	2009/10 UK National Rail Average				55.0 (Office of Rail Regulation, 2011)	
	Class 221 (Intercity Diesel)		31.8 (RSSB, 2007)	31 (RSSB, 2007)	*102.5*	Assumes 1.2 litres of diesel per 100-seat km (RSSB, 2007)
	Class 357 (Suburban Electric)		14.2 (RSSB, 2007)		*45.8*	Assumes 455g CO_2 per kWh of electricity (RSSB, 2007)
	Class 390 (Intercity Electric)		14.6 (RSSB, 2007)		*47.0*	
Domestic Aviation				70 (RSSB, 2007)	165.1 (Defra, 2012)	Does not include an uplift factor

When it comes to driving, a reasonable amount is known about the factors which affect the emissions from a journey, including the effects of motorway and urban driving, congestion and cold-starting. The Department for Transport in the UK, for example, suggest increasing the figures from the test-cycles by 15% to take in to account some of these real-world effects (Defra, 2010). Transport Direct's emissions calculations for car journeys are relatively sophisticated. The fuel type (petrol or diesel) can be specified in the journey planning stage, and if the user has fuel economy data for their particular car this can be entered. Otherwise, the user is able to categorise their car by size. According to the published methodology, the calculations take into account the predicted congestion and the amount of urban driving (Transport Direct, 2012).

The same cannot be said for public transport, including rail, where Transport Direct's methodology relies on general averages for each mode, and a number of assumptions for calculating the distance travelled. Part of the problem is that data for trains are comparatively scarce, and traditionally hard to collect. Extensive testing on an operational railway is not a practical option in many cases because it requires valuable train paths and the removal of rolling-stock from revenue earning service (Rochard & Schmid, 2000).
It is, however, possible to simulate the energy consumption of a train, and by extension the levels of emissions. Data have also been obtained from Train Operating Companies (TOCs) who meter the electricity consumption on some of their trains, and work is now ongoing to quantify the factors which affect the operational energy consumption of a train in order to better understand the variations in the existing data and to be able to make more realistic comparisons between modes.

Factors which affect the energy consumption of a train

It is postulated that the factors which affect the energy consumption of a train can be categorised as follows:

- **Features of the infrastructure**. It is thought that gradients, and other features of the infrastructure such as tunnels, may have a notable impact.
- **The type of service**. In the same way that urban driving uses more fuel than driving on an open-road, it is thought that the type of service, including the stopping density, may impact the energy consumption of a rail journey.
- **Driving style.** Train drivers, like car drivers, are not always consistent, particularly when it comes to rates of acceleration and braking.
- **The type of rolling stock.** Some trains will be more efficient than others, and Table 1 implies that electric trains are significantly better than diesel ones.

This investigation will focus on the factors which might impact the energy consumption for a particular journey, for which it might reasonably be assumed that the allocated rolling stock remains the same. Additionally, although it is abundantly clear that the energy consumption on a per passenger basis is greatly impacted by the load factor, the focus here is on the energy consumption of the train as a whole.

Modelling the energy consumption of and emissions from a train

The Davis Equation

Modelling the energy consumption of a train is not straightforward. One of the main challenges is that it is dependent on the train's resistance to motion (due to friction and aerodynamics); although this can be calculated theoretically, with the help of computational fluid dynamics (CFD), "the approaches are complex, require knowledge of very many parameters and do not necessarily lead to useable train resistance data" (Rochard & Schmid, 2000, p.186). Rochard & Schmid go on to suggest that the resistance of a train can be "estimated by the application of a sufficiently accurate empirical calculation tool," several of which are subsequently reviewed in their paper. One such method of calculating the resistance, R, experienced by a moving train is the Davis Equation (Rochard & Schmid, 2000) – an empirical quadratic function of the train's velocity v, written as

$$R = A + Bv + Cv^2 \qquad [1]$$

If R is in Newtons [N] and v is in meters per second [ms^{-1}], then the coefficients A, B and C have units N, Nsm^{-1} and Ns^2m^{-2} respectively, although in this paper the values will be scaled for velocities in terms of km/h. A and B include the mechanical resistances (and are mass related), whilst the third term accounts for the aerodynamic resistance (Rochard & Schmid, 2000). "Numerous methods are available for determining the values of the coefficients" (RSSB, 2010, Section E1.3), including fitting an appropriate curve to data obtained from empirical testing (Rochard & Schmid, 2000).

