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On the right track? Energy use, carbon emissions, and intensities of world rail transportation, 1840–2020

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ABSTRACT

The history of rail transport can offer valuable insights for future energy transitions due to its importance in promoting clean mobility. There is a complex interplay between the evolution of the railway network, fuel consumption, efficiency, energy service, and CO_2 emissions that requires further exploration. We developed a dataset that covers energy use in all stages of rail transportation, as well as the length of track, energy service, and CO_2 emissions at the world scale. To deal with missing data we utilized machine learning techniques for the first time in a historical energy reconstruction study. Our analysis reveals that for world rail transport (1) the final-to-useful efficiency has increased by 30-fold from 1840 to 2020, mainly due to the replacement of steam trains with diesel and electric ones, (2) the peak in final energy use occurred in the 1940s, while useful energy use and transport service continue to grow, (3) there was a reduction in the energy (carbon) intensity from approximately 20 to 0.2 MJ/tkm (2 to 0.02 kg CO_2/tkm) between 1840 and 2010, due not only to the increase in final-to-useful efficiency but also to rising occupancy, better operating conditions, and reduced losses by the passive system.

1. Introduction

1.1. Railways: past, present, and future

Rail transport has been promoted by the International Energy Agency (IEA) as the backbone of sustainable mobility due to its high efficiency and low environmental impacts. According to the IEA, moving one passenger along one kilometer by rail releases one-sixth and one-eight of the CO_2 emitted by air travel and car travel, respectively [1]. High-speed train routes have the potential to replace medium-distance airplane flights, which would reduce the environmental footprint of travelers. Furthermore, railways play a major role in sustainable city planning, providing reliable, affordable, and high-quality public transport. As cities grow and people are forced to live further away from the center, greater demand for transport is expected. Fulfilling this demand by individual vehicles means increases in air pollution, traffic, and CO_2 emissions. Rail transport provides a cleaner alternative.

However, trains were not always the most environmentally friendly transport mode, as enormous amounts of coal were once consumed by steam engines with engine efficiencies of around 2.5% [2]. The UK was the first country to develop a railway system, beginning in 1821 with the Stockton-Darlington line [3]. The expansion of railways in the UK was extremely fast, tripling its length of track between 1850 and 1900 [4]. France, Germany, Russia, and the USA, following the UK's lead, developed their rail network later in the 19th century, consolidating train travel as the most relevant transport mode of the time [4,5]. Most of the 20th century would still be dominated by steam trains until electric and diesel-electric locomotives replaced them. Even though both technologies implied a great increase in engine efficiency, environmental impacts did not necessarily decline. The evolution of railway network, passenger and freight traffic, fuel consumption, energy efficiency, and environmental impacts are complexly intertwined and yet to be explored.

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1.2. Literature background

Other authors have partially studied the historical evolution of energy use in railways, however, the lack of data is a main challenge that is still to be overcome. Bond et al. [6] estimated the world fuel (coal and diesel) consumption in railways between 1850 and 2000, focusing on black and organic carbon aerosol emissions, based on passenger and freight service (measured in passenger-km and ton-km). Energy intensity (fuel consumption per unit of energy service) was assumed to be equal across different countries. Neither electricity consumption in railways nor the useful stage (i.e. the physical work done at the drawbar) were explored. Moreover, the fuel consumption dataset developed by Bond et al. [6] was not made available. De Stercke [7] also built a worldwide database from 1900 to 2014 of final energy consumption, by modeling solid fuel consumption as a linear combination of passenger and freight service using exclusively data for the UK before 1940. After that year, the trend was adjusted to fit IEA data in 1960 or 1971 (depending on data availability). De Stercke's [7] method assumes that before 1940 energy intensities were constant and homogeneous across different countries. The primary, final, and useful stages were included in this study, although energy efficiencies were estimated based solely on GDP. De Stercke's database is publicly available, however, transport is reported as a single end-use, not divided into different modes. Pinto et al. [8] built a database of world electricity consumption from 1900 to 2017 by end-use, including transport, at primary, final, and useful stages. On the country level, Serrenho et al. [2] estimated the primary, final, and useful energy use by rail transport in Portugal between 1856 and 2016 based on the growth rate of the length of track, which might not be related to the actual fuel consumption.

World historical energy transitions in railways remains an understudied topic, as previous studies have struggled with incomplete temporal and spatial data coverage. A way to cover partial datasets is by utilizing machine learning techniques. In supervised machine learning, the process begins with selecting one or more types of models, along with the input variables that will be used to predict the desired outputs. The next step involves using a dataset that contains both inputs (features) and known outputs to train the model. This training adjusts the model's parameters by minimizing the error between the predicted values and known outputs. Once trained, the final model can then be applied to estimate unknown outputs. Machine learning applications have been increasing significantly over recent years, providing a consistent method for solving many problems, including sparse data issues.

None of the studies on long-term historical energy reconstruction previously mentioned used machine learning algorithms, apart from simple linear regression. Previous studies that rely on expert-based knowledge are highly dependent on author bias. Machine learning has the potential to improve the accuracy of estimations, avoid repetitive manual work, incorporate different types of data (e.g., numerical and categorical), and standardize a consistent method for both estimation and validation, a critical missing step in previous studies. Past historical energy reconstruction problems did not estimate confidence intervals or error metrics; therefore, it is difficult to assess their uncertainty.

Other fields used machine learning to predict time-dependent data. Dudek [9] estimated short-term electricity load using a random forest, obtaining high accuracy results. Wu et al. [10] used a random forest regressor to forecast influenza-like illness rates using historical observations, first-order differences, and weather conditions as inputs. Furthermore, Herrera et al. [11] compared traditional econometric methods with random forests and neural networks for long-term forecasting of energy commodities prices, concluding that random forests had the best performance. All in all, research across various fields has increasingly employed machine learning techniques, particularly the random forest regressor, to handle variables that change over time in complex, non-trivial patterns. This approach facilitates the generation of estimates using datasets comprising diverse types of data. A description of the random forest regressor, the choice of the algorithm, and model training are more deeply explored in Section 2.3.2.

In this work we aim to address two research gaps: (1) the first time to our knowledge use of machine learning in historical energy reconstruction problems, accompanied by the quantification of uncertainty, and (2) the analysis of rail primary energy to service, on a large timescale, which is an opportunity to obtain insights not previously seen in studies focused on a single energy stage or in shorter timespans.

1.3. Aim, contribution, and structure

The aim of this study is to gain a deeper understanding of the historical evolution of rail transport, focusing on the efficiency of energy use and the energy and carbon intensities of freight and passenger service. The key contributions of this research are: (a) a publicly available long-term database of rail energy use, (b) the application of machine learning techniques to the relatively unexplored domain of reconstructing historical energy data, and (c) insights regarding the transitions in rail energy use over time. The long-term dataset on energy usage offers a comprehensive overview of primary, final, and useful energy, along with data on CO_2 emissions, energy efficiencies, energy services, and carbon and energy intensities. It was developed using an extensive array of public but incomplete data on final energy (fuel consumption) and energy service demand. This study adds value by pre-processing existing datasets, estimating missing data, and estimating other variables (e.g., energy intensity, useful energy).

This paper is divided into 5 sections: Section 2 describes the methods used to build the database, including the description of the machine learning approach to estimate final energy use. Section 3 presents the main results, followed by their discussion in Section 4, and Section 5 concludes.

2. Methods and data

In this section, we present the main data sources used, describe the methods used to estimate variables not addressed in previous studies (e.g., carbon and energy intensities), and describe the methods used to improve estimations from previous works. We begin with a brief overview of the framework used, followed by a description of our reconstruction.

2.1. Overview

The starting point of the database construction was identifying the most relevant stages in the energy conversion chain regarding rail transportation. Primary-to-final efficiency measures how much of the natural resources extracted from nature reach the final consumer. The final energy consumed by the engine is transformed into mechanical work by spinning a shaft, which will then spin the wheels, pulling the drawbar. The useful energy stage is defined as the closest to delivering the energy service. In rail transport, one locomotive (typically) pulls the cars behind it, connected by a drawbar, exerting a force through a certain displacement. Energy efficiency in trains is measured from the fuel consumed (final stage) to either (a) immediately after the engine, defined as engine efficiency, or (b) to the drawbar, defined as drawbar efficiency. The drawbar efficiency takes into account the transformation of chemical energy into heat and from heat into mechanical work, first at the driveshaft and then at the drawbar. The final-to-useful efficiency may be estimated by multiplying the engine efficiency by the engine-to-drawbar efficiency. Energy intensity is usually defined as the final energy consumption per unit of service. Rail energy service is divided into freight and passenger, accounted as ton-km (tkm) and passenger-km (pkm). In other words, energy intensity directly links fuel consumption to service, bypassing the useful stage. On the other hand, useful energy intensity measures how much useful energy is consumed

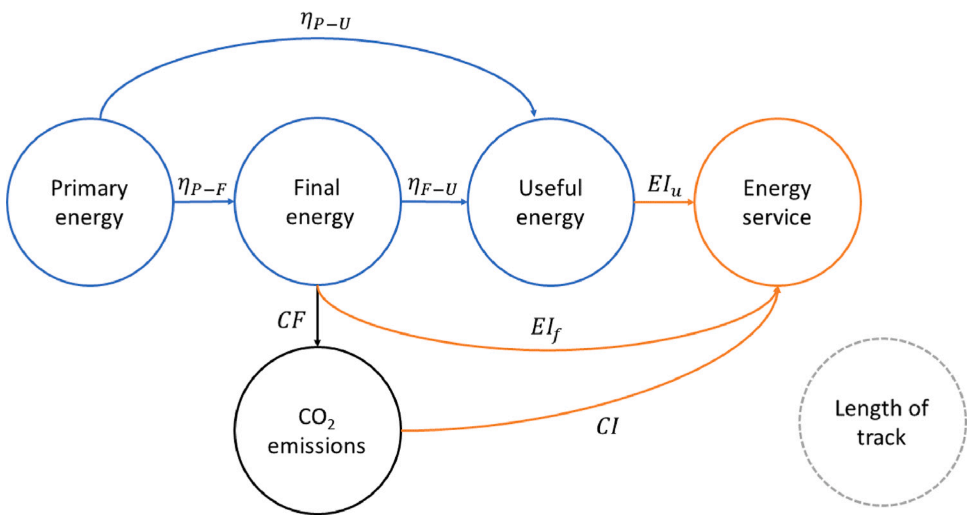

Fig. 1. Energy stages, CO_2 emissions, length of track, and their relations: primary-to-useful efficiency (η_{P-U}), primary-to-final efficiency (η_{P-F}), final-to-useful efficiency (η_{F-U}), useful energy intensity (EI_u), final energy intensity (EI_f), carbon intensity (CI), and carbon (emission) factor (CF).

Table 1
Variables quantified in this work, their units, time span they were quantified, and their description.

Variable	Units	Time span	Description
Primary energy	Energy units (e.g., PJ)	1840–2016	Energy content of the natural resources extracted
Final energy	Energy units (e.g., PJ)	1840–2020	Energy content delivered to the final consumer
Useful energy	Energy units (e.g., PJ)	1840–2020	Mechanical work at the drawbar
Energy service	Transportation units (passenger-km, ton-km)	1840–2010	Passenger or freight movements
CO_2 emissions	Mass units (e.g., kg)	1840–2016	Mass of CO_2 released
Final energy intensity	Energy per unit of transportation (e.g., MJ/passenger-km)	1840–2010	Final energy required to deliver one unit of energy service
Useful energy intensity	Energy per unit of transportation (e.g., MJ/passenger-km)	1840–2010	Useful energy required to deliver one unit of energy service
Carbon intensity	Mass per unit of transportation (e.g., kg CO_2/passenger-km)	1840–2010	CO_2 emissions per unit of energy service
Primary-to-final efficiency	Unitless	1840–2016	Efficiency of the conversion of primary into final energy
Final-to-useful efficiency	Unitless	1840–2020	Efficiency of the conversion of final into useful energy
Primary-to-useful efficiency	Unitless	1840–2016	Efficiency of the conversion of primary into useful energy

per unit of service, which is not directly influenced by the drawbar efficiency. Instead, useful energy intensity depends mainly on operation conditions, such as occupancy, velocity, and comfort demanded by passengers. Fig. 1 summarizes the main energy stages described above and their connections. In the subsections below, we delve deeper into the specific methods used to quantify each energy stage, as well as explore other essential factors in rail transport, including track length, and CO_2 emissions (see Table 1).

2.2. Energy service

Data for energy service in railways was found in Mitchell “International Historical Statistics” [4,5,12] for 94 countries from 1840 to 2010. A few gaps were filled with estimations from other authors. Fouquet [13] provides estimations for both UK’s freight and passenger service before 1920 and 1938 respectively, a period for which Mitchell [4] does not have data. Fishlow [14] estimated energy service for the USA between 1839 and 1880, which was added to complement Mitchell’s [5] database. A few errors were manually spotted (e.g., values that suddenly changed in order of magnitude) and substituted by missing values, which were filled with linear interpolation. Since no comparable dataset for rail energy service was available for the period 2010–2020, the analysis of energy service is limited to data up until 2010. Passenger and freight service per capita were calculated for the world and selected countries by dividing service per population data [15,16].

