Potential Profitability of a European High-Speed Rail Network

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SHORT SUMMARY

Despite being a long-standing European ambition and an important step to achieving climate goals, there is still no European High-Speed Rail (HSR) network. To gain insights into a profitable network design, this study develops a new formulation for the "Transport Network Design & Frequency Setting Problem" (TNDFSP), as current literature lacks one that can optimally solve the problem for instances of this size while also accounting for demand elasticity. The optimal solution is largely insensitive to fare changes and outperforms the current state-of-the-art in several aspects. Our model considers the 111 most populous European cities, along with all their origin-destination (OD) pairs, and finds the most profitable network design within a reasonable solution time frame. The results show HSR can be very profitable in Europe, but only when concentrated around a selected group of the largest cities in the western part of the continent.

Keywords: High-speed rail, Network design, Frequency setting, Optimisation, Demand forecasting, Profitability.

1. INTRODUCTION

In Europe, the long-distance travel market (>700 km) has been dominated by planes, as it is often considered the only practical option. The market showed continuous exponential growth in air passenger numbers of 6.0% yearly on average (Eurostat, 2019) and is projected to double in passenger numbers by 2040 (Timperley, 2020), tripling its contribution to climate change between 2020 and 2050 (ICAO, 2019). This is incompatible with the active Climate Agreements (Gössling & Humpe, 2020), and therefore, the European Union is forced to look for greener travel alternatives, the most promising candidate being High-Speed Rail (HSR).

High-speed trains emit on average seven times less CO2 per passenger-km (Strauss et al., 2021), when compared to air or road alternatives. With commercial speeds reaching up to 350 km/h, relatively low waiting times and the ability to directly connect city centres (Martín et al., 2014), they have a competitive advantage for travel times up to four hours (UIC, 2018). Japan was the first country to develop HSR with the introduction of the Shinkansen in 1964. In recent decades, fuelled by HSR-backing governmental policy and subsidies, China has built a network comprising more than two-thirds of the global rail length (Chen, 2020), proving very successful by serving 2.4 million passengers in 2019 (Zhang, 2024), and decimating local airplane's market share (Bradsher, 2013). Following this example, it comes as no surprise that the EU has been pushing governments to develop international high-speed rail connections.

Even though Europe has an extensive conventional rail network, it was developed with national focus, complicating interoperability and efficiency when travelling internationally. Despite HSR-backing policy acting since the 1990s and investments of €23.7 billion into HSR development, the total transport-related greenhouse gas emissions have only increased since then (EEA, 2023). It can be concluded that the EU is not on track to meet its climate goals. As of today, still no European network exists (European Court of Auditors, 2018). 3.

As pointed out by Grolle et al. (2024), no HSR network design methods are currently available – a crucial literature gap. The great complexity of the "Transport Network Design & Frequency Setting Problem" (TNDFSP), primarily caused by demand elasticity, has led to the problem being primarily solved by (meta)heuristic algorithms, providing a good but not optimal solution. Due to the complexity of the problem, many assumptions and simplifications are made, putting the value of the found solutions under scrutiny. Prominent examples of these are the usage of fixed demand (despite its elastic nature) and network simplification (Cascetta & Coppola, 2012). Current literature lacks one that can optimally solve the problem for instances of this size while also accounting for demand elasticity.

To address the problems mentioned above, this study aims to develop a model that can assess European HSR profitability through mathematical optimisation, finding the optimal configuration of connections, lines and their frequencies. Therefore, the goal is to answer the main research question of which European cities must be connected via High-Speed Rail, and how should these connections be served to lead to an (optimally) profitable network. The methodological framework required to answer this question consists of three parts: new and comprehensive demand forecasting, profitability estimation and a new network design model.

2. METHODOLOGY

The methodological approach builds demand forecasting, profitability analysis, and network design modelling, as introduced in the subsequent sections.

Demand forecasting

The model must incorporate factors. As the most established and used method in practice, a logit model is used to forecast HSR demand. A direct consequence of this choice is that the HSR demand has to be estimated via its market share, by multiplying a total demand flow with the HSR market share (Sánchez-Borràs et al., 2010). Table 1introduce parameters used for the demand

Table 1: Nomenclature of Demand Forecasting Model

Parameter	Unit	Definition
$D_{AIR,ij}$	[pax]	air demand for city pair ij
$V_{k,ij}$	[-]	observed utility of alternative k for city pair ij
$z_{k,ij}$	[-]	presence of alternative k for city pair ij
β^{TT}	[util/h]	MNL coefficient for travel time
β^{TC}	[util/€]	MNL coefficient for travel cost
$TT_{k,ij}$	[h]	travel time of alternative k for city pair ij
$TC_{k,ij}$	[€]	travel cost of alternative k for city pair ij
k	[-]	intercept gravity coefficient
α	[-]	gravity coefficient for population
β	[-]	gravity coefficient for GDP
γ	[-]	gravity coefficient for distance
P_i	[pax]	population of city i
GDP_i	[€]	GDP of city i
d_{ij}	[km]	distance between city pair ij