Sample values for the Davis coefficients for three different types of train are given in Table 2 The standard coefficients for the Suburban and Intercity trains are taken from the RSSB (2010). The values for the High-Speed train are taken from those attributed to the AGV-11 (SYSTRA, 2011).

Table 2 - Davis Coefficients for different types of electric train

Train		Suburban Electric	Intercity Electric	High-Speed Electric
Davis Coefficients	A	2158	5311	2500
	B	5.384	21.696	29
	C	0.4158	0.9097	0.45

The resistance curves for each of these trains were generated using the Davis Equation and are plotted in Figure 1.

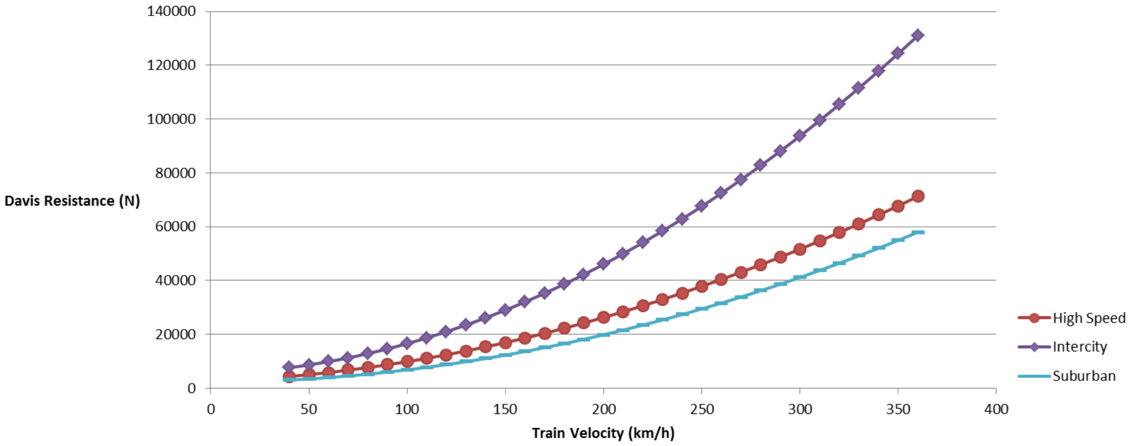

Figure 1 - Davis resistance curves for different types of electric train

It is well documented – for example by the RSSB (2010) and by Raghunathan et al. (2002) - that the value of C is proportional to both the length of the train and the head and tail drag coefficients. It is therefore postulated that train length is a key reason for the fact that the High Speed and Intercity trains (comprising 10 and 9 vehicles respectively) experience a greater resistance force than the Suburban train (comprising just 4 vehicles). The fact that the High-Speed train experiences less resistance than the Intercity train may well be down to reduced head and tail drag coefficients.

The Davis Equation can be used to estimate how the resistance experienced by a train may be affected by features of the infrastructure such as tunnels. A train running through a tunnel will experience a change in aerodynamic resistance compared with running in the open, because the air is pushed against the tunnel walls and the pressure inside the tunnel is increased compare with that outside. The impact this has can be modelled by varying the aerodynamic coefficient, C, of the Davis Equation accordingly.

Other resistance forces

The Davis Equation does not encompass all of the resistance forces experienced by a moving train. Other forces include grade resistance (the additional force required to overcome gradient) and curve resistance (the added resistance experienced by a train operating through a horizontal curve) (AREMA, 2003), although these can be neglected if the additional assumption is made that the track is straight and level.
It is also noted that the resistance caused by friction within a railway vehicle's wheel bearings can be significantly higher at starting than when the vehicle is moving. As a result, the Davis Equation does not accurately reflect the initial resistance at very low speed and starting resistance may therefore need to be additionally accounted for when considering the motion of a train from rest.