World energy service in railways was calculated per year by summing the data from all countries listed by Mitchell. The most relevant countries were identified so that together they represent at least 90% and 85% of world freight and passenger service respectively, from 1840 until 1970. These countries are the USA, Canada, the UK, Germany, France, Italy, Austria, Belgium, Hungary, Czechoslovakia (until 1992, then Czech Republic), Poland, the USSR (until 1991, then Russia), Spain, China, Japan, and India.

2.3. Final energy

2.3.1. Data sources

After 1971, the IEA [1] provides final energy use data per energy carrier and end-use, including rail transport. Before 1971, there are not many records for final energy use, which has been a difficulty in previous studies [6,7].

Wood was the main fuel in the USA when steam trains were developing, however, it was gradually replaced by coal. Fishlow [14] estimated the consumption of wood in railways in the USA for selected years before 1910 and the United States Bureau of the Census [17] provides wood consumption after 1920. Missing values were filled by linear interpolation.

A few data points were found for coal combusted by steam trains in the USA [14,17], UK [13], France [18,19], China [20], and Germany [21,22] as shown in Fig. 2. For the USA, until 1920 we only found data every ten years. The USA after 1920 and the UK have each year covered. A few irregularly spaced observations were found for France and Germany. We found for China the average coal consumption in railways at selected year intervals. Because many values are missing from the world coal consumption in railways, we developed a machine learning model to estimate final energy consumption across different countries, as explained in Section 2.3.2.

The transition from steam to diesel trains began in the USA around the 1930s, followed by the USSR in the 1940s and the UK in the

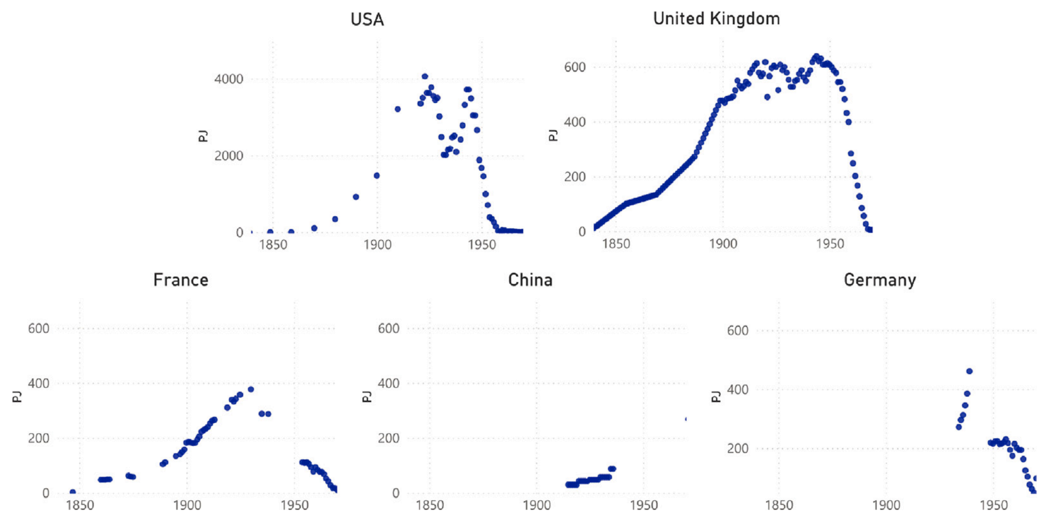

Fig. 2. Raw data for coal consumption by steam trains for several countries between 1840 and 1960.

Table 2
Summary of the data sources for wood (W), coal (C), diesel (D), and electricity (E) consumption in railways.

Wood	Coal	Diesel	Electricity	Reference	Time span	Region covered
✓	✓			[14]	1839–1910	USA
✓	✓	✓		[17]	1920–1970	USA
	✓	✓		[13]	1840–2018	UK
	✓			[18]	1847–1938	France
	✓	✓		[19]	1954–1959	France
	✓			[21,22]	1934–1959	Germany
	✓			[20]	1915–1936	China
✓	✓	✓	✓	[1]	1960–1970	OECD
✓	✓	✓	✓	[1]	1971–2020	World
			✓	[8]	1900–2018	World

1950s [13,23,24]. China and India took longer to replace coal-fired locomotives, starting in the 1960s, whereas in the USA the transition was already complete [1,25]. Data for diesel consumption in railways from the beginning of the steam-to-diesel transition to 1971 was found only for the USA and the UK [13,17]. For this reason, diesel consumption was also estimated by our machine learning model.

Pinto et al. [8] estimated world electricity consumption for different end-uses between 1900 and 1971. Some countries which used hydropower and had no coal reserves (e.g., Switzerland, Sweden, and Italy) had very early electrification of their train lines. During that period, we assumed that 100% of the electricity consumption allocated to transport was used in railways. Before 1900, electricity consumption was extremely low, consequently, there was no need to estimate electricity consumption in the 19th century. As a result, there are no missing values for electricity consumption for rail transport. Table 2 summarizes the data sources for final energy consumption in railways.

2.3.2. Machine learning estimations: 1840–1970

A random forest regressor was used to estimate the final energy use in railways across different countries, accompanied by an uncertainty quantification. A random forest regressor consists of training several regression trees, each with a bootstrap sample of the original dataset and a subset of features (inputs) chosen randomly [9]. A regression tree is a non-parametric model that approximates an unknown nonlinear function with local predictions by partitioning the feature space [26,27]. The predictions from individual trees are then aggregated by averaging their results. The random forest algorithm was chosen for its robustness against outliers and its capability to combine numerical and categorical features effectively. This approach generally yields higher accuracy compared to a single regression tree. Additionally, it is particularly suited for datasets like historical energy consumption, which tend to exhibit significant fluctuations in short time frames, which are expected to be captured by the random forest algorithm.

To train any supervised machine learning model it is necessary to have a training set with both inputs and their respective outputs, that is, coal and diesel consumption. Wood was not estimated by this method, as we assumed its use for rail transport to be restricted to the USA. The known values of final energy consumption were taken from the sources cited in Section 2.3.1. The features selected to train the model were: the year, the freight and passenger energy service, the country's coal consumption in that year, and a country identifier. The total coal consumption in each country was found in the IEA [1], Etemad et al. [28], and the United Nations Statistical Division [29]. The total diesel consumption was not included as a feature, as the percentage of these energy carriers allocated to rail transport is expected to be significantly smaller when compared to coal. The country identifier was introduced with one-hot encoding. In other words, 6 binary features were created, one per country, taking the value 1 for the country they correspond to and 0 otherwise. All European countries were aggregated in one feature, as well as Canada and USA. Japan, Russia (then USSR), China, and India are the remaining 4 features.

The number of regression trees to be used can be determined experimentally by adding trees until the mean squared error (MSE) in the validation set stabilizes [9]. MSE may be calculated by

$$MSE = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}, \quad (1)$$

where n is the number of samples in the validation set, y_i is the true value, and $\hat{y}_i$ is the predicted value of observation i. The original dataset was randomly split into a training and validation set. The first was used to train several random forests with different numbers of trees, and the second was to compute the MSE. After $n_{trees} = 350$, the MSE stabilized, so it was selected as the model parameter. Tree size was not controlled. Fig. 3 summarizes the machine learning estimation procedure.

Predictions were made for the most relevant countries identified in Section 2.2, obtaining a complete time series for each country's coal and diesel consumption in railways. These values were summed to obtain final energy use for the world.

As the training set is scarce, taking observations for a test set would imply wasting around 20% of the observations, significantly influencing the results. Therefore, the model validation was done with K-fold cross-validation, which consists of randomly splitting the training set into different blocks and using one at a time for testing. This method assures that every data point is eventually used for training and testing. Even

Fig. 3. Machine learning method for coal and diesel final energy estimations.

though cross-validation methods are more common for independent data, there is still no consensus on which method to use in spatiotemporal datasets [30]. Most of the cross-validation methods developed for time-dependent data are for forecasting short periods in the future, which is a different problem. K-fold cross-validation was repeated 10 times using 5 splits. The metrics computed for evaluating the model were the root-mean-squared error (RMSE) and the median absolute error (MedAE), described by the following equations:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}}, \tag{2}$$

$$MedAE = median(|y_1 - \hat{y}_1|, \ldots, |y_n - \hat{y}_n|). \tag{3}$$

As mentioned in Section 1.2, previous historical energy reconstruction studies rely on expert-based knowledge to estimate missing values [2,6–8]. We estimated final energy use based on the methods of previous studies to compare the random forest results with the more traditional approach to this problem. The description of the method used for our expert-based knowledge approach is in Appendix B (Supplementary Information I).

In addition, an uncertainty estimate for the random forest model was obtained based on the method proposed by Coulston et al. [31]. The uncertainty estimation addresses a missing gap in previous studies that rely on expert-based knowledge methods. The method used to estimate the confidence interval is described in Supplementary Information I.

The model was implemented using the Scikit-Learn library [32] in Python.

2.4. From final to primary energy

Primary energy, that is, the amount of energy extracted from nature for the purpose of running the world's rail system, was calculated based on the final energy results. Both wood and coal were directly used as fuel in locomotives. For these two energy carriers, the primary-to-final efficiency was assumed to be 100%.

As for diesel, the petroleum extracted from nature is submitted to a refining process which results in different products, such as gasoline, fuel oil, and kerosene. Oil refining has typically a high efficiency and there is not much information available on the evolution of this process. For this reason, primary-to-final efficiency was assumed to be constant through time at 100%. By assuming 100% we are introducing an upward bias in the primary-to-final efficiency, resulting in the estimated value of primary energy being lower than the expected true value.

Electricity's primary-to-final efficiency should not be assumed constant over time. The world energy mix changes every year, which highly impacts the efficiency of electricity production. Moreover, power plants increased their efficiency due to improvements in technology. Pinto et al. [8] estimated the world's primary-to-final efficiency evolution since 1900 using the resource content method (RCM), physical content method (PCM), and partial substitution method (PSM) for renewables. The efficiencies calculated by the PCM were used in this work, as it is the method adopted by the IEA [33]. It was assumed that electricity consumption in railways has the same generation mix as the total world electricity consumption.

2.5. From final to useful energy

As steam, diesel, and electric engines work very differently, their final-to-useful efficiencies were estimated separately. In addition, as technologies improved with time, it was necessary to model the evolution of final-to-useful efficiencies. Technologies were assumed to be homogeneous across countries in the same year.

Serrenho et al. [2] estimated the engine efficiency of steam trains powered by coal in Portugal based on Ayres et al. [23] between 1855 and 1975, beginning at 2.5% and reaching 9% in the 1970s. On the other hand, several authors [34,35] indicate that engine efficiency reached at most 8%. Bond et al. [6] points to a significant increase in engine efficiency at the beginning of the 20th century due to the way coal was introduced in the firebox and improvements in the boiler. Taking into account the above information, we modeled engine efficiency as a linear function beginning at 2.5% in 1840 and reaching 8% in 1930. From 1930 onward, we assumed a constant engine efficiency at 8%, based on the increasing significance of diesel locomotives, suggesting a likely halt in the improvement of engine efficiency for steam locomotives. The stagnation in 1930 also coincides with the plateauing of average locomotive weight, indicating a mature stage of technology (Appendix A, Fig. A.1). We estimated that engine-to-drawbar efficiency was 75%, assuming that the drawbar and engine efficiencies stagnated respectively at 6% and 8% [34–36]. The engine-to-drawbar efficiency was assumed to be constant through time as no more values were found.

Marshall et al. [36] estimated the final-to-useful (drawbar) efficiency of diesel trains between 1960 and 2020. Values range from 23% (1960) to around 37% (2020). These values are in agreement with efficiency values presented by other authors [24,34,35] referred in Table 3. Before 1960 no values for the efficiency of diesel trains were found. Thus, it was assumed that the efficiency of diesel trains had the same growth rate as electric trains.

Table 3
Summary of the different engine (Eg), final-to-useful (F-U), and engine-to-drawbar (Eg-D) efficiencies from previous studies.