This allows to formulate the air demand per city pair – which is key input for the HSR network design model – as follows:

$$D_{AIR,ij} = \frac{\exp{(V_{plane,ij})}}{\sum_{k\in\boldsymbol{K}} z_{k,ij} \cdot \exp{(V_{k,ij})}} \cdot k \cdot \frac{\left(P_i \cdot P_j\right)^{\alpha} \cdot \left(GDP_i \cdot GDP_j\right)^{\beta}}{\left(d_{ij}\right)^{\gamma}} \quad (1)$$

where

$$V_{k,ij} = \beta^{TT} \cdot TT_{k,ij} + \beta^{TC} \cdot TC_{k,ij}. \quad (2)$$

Profitability estimation

To estimate the profitability of a potential HSR line, the central monetary flows are defined in the following paragraphs using the nomenclature in Table 2.

Table 2: Nomenclature of Profitability Estimation Model

Parameter	Unit	Definition
$C_{ij}^{X,infra}$	[€]	infrastructure construction costs between city i and j
$C_{ij}^{X,train}$	[€]	rolling stock acquisition costs between city i and j
$C_{ij}^{T,infra}$	[€/year]	infrastructure operation & maintenance costs between city i and j
$C_{ij}^{T,train}$	[€/year]	rolling stock operation & maintenance costs between city i and j
$k^{X,infra}$	[€/km]	unit infrastructure construction cost
$k^{X,train}$	[€/train]	unit rolling stock acquisition cost
$k^{T,infra}$	[€/km/year]	unit infrastructure operation & maintenance cost
$k^{T,train}$	[€/seat-km]	unit rolling stock operation & maintenance cost
s	[pax]	seats per train set
H	[h/day]	operating hours per day
D	[day/year]	operating days per year
v^{max}	[km/h]	maximum operating speed
T^{life}	[year]	project lifetime
l_{ij}	[km]	distance between city i and j
t_{ij}	[h]	travel time between city i and j
n_{ij}	[-]	trains to serve demand between city i and j

Ticket revenue: The revenue depends on the outcome of the product of the ticket fare and demand. The fare setting is a design choice. Operators generally set a price that maximises their passenger revenue (Qin et al., 2019). This study will follow the same approach, aided by Python library SciPy. It can be mathematically proven that optimising for maximum revenue will always yield exactly one, nonnegative, optimal fare setting.

Construction costs: It was determined that the total costs depend on the line length, and a unit cost for each km $k_{ij}^{X,infra}$. This unit cost depends on the location and difference in height. Borgogno (2023) quantifies these relationships and produces unit construction cost per km, for surface ($C^{surface}$) and tunnelling (C^{tunnel}) separately for European countries. It is assumed that $k_{ij}^{X,infra}$ is a result of a convex combination of $C^{surface}$ and C^{tunnel}, dependent on a normalised height difference. Thus, the maximum possible height difference between two cities in Europe is set to 1 and the minimum is set to 0, with linear interpolation in between. The formula calculating the total infrastructure construction cost is displayed as:

$$C_{ij}^{X,infra} = k_{ij}^{X,infra} \cdot l_{ij} \qquad (3)$$

Acquisition costs: As mentioned, these depend solely on the number of train sets bought and a unit price. The minimum number of trains needed to operate a line is product of the frequency and the full round-trip time:

$$C_{ij}^{X,train} = k^{X,train} \cdot \lceil 2 \cdot f_{ij} \cdot t_{ij} \rceil \tag{4}$$

Infrastructure maintenance & operation costs: As stated, these are calculated based on yearly sum per km $k^{T,infra}$.

$$C_{ij}^{T,infra} = k^{T,infra} \cdot l_{ij} \tag{5}$$

Rolling stock maintenance & operation costs: These are calculated based on a value per seat-km $k^{T,train}$, and has to be multiplied with a number of factors in order to acquire the total yearly costs:

$$C_{ij}^{T,train} = k^{T,train} \cdot s \cdot H \cdot D \cdot \frac{n_{ij} \cdot l_{ij}}{t_{ij}} \tag{6}$$