Work done and energy consumption

The work done by a moving train can be calculated by multiplying the applied force by the distance moved. The work done, E, by the train exerting tractive effort T over a distance d is thus estimated by:

$$E = Td \qquad [2]$$

If T is given in Newtons [N] and d is given in meters [m] then this gives work done in terms of joules [j]. One kilowatt-hour [kWh] is 3.6 mega-joules. The assumption is that T is constant over the given distance; which is reasonable if d is chosen to be small enough or the velocity and resistance forces both remain constant. On this basis, the work done over a whole route can be estimated by dividing the route into appropriate segments and summing the work done for each one.

In any case, something must be known about the tractive effort, T, in order to model the work done, E. If the train is moving at constant velocity, then T is equal and opposite to the resistance force, R; hence the importance of knowing the resistance to motion.
If the train is accelerating, then the tractive effort T will be greater than the resistance force R. If both the mass of the train m and the rate of acceleration a are known at a given point, then according to Newton's second law:

$$T = ma \qquad [3]$$

If the rate of acceleration also needs to be determined, further data about the tractive performance of the specific train need to be obtained. When a train is slowing down, no forward force is applied and T is typically zero.

The work done is not equivalent to the total energy consumption of the train, for several reasons. The actual energy required to move the train will be higher, due to the fact that the engine and transmission systems are not 100% efficient. In addition, energy is required for on-board 'hotel' services, including heating and lighting.

GHG emissions

Energy efficiency is directly linked to the reduction of GHG emissions, because a lot of energy is provided by the burning of fuels which release GHGs. Diesel trains produce emissions at the point of use by the combustion of fuel in the engine, and could arguably be responsible for emissions arising from the extraction, production and transportation of the fuel. Although electric trains do not produce emissions at the point of use, the generation processes for over 70% of the electricity generated in the UK between April 2011 and March 2012 directly resulted in CO_2 emissions (Department of Energy & Climate Change, 2012b).

In the UK, the Department for Environment, Food and Rural Affairs (DEFRA) produce annual guidelines for converting "activity data" (such as amount of fuel used or electricity consumed) in to GHG emissions (Defra, 2012). This paper uses the 2012 Guidelines, which gives a figure of 516.9g of CO_2 emitted per kWh of electricity consumed (for the year 2010).

As an aside, it is worth noting that this figure is dependent on the generation mix and thus could be expected to be decreased as the electricity grid is "decarbonised" with a higher proportion of renewable energy and less reliance on fossil fuels. In the UK, this may help electric rail to retain its position overall as a relatively low-polluting mode of transport. Conversely, countries with a more carbon-intensive electricity generation mix may find that the gap between rail and other modes is much narrower.

USE OF A TOOL TO SIMULATE THE ENERGY CONSUMPTION OF AND EMISSIONS FROM A TRAIN

This research has included the development of a simulation tool for Ove Arup & Partners (Arup) to provide an estimation of the tractive effort expended and work done by a train over a given route. The tool takes data about a route (including speed limits, stops and gradients) and breaks it down in to incremental segments. Following the principles described above, the work done [2] is calculated for each segment and summed for the whole route.

A library of rolling stock was provided by Arup, which includes Tractive Effort (TE) and Train Resistance (TR) data for different types of train, and their variation with train speed. A key use of the simulation tool to date has been to predict the variation in energy consumption with stopping density. Initially, theoretical flat routes with varying uniform stopping density were generated. An intercity electric train (based on that for which empirical on-train monitoring data were also provided) was selected from the rolling stock library. Two sets of simulations were run; the first allowed the train to reach its maximum speed of 225km/h (140mph), and the second imposed an operating limit of 201km/h (125mph), to reflect the conditions under which such a train is run in the UK. Initially, rates of acceleration and braking were left at their default (maximum) values.

Recognising the fact that the stops on a rail service are rarely spaced uniformly, it was then decided to generate two route profiles based on actual mainline intercity services in the UK. The basic route profiles are given in Table 3.