Locomotive	Reference	Efficiency	Year	Value
Steam	[35]	Eg	Unspecified	5%–8%
	[34]	Eg	Unspecified	8%
	[2]	Eg	1855–1975	2.5%–9%
	[36]	F-U	1960–2018	6%
Diesel	[23]	Eg	1950	35%
	[35]	Eg	Unspecified	20%–25%
	[34]	Eg	2019	40%
	[24]	Eg	1933	22%–31%
	[23]	F-U	1950	28%
	[36]	F-U	1960–2018	22.5-36.5%
	[39]	F-U	2007	30%
Electric	[23]	Eg	1900–2000	60%–85%
	[8]	Eg	2000–2017	85%–89%
	[38]	Eg-D	2014	88%
	[39]	Eg-D	2006	91.2%

As for electric trains, Ayres et al. [37] estimated the evolution of the engine efficiency of electric motors for transport use from 1900 to 2000 and Pinto et al. [8] from 2000 to 2017. Even though no time series of the engine to drawbar efficiency was found, recently different authors have studied it for modern electric trains [38,39]. For this reason, engine-to-drawbar efficiency was also assumed to be constant through time, equal to 90% based on an average of the data obtained. This value was multiplied by the time series provided by Ayres et al. [37] and Pinto et al. [8] to determine the final-to-useful efficiency. Table 3 summarizes the efficiencies from previous studies.

The useful energy obtained use per final energy carrier was calculated by multiplying the final-to-useful efficiency by the final energy use estimations. Finally, a time series of aggregated rail final-to-useful efficiency was computed by dividing useful by final energy use.

2.6. Energy intensity

Energy intensity is the amount of either final or useful energy required to deliver one unit of service, both passenger and freight. Our results for final energy use in railways are not divided into freight or passenger use, so it was necessary to aggregate both services. We converted passenger into freight service based on a turnover volume equivalent (V_e) to obtain the total service. Liu et al. [40] suggest that the turnover volume equivalent between passenger and freight is 1 for China in 2012 (i.e., 1 unit of freight service in tkm consumes the same amount of energy as 1 unit of passenger service in pkm). The UK's Office of Rail and Road [41] provides data for the final energy use of passenger and freight separately between 2005 and 2020, which enabled the calculation of the passenger and freight energy intensity in MJ/pkm and MJ/tkm. By dividing both intensities we obtained a conversion factor which varied between 0.8 and 0.96. Since there is limited data available on the V_e coefficient, it was assumed to remain constant throughout time with a value of 1. For $V_e = 1$, the energy intensity of freight and passenger service are numerically equal. Energy intensity (EI) was calculated by

$$EI(t) = \frac{FE_{wood}(t) + FE_{coal}(t) + FE_{diesel}(t) + FE_{electricity}(t)}{pkm(t) \times V_e + tkm(t)}, \quad (4)$$

where FE is the final energy use, tkm and pkm are the freight and passenger energy service, and t is the year. The useful energy intensity was calculated by multiplying the world final energy intensity by the final-to-useful efficiency.

2.7. CO_2 emissions and intensity

Carbon dioxide emissions were calculated by multiplying the final energy use by the respective carbon emission factor. The IPCC [42] provides emission factors for coal and diesel-fueled trains, which were assumed to be constant through time. For wood-fueled steam trains, it was assumed that the carbon emitted by wood combustion would be captured by biomass growing elsewhere, resulting in a zero-emission factor. Emissions from biomass could also be accounted for, as there is no guarantee that this carbon was captured by growing biomass. Nevertheless, coal consumption was much higher than wood, so disregarding CO_2 emissions from wood does not impact our results significantly. Emissions from electric trains were estimated using a time series of emission factors for the world electricity mix since 1900 from Pinto et al. [8] (Fig. 4), making the same assumption discussed in Section 2.4 about the mix of electricity consumed in railways. Emission factors for wood, coal, and diesel are presented in Table 4.

Table 4
Emission factors in ton CO_2/TJ of each energy carrier. For electricity, the maximum (1900) and minimum (2017) values are presented.

	Wood	Coal	Diesel	Electricity
Emission factor	0	96.1	74.1	136.3–1453

We divided the emission factors in Table 4 by the final-to-useful efficiency to calculate the emissions per useful energy consumed. Carbon intensity, expressed kilograms of CO_2 per unit of service, was calculated by multiplying the emission factors in Table 4 by the energy intensity estimations described in Section 2.6.

2.8. Length of track

The rail track is crucial infrastructure for rail transport since trains can move only on tracks. There is a wealth of data available on the length of train tracks. In Fig. 1, length of track is disconnected from the energy stages, as it is not directly related to them. Even though the length of the railway may not directly relate to energy consumption, observing its evolution can enhance our comprehension of rail transport. Mitchell [4,5,12] has a dataset for the length of rail track for 114 countries from 1840 to 2010, which were summed to obtain the world length of track. Moreover, we calculated the length of track per capita for the world and selected countries with population data [15,16].

Fig. 5 summarizes the existing data sources used and the method flow in this study.

3. Results

In this section, we will present our main results. The validation of the estimations of coal and diesel consumption using machine learning is assessed in Section 3.2.

3.1. World energy service

Fig. 6 shows a time series of the world freight and passenger service. Both freight and passenger energy service increased significantly since 1840, except for a brief period between 1989 and 1998. Global economic crises such as The Great Depression in 1929 and the 2008 Global Financial Crisis also negatively influenced service, especially freight (Figs. A.2 and A.3). Even so, both freight and passenger traffic increased around 25-fold between 1900 and 2010.

Figs. 7 and 8 show the contribution of the most relevant countries for the total freight and passenger service, respectively. In the 19th century very few countries, mainly the USA, Germany, France, the UK, and Russia, contributed to almost 100% of the total service. In Fig. 7, from 1882 to 1883 there is a discontinuity due to the way Mitchell [5] accounted for the freight service in the USA. Recently, India and China have a significant percentage of the world passenger energy service, while the UK and France decreased their share. Moreover, countries that are extremely relevant in passenger service, might not have such a

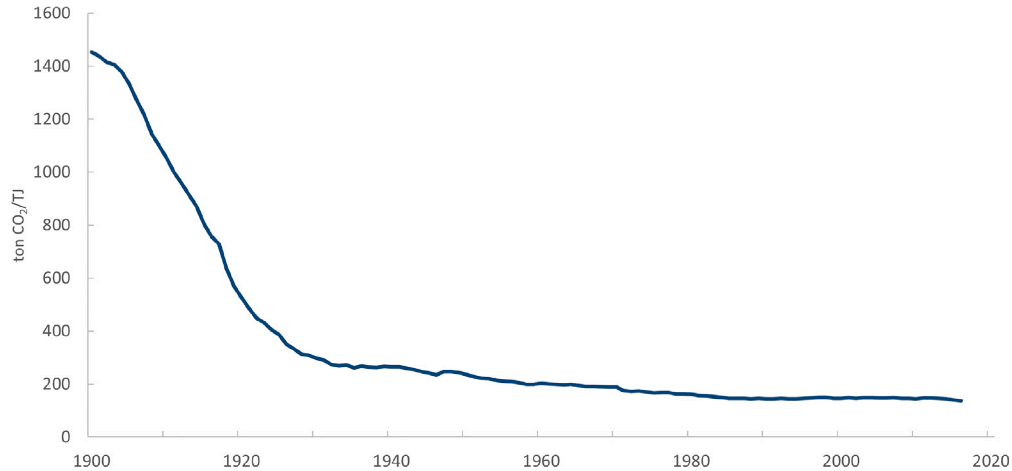

Fig. 4. World carbon emission factors of electricity production between 1900 and 2020.
Source: Adapted from Pinto et al. [8].

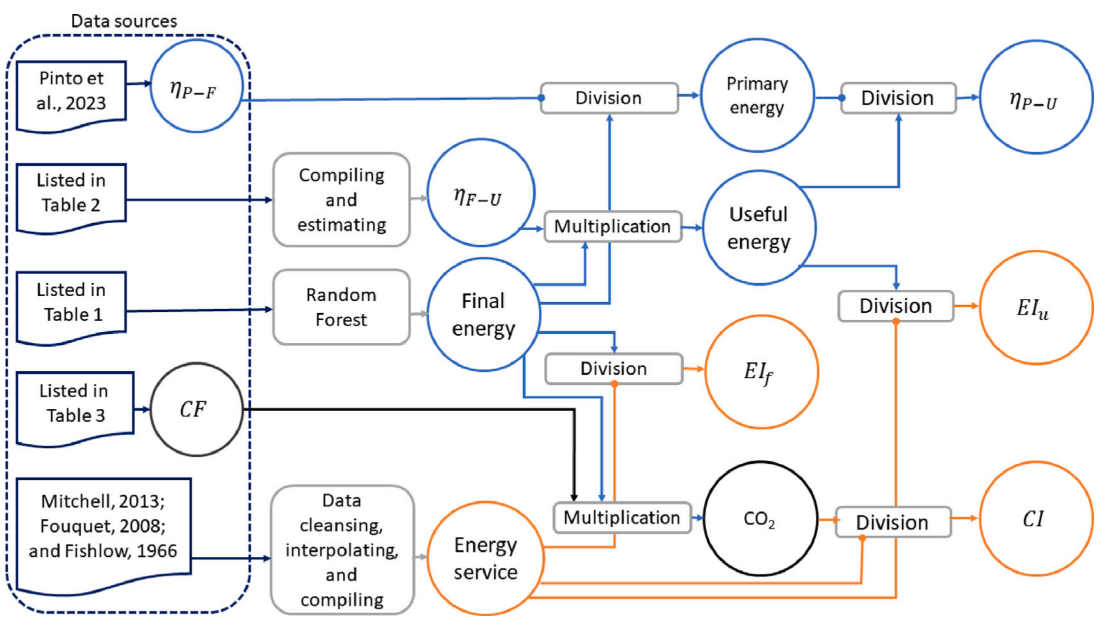

Fig. 5. Flow chart summarizing the method flow, main data sources, and variables estimated in this study. The relationship between variables is shown in more detail in Fig. 1.

representative share in freight and vice-versa. For example, since 1921, Japan contributed at least 5% of the world's passenger service, although it never exceeded 2.5% in terms of freight.

Fig. 9 shows the rail passenger service per capita for selected countries and the world (freight service per capita is shown in Fig. A.4). Passenger service per capita grew for most countries and the world until the 1920s when it started decreasing in France, the USA, and the UK. During the Second World War, there was a significant increase in passenger service per capita in Japan, the USA, and the UK. After that, Japan and the USSR kept investing in rail transport for passenger purposes. In 2010, Japan was still by far the country that provides more passenger service per inhabitant. China and India have been growing their service per capita steadily since the 1960s and are already above the world average.

3.2. World final energy use

Fig. 10 shows the wood, coal, diesel, and electricity consumption in railways, as well as the time periods that are explored in Section 4. The contribution of wood to the fuel consumption by trains is shown in more detail in Fig. A.5. Coal was the most dominant energy carrier between the 19th until the middle of the 20th, peaking in the 1940s. After that, steam trains were rapidly replaced by diesel and electric ones. Currently, these two technologies co-exist, though the share of electricity use has been increasing over recent years. Electric trams have been a reality since 1900, nevertheless, it was only in 1960 that electricity consumption rose above 5% of total final energy use in railways.

Figs. 11 and 12 show the results for the world coal and diesel consumption in railways obtained with machine learning and the estimated 95% confidence interval. Before 1910, the confidence interval is narrow because there is data for UK and USA, which were the main countries consuming coal in railways, for which there is known data. From 1910 to 1971, several countries with limited available data experienced an increase in their share, resulting in higher uncertainty surrounding these estimates. After 1971, the uncertainty is zero for both coal and diesel, as IEA [1] data were used. The description of the method used to estimate the confidence interval is detailed in Supplementary Information I.

Fig. 11 also shows expert-based estimations. Most of the expert-based knowledge estimations are within the 95% confidence interval,

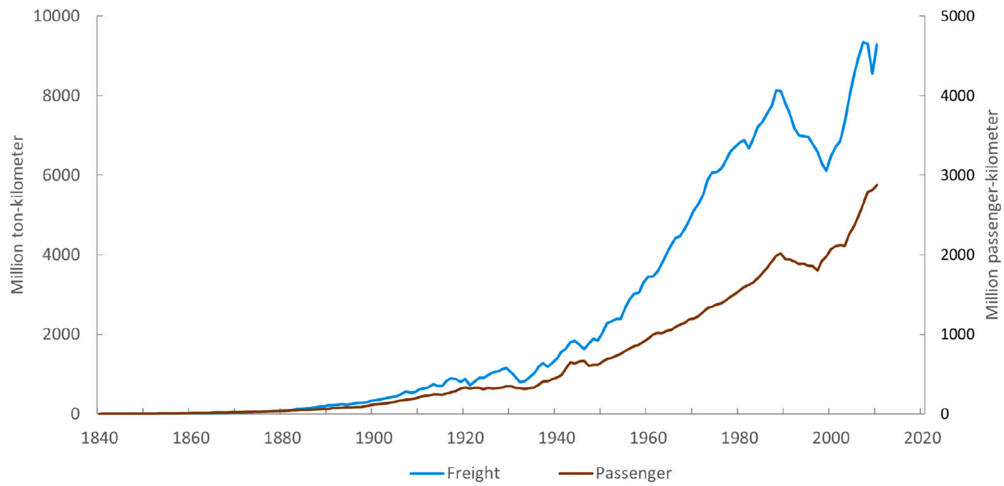

Fig. 6. World freight and passenger energy service evolution in billion ton-km and passenger-km.