Network design model

We formulate the HSR Transport Network Design & Frequency Setting Problem as a mixed integer program that generalises the Network Design & Frequency Setting Problem (TNDFSP). The TNDFSP extends the Multi-Commodity Flow Problem (MCFP), which is often used as an efficient formulation to handle city-scale transit networks (Ng et al., 2024). The objective function of the formulation maximises the profit of the network according to Equation (7).

$$\begin{aligned} &\sum_{r\in \boldsymbol{R}} (x_r \cdot f_r^{rev}) \\ &- \sum_{a\in \boldsymbol{A}} (y_a \cdot f_a^{cost}) \\ &- \left[k^X \cdot \sum_{r\in \boldsymbol{R}} \left(n_r^{train}\right)\right] - \left[T^{life} \cdot k^T \cdot s \cdot H \cdot D \cdot \sum_{r\in \boldsymbol{R}} \left(\frac{n_r^{train} \cdot d_r}{t_r}\right)\right] \\ &- \left[T^{life} \cdot k^{transfer} \cdot \sum_{p\in \boldsymbol{P}} \left[\left(u_p - v_p\right) \cdot \sum_{r\in \boldsymbol{R}} \left(c_{pr}^{ODpair} \cdot q_r^{year}\right)\right]\right] \end{aligned} \tag{7}$$

Here, x_r models the decision of whether OD flow route $r \in \boldsymbol{R}$ is selected, with f_r^{rev} as lifetime revenue for OD flow route. y_a models the decision of whether arc $a \in \boldsymbol{A}$ is selected, with f_a^{cost} as lifetime cost for the arc. Next to these costs, the acquisition costs (based on Equation (4)) and the rolling stock maintenance and operation costs (based on Equation (6)) are deducted. Furthermore, the lifetime (T^{life}) transfer costs are subtracted for each $p \in \boldsymbol{P}$ of OD pairs that require a transfer, where $k^{transfer}$ is the respective transfer penalty.

3. RESULTS AND DISCUSSION

The data set by Florczyk et al. (2019) provides data on 160 metrics for 13,135 urban centres (hereafter referred to as cities). After pre-processing, it was found that 726 cities, originating from 35 countries, comply with all scope requirements. Together, they form the set of potential nodes N, sharing 263,175 possible connections among them. These 726 cities encompass a wide range of values in all characteristics. With all settlements of population over 50,000 represented, there is confidence that the set encompasses all potential HSR stations. The required data was successfully gathered regarding all cities. Optimising for a network of 111 cities (effectively: 109, as explained earlier), 589 arcs, 2,269 OD pairs and 77,067 routes resulted in construction of a model with 243,671 integer decision variables (of which 89,537 are binary) and 1,035,732 constraints. The optimal solution was found after a little under six hours, an optimal lifetime profitability of €222.8 bn was reported.

The optimal configuration consists out of 15 cities, connected by 15 arcs and is displayed in Figure 1. The yellow dots not connected by lines, are cities that the model considered, but did not add to the network. Most of the arcs will be newly built, as only two are currently in high-speed operation: Brussels-Paris (average speed: 229 km/h) and London-Paris (200 km/h). Another remarkable finding is that for a maximally profitable network, not all individual arcs have to be profitable on their own: 5 out of 15 arcs are not, which are all situated at an end point of the network. Table 3 shows the profitability for each selected arc, only considering ticket revenue and infrastructural costs, as rolling stock-related costs depend on the design of lines, which will be addressed in the next section.