Table 3 - Route profiles chosen for analysis

Route	**A**	**B**
Distance to Stop 1 (km)	133	254
Total Distance to Stop 2 (km)	151	285
Total Distance to Stop 3 (km)	169	295
Total Distance to Destination (km)	182	304

Like many intercity routes in the UK, each route considered here is non-stop for a considerable distance before there are several stops in relatively quick succession. To allow for better analysis of the effect of stopping patterns it was therefore decided to split each route in to two and consider the non-stop section (until Stop 1) and the stopping section (from Stop 1 until the destination) separately.

Initial analysis of the empirical data recorded from on-train monitoring (OTMR) systems was then used to make a more informed choice about the acceleration and braking parameters set in the simulation, and enhanced results were produced accordingly.

USE OF RECORDED DATA FROM ON-TRAIN MONITORING SYSTEMS

Recorded data from on-train monitoring systems has been obtained for a fleet of intercity electric trains. Data for each train include a log of electricity meter readings at regular intervals and a record of the train's position.

Work has been undertaken to assimilate the relevant data for analysis in this context. Energy and position data were combined with rolling stock allocation data (the assignment of a particular train to a particular route on a particular day) and timetable data in order to group the data by known routes. The points at which each train actually stopped were checked to ensure that the monitored data correctly matched the timetable allocations.

For this analysis, the two routes used in the simulations, as outlined in Table 3, were chosen. The data were filtered to ensure that only standard weekday runs which matched the exact stopping pattern, and on which the train was within a few minutes of its allocated timings were considered. For each of the selected runs, the mean net energy consumption (taking in to account regenerative braking) was calculated in terms of kWh per km. In keeping with the simulation work, each run was split at the first stop, so that the differences between the initial non-stop section and final stopping-section could be considered. This led to the creation of four different data sets, as follows:

A1 – Data pertaining to the initial non-stop section of Route A (133km)
A2 – Data pertaining to the final stopping section of Route A (49km)
B1 – Data pertaining to the initial non-stop section of Route B (254km)
B2 – Data pertaining to the final stopping section of Route B (50km)

In each case, additional data considered for each run include an identifier to differentiate between different train drivers (no personally identifiable information was supplied for the purposes of this study). As a basic indicator of driving style, the mean rates of acceleration and deceleration were also calculated for each run. Finally, to help quantify the potential impacts of other factors, such as seasonal variations and weather, the month of operation was also considered.

Statistical analysis conducted on the data included tests to check whether the energy data are normally distributed and non-parametric tests to look for a potential correlation between the driver identifier and the energy consumption and the month and the energy consumption. An attempt was also made at developing a linear regression model, with average acceleration being the independent variable, and energy (in terms of kWh per km) being the dependent variable.

THE PREDICTED EFFECT OF TUNNELS ON ENERGY CONSUMPTION

Having stipulated that features of the infrastructure may have an impact on the operational energy consumption of a train, the Davis Equation [1] was used to estimate the increase in energy consumption of a train in a tunnel due to increased air resistance. The size of the increase depends on the cross-sectional area of the tunnel relative to the train; a report by the RSSB (2010) suggests that the increased aerodynamic resistance in a tunnel can be modelled by using a new value for C in the Davis equation, typically between 1.5 and 2 times the standard value. This is corroborated by Rochard & Schmid (2000) who suggest that the aerodynamic resistance encountered in a tunnel may be double that experienced in the open.

In this case, two basic scenarios were considered – a wide tunnel (relative to the train), for which C was multiplied by 1.5 and a narrow tunnel (relative to the train) for which C was multiplied by 2. The modified Davis coefficients for the RSSB's Intercity Electric Train D (RSSB, 2010) are given in Table 4. Using the Davis Equation [1], and an estimation of work done [2], some predictions about the impact of tunnels on operational energy consumption were calculated accordingly.

Table 4 - Modified Davis Coefficients for an intercity electric train in a tunnel

Standard C Value	0.9097
Modified C for a wide tunnel	1.3646
Modified C for a narrow tunnel	1.8194

RESULTS

Initial analysis of OTMR data

For each of the different route segments, the energy consumption of the trains on that route in terms of kWh per km was considered.