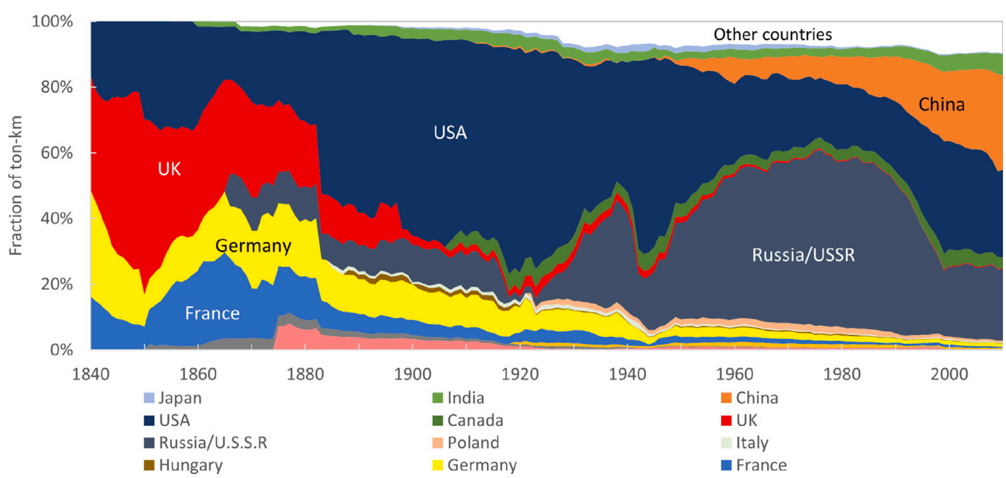

Fig. 7. Contribution of the most relevant countries for world freight energy service.

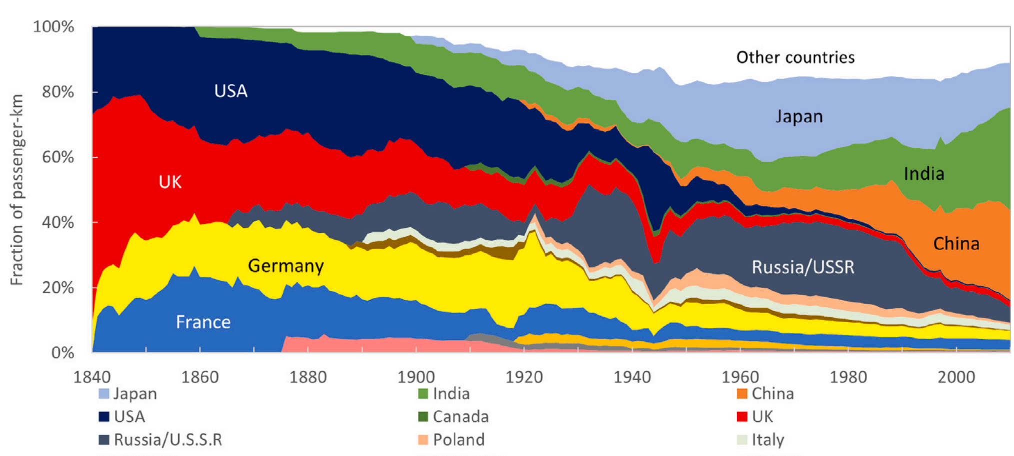

Fig. 8. Contribution of the most relevant countries for world passenger energy service.

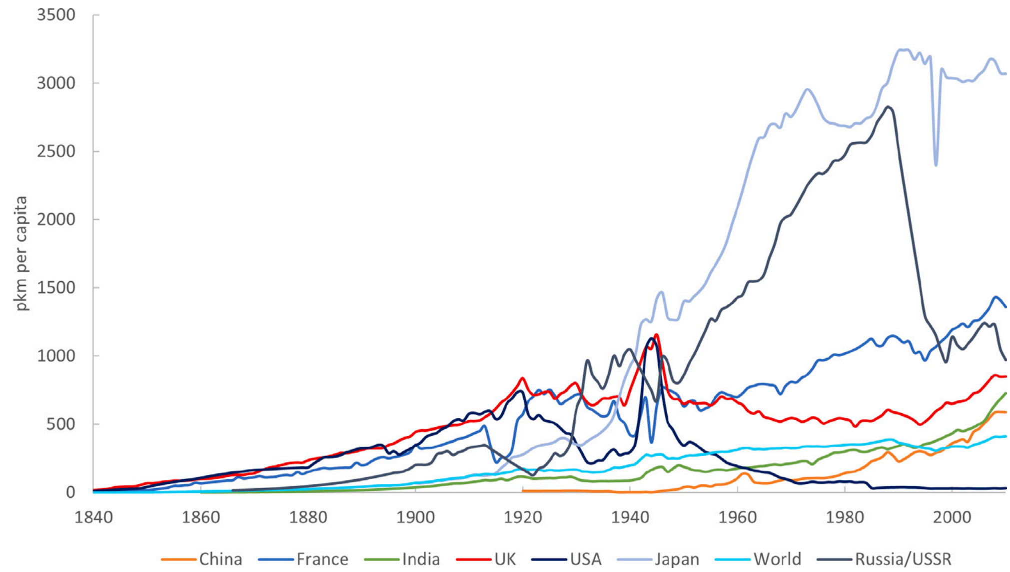

Fig. 9. Passenger service per capita for selected countries and the world.

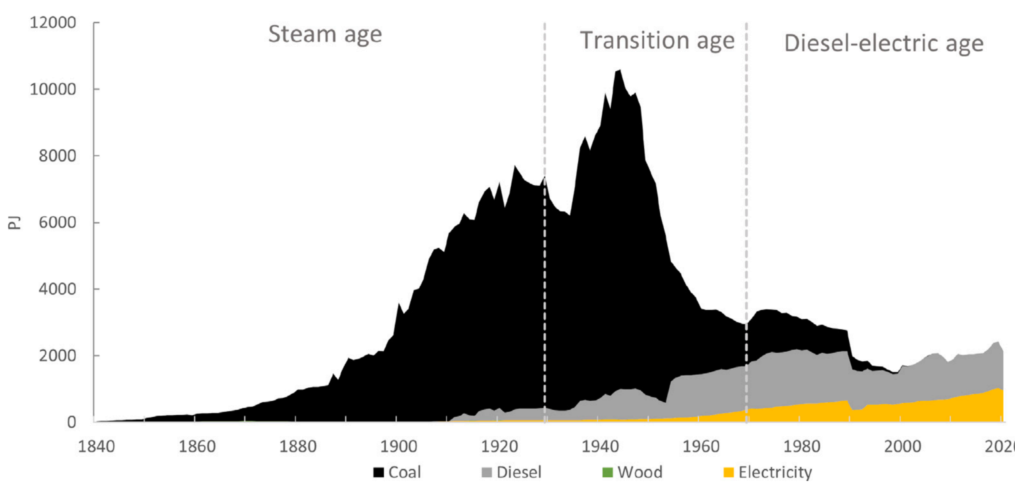

Fig. 10. World final energy use in railways by energy carrier and the ages defined.

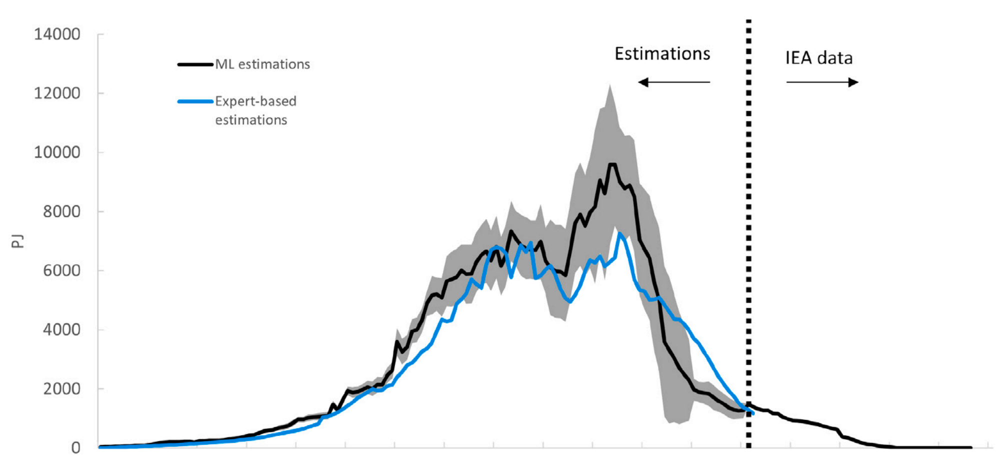

Fig. 11. World coal consumption in railways estimations by the random forest approach (black line), the respective confidence interval, and the estimations by the expert-based knowledge approach (blue line).

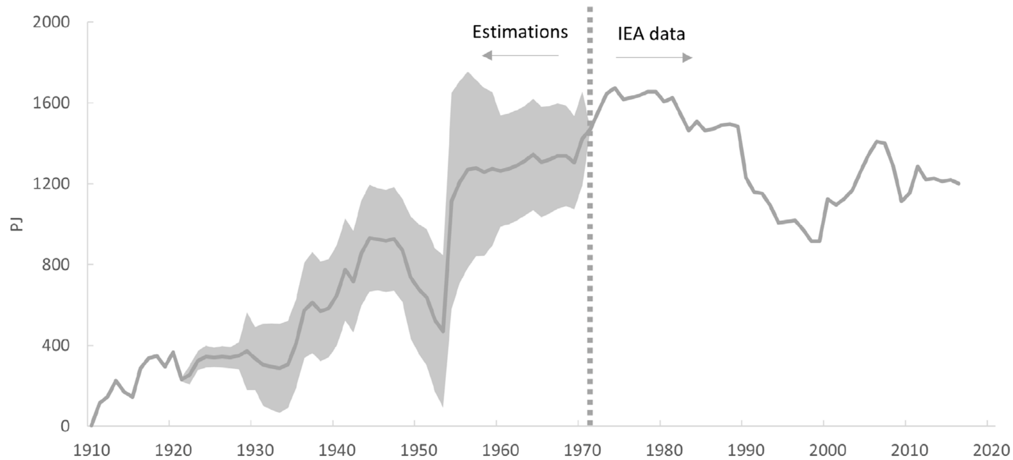

Fig. 12. World diesel consumption in railways estimations and the estimated 95% confidence interval.

Table 5
Results for the error metrics computed with K-fold cross-validation.

	Metric	Mean	Standard deviation
Coal	RMSE	71.385	31.840
	MedAE	1.875	0.523
Diesel	RMSE	23.196	6.232
	MedAE	1.292	0.309

which increases our confidence in the results obtained with machine learning. Since the expert-based knowledge approach does not provide an uncertainty measure, any values outside the confidence interval should not be considered unreliable but rather as a discrepancy between the results obtained with the expert-based knowledge and machine learning approach. The two methods differ more significantly during the Second World War and the transition from coal to diesel, which are periods when limited data is available for both approaches. The diesel consumption was not estimated by expert-based knowledge, as diesel use is more recent and there is more data available on it.

Table 5 shows the results for the RMSE and MedAE, calculated with cross-validation. These metrics attribute an overall score for the model, allowing the comparison between different trials.

3.3. World primary energy use

Fig. 13 presents the primary energy use in railways from 1840 to 2016. The evolution of the primary energy follows the trend observed in Fig. 10 until around 1960. After that, the share of electricity increased significantly, and primary energy deviates from the final energy results, as electricity presents a much lower primary-to-final efficiency. Over the last few years, primary energy use has been growing sharply, as the share of electricity increases.

3.4. World useful energy use

The left side of Fig. 14 presents the curves for the final-to-useful efficiency of steam, diesel, and electric locomotives, as well as the aggregated efficiency. Electric locomotives are by far the most efficient, as the energy conversion is from electrical energy into mechanical work, followed by diesel and then steam locomotives. Aggregated final-to-useful efficiency was approximately 30 times higher in 2016 when compared to 1840.

Nevertheless, the final-to-useful efficiency does not consider the efficiency of electricity generation, which does not allow a fair comparison in terms of natural resource use. On the right side of Fig. 14, where the primary-to-useful efficiencies are represented, electric and diesel curves are much closer.

Fig. 15 shows the evolution of useful energy use in railways. Useful energy use has been growing since 1840, except for three periods: the Great Depression (1930–1935) the transition from steam to diesel and electric trains (1945–1970), and the dissolution of the USSR (1991).