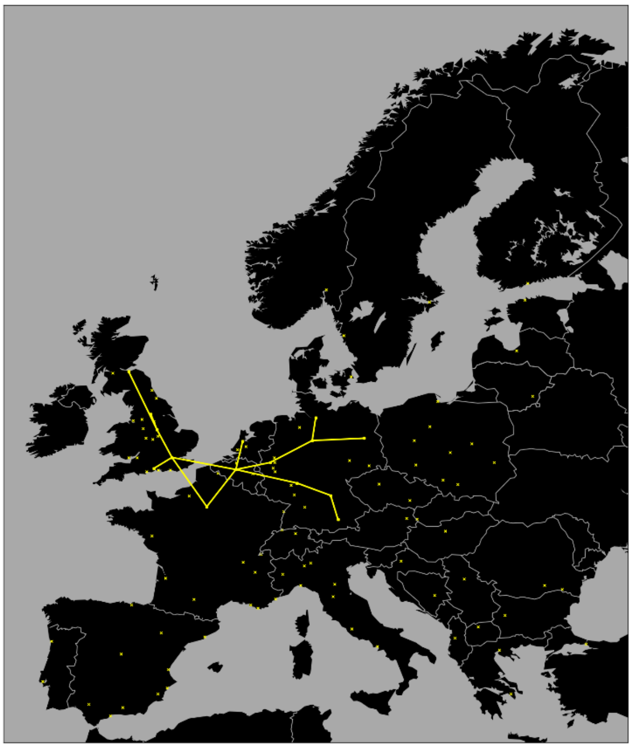

Figure 1: Optimal Network Topology

Table 3: Profitability of Connections

Connection name	**Length [km]**	**Flow [pax/ day]**	**Reve-nue [B€]**	**Costs [B€]**	**Profit [B€]**
Brussels-London	364	131,680	199.943	17.513	182.430
London-Paris	464	42,105	106.965	13.023	93.941
Brussels-Dusseldorf	201	67,474	54.182	9.890	44.292
Amsterdam-Brussels	211	56,345	45.245	9.563	35.683
Brussels-Paris	317	45,726	40.057	6.934	33.122
Brussels-Frankfurt	397	46,779	46.443	21.436	25.007
London-Nottingham	206	42,771	33.721	12.233	21.488
Dusseldorf-Hanover	280	33,654	26.042	17.371	8.671
London-Southampton	123	13,021	9.125	7.323	1.803
Edinburgh-Nottingham	449	17,155	26.800	26.017	0.783
Leeds-Nottingham	120	11,931	7.490	7.646	-0.155
Frankfurt -Nuremberg	223	22,566	16.473	18.474	-2.000
Munich-Nuremberg	172	16,618	12.131	14.557	-2.426
Berlin-Hanover	290	20,093	14.375	17.865	-3.490
Hamburg-Hanover	152	8,249	5.420	9.840	-4.420
TOTAL	3,969	576,167	644,413	209,685	434,728

The line design ensures direct connections for 52 out of 60 (87%) of OD pairs and 95% of passengers. All OD pairs are served with at most one transfer. Brussels can be considered a main hub, being associated with nine out of eleven lines, while having a direct connection with all but one of the other cities. Serving 95% of passengers directly, the inclusion of transfer penalties resulted in a well-balanced line design, which appears to “care” about the number of transfers passengers make, but does not overdo it in the sense that every OD pair is served by a separate line. Together, the lines serve all arcs, most often with the minimum required frequency. Figure 2 shows the optimal line map.

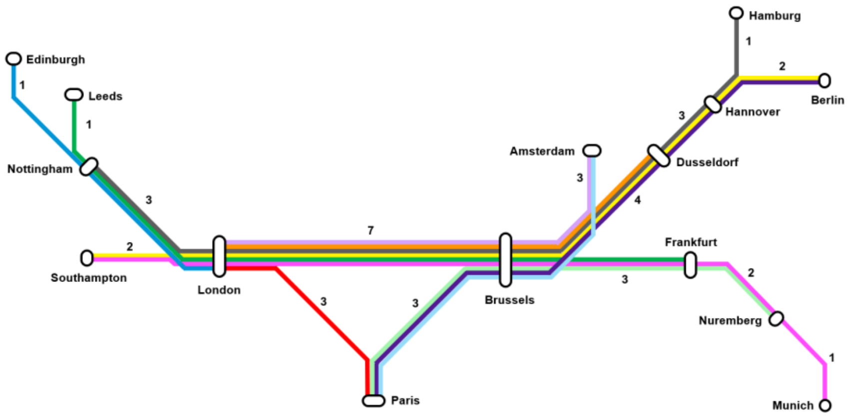

Figure 3: Line Design Map (the numbers denote the joint frequency per arc)

4. CONCLUSIONS

This study addresses the limitations in demand forecasting, profitability estimation, and network design for high-speed rail (HSR) in Europe, contributing new insights into the Transport Network Design Problem (TNDP) under elastic demand. The presented network design model performs strongly, efficiently solving for larger networks while taking demand elasticity into account.

However, the model's reliance on 'smart restrictions' to reduce the number of OD flow routes and the inherent assumptions about fare sensitivity reveal areas where further work, particularly online design robustness, could enhance its applicability to real-world scenarios. Similarly to the profitability estimation model, the network design model's focus on profitability leaves untouched potential for considering non-monetary benefits such as sustainability gains.

While the demand forecasting model used was functional, its simplifications—such as the exclusion of certain travel modes (e.g. bus) and impact factors—indicate room for further accuracy improvements, particularly through incorporating mixed logit or dynamic gravity models. The inability to fully capture inter-modal competition limits the precision of the demand forecasts, primarily when working with trips with a touristic character, but these were not the primary focus of the research.

The profitability estimation model, though simplified, provides reasonable insights into HSR viability under current assumptions. However, it overlooks critical factors such as fare competition and inflation, which could significantly change the results over a 40-year project span. Additional research could explore greener policies for optimising HSR demand, looking beyond only the maximisation of revenue.

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