Table 5 – Mean energy consumption on each Route Segment

Route Segment	**A1**	**A2**	**B1**	**B2**
Distance (km)	133	49	254	50
Number of Stops	1	3	1	3
Number of trains in sample	242	242	251	251
Mean Energy Consumption (kWh per km)	13.5	14	12.78	12.82
Standard Deviation	1.21	1.8	1.11	1.98

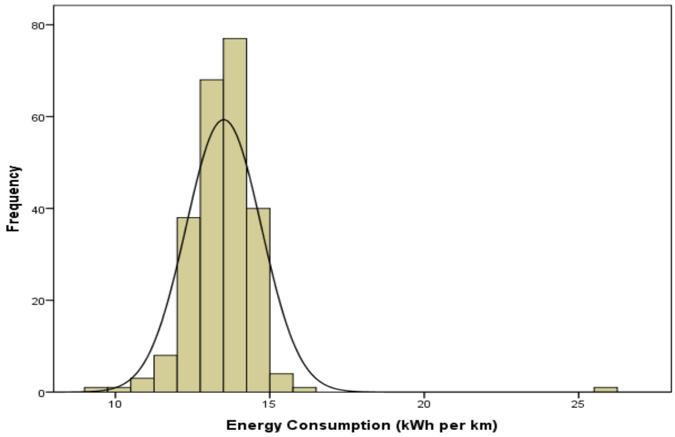

Figure 2 – The distribution in energy consumption for trains on route section A1

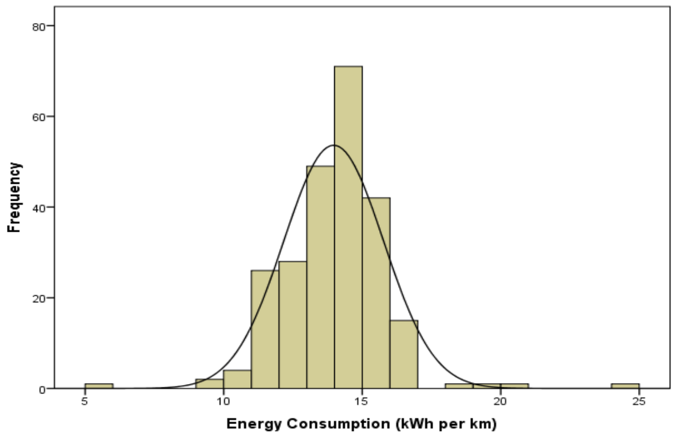

Figure 3 – The distribution in energy consumption for trains on route section A2

For each route segment, an Independent-Samples Kruskal-Wallis Test was conducted to determine whether the distribution of energy consumption in kWh per km was the same across each month and for each driver. The results are given in Tables 6 and 7. The significance level is 0.05 and results above that (shown in italics) suggest that there is no dependence.

Table 6 - Kruskal-Wallis Test Results for the null hypothesis that energy is independent of month

Route Segment	**A1**	**A2**	**B1**	**B2**
Asymptotic Significance	0	*0.235*	0	*0.18*

Table 7 - Kruskal-Wallis Test Results for the null hypothesis that energy is independent of driver

Route Segment	**A1**	**A2**	**B1**	**B2**
Asymptotic Significance	0.002	0.003	0	0.027