The reduction in useful energy use in 1991 is explained either by the reduction in both passenger and freight service in the ex-USSR countries or by an error in accounting due to its dissolution. The service reduction shown in Figs. 7 and 8 appears less abrupt compared to Fig. 15, as linear interpolation was employed to estimate the missing data for USSR/Russia between 1990 and 1998. The GDP of former USSR countries dropped by nearly 10% between 1989 and 1991, which indicates that the economic impact was abrupt when the USSR dissolved [43].

3.5. World energy intensity

Fig. 16 shows the time series of both final and useful energy intensity. Final energy intensity decreased by a factor of 100 between 1840 and 2010. Useful energy intensity presents a different trend from the final energy intensity between 1900 and 1942 when useful energy intensity increased, while final energy intensity remained fairly constant.

In order to highlight the gains in final energy intensity due to the development of energy conversion devices (increases in final-to-useful efficiency) or improvements in the conversion from useful energy to service (reduction in useful energy intensity), we drew two hypothetical scenarios: one at constant 1840 final-to-useful efficiency (scenario 1) and another at constant 1840 useful energy intensity (scenario 2). Fig. 17 shows both scenarios and the actual final energy intensity. From this graph, we observe that increases in final-to-useful efficiency contributed greatly to the decrease in final energy intensity, however, the reduction in useful energy intensity was essential to further reduce final energy intensity.

3.6. World CO_2 emissions and intensity

Fig. 18 shows the CO_2 emissions and intensity in railways. Even though carbon intensity decreased by 64% from 1840 to 1900, CO_2 emissions have increased 260-fold. Carbon emissions followed the carbon intensity's decrease after the 1940s, when diesel and electricity were replacing coal as the main energy carriers in rail transport. Subsequent reductions in the carbon emission factor of electricity enabled a continued decline in emissions until the early 2000s. After that, emissions started rising but at a lower rate than in the 19th and first half of 20th century.

Fig. 19 shows the CO_2 emissions per useful energy for steam, diesel, and electric locomotives. Surprisingly, in 1910, electric trains emitted

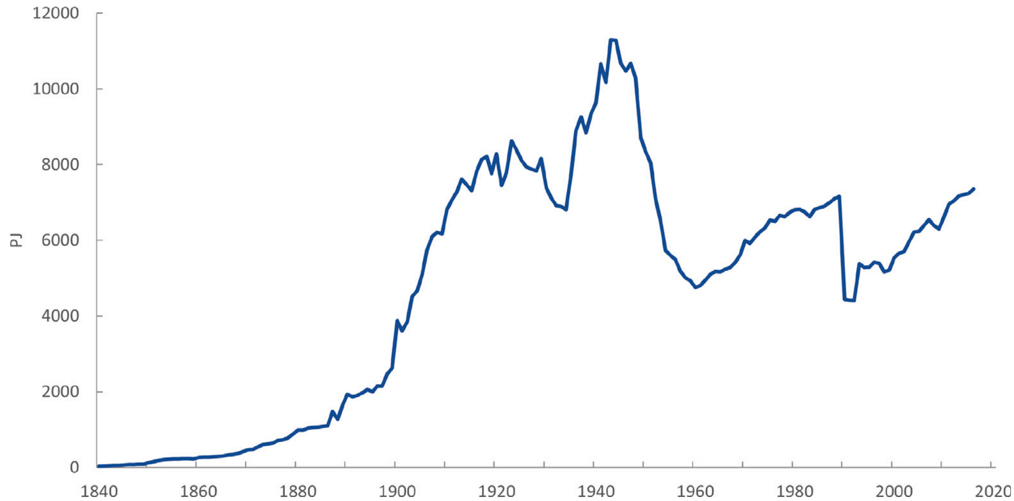

Fig. 13. World primary energy use in railways estimations.

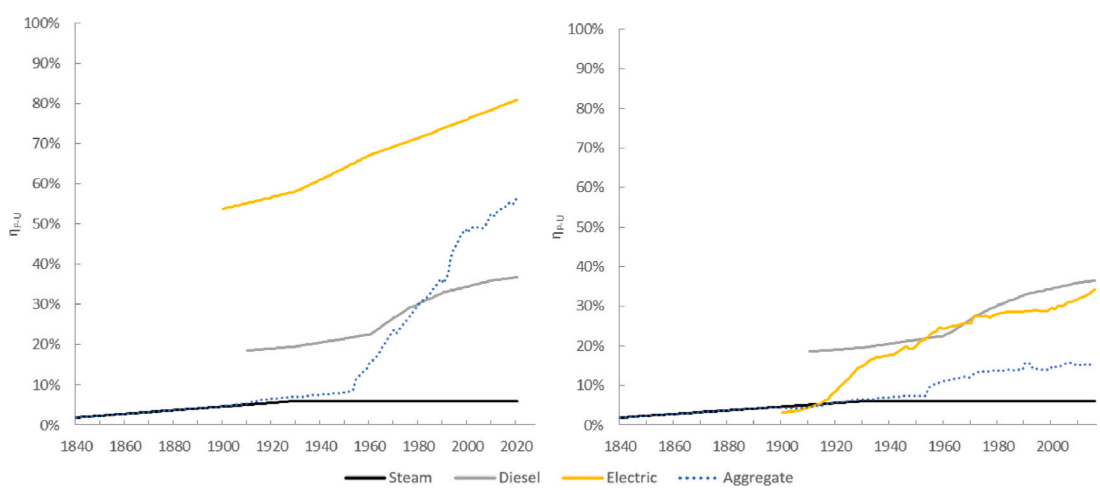

Fig. 14. Final-to-useful (left) and primary-to-useful (right) energy efficiencies per type of locomotive and aggregated efficiency.

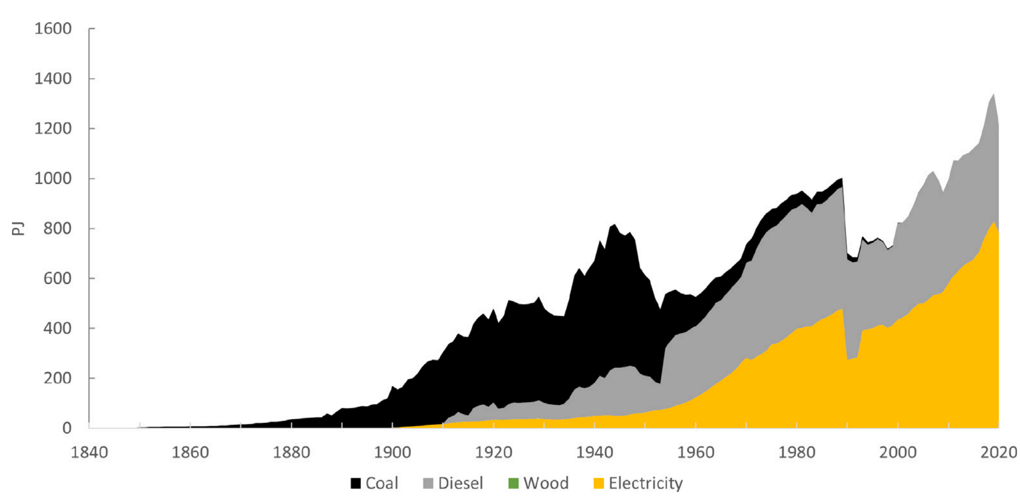

Fig. 15. World useful energy consumption in railways by energy carrier.

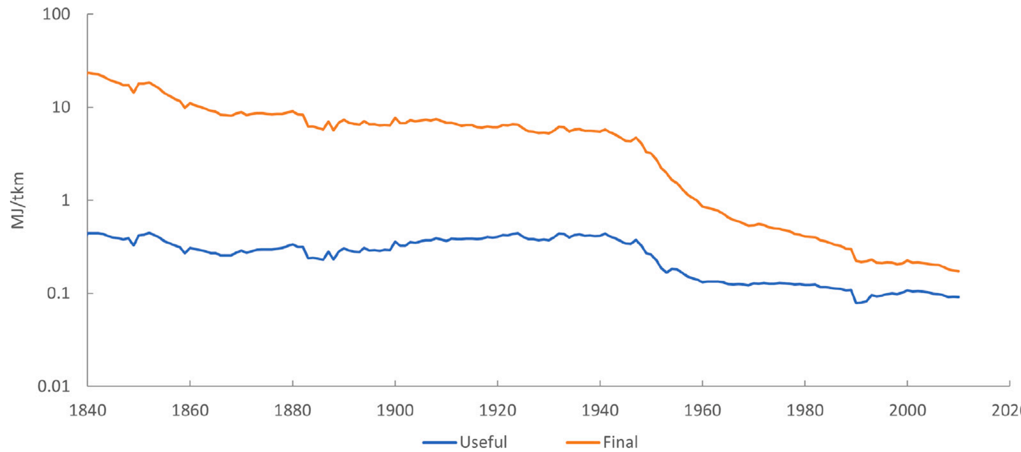

Fig. 16. World final and useful energy intensity in railways (log scale).

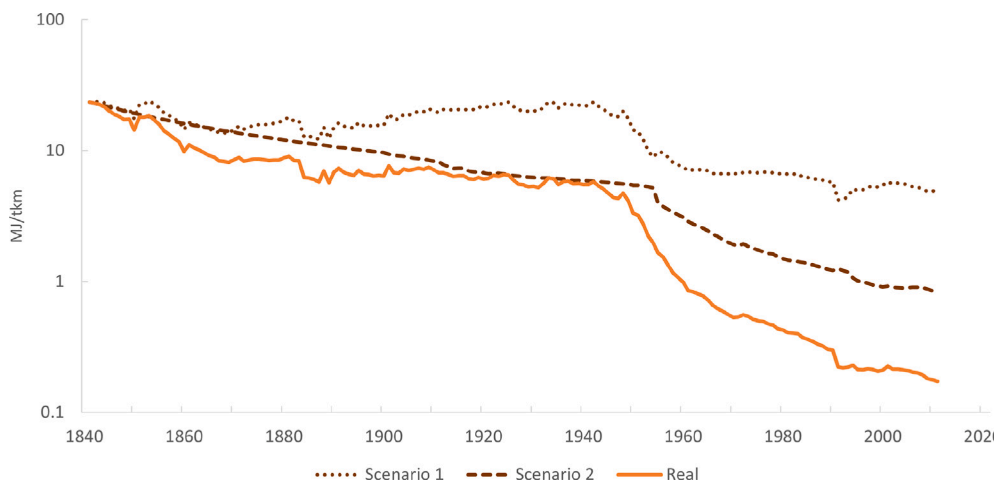

Fig. 17. Scenarios for world final energy intensity in railways at (1) constant final-to-useful efficiency, (2) constant useful energy intensity, and the actual intensity (log scale).

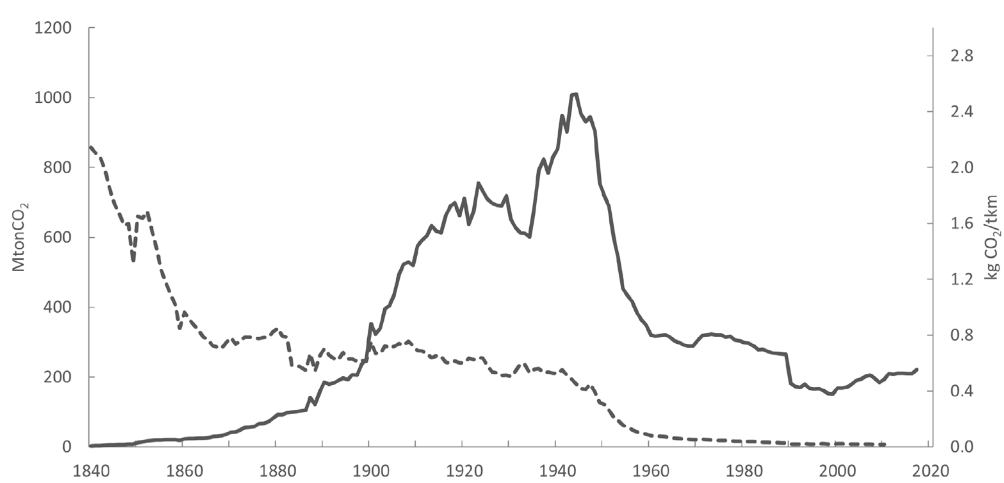

Fig. 18. World CO_2 emissions (left axis) and carbon intensity (right axis) in railways.

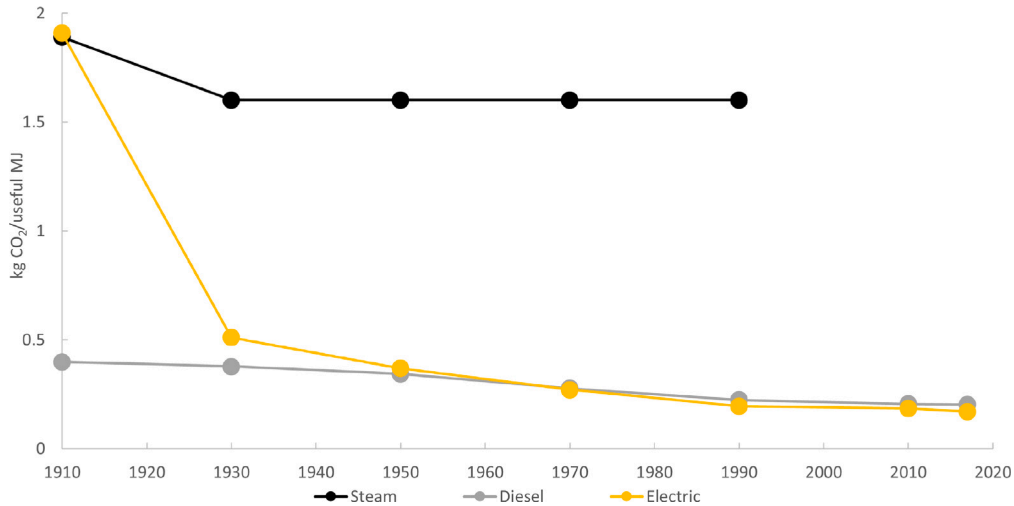

Fig. 19. World CO_2 emissions per useful energy for the different types of locomotive.

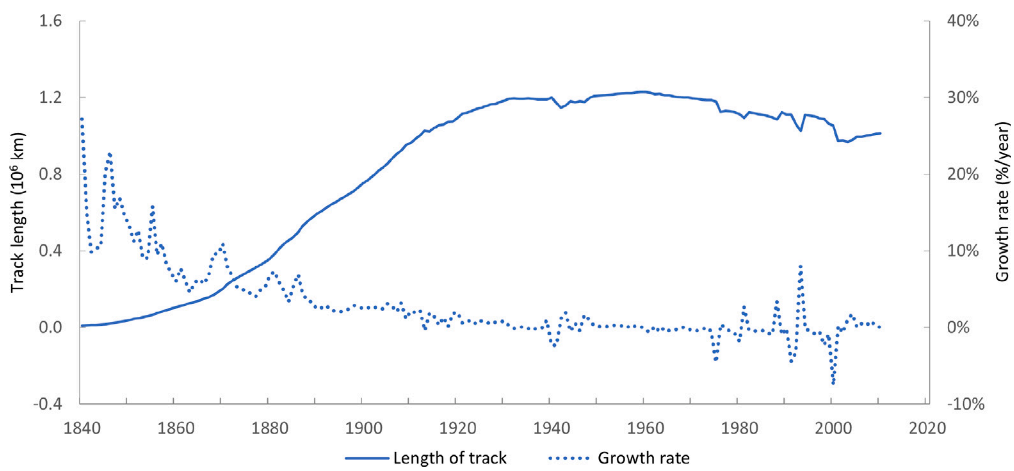

Fig. 20. World length of track (left axis) in million kilometers and the respective growth rate (right axis).

more CO_2 per useful energy compared to steam trains, despite operating at a significantly lower final-to-useful efficiency. It was not until the 1950s that electric trains matched diesel trains in achieving lower emissions per useful energy, a trend that has persisted ever since.

3.7. World length of track

Fig. 20 shows the length of track evolution and the respective growth rate. Length of track per capita is shown in Fig. A.6. Between 1840 and 1930, significant efforts were made to expand the railway infrastructure, resulting in a remarkable 170-fold increase in the length of railway track. However, after 1930, the length of track stabilized for roughly three decades. From the 1960s onwards, the length of railway track began to decline gradually, eventually reaching in 2010 the same length as it was in 1912.

4. Discussion

In this Section, results are analyzed in an integrated way from a historical perspective to get insights for future transitions. This historical analysis is divided into 3 time periods: the steam age: 1840–1930 (Section 4.1), the transition age: 1930–1970 (Section 4.2), and the diesel-electric age: 1970–2020 (Section 4.3) shown in Fig. 10, followed by a section dedicated to future implications. Finally, the main limitations of this study are assessed.

4.1. Steam age: 1840–1930

The steam age was marked on one hand by large amounts of coal burned in very inefficient steam engines, but also as a period of great innovation in the transport sector. As coal prices were dropping around the world, freight and passenger traffic, fuel consumption, and length of track grew rapidly (Figs. 6, 10, 20). The expansion of railways was motivated by the goal of increasing speed and improving reliability when compared to animal and canal transport. For example, in 1830, a journey from Liverpool to Manchester would take around 3 h by horse coach at the cost of 12 shillings. Railways reduced that time to 2 h, at the price of 7 shillings for first class and 5 shillings for second class [3].

In the USA, wood and coal competed until 1890 when coal became the most dominant fuel. Around 1860, advancements in coal-burning locomotives shifted the energy carrier choice towards price considerations. Wood was highly valued, in addition to its limited supply, both of which favored the transition to inexpensive coal, particularly abundant in the Eastern regions [14].

In 1922, global final energy use in the rail sector reached its first peak, when automobiles were revealed to be a more flexible mode of transportation (Fig. 10). The crisis in the rail sector was consolidated by the period of trade protectionism that followed the Great War, aggravated by the Great Depression of 1929, when freight traffic, final, and useful energy use dropped in many countries, such as the USA, Canada, France, and the UK, marking the beginning of the transition age.

4.2. Transition age: 1930–1970

As publically appealing as steam trains were, and still are, the transition to more efficient technologies was inevitable. Around 1930, the price of coal in the USA was increasing rapidly, which was an opportunity for the rail sector to invest in diesel-electric trains. In the steam age, only small amounts of diesel and electricity were utilized, while in the transition period, these two energy sources gained dominance (Fig. 10). In 1930, the final-to-useful efficiency of diesel locomotives was almost 5 times greater than steam locomotives (Fig. 14). While electric trains' final-to-useful efficiency was 15 times more efficient than coal-burning trains, their primary-to-useful efficiency was only 1.7 times greater (Fig. 14). At that time, the efficiency of thermo-electricity was still low, decreasing the overall primary-to-useful efficiency [8].

Another mark of the transition age is the interruption in the length of track expansion, not only in absolute value but also in per capita terms (Figs. 20 and A.6). This trend is observed at the individual country level, as well as the world scale. Curiously, both freight and passenger service continued to grow steadily, indicating an increased utilization of the existing infrastructure (Fig. 6). Furthermore, automobiles, trucks, and buses started to compete with trains, beginning a crisis in the rail sector in many countries, such as the USA and the UK.

Around 1935 the world was recovering from the Great Depression so both final and useful energy use by rail transport increased. During the Second World War, oil rationing policies in the USA were in place, delaying the inevitable end of steam trains. The revival of the rail sector in the USA and the growth of the USSR were the main contributors to the world peak of final energy use and CO_2 emissions for railways in 1944 (Figs. 10 and 18). This period also shows a significant increase in useful energy use, highlighting the continued importance of railways during wartime (Fig. 15). After the war, large oil reserves in the Middle East were discovered, dropping oil prices across the globe, which was an important driver for the replacement of coal-fueled by diesel and electric-fueled trains (Fig. 10).

4.3. Diesel-electric age: 1970–2020

After 1970, most countries had already significantly reduced their coal consumption for rail purposes, although India and China would still take around 25 years. The diesel-electric age is characterized by the dual use of diesel-electric and electric trains. When steam trains were replaced, some countries such as the USA heavily invested in diesel-electric trains, while other countries, namely Japan, focused on electrifying their lines. Railway electricity consumption has not yet surpassed diesel consumption, but it is expected to do so within a few years (Fig. 10).

Useful energy from electricity has been higher than useful energy from diesel since 1993, therefore nowadays electricity provides more power than diesel for moving people and freight in railways (Fig. 15). The useful energy use shows no sign of declining, while the final energy peak was reached in the transition age. With the improvement of primary-to-useful efficiency in diesel and electric trains, coupled with the growing adoption of renewables in the electricity generation mix and the steady growth of both passenger and freight services, the CO_2 and energy intensities (final and useful) of rail transport have reached their lowest levels in history (Figs. 6, 14, 16, and 18). Another important indicator for decarbonization is the CO_2 per unit of useful energy. In 2016, electric trains emitted 16% less CO_2 per useful energy than diesel, while in 1910 electric trains emitted 5 times more CO_2 than diesel (Fig. 19).

Table 6 summarizes the key characteristics, technological developments, and economic, social, and environmental impacts of the rail transport eras previously identified.

4.4. Learning from the past

Rail transport went through many technological changes in the past, nevertheless, the development of new technologies did not fully dictate energy transitions. In the 1930s, when diesel trains were already known to be a more efficient alternative to steam trains, the 20-year delay in the reduction of coal consumption was not expected. The rail sector quickly adapted to World War II, increasing fuel consumption to meet the demand for transport. Moreover, although electric trams had already been in use since 1900, initially they were not meant to scale to electric trains, capable of replacing steam or diesel trains. New fuels that might provide more sustainable alternatives such as hydrogen and advanced biofuels are now in a similar unpredictability phase, where sudden technological advances and other societal matters might change completely the course of their future use.

The historical analysis of our results showed that the cost of energy service and travel speed were the main factors associated with past transitions. Cost is a common driver in most transitions, especially in the development of railways and in the transition from wood to coal-fueled steam trains in the USA. Cost reduction due to an increase in the final-to-useful efficiency was the main driver for the end of steam trains, which could not compete with the 5 times more efficient diesel trains. While speed was crucial to the development of railways, it also contributed to their decreased competitiveness against air and road travel. For future transitions, mainly driven by environmental concerns, speed and cost of service should be considered as priorities to impulse low-carbon technologies.

The evolution of electricity usage in railways highlights the fact that electrification is an opportunity for the rail sector to reduce its carbon intensity, but only if electricity is generated from low-carbon resources. With the current global electricity generation mix, electricity emits around 16% less CO_2 per useful energy than diesel, however in 1910 electric trains emitted 42 times more CO_2 per useful energy. Moreover, the final-to-useful efficiency of electric trains is 2.2 times higher than diesel trains, though historically diesel presents a higher primary-to-useful efficiency. If electric trains are indeed the future of clean mobility, their effectiveness at reducing CO_2 intensity is highly dependent on the success of renewables in the power sector.

Regarding final energy intensity, its 100-fold decrease from 1840 to 2010 cannot be explained exclusively by the 30-fold increase in final-to-useful efficiency, but rather as a combination with occupancy, operating conditions, and lower losses by the passive system. At the beginning of the 20th century, despite the increase in final-to-useful efficiency, final energy intensity did not decrease as expected, which could be explained by heavier and faster locomotives (see Fig. A.1), leading to an increase in useful energy intensity. The transition from steam to diesel locomotives saw a decrease in useful energy intensity, attributed to factors such as the reduced weight per unit of power in diesel locomotives (approximately 12% lower than steam locomotives [44]). Additionally, the rise of trucks for short-distance travel, evidenced by a 60% increase in truck numbers in the USA between 1940 and 1960 [45] and advancements in train aerodynamics contributed to this trend [46]. Future policies to further reduce final energy intensity should focus on improving occupancy, traffic optimization, and reducing losses by the passive system, especially since gains in efficiency are expected to be limited in the future.

4.5. Limitations

Before 1971, only a few countries reported their rail fuel consumption, posing a challenge for the estimation at the world scale and the quantification of uncertainty. This paper gives a way forward, introducing machine learning, and creating an opportunity to determine a confidence interval. As with most data-driven models, there is always room for improvement. We suggest the use of random forest, however, other machine learning algorithms might outperform our model.

Table 6
Overview of the key characteristics, technological developments, and economic, social, and environmental impacts of the rail transport eras identified.

Era	Key characteristics	Technological developments	Economic, social, and environmental impacts
Steam age (1840–1930)	Rapid growth in freight and passenger traffic and coal consumption. Final and useful energy intensities decreased until 1900 while final-to-useful energy efficiency increased.	Inefficient steam trains. Replacement of wood by coal. Construction of smoother tracks and improvements in train speed and comfort.	Optimization of schedules. Increase in occupancy. Rapid growth in track length. Decrease in travel cost and time.
Transition age (1930–1970)	Increase in final energy use during WWII, followed by an abrupt decline. Significant decrease in useful and final energy intensity.	Transition to diesel-electric and electric trains. Improvements in aerodynamics and lighter locomotives per unit of power.	Oil rationing and significant use of steam trains during WWII. Interruption in track expansion. Increased competition from road vehicles.
Diesel-electric age (1970–2020)	Dual use of diesel and electric trains. Lowest energy and carbon intensities in history.	Advancements in primary-to-useful efficiency in diesel and electric trains. Growing adoption of renewables in electricity generation.	Economic impact of USSR dissolution. Electric trains emitting less CO_2 per unit of useful energy compared to steam and diesel trains. Increasing efforts for decarbonization.