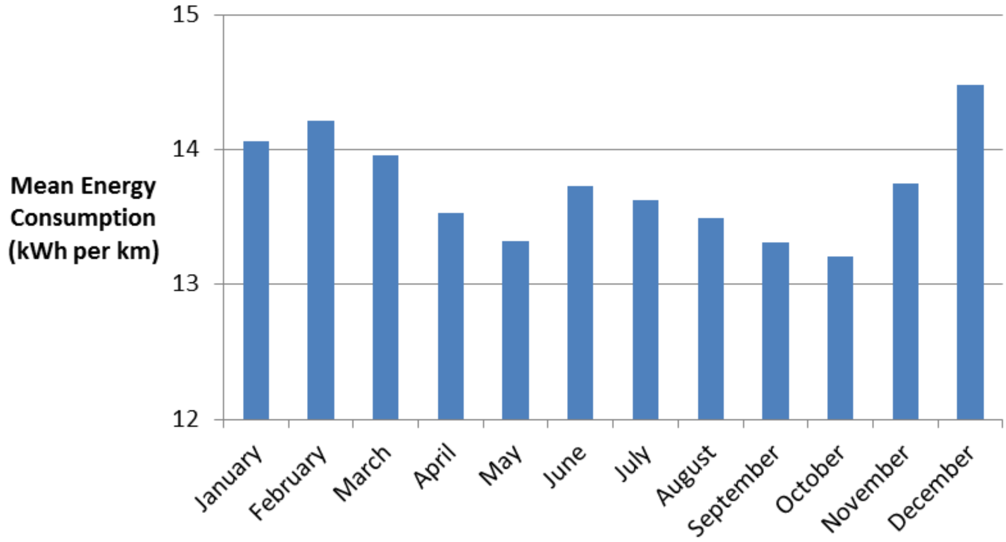

Figure 4 – The variation in energy consumption on a monthly basis for Routa A

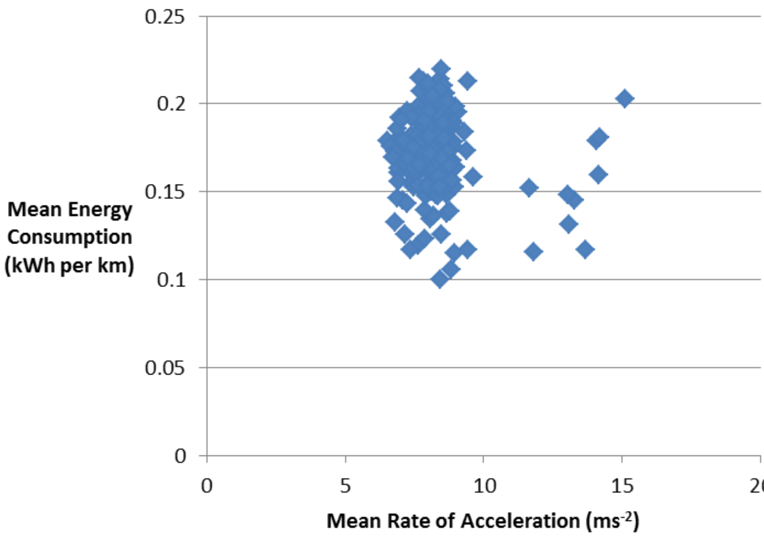

Figure 5 – The relationship between acceleration and energy consumption for Route A

The effect of stopping patterns on energy consumption

Simulation results from the Arup tool, showing the variation in energy consumption with stopping density are graphed in Figure 6. For comparative purposes, mean data from the OTMR data for each route section (Table 5) is also included.

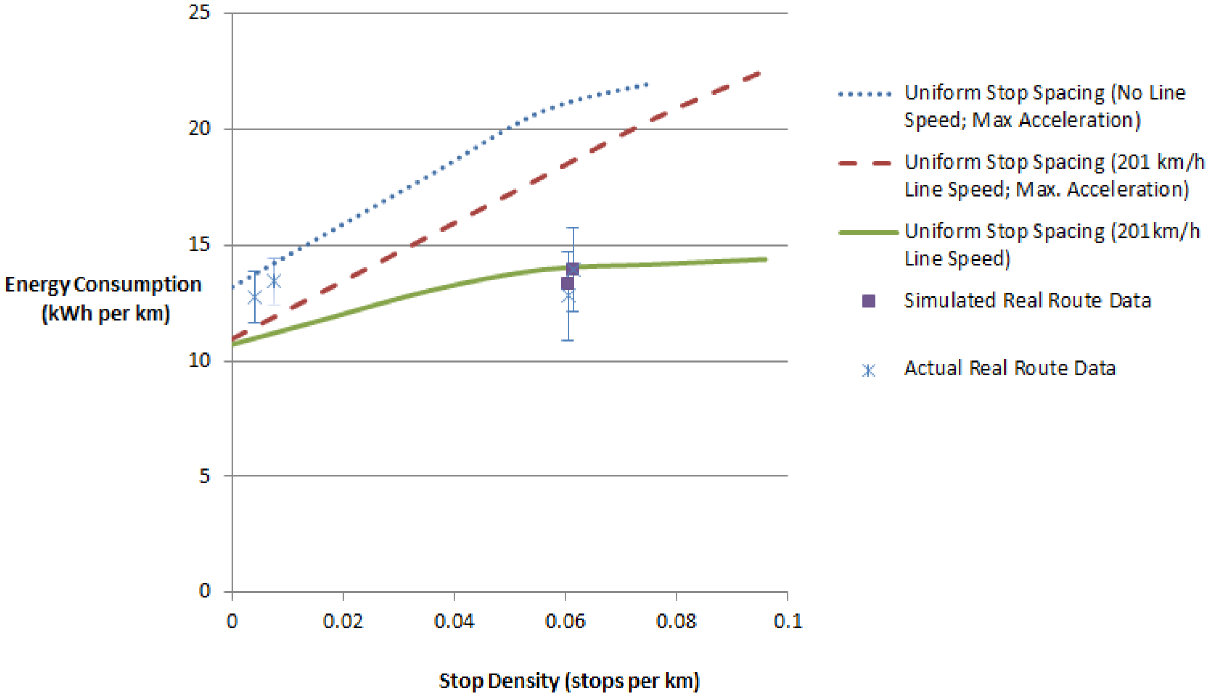

Figure 6 – The variation in energy consumption with stop density for an intercity electric train

Predicted effect of tunnels on operational energy consumption

Table 8 – Estimated work done by an intercity electric train

Velocity (km/h)	Work Done (kWh) [% Increase w.r.t. Open Air]		
	Train in Open Air	Train in Wide Tunnel	Train in Narrow Tunnel
100	46	59 [27]	71 [55]
160	89	121 [36]	154 [73]
240	175	248 [42]	320 [88]

ANALYSIS

It was postulated that there are many reasons for variation in the operational energy consumption of a train, and that these could broadly be broken up in to four different categories. Three of these categories (driving style, service-type and features of the infrastructure) were explored in this study.

The impact of driving style

From the OTMR data, Figures 2 and 3 illustrate that even for the same type of train on the same route, considerable variation can be observed in energy consumption. For each of the two whole routes considered, the standard deviation of the observed energy consumption was bigger on the stopping section than the initial non-stop section. This is not particularly surprising given that there are more periods of acceleration and braking on these latter sections of the route and hence more opportunity for variation compared with periods of running at constant speed. It can also be seen that the mean energy for Route B is higher than that for Route A; reasons for this may include variations in characteristics of the route, including features of the infrastructure, line-speed limits and signals.

The non-parametric tests suggest that the energy consumption is typically higher for some drivers than others. This implies that differences in driving style do indeed lead to some of the observed variations. To test this further, the average rate of acceleration (during periods of acceleration on each route) was considered as a proxy for driving style; however, as Figure 5 shows there is no obvious correlation with energy consumption for Route A.
A similar result was observed for Route B. This may be because rates of acceleration between different speed intervals differ, whilst individual drivers will vary their rates of acceleration on a given run, making it harder to get meaningful results over a long section. It is proposed that looking at much shorter sections of a route may give greater insight, both in to the size of the impact of driving style and how it is that some drivers are more efficient than others.

The impact of service type

A key variable when it comes to the type of service is the stopping pattern. The simulation results shown in Figure 6 predict a steady increase in energy consumption with increasing stop density. This makes sense in light of the fact that increasing the number of stops increases the number of periods of acceleration and deceleration at the expense of time running at constant speed. Although the effect is broadly linear, there is an observed change in gradient at the point where the stopping density becomes so high that the train cannot reach its maximum speed before it needs to slow down again. Rates of acceleration and deceleration are shown to be of vital importance, and when these were reduced from their maximum values in order to better reflect reality, the predicted effects of increased stopping density were significantly lessened. Reasons for the differences between the simulated data and the observed data, particularly at lower stopping densities, may include the fact that the simulation does not consider the 'hotel load.' Additionally, the route profiles used in the simulation contained limited data and assumed that the speed limit is always 125mph. There may also be other factors – including the reliability of the tractive effort and resistance data for the trains in the simulation's rolling stock library.