Autoregressive models are often used for time series forecasting. These models use the N previous values of the outcome variable, referred to as lag variables, as features. This approach is effective in capturing time patterns and producing accurate predictions. However, autoregressive models are dependent on many consecutive observations, and this can be problematic when working with a limited dataset. In this particular case, many observations from the 19th century and the early 20th century are either isolated or spaced over long intervals, rendering them unusable. Furthermore, autoregressive models rely on the assumption that the behavior of the phenomenon being studied is consistent across both known and forecasted values. For the present study, consecutive observations mainly come from after 1971, a period in which the behavior of coal consumption changed significantly. For these reasons, autoregressive models are not appropriate for this problem. If more data are found, forecasting methods might be an opportunity to generate more accurate estimations.

One of the limitations of this work is assuming the primary-to-final efficiency of oil products to be constant at 100%. This value was used to be consistent with Pinto et al. [8], since we utilized their estimations of primary-to-final efficiency of electricity production. Moreover, estimating the evolution of the world's primary-to-final efficiency since 1900 is out of the scope of this work. Brockway et al. [47] estimated the evolution of the average world energy return on investment (EROI) of final oil products between 1995 and 2011, however, for the early 20th century very little data is available. Their suggested values would result in primary-to-final efficiencies of around 87%–88%, which would only influence the diesel directly used as fuel and the oil used in electricity production, particularly around the 1950s. However, overall trends should remain largely unaffected. Future work could be to explore the primary-to-final efficiency of oil products to enhance the accuracy of our estimations.

The final-to-useful efficiencies are another source of uncertainty. These efficiencies were estimated under the assumption that technology is homogeneous across different countries in the same year. This assumption is reasonable, as trains are produced by very few companies that export to the rest of the world. Nevertheless, some countries might exhibit an efficiency lag, operating with outdated technology. As there is no information available on it, it was not possible to consider this technology lag in this study. Furthermore, our final-to-useful efficiencies were determined with expert-based knowledge, therefore it is not possible to provide a precise estimate of uncertainty.

Regarding CO_2 emissions, the emission factors listed in Table 4 assume that coal burned in locomotives is exclusively sub-bituminous coal, although other types of coal were used. The emission factors of the different types of coal range from 94,600–101,000 kg CO_2/TJ [42]. We assumed the emission factor of sub-bituminous coal is equal to 96,100 kg CO_2/TJ, so we expect a maximum upper and lower bias in emission factors of 0.5% and 1.5%. As for diesel, other types of oil, such as fuel oil, were used in smaller amounts, adding uncertainty. In addition, emissions associated with the extraction, transport, and refining of fossil fuels were not accounted for as there is little data available, leading to an expected underestimation of CO_2 emissions. In 2000, upstream emissions in Western Europe were responsible for 12.4% and 13.3% of the emissions associated with coal and diesel burning, respectively [48].

5. Conclusion

This work produced a long-run dataset (1840–2020) of energy use for rail transport that embraces primary, final, and useful stages, including energy service, CO_2 emissions, length of track, and their interconnections. The main conclusions achieved from this work are:

1. Final energy and carbon intensities decreased 100-fold from 1840 to 2010, while final-to-useful efficiency increased 30-fold;
2. The highest level of final energy use in rail transport was recorded in the 1940s, reaching 10,536 PJ, while useful energy use continues to grow;
3. Currently, the carbon intensity of useful energy in electric trains is 16% lower than that of diesel trains. This marks a significant change from 1910, when it was five times higher;
4. There are three distinct periods in the overall progression of the world's final energy use in rail transport: the Steam Age (1840–1930), characterized by coal as the primary energy source with an annual increase in final energy use of 8%; the Transition Age (1930–1970), marked by the peak and subsequent rapid decline of coal usage in the 1940s; and the Diesel-Electric Age (1970–2020), during which diesel and electricity became the dominant energy carriers, with an annual 2% decrease in final energy use.

This work also shows that machine learning is an opportunity to fill gaps in available datasets, reveal hidden patterns in data, and improve the validation step in historical studies by estimating confidence intervals. Future work in this area should consider using a machine learning approach to similar problems and explore other algorithms apart from the random forest regressor. Moreover, the dataset produced from this work allows researchers from several fields to further investigate the role of railways in economic development and strategies to achieve clean mobility.

Insights gained from this study provide valuable knowledge and understanding of transitions in rail transport. Are we on the right track? Regarding technology, yes. Carbon and final energy intensities of railways reached their lowest levels in history. However, when looking at overall transport demand, not necessarily. While railways experienced great technology improvements and have been expanding their transportation services, their overall share in the transportation demand has been declining, giving way to CO_2 intensive transport modes such as cars, trucks, and airplanes.

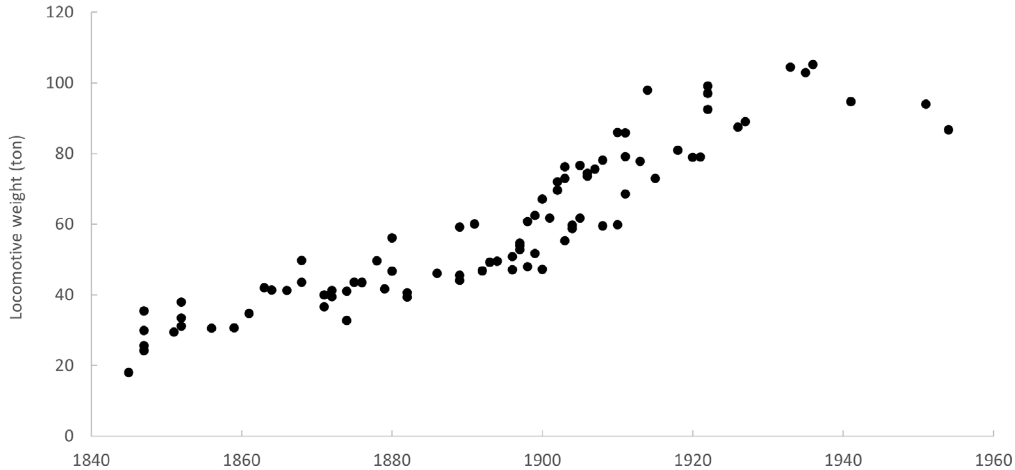

Fig. A.1. Average weight (in tons) of several steam locomotives.
Source: Adapted from Hayward [49].

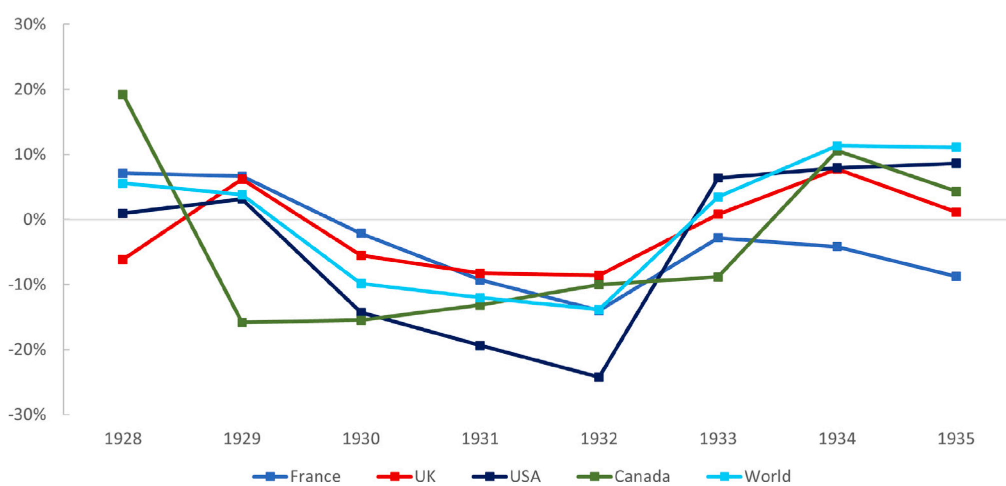

Fig. A.2. Growth rate of freight service for selected countries during the Great Depression.

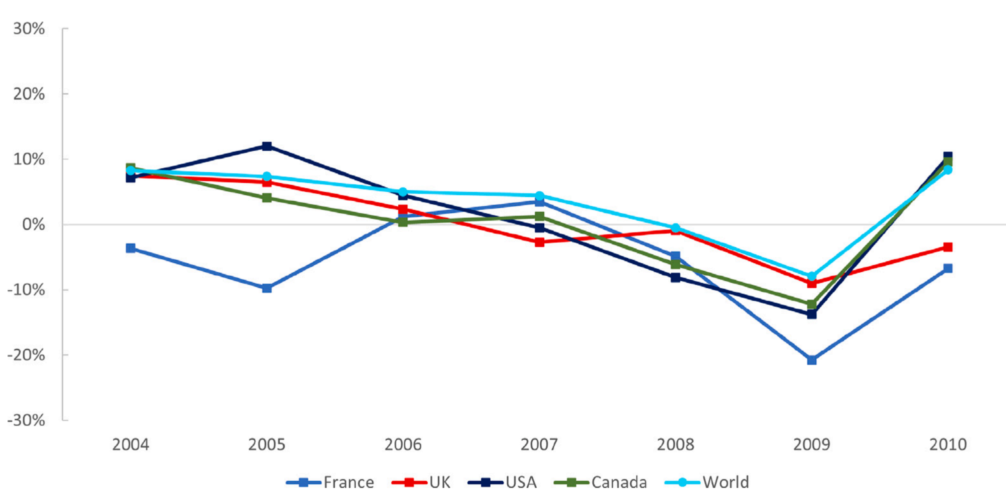

Fig. A.3. Growth rate of freight service for selected countries during the Global Financial Crisis.

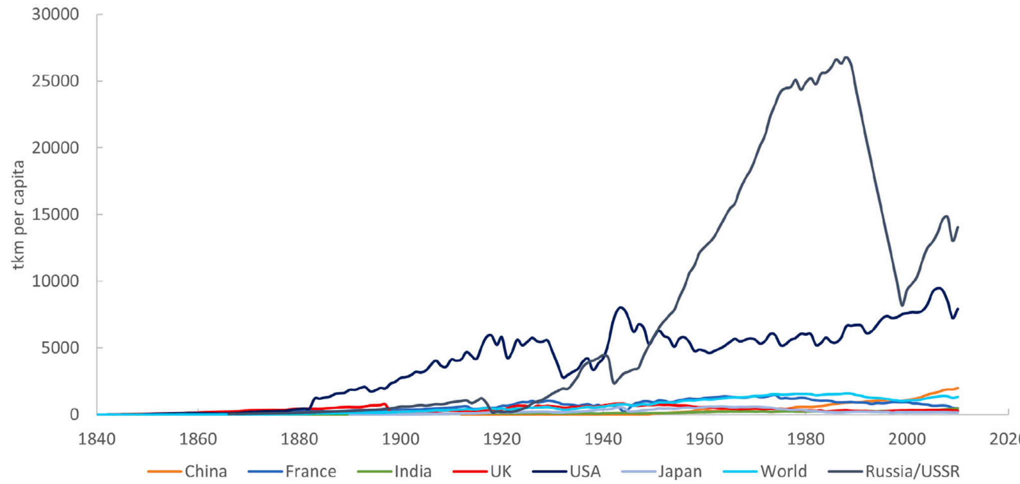

Fig. A.4. Freight service per capita for selected counties and the world.

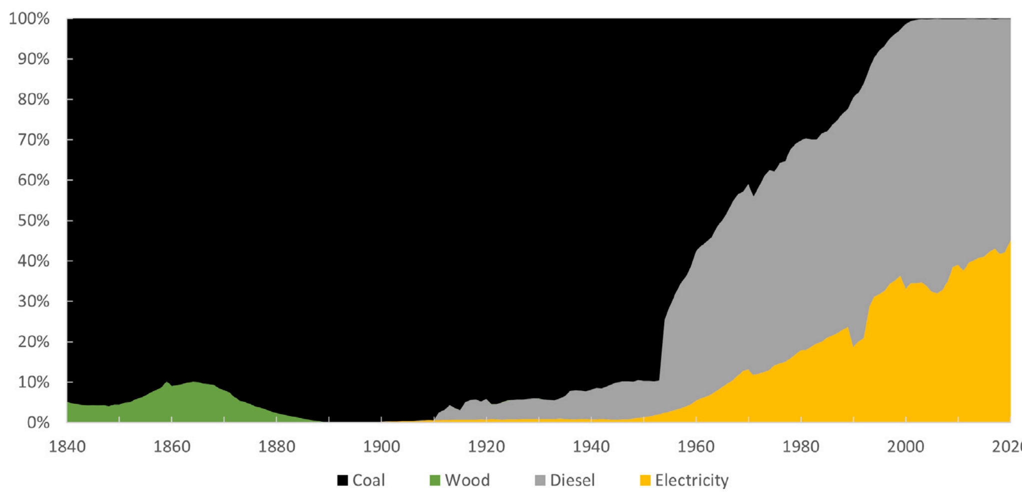

Fig. A.5. Fraction of the different final energy carriers used to move locomotives.