Another key aspect of the service type is the running speed. The simulation results in Figure 6 also show that allowing the train to run at a higher speed of 140mph noticeably increases the energy consumption, which is in accordance with the theory and the increase in resistance forces with speed (Figure 1). This is particularly noteworthy given a focus on high-speed rail.

Features of the infrastructure

The predicted results for the effects of tunnels compare favourably with some existing simulation results for the proposed High Speed 2 line between London and Birmingham (HS2 Ltd, 2009). It is suggested in that case that for a high-speed train running at 320km/h, the increase in work-done ranges from 39% for a 12m diameter tunnel right up to 94% for an 8.5m diameter tunnel. It is clear that in theory, tunnels have a detrimental effect on energy consumption, especially at high speed. Although most tunnels are comparatively very short, the cumulative effect could be quite large. Further work needs to be done to verify the findings empirically, which may be possible by matching recorded data with the location of tunnels en route.

Additional factors to consider

Even for the same type of train on the same route, driving style alone is unlikely to account for all of the observed variations, and there may be some sense in broadening the scope of that category. As noted by Grigorchenkov, Johnson, & Pullen (2012), "there is a randomness associated with railway operations." This includes variations in traffic and passenger loads which can have a considerable effect on the performance of regenerative braking and on the overall energy consumption.

Other factors which may affect the energy consumption include the weather and levels of train maintenance. The variation in energy consumption on a monthly basis would suggest that weather is a factor, although the results of the non-parametric tests on the stopping sections of the route imply that other factors are more important. Nonetheless, Figure 4 clearly shows some seasonal variations in energy consumption. The amount of energy used for on-board heating and air-conditioning will be dependent on the ambient temperature, whilst rail conditions (affected by ice and precipitation in conjunction with autumnal leaf fall) will affect acceleration and braking rates. It is presumed that rail conditions and cold temperatures lead to the winter peak in energy consumption, whilst the slight rise in energy consumption in the summer months is likely to be due to increased demand for air-conditioning. The implication is that the 'hotel load' is not insignificant in the overall demand for energy, and this should be further investigated.

GHG Emissions

From the energy data given, it is possible to extrapolate an estimation of the GHG emissions. For electric rail, a conversion factor of 516.9g of CO_2 per kWh (Defra, 2012) can be used. The average load factor appropriate for intercity rail journeys of 40% (RSSB, 2007), and the number of seats on the train was given with the OTMR data as 439. It should be noted that despite the size of the variations, the estimated GHG emissions per passenger-km for the monitored data are consistently about 25% lower than the data for the cleanest new car (Hyundai i20) given in Table 1. Although other types of rail service remain to be investigated, long distance intercity routes operated by such electric trains make a good target for modal shift from car travel.

CONCLUSIONS

This paper has highlighted a number of key points about rail's operational energy consumption and emissions:

- As the transport industry strives to meet stringent emissions targets, technological development in the motor industry means that rail travel may not always be less polluting than car travel. However, it has been shown that intercity electric trains in the UK remain a comparatively clean mode of transport.

- The use of average data in journey comparison tools may not be particularly helpful, due to the potential for variation between different routes, trains and service types. The use of comprehensive empirical data in this study has also highlighted the variation in energy consumption for the same trains on the same service.

- Simulations and analysis of empirical data have shown that driving style, service type and other variables such as time of year contribute in some way to the variations observed. Rate of acceleration was found not to be a good proxy for quantifying the effects of driving style, so further studies need to be done. Some of the results imply that the size of the 'hotel load' for the provision of on-board services is significant.

- When it comes to features of the infrastructure, the effect of increased resistance in a tunnel is theoretically significant, and needs to be verified in practice. Tunnels and other features of the infrastructure are often a necessity, but these findings nonetheless need to be considered when planning a new railway line, or when comparing an existing rail journey with other modes.

The provision of a comprehensive empirical data set has been vital for understanding the scale of the variations in the operational energy consumption of a train. The next stage of the research is to consider things in more detail. As well as quantifying both the impact of driving style and of the size of the 'hotel load,' the aim is to develop an understanding which can be used to inform energy efficient policy and design.

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