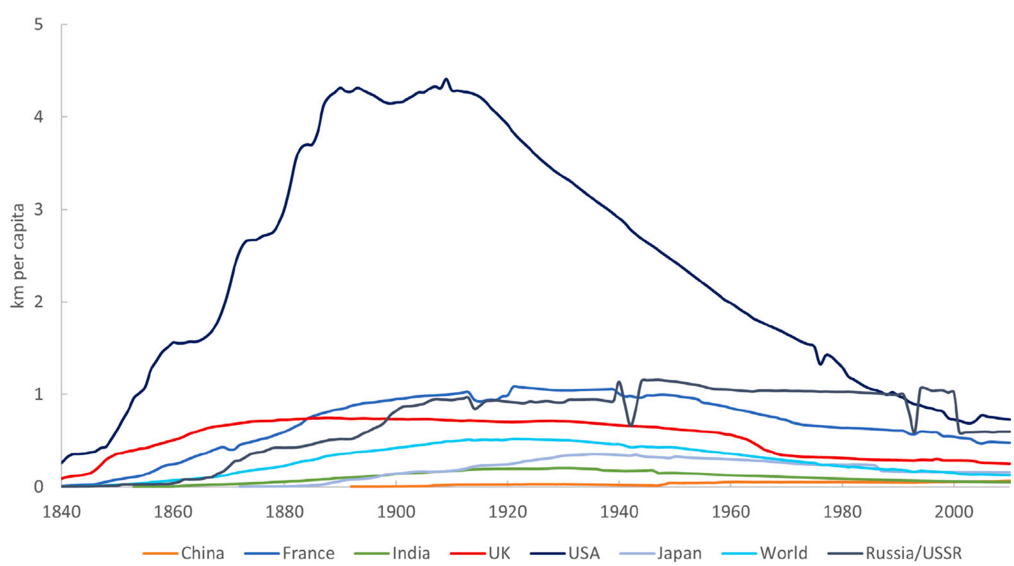

Fig. A.6. Length of track per capita for selected counties and the world.

CRediT authorship contribution statement

Bernardo Tostes: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sofia T. Henriques:** Conceptualization, Formal analysis, Methodology, Supervision, Validation, Writing – review & editing. **Paul E. Brockway:** Conceptualization, Formal analysis, Methodology, Supervision, Validation, Writing – review & editing. **Matthew Kuperus Heun:** Conceptualization, Formal analysis, Methodology, Supervision, Validation, Writing – review & editing. **Tiago Domingos:** Conceptualization, Formal analysis, Methodology, Supervision, Writing – review & editing. **Tânia Sousa:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Conceptualization, Formal analysis, Funding acquisition, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Supplementary Information II contains the data used to build the graphs displayed in this paper. More detailed data will be made available on request.

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Appendix A. Auxiliary graphs

See Figs. A.1–A.6.

Appendix B. Supplementary data

The supplementary information of this paper is divided into two documents: a pdf document entitled “Supplementary Information I” with a description of the expert-based knowledge method for estimating final energy and an Excel file entitled “Supplementary Information II” with the data used to build the graphs shown in this paper.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123344.

References

[1] IEA. World energy outlook 2022. IEA/OECD; 2022.
[2] Serrenho AC, Warr B, Sousa T, Ayres RU, Domingos T. Structure and dynamics of useful work along the agriculture-industry-services transition: Portugal from 1856 to 2009. Struct Change Econ Dyn 2016;36:1–21. http://dx.doi.org/10.1016/j.strueco.2015.10.004.
[3] Gilbert R, Perl A. Transport revolutions: moving people and freight without oil. 2nd ed.. Earthscan; 2010.
[4] Mitchell BR. International historical statistics: Europe, 1750-2010. 7th ed.. Basingstoke: Palgrave Macmillan; 2013.
[5] Mitchell BR. International historical statistics: The Americas, 1750-2010. 7th ed.. Basingstoke: Palgrave Macmillan; 2013.
[6] Bond TC, Bhardwaj E, Dong R, Jogani R, Jung S, Roden C, Streets DG, Trautmann NM. Historical emissions of black and organic carbon aerosol from energy-related combustion, 1850–2000. Glob Biogeochem Cycles 2007;21. http://dx.doi.org/10.1029/2006GB002840.
[7] Stercke SD. Dynamics of energy systems: a useful perspective (IIASA interim report No. IR-14-013). Laxenburg, Austria: International Institute for Applied Systems Analysis (IIASA); 2014.
[8] Pinto R, Henriques ST, Brockway PE, Heun MK, Sousa T. The rise and stall of world electricity efficiency:1900–2017, results and insights for the renewables transition. Energy 2023;269:126775. http://dx.doi.org/10.1016/j.energy.2023.126775.
[9] Dudek G. Short-term load forecasting using random forests. Adv Intell Syst Comput 2015;323:821–8. http://dx.doi.org/10.1007/978-3-319-11310-4_71.
[10] Wu H, Cai Y, Wu Y, Zhong R, Li Q, Zheng J, Lin D, Li Y. Time series analysis of weekly influenza-like illness rate using a one-year period of factors in random forest regression. BioSci Trends 2017;11:292–6. http://dx.doi.org/10.5582/bst.2017.01035.
[11] Herrera GP, Constantino M, Tabak BM, Pistori H, Su JJ, Naranpanawa A. Long-term forecast of energy commodities price using machine learning. Energy 2019;179:214–21. http://dx.doi.org/10.1016/j.energy.2019.04.077.
[12] Mitchell BR. International historical statistics: Africa, Asia, and Oceania, 1750-2010. 7th ed.. Basingstoke: Palgrave Macmillan; 2013.
[13] Fouquet R. Heat, power and light: Revolutions in energy services. Cornwall: Edward Elgar Publishing; 2008, p. 162–8. http://dx.doi.org/10.4337/9781782542520.
[14] Fishlow A. Productivity and technological change in the railroad sector, 1840–1910. In: Output, employment, and productivity in the United States after 1800. NBER; 1966, p. 583–646.
[15] Fink-Jensen J. Total population. 2015, http://hdl.handle.net/10622/SNETZV.
[16] Department of Economic and Social Affairs, Population Division United Nations. World population prospects. 2022, https://population.un.org/wpp/Download/Standard/Population/.
[17] United States Bureau of the Census. Transportation. In: Historical statistics of the United States, colonial times to 1970. bicentennial ed.. Washington, D. C.: United States Government Printing Office; 1975, p. 723–41.
[18] Direction des routes, de la navigation e des mines Ministére des travaux publics. Statistique de l'industrie minerale et des appareils à vapeur en France et en Algérie.
[19] Institut national de la statistique et des Études Économiques. Ánnuaire statistique de la France.
[20] Wright T. Coal mining in China's economy and society. New York: Cambridge University Press; 1984.
[21] Statistisches jahrbuch für das deutsche reich, https://www.digizeitschriften.de/id/514401303_1941|log1.
[22] Statistisches jahrbuch für die bundesrepublik deutschland, https://www.statistischebibliothek.de/mir/receive/DESerie_mods_00006972.
[23] Ayres RU, Ayres LW, Warr B. Exergy, power and work in the US economy, 1900 – 1998. Energy 2003;28:219–73. http://dx.doi.org/10.1016/S0360-5442(02)00089-0.
[24] Lomonossoff GV. Diesel traction. Proc Inst Mech Eng 1933;125:537–613. http://dx.doi.org/10.1243/PIME_PROC_1933_125_024_02.
[25] Sinton J, Fridley D, Levine M. China energy databook. Berkeley, CA: Lawrence Berkeley National Laboratory (LBNL); 1996, http://dx.doi.org/10.2172/236277.
[26] Masini RP, Medeiros MC, Mendes EF. Machine learning advances for time series forecasting. J Econ Surv 2021. http://dx.doi.org/10.1111/joes.12429, Blackwell Publishing Ltd.
[27] Hastie T, Tibshirani R, Friedman J. The elements of statistical learning. 2nd ed.. New York, NY: Springer New York; 2009, http://dx.doi.org/10.1007/b94608.
[28] Etemad B, Luciani J, Bairoch P, Toutain J-C. World energy production 1800-1985. Geneva: DROZ; 1991.
[29] Department of Economic Affairs. World energy supplies in selected years, 1929–1950, statistical paper, series j, number 1. 1952, https://unstats.un.org/unsd/energy/yearbook/Series_J_No_1.World_Energy_Supplies-1929-1950.pdf.
[30] Oliveira M, Torgo L, Costa VS. Evaluation procedures for forecasting with spatiotemporal data. Mathematics 2021;9:691. http://dx.doi.org/10.3390/math9060691.

[31] Coulston JW, Blinn CE, Thomas VA, Wynne RH. Approximating prediction uncertainty for random forest regression models. Photogramm Eng Remote Sens 2016;82:189–97. http://dx.doi.org/10.14358/PERS.82.3.189.

[32] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J, Passos A, Cournapeau D, Brucher M, Perrot M, Duchesnay E. Scikit-learn: Machine learning in Python. J Mach Learn Res 2011;12:2825–30.

[33] Sousa T, Brockway PE, Cullen JM, Henriques ST, Miller J, Serrenho AC, Domingos T. The need for robust, consistent methods in societal exergy accounting. Ecol Econom 2017;141:11–21. http://dx.doi.org/10.1016/j.ecolecon.2017.05.020.

[34] Iden ME. U.S. freight rail fuel efficiency: 1920–2015 review and discussion of future trends. In: 2019 joint rail conference. Snowbird, Utah, USA: American Society of Mechanical Engineers; 2019, http://dx.doi.org/10.1115/JRC2019-1296.

[35] Hay WW. Railway engineering. In: Meyers RA, editor. Encyclopedia of physical science and technology. 3rd ed.. New York: Academic Press; 2003, p. 807–44. http://dx.doi.org/10.1016/B0-12-227410-5/00650-5.

[36] Marshall Z, Heun MK, Brockway PE, Aramendia E, Steenwyk P, Relph T, Widjanarko M, Kim J, Sainju A, Franzius JI. A Multi-Regional Primary-Final-Useful (MR-PFU) energy and exergy database v1.2, 1960-2020. University of Leeds. [Dataset]. 2024, http://dx.doi.org/10.5518/1199.

[37] Ayres RU, Ayres LW, Pokrovsky V. On the efficiency of US electricity usage since 1900. Energy 2005;30:1092–145. http://dx.doi.org/10.1016/j.energy.2004.07.012.

[38] Andersson E, Carlsson U, Lukaszewicz P, Leth S. On the environmental performance of a high-speed train. Int J Rail Transp 2014;2:59–66. http://dx.doi.org/10.1080/23248378.2013.878296.

[39] Hoffrichter A, Miller AR, Hillmansen S, Roberts C. Well-to-wheel analysis for electric, diesel and hydrogen traction for railways. Transp Res D 2012;17:28–34. http://dx.doi.org/10.1016/j.trd.2011.09.002.

[40] Liu W, Lin B. Electrification of rails in China: Its impact on energy conservation and emission reduction. Energy 2021;226. http://dx.doi.org/10.1016/j.energy.2021.120363.

[41] Office of Rail and Road. Rail emissions. 2022, https://dataportal.orr.gov.uk/statistics/infrastructure-and-emissions/rail-emissions/.

[42] IPCC. IPCC guidelines for national greenhouse gas inventories. Tech. rep., 2006, URL https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol2.html.

[43] Bolt J, van Zanden JL. The Maddison Project: collaborative research on historical national accounts. Econ Hist Rev 2014. http://dx.doi.org/10.1111/1468-0289.12032.

[44] Aldag R. Steam vs. diesel locomotives. Railr Hist 1992;(167):148–57, URL http://www.jstor.org/stable/43521604.

[45] of Public Roads B. Highway statistics. Washington: United States Government Printing Office; 1947.

[46] Baker C, Johnson T, Flynn D, Hemida H, Quinn A, Soper D, Sterling M. Chapter 1 - Historical context. In: Baker C, Johnson T, Flynn D, Hemida H, Quinn A, Soper D, Sterling M, editors. Train aerodynamics. Butterworth-Heinemann; 2019, p. 3–15. http://dx.doi.org/10.1016/B978-0-12-813310-1.00001-0.

[47] Brockway PE, Owen A, Brand-Correa LI, Hardt L. Estimation of global final-stage energy-return-on-investment for fossil fuels with comparison to renewable energy sources. Nat Energy 2019;4(7):612–21. http://dx.doi.org/10.1038/s41560-019-0425-z.

[48] Dones R, Heck T, Hirschberg S. Greenhouse gas emissions from energy systems, comparison and overview. 2004.

[49] Hayward ACG. Train loads on bridges 1825 to 2010. Int J Hist Eng Technol 2011;81(2):159–91. http://dx.doi.org/10.1179/175812111x13033852943